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Individual Differences in Lapses of Attention: A Latent Variable Analysis

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Individual differences in lapses of attention were examined in the present study. Participants performed various attention control, working memory, and reaction time (RT) tasks to assess lapses of attention. Task-unrelated thoughts, task-specific motivation, alertness, and trait factors were also assessed. Behavioral indicators of lapses of attention correlated and loaded on the same general lapse of attention factor. The lapse of attention factor correlated with, but was distinct from, attention control and task-unrelated thoughts factors. The lapses of attention factor further related to working memory capacity, speed of processing, motivation, alertness, boredom proneness, and self-reports of everyday cognitive failures. Structural equation modeling suggested that attention control, task-unrelated thoughts, variance shared across task unrelated thoughts, motivation, and alertness, and boredom proneness all accounted for unique variance in lapses of attention. These results provide important evidence for the general tendency to experience lapses of attention in a variety of tasks and situations and further suggest that multiple factors contribute to variation in lapses of attention.

Keywords: lapses of attention, task-unrelated thoughts, attention control, individual differences

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The ability to sustain attention on an important task is a central characteristic of our attentional system. The attentional system allows us to perform both essential as well as routine tasks. Although this system typically performs very efficiently, sometimes we experience lapses of attention. These include, for example, forgetting to attach a document to an e-mail, being distracted by people talking, daydreaming about an upcoming vacation, or even forgetting to put the landing gear down before landing a plane. These attentional failures reflect temporary shifts of attention away from the task at hand to either external stimuli (distractions) or to internal thoughts and ruminations (mind-wandering/daydreaming) that can result in failures to perform an intended action. Although there may be some benefits to these lapses (e.g., attentional capture toward a threat stimulus, problem solving an unrelated task), for the most part these attention failures are seen as unwanted breakdowns of our attentional system. As such, lapses have been linked to a number of real world outcomes such as both minor and major accidents (Broadbent et al., 1982; Casner & Schooler, 2014; Edkins & Pollock, 1997; Galéra et al., 2012; Griffiths & Griffiths, 2013; Larson et al., 1997; Reason, 2016; Reason & Mycielska, 1982; Wallace & Vodanovich, 2003), professional problems (Jones & Martin, 2003; Reason, 1990), as well problems in educational settings (Brown, 1927; Lindquist & McLean, 2011; Unsworth, McMillan, et al., 2012; Unsworth & McMillan, 2017; Wammes et al., 2016). Given the prominence of attention in a range of different circumstances, it is critically important to understand for whom and under what situations lapses of attention are most likely. That is, are there stable individual differences in who is susceptible to lapses of attention, and if so, what are the factors that are associated with lapses of attention?

Lapses of Attention

Attention control processes are needed to maintain and sustain attention on task-relevant information to ensure active goal-maintenance and task appropriate behaviors. However, attention fluctuates. Sometimes attention is focused on the current task leading to high levels of task engagement and subsequent performance, and other times the intensity of attention is lessened, leading to reduced levels of task engagement and poorer subsequent performance. These fluctuations in attention can lead to relatively minor changes in task engagement (and minor shifts in performance), or these fluctuations can lead to much larger changes in task engagement (and large shifts in performance). Both minor and major fluctuations in attention can be conceptualized as lapses of attention whereby an individual briefly disengages from the current task resulting in failures or delays in performing an intended action (Cheyne, 2010; Reason & Mycielska, 1982).

Historically, lapses of attention have been examined in a number of ways. One of the most common approaches has been to examine reaction time (RT) and variability in RTs as indices of fluctuations and lapses of attention. Early work examining RTs in various tasks found a great deal of trial-to-trial variability in RTs and suggested that this variation reflected fluctuations, oscillations, or lapses in

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attention (e.g., Bills, 1931a and 1931b, 1935; Hylan, 1898; Obersteiner, 1879; Oehrn, 1895; Robinson & Bills, 1926; Spearman, 1927; Woodworth, 1938). For example, Bills (1931a, 1931b, 1935, 1943) found that in continuous work tasks occasionally very long RTs occurred and these tended to increase during the duration of the task. Bills (1931a, 1931b, 1935, 1943) called these particularly long RTs "blocks" and suggested that they reflected pauses due to increased fatigue associated with fluctuations of attention (see also Woodworth, 1938). The assumption being that on some trials participants are focused on the current task resulting in a fast RT, whereas other trials they are experiencing a block or lapse resulting in a longer RT. Thus, RT distributions reflect a mixture of focused and lapsed trials (e.g., Van Breukelen et al., 1995) as well as gradations between completely focused and completely lapsed (e.g., Sanders, 1998). Broadbent (1958) suggested that blocks were a result of shifts of attention to task-irrelevant sources. Subsequent work has further suggested that trial-to-trial variability in RTs and particularly long RTs are indicative of lapses of attention (e.g., Bertelson & Joffe, 1963; Broadbent, 1958; Cheyne et al., 2009; Coyle, 2003, 2017; De Jong et al., 1999; Dinges & Powell, 1985; Duchek et al., 2009; Esterman et al., 2012; McVay & Kane, 2012a; Kane & Engle, 2003; Jensen, 1992; Larson & Alderton, 1990; Leth-Steensen et al., 2000; Lim & Dinges, 2008; Steinborn et al., 2016; Stuss et al., 2003; Tse et al., 2010; Unsworth, 2015; Unsworth et al., 2010; Unsworth, Redick, et al., 2012; Unsworth & Robison, 2020; Van Breukelen et al., 1995; Weissman et al., 2006; West, 2001; West et al., 2002; Williams et al., 1959). For example, research on sleep deprivation has long suggested that sleep deprivation is associated with an increased susceptibility to lapses of attention resulting in an increase in particularly long RTs on simple RT tasks (Dinges & Powell, 1985; Lim & Dinges, 2008; Williams et al., 1959). Consider the psychomotor vigilance task which is a simple RT task where participants see a row of zeros and are told that when the numbers begin counting up (like a stop watch) that they must press a key as fast as possible. Critically, the numbers begin counting up anywhere from 1 s to 10 s after they appear. Thus, participants must remain focused on the stimulus and maintain a high level of preparation in order to rapidly detect the occurrence of the signal and press the corresponding key once the signal occurs. On most trials participants' RTs are relatively fast, but occasionally there are substantially longer RTs. These long RTs (RTs $\geq$500 ms) are thought to be due to lapses in attention which tend to increase with time-on-task and when sleep deprived (Dinges & Powell, 1985; Lim & Dinges, 2008; Unsworth & Robison, 2016b; Williams et al., 1959). Collectively, a great deal of prior research suggests that lapses of attention can manifest as increased RT variability and particularly long RTs. Note, that this does not mean that all RT variability or all long RTs are necessarily due to lapses of attention. Lapses of attention likely contribute to RT variability and long RTs, but RT variability and long RTs could also be due to shifts in the overall RT distribution, speed–accuracy trade-offs, and even blinks and eye movements (e.g., Johns et al., 2009). Thus, while RT measures have been used to examine lapses of attention, it is important to recognize that, like all measures, they are not process pure indicators.

Another means of examining lapses of attention is to examine reflexive responses in a variety of attention demanding tasks. In particular, when a prepotent response conflicts with a task goal, a loss of goal maintenance due to a lapse in attention should result in the prepotent response guiding behavior and an error in tasks like Stroop (e.g., Balota & Duchek, 2015; Hutchison et al., 2010; Kane & Engle, 2003) and antisaccade (Kane et al., 2001; Unsworth et al., 2004). Another example of how lapses of attention can result in reflexive responding is found in errors in the Sustained Attention to Response Task (SART; Manly et al., 1999; Robertson et al., 1997). The SART is a go/no-go continuous performance task requiring responses to all stimuli except for infrequent targets. Attention must be sustained throughout long runs of go trials in order to prevent a response on the rare no-go trials. Any lapse of attention will result in a relatively fast no-go error (e.g., Cheyne et al., 2009; Manly et al., 1999; McVay & Kane, 2009; Robertson et al., 1997). Thus, in some situations where there are strong prepotent response tendencies, lapses of attention can result in a fast overt error. Of course, just like particularly long RTs, this does not mean that all errors reflect a lapse of attention as errors in these (and other tasks) could reflect failures of response competition, speed–accuracy trade-offs, or some other cause. Reflexive responding in the SART is also indicated by extremely fast RTs on go trials (Cheyne et al., 2009; McVay & Kane, 2012a; Robertson et al., 1997; Smallwood et al., 2008; Unsworth, 2015). Here it is assumed that participants are in a state of inattention (where lapses are more likely) and are relying on habitual/mindless responding leading to a premature response. This suggests that very fast RTs (in addition to very slow RTs) can result from lapses of attention in some contexts.

Lapses of attention can also result in overall performance failures such as a failure to respond on a given trial or performance on a given trial that is far below what would normally be expected. For example, in the SART participants are usually quite accurate on go trials, but occasionally participants fail to respond on go trials resulting in an omission error. These omission errors are thought to reflect overall task disengagement due to lapses of attention whereby participants are so disengaged with the task that they fail to respond entirely (Cheyne et al., 2009; Johnson et al., 2007). A similar failure to respond is found on continuous tracking tasks in which participants are required to track an object by keeping the cursor (via mouse or joystick) on the object as it moves around the computer screen (Kam et al., 2012; Peiris et al., 2006; Poudel et al., 2014; Robison et al., 2019; Van Orden et al., 2000). For example, Peiris et al. (2006) had participants perform a continuous tracking task and examined not only overall tracking error, but also instances where participants completely stopped tracking the object (i.e., the cursor did not move) for a period of time. Peiris et al. (2006) called these failures to respond "flat spots" and suggested that they reflected lapses of attention. Thus, like omissions in the SART, flat spots reflect moments of task disengagement whereby the participant is likely no longer paying attention to the task at hand. In many ways, these two performance failures are similar to Bills's (1931b) blocks in that there is a failure to respond for some significant amount of time.

Another, slightly different performance failure are low performance trials on visual working memory tasks (Adam et al., 2015; Adam & Vogel, 2016, 2017; Adam et al., 2018; Robison & Unsworth, 2019). In these studies participants perform a whole report visual working memory task in which typically six colored squares are briefly presented. After a delay participants must recall the color of all six squares. Generally, on any trial participants can recall approximately three items (Cowan, 2001), but participants also demonstrate frequent failures where their performance is close to chance (recalling 0 or 1 items correctly). These failures of working memory have been suggested as being due to lapses of attention whereby participants are temporarily disengaged (either partially or fully) from the task leading to poor encoding and/or maintenance of the task relevant information in working memory (Adam et al., 2015; Adam & Vogel, 2016, 2017; Adam et al., 2018; Robison & Unsworth, 2019).

Overall, prior research suggests that there are multiple behavioral indicators of lapses of attention. Furthermore, there is some suggestion that these different indicators might be related to different states of task disengagement. For example, Cheyne et al. (2009) suggested that variability in RTs indexed a state of relative inattention during the SART, whereas anticipatory RTs (very fast go RTs) were associated with a deeper level of zoning out during the SART. Finally, omission errors on go trials represented an overall deeper level of task disengagement. In support of this Cheyne et al. (2009) found that these three indicators of lapses were all strongly correlated, but importantly each accounted for unique variance in no-go errors, suggesting that the states were somewhat distinct. A critical question is whether all of these various behavioral indicators of lapses of attention index the same basic construct, or whether they reflect distinct aspects of lapses of attention. An important goal of the current study was to examine whether these different indicators of lapses reflect the same general construct.

Another way of examining different types of lapses of attention is to utilize thought-probe techniques in which periodically during a task participants are required to report whether their attention was currently focused on-task or whether they were thinking of things unrelated to the task (Antrobus, 1968; see Smallwood & Schooler, 2006, 2015 for reviews). Research has consistently found that participants report extensive task-unrelated thoughts (TUTs) during tasks and self-reports of TUTs are negatively associated with task performance (e.g., Kane et al., 2016; Maillet & Rajah, 2013; McVay & Kane, 2010, 2012b; Mrazek et al., 2012; Smallwood et al., 2004; Schooler et al., 2004; Stawarczyk et al., 2011; Unsworth & McMillan, 2014; see Mooneyham & Schooler, 2013; Smallwood & Schooler, 2006, 2015 for reviews). For example, TUTs have been found to be associated with slower and more variable RTs in sustained attention tasks (Bastian & Sackur, 2013; Stawarczyk et al., 2011; Stawarczyk et al., 2014; Unsworth & Robison, 2016b, 2017a), errors in the SART (McVay & Kane, 2012b; Smallwood et al., 2004; Stawarczyk et al., 2011), tracking errors and flat spots in continuous tracking tasks (Kam et al., 2012; Robison et al., 2019), as well as lapses in working memory (Adam & Vogel, 2017; Mrazek et al., 2012; Robison & Unsworth, 2019; Unsworth & Robison, 2016a). These results suggest a relation between behavioral markers of lapses of attention and TUTs. Thus, thought probe techniques have been shown to be reliable and valid indicators of lapses of attention in a variety of settings.

Stawarczyk et al. (2011) found that TUTs could be broken down into either external distraction or mind-wandering and both are detrimental to performance. Subsequent research has further found that mind-wandering and external distraction are related to variable and slow RTs (McVay & Kane, 2012a; Robison & Unsworth, 2018; Unsworth & McMillan, 2014; Unsworth & Robison, 2017a). Thus, off-task thinking can be directed toward internal thoughts and concerns (mind-wandering) or toward external stimuli unrelated to the task at hand (external distraction) and both of these can lead to lapses in performance. Finally, participants also report that sometimes they are simply zoning out or experiencing mind-blanking (Ward & Wegner, 2013) leading to lower behavioral performance (Stawarczyk & D'Argembeau, 2016; Unsworth & Robison, 2016b). Thought probe techniques can be used to examine fluctuations in attentional state and be used to classify various lapses of attention (i.e., distracted, mind-wandering, and/or mind-blanking). A critical question is whether TUTs assessed with thought probes are reflecting the same construct as behavioral indicators of lapses, or whether they reflect different aspects of lapses of attention.

Individual Differences in Lapses of Attention

The notion that there are important individual differences in lapses of attention has a long history. For example, Spearman (1927) suggested that fluctuations in attention were an important individual differences factor in addition to variation in general intelligence. Similarly, Reason and Mycielska (1982) suggested that it was likely that individuals differed in attention control which resulted in variation in lapses of attention. Subsequent research has largely corroborated these notions by suggesting that there are robust individual differences in lapses of attention measured both behaviorally and with self-report thought-probe techniques (e.g., Cheyne et al., 2009; Kane et al., 2016; McVay & Kane, 2012b; Unsworth et al., 2010; Unsworth & McMillan, 2014). For example, Unsworth et al. (2010) found that the slowest RTs on the psychomotor vigilance task were correlated with working memory capacity, attention control, and fluid intelligence (see also Robison & Unsworth, 2018; Unsworth, Redick, et al., 2012; Unsworth et al., 2009; Unsworth & McMillan, 2014, 2017; Unsworth & Robison, 2017a, 2020; Unsworth & Spillers, 2010). These results suggest that low ability individuals experienced more lapses of sustained attention than high ability individuals (see also Unsworth, 2015; Unsworth & Robison, 2020). Similarly, particularly slow and variable RTs in the SART have been found to be related to working memory, attention control, and fluid intelligence (McVay & Kane, 2012a, 2012b; Stawarczyk et al., 2014; Unsworth & McMillan, 2014, 2017). Fast anticipatory RTs in the SART tend to be positively correlated with working memory capacity and fluid intelligence, but negatively related to TUTs (McVay & Kane, 2012a; Unsworth, 2015). Thus, there are clear relations between variability in RTs and cognitive abilities (Flehmig et al., 2007; Jensen, 1992; Kane et al., 2016; Schmiedek et al., 2007; Unsworth, 2015). Additional research has suggested that other behavioral indicators of lapses including various errors in the SART (e.g., McVay & Kane, 2009, 2012a, 2012b; Kane et al., 2016; Stawarczyk et al., 2014; Unsworth & McMillan, 2014, 2017) as well as lapses in working memory tasks (e.g., Adam et al., 2015; Adam & Vogel, 2017; Robison & Unsworth, 2019), have been found to be related to cognitive abilities such as working memory capacity, attention control, and fluid intelligence. Thus, prior research suggests that low cognitive ability individuals tend to experience more fluctuations and lapses in attention than high cognitive ability individuals (see also Fortenbaugh et al., 2015; Seli et al., 2013; Seli et al., 2014; Steinborn et al., 2008).

Lapses of attention can also be examined via self-reports of TUTs during cognitive tasks where thought probes are embedded in various tasks. Research suggests that TUTs are related to working memory capacity, attention control, reading comprehension, and fluid intelligence (Kane et al., 2016; Forster & Lavie, 2014; McVay & Kane, 2009, 2012b; Randall et al., 2014; Robison & Unsworth, 2015, 2018; Stawarczyk et al., 2014; Unsworth & McMillan, 2013, 2014, 2017; Unsworth & Robison, 2017a). TUTs measured in the laboratory have also been found to correlate with TUTs in everyday life (Kane et al., 2007, 2017; McVay et al., 2009; Unsworth, McMillan, et al., 2012; Unsworth & McMillan, 2017). Thus, individual differences in TUTs assessed with thought-probe techniques have been found to be consistently related to variation in a number of cognitive abilities in a manner similar to studies demonstrating variation in lapses of attention assessed with behavioral measures.

Collectively, prior research suggests there are robust individual differences in lapses of attention and lapses of attention tend to be related to various cognitive abilities. Recent research suggests that lapses of attention are also related to other factors such as task-specific motivation, interest, and alertness levels (Robison & Unsworth, 2015, 2018; Seli et al., 2015; Stawarczyk & D'Argembeau, 2016; Unsworth & McMillan, 2013). Furthermore, recent research suggests that TUTs are related to some personality variables such as neuroticism (Jackson et al., 2012; Kane et al., 2017; Robison et al., 2017), which is consistent with the notion that current concerns tend to dominate our thoughts and intrude on task focus (Klinger, 1999; McVay & Kane, 2010). This is also consistent with the notion that neuroticism is associated with mental noise and lapses of attention (Robinson & Tamir, 2005; Klein & Robinson, 2019). In a recent study, Robison et al. (in press) examined cognitive, contextual, and dispositional correlates of TUTs in large sample of participants and tasks. Robison et al. (in press) found that individual differences in TUTs were negatively related to working memory capacity, attention control, task motivation, alertness, conscientiousness, and sleep quantity consistent with prior research. TUTs were further positively related to current mood state (i.e., anxious), boredom, and daydreaming traits. These results along with prior research suggest that there are a number of factors that are important for normal variation in the propensity to experience lapses of attention.

A number of prior studies have further suggested that individual differences in lapses of attention assessed in laboratory settings have some ecological validity in terms of predicting lapses and cognitive failures in everyday life. As noted above, TUTs measured in the laboratory correlate with TUTs in everyday life (Kane et al., 2007, 2017; McVay et al., 2009; Unsworth, Redick, et al., 2012; Unsworth & McMillan, 2017). Working memory and attention control are also related to lapses in everyday life (Kane et al., 2007, 2017; Unsworth, McMillan, et al., 2012; Unsworth & McMillan, 2017). Lapses assessed in the laboratory (both behavioral indicators and TUTs) also correlate with self-reports of everyday cognitive failures in some studies (Carrigan & Barkus, 2016; Cheyne et al., 2006; McVay & Kane, 2009; Robertson et al., 1997; Smilek et al., 2010; Steinborn et al., 2016). A common means of examining individual differences in everyday cognitive failures is to use questionnaires such as Cognitive Failures Questionnaire (CFQ; Broadbent et al., 1982), which asks participants about various normal attention and memory failures (e.g., "Do you daydream when you ought to be listening to something?"). Prior research has shown that CFQ scores are related to ratings of cognitive failures by marital partners and to other self-report questionnaires (Broadbent et al., 1982; Martin, 1983; Martin & Jones, 1984) as well to boredom proneness and daytime sleepiness (Wallace et al., 2003). Furthermore, CFQ scores have been found to be related to various accidents (Larson et al., 1997; Wallace & Vodanovich, 2003). In terms of lapses of attention, CFQ (and other questionnaires) have been found to be related to behavioral indicators of lapses in the SART in some studies (Cheyne et al., 2006; McVay & Kane, 2009; Smilek et al., 2010) and to particularly slow RTs (Steinborn et al., 2016). Additionally, scores on the CFQ (and other questionnaires) have been found to be related to self-reports of TUTs (McVay & Kane, 2009; Smallwood et al., 2004). Thus, there seems to be some support for the ecological validity of lapses of attention assessed in the laboratory settings.

Present Study

Prior research suggests that there are important individual differences in lapses of attention assessed in multiple ways. Furthermore, it is likely that there are a number of different reasons for lapses. Thus, two individuals may experience a high frequency of lapses, but for very different reasons. For example, lapses could be due to attention control failures whereby lowered attention control abilities result in a greater likelihood of lapses. Lapses of attention could also arise due to low motivation and effort whereby little attention is allocated to the task at hand leading to a greater likelihood of attentional capture from external or internal sources. Lapses could also arise due to low arousal or alertness (such as when sleep deprived) or due to high arousal associated with stress and anxiety. Prior research has suggested that lapses are related to a number of factors including cognitive control abilities (working memory capacity, attention control), self-reports of TUTs, current motivational levels, current alertness levels, and personality traits. While these results are encouraging, one issue is that in these prior studies only a single measure of behavioral lapses was typically used (such as RT variability). As such, it is not clear that similar results will be obtained using different indicators of lapses. A major goal of the current study was to examine whether different behavioral indicators of lapses are the same from an individual differences perspective. That is, will putative lapses from different paradigms (lapses on sustained attention tasks and lapses on working memory tasks) load onto the same overall factor in a confirmatory factor analysis? If the various indicators of lapses all load onto the same factor, this would provide important information that there is a domain general tendency to experience lapses in a variety of domains. Thus, our first goal was to examine whether various indicators of lapses of attention correlate and load onto the same general lapse factor or whether different indicators of lapses represent fundamentally distinct types of lapses of attention. No prior research has examined the factor structure of various measures of behavioral lapses of attention. To examine this question, we assessed a variety of different behavioral indicators of lapses including lapses in the psychomotor vigilance task (Dinges & Powell, 1985; Lim & Dinges, 2008), blocks in choice RT (Bertelson & Joffe, 1963; Bills, 1931a, 1931b), flat spots in a continuous tracking task (Peiris et al., 2006), lapses in working memory performance (Adam et al., 2015), as well as three indicators of lapses in the SART (omission errors, anticipatory RTs, and variability in RTs; Cheyne et al., 2009). These measures were chosen because they have been used extensively in past research on lapses and because they represent a number of different dependent variables to ensure that the results are not simply measurement specific (e.g., not all RTs). Though, as will be seen, many of these measures rely on count variables which tend to be highly skewed given the rarity of lapses. In the General Discussion (and Appendix A) we examine potential alternative measures of lapses from some of these tasks.

In addition to examining whether behavioral indicators of lapses represent the same construct, we also assessed whether behavioral lapses and self-reports of TUTs represent the same or different constructs. While prior research has suggested that behavioral indicators of lapses and TUTs are related at the task level, it is not clear that these two constructs are necessarily the same at the latent factor level. That is, not only are there methodological differences in how these are assessed (behavior vs. self-report), but there may also be fundamental differences between these constructs. For example, there is some suggestion that in some situations high ability participants experience more mind-wandering than low ability participants (e.g., Levinson et al., 2012; Robison et al., in press; Rummel & Boywitt, 2014). This may represent intentional forms of mind-wandering, rather than unintentional/spontaneous mind-wandering (Seli et al., 2015; Seli et al., 2016; Robison & Unsworth, 2018; Robison et al., in press). Yet, these same participants might demonstrate few behavioral lapses of attention compared to low ability participants. Thus, there may be a divergence between behavioral lapses and self-reports of TUTs depending on task and situational factors. As such, it is possible that behavioral indicators of lapses and TUTs are related, but distinct constructs. To examine this notion, thought probes assessing participants' current attentional state were included in several tasks (psychomotor vigilance, whole report working memory, Stroop, and SART).

Relatedly, we assessed whether lapses of attention and variation in attention control abilities represent the same or different constructs. As noted above, it is likely that failures in broad attention control abilities partially account for variation in lapses of attention. Thus, it is possible that much of the variation in lapses are due to variation in attention control abilities. Indeed, in prior research, we have used long RTs in the psychomotor vigilance task along with other attention control tasks (such as antisaccade, Stroop, flankers) to model an attention control factor (e.g., Unsworth & McMillan, 2014; Unsworth & Spillers, 2010). The idea being that there is a broad attention control factor composed of shared variance across lower-order attentional restraint (tasks like antisaccade), attentional constraint (tasks like flanker), and sustained attention (tasks like psychomotor vigilance) factors (e.g., Kane et al., 2016; Poole & Kane, 2009; Unsworth & Robison, 2020; Unsworth & Spillers, 2010). Thus, this suggests that lapses of attention (associated with the sustained attention factor) are likely strongly related to attention control abilities indexed with restraint and constraint tasks, but they are also likely distinct factors. To examine this notion we assessed broad attention control abilities with the antisaccade, Stroop, and cued visual search tasks to represent restraint and constraint aspects of attention control (e.g., Kane et al., 2016; Poole & Kane, 2009; Unsworth & Spillers, 2010).

Our second goal was to examine how behavioral lapses are related to cognitive, contextual, and trait factors. As noted above, given strong prior relations between broad attention control abilities and lapses of attention, we examined how lapses would be related to attention control. We also examined how lapses would be related to working memory capacity (measured with three complex span tasks) given prior research which has suggested that individual differences in working memory capacity are related to lapses of attention in different paradigms (e.g., McVay & Kane, 2012b; Kane et al., 2016; Unsworth, 2015; Unsworth et al., 2010; Unsworth & Robison, 2020). Given that some (not all) of the lapse measures are RT based, we also examined variation in basic speed of processing to determine if any relations with the lapse measures were really just due to speed of processing. That is, a participant could have many long RTs simply because they are slower than other participants (a shift in the entire RT distribution) rather than having many lapses of attention. Thus, it is important to examine whether variation in behavioral lapses are really just due to differences in processing speed. To assess speed of processing we used the fastest RTs in the psychomotor vigilance task, the choice RT task, and Stroop (congruent trials).

In terms of contextual factors we assessed both task-specific motivation and overall alertness levels during several tasks (antisaccade, psychomotor vigilance, choice RT, and continuous tracking) given prior research has suggested that both motivation and alertness are associated with TUTs (Seli et al., 2015; Robison & Unsworth, 2015, 2018; Robison et al., in press; Unsworth & McMillan, 2013). We also examined variation in sleep quantity (number of hours of sleep from the previous night) given that prior research has suggested that sleep is related to lapses (Robison et al., in press; Stawarczyk & D'Argembeau, 2016). Thus, contextual factors such as motivation, alertness, and sleep quantity should be related to lapses of attention. In terms of trait factors we assessed personality with the Big Five Inventory (John et al., 2008) given that prior research has suggested that neuroticism and conscientiousness may be associated with lapses of attention (Jackson et al., 2012; Kane et al., 2017; Robison et al., 2017; Robison et al., in press; Robinson & Tamir, 2005). We also assessed boredom proneness (Vodanovich & Kass, 1990) given that some prior research has found a relation between boredom proneness and lapses (Malkovsky et al., 2012; Robison et al., in press). Thus, in addition to examining how various cognitive abilities relate to lapses of attention, we also examined how contextual and trait factors may jointly or independently account for individual differences in lapses of attention. Importantly, no prior study has examined how these factors are potentially related to behavioral lapses of attention at the latent factor level.

Our final goal was to examine how lapses assessed in the laboratory are related to self-reports of everyday cognitive failures. In particular, we wanted to examine whether behavioral lapses and TUTs measured in the laboratory are related to cognitive failures and lapses that reportedly occur in more real world settings, thereby providing some ecological validity to the laboratory assessments of lapses. To do so, participants completed a variant of the CFQ (Broadbent et al., 1982) that specifically measures memory and attention lapses (CFQ-MAL; McVay & Kane, 2009).

To summarize, in a novel latent variable study, we examined normal variation in lapses of attention in order to (a) assess whether various measures of behavioral lapses would correlate and form a coherent lapse factor; (b) assess similarities and differences between the lapse factor with TUTs and attention control factors; (c) assess whether the lapse factor was correlated with additional cognitive ability factors such as working memory capacity and speed of processing; (d) assess whether contextual (motivation, alertness, sleep quantity) and trait factors (personality) correlate with the lapse factor; and (e) assess whether the lapse factor would be associated with self-reports of everyday cognitive failures. No prior study has comprehensively examined these issues. To address these issues we used a latent variable approach in which multiple indicators of each construct were assessed. This was done in order to ensure that any lack of relations found are not due to unreliability or idiosyncratic task effects. By examining a large number of participants and a large and diverse number of measures we should be able to better characterize individual differences in lapses of attention and address our questions of primary interest. That is, by examining various factors that are associated with lapses of attention, we should be able to better understand why some people are more susceptible to lapses of attention and what factors are most critical in determining variation in lapses of attention.

Method

We report how we determined our sample size, all data exclusions, all manipulations, and all measures in our study.

Participants

A total of 358 participants were recruited from the subject-pool at the University of Oregon, a comprehensive state university. The study was approved by the Institutional Review Board at the University of Oregon. Each participant was tested individually in a laboratory session lasting approximately 2 hr. We tested participants over two full academic quarters, using the end of the second quarter as our stopping rule for data collection with the aim of getting a minimum of 300 participants. Two participants' data were post hoc excluded on the psychomotor vigilance task (mean RTs >1,200 ms; one participant's mean RT was >18 s), one participant's data were post hoc excluded on Stroop (mean RTs >2,400 ms), and one participant's data were post hoc excluded on the choice RT task (mean RTs >1,200 ms) due to having long RTs. Additionally, data for 30 participants were excluded on the whole report working memory task because these participants had more than 75% lapse trials. This was due to the fact that these participants clicked on the same square for all responses rather than clicking on each individual square. Most of these participants were run at the beginning of the study and once we figured out what was happening we provided more detailed instructions to participants. Furthermore, data for 16 participants were excluded on the SART because these participants had more than 50% omission errors on go trials because they were rarely pressing any keys during the task. Finally, one participant's data was excluded on the SART because they had an excessive number of anticipation trials. Data on the other measures for those participants were included. Data will be made available on the Open Science Framework.

Materials and Procedure

After signing informed consent, all participants completed operation span, symmetry span, reading span, antisaccade, cued visual search, psychomotor vigilance task, Stroop, SART, choice RT, continuous tracking, and whole report visual working memory. All tasks were administered in the order listed above. Following the tasks participants completed a set of questionnaires.

Working Memory Capacity (WMC) Tasks

Operation Span. Participants solved a series of math operations while trying to remember a set of unrelated letters (see Unsworth et al., 2005). Participants were required to solve a math operation, and after solving the operation, they were presented with a letter for 1 s. Immediately after the letter was presented the next operation was presented. At recall participants were asked to recall letters from the current set in the correct order by clicking on the appropriate letters. For all of the span measures, items were scored correct if the item was recalled correctly from the current list. Participants were given practice on the operations and letter recall tasks only, as well as two practice lists of the complex, combined task. List length varied randomly from three to seven items, and there were two lists of each list length for a maximum possible score of 50. The score was total number of correctly recalled items.

Symmetry Span. Participants recalled sequences of red squares within a matrix while performing a symmetry-judgment task (see Unsworth et al., 2009). In the symmetry-judgment task, participants were shown an 8 × 8 matrix with some squares filled in black. Participants decided whether the design was symmetrical about its vertical axis. The pattern was symmetrical half of the time. Immediately after determining whether the pattern was symmetrical, participants were presented with a 4 × 4 matrix with one of the cells filled in red for 650 ms. At recall, participants recalled the sequence of red-square locations by clicking on the cells of an empty matrix. Participants were given practice on the symmetry-judgment and square recall task as well as two practice lists of the combined task. List length varied randomly from two to five items, and there were two lists of each list length for a maximum possible score of 28. We used the same scoring procedure as we used in the operation span task.

Reading Span. While trying to remember an unrelated set of letters, participants were required to read a sentence and indicated whether or not it made sense (see Unsworth et al., 2009). Half of the sentences made sense, while the other half did not. Nonsense sentences were created by changing one word in an otherwise normal sentence. After participants gave their response, they were presented with a letter for 1 s. At recall, participants were asked to recall letters from the current set in the correct order by clicking on the appropriate letters. Participants were given practice on the sentence judgment task and the letter recall task, as well as two practice lists of the combined task. List length varied randomly from three to seven items, and there were two lists of each list length for a maximum possible score of 50. We used the same scoring procedure as we used in the operation span and symmetry span tasks.

Attention Control (AC) Tasks

Antisaccade. In this task (Kane et al., 2001) participants were instructed to stare at a fixation point which was onscreen for a variable amount of time (200–2,200 ms). A flashing white "=" was then flashed 12.7 cm either to the left or right of fixation for 100 ms. The target stimulus (B, P, or R) then appeared onscreen for 100 ms, followed by masking stimuli (an H for 50 ms followed by an 8, which remained onscreen until a response was given). The participants' task was to identify the target letter by pressing a key for B, P, or R (the keys 4, 5, 6 on the numberpad) as quickly and accurately as possible. In the prosaccade condition the flashing cue (=) and the target appeared in the same location. In the antisaccade condition the target appeared in the opposite location as the flashing cue. Participants received, in order, 10 practice trials to learn the response mapping, 15 trials of the prosaccade condition, and 60 trials of the antisaccade condition. The dependent variable was proportion correct on the antisaccade trials.

Cued Visual Search. In this task (Poole & Kane, 2009) participants must decide whether an F located within a 5x5 array of 25 letters (comprising Es, backward Es, 90°-tilted Ts, 270°-tilted Ts) is mirror-reversed (facing left) or normal (facing right). Subjects make their responses using the z and/keys, labeled with left and right arrow stickers, respectively. Subjects completed eight response-mapping trials with a lone mirror-reversed or normal F before proceeding to the cued search section of the task. Each trial began with a blank screen (500 ms), and then subjects were given an arrow cue (500 ms) indicating in which two or four of the eight possible array locations the relevant letter F may appear (always along the internal 3x3 "ring" of the array). A blank screen was then shown for 50 ms, before the 5x5 grid of 25 possible locations was shown for 1,500 ms. A blank screen of 50 ms was shown again, and the array of 25 letters was shown until the subject responds (up to 4,000 ms). Because other Fs are randomly presented in noncued locations as irrelevant distractors, the subject must maintain the cue information to respond correctly. Subjects completed 8 practice trials and 80 trials in the experimental block. Cue type, target direction, and target location were randomly and equally presented in the experimental block. The mean RT for correct responses across the experimental trials was used as the dependent variable.

Stroop. Participants were presented with a color word (red, green, or blue) presented in one of three different font colors (red, green, or blue; Stroop, 1935). The participants' task was to indicate the font color via key press (red = 1, green = 2, blue = 3). Participants were told to press the corresponding key as quickly and accurately as possible. Participants received 15 trials of response mapping practice and 6 trials of practice with the real task. Participants then received 100 experimental trials. Of these trials, 67% were congruent such that the word and the font color matched (i.e., red printed in red) and the other 33% were incongruent (i.e., red printed in green). The dependent variable was the difference in mean RT for accurate incongruent and congruent trials. Twelve thought probes were randomly presented after incongruent trials. Additionally, in order to examine possible influences of speed of processing we rank ordered all of the correct congruent RTs from fastest to slowest, and used the fastest 20% of RTs as a measure of processing speed.

Lapses of Attention Tasks

Psychomotor Vigilance Task (PVT). The psychomotor vigilance task (Dinges & Powell, 1985) was used as the primary measure of sustained attention. Participants were presented with a row of zeros on screen. After a variable amount of time the zeros began to count up in 17 ms intervals from 0 ms (as determined by the 60 Hz monitor refresh rate). The participants' task was to press the spacebar as quickly as possible once the numbers started counting up. After pressing the space bar the response time was left on screen for 1 s to provide feedback to the participants. Interstimulus intervals were randomly distributed and ranged from 2 s to 10 s. The entire task lasted for 10 min for each individual (roughly 75 total trials). The dependent variable was the number of trials with RTs ≥500 ms (Dinges & Powell, 1985). This measure was chosen given that it is the standard measure of lapses used in this task and this measure has been shown to be sensitive to fatigue, sleep deprivation, and time-on-task and is related to TUTs (Lim & Dinges, 2008; Unsworth & Robison, 2016). Furthermore, prior research has found that RT distributions in this task are bimodal (especially when sleep deprived) with a second mode occurring for very long RTs (Lim & Dinges, 2008). We also examined the 20% of slowest RTs (see Appendices A, B, C, D, & E) given that we have previously used this measure as a measure of lapses in individual differences research (Unsworth et al., 2010). Thought probes were randomly presented after 20% of trials. Additionally, in order to examine possible influences of speed of processing we rank ordered all of the RTs from fastest to slowest, and used the fastest 20% of RTs as a measure of processing speed.

Sustained Attention to Response Task (SART). Participants completed a version of a SART with semantic stimuli adapted from McVay and Kane (2009, 2012b). The SART is a go/no-go task where subjects must respond quickly with a key press to all presented stimuli except infrequent (11%) target trials. In this version of SART, word stimuli were presented in Courier New font size 18 for 300 ms followed by a 900-ms mask. Most of the stimuli (nontargets) were members of one category (animals) and infrequent targets were members of a different category (foods). There were 315 experimental trials, 35 of which were targets. The dependent variables were number of omissions on go trials, number of anticipatory RTs (RTs <100 ms), and coefficient of variation for correct go RTs >200 ms (Cheyne et al., 2009). We specifically used these three dependent variables given prior research which has suggested that they reflect slightly different aspects of lapses of attention (Cheyne et al., 2009). Thought probes followed 60% of target trials.

Choice RT. In this task, participants responded as quickly as possible to the appearance of a stimulus in one of four locations on the screen (Unsworth, Redick, et al., 2012). The stimulus consisted of a cross presented in white Courier New 32-point font centered at one of four underlined locations. After a random time interval (300–550 ms in 50-ms intervals), the cross appeared randomly in one of the four locations with the exception that the stimulus could not appear in the same location on consecutive trials. During the intertrial interval, the four possible stimulus locations were marked by four equally spaced horizontal lines as place holders along the vertical center of the screen. Participants were instructed to be as fast and accurate as possible. They indicated the location of the cross by pressing one of four buttons on the keyboard (F, G, H, J), corresponding to the four possible locations. Participants completed 15 practice trials and 210 experimental trials. The main dependent variable was the number of "blocks" defined as RTs that are twice as long each individual's mean RT (Bills, 1931a, 1931b, 1935; see also Bertelson & Joffe, 1963). This measure was chosen given that it is the conventional method for defining blocks. Although as noted by Bills (1931a), this measure was arbitrarily defined and really just reflects longer than normal RTs taking into account individual differences in mean RT. Bills (1935) reported that the RT distributions tended to be somewhat bimodal, with one mode occurring for the main distribution of RTs, and a second mode occurring for the longest RTs. Blocks measured in this way have been shown to be sensitive to fatigue, sleep deprivation, practice, stressors, and time-on-task (Bertelson & Joffe, 1963; Bills, 1931a, 1931b; Broadbent, 1958; Williams et al., 1959). We also examined the 20% of slowest RTs as a measure of lapses (see Appendix A). Additionally, in order to examine possible influences of speed of processing we rank ordered all of the correct RTs from fastest to slowest, and used the fastest 20% of RTs as a measure of processing speed.

Continuous Tracking. Participants were presented with a small black circle on a gray background. The participants' task was to track the black circle as closely as possible with the cursor of the mouse. Each trial began with a 3-s screen saying, "Please focus on the black dot." The text then disappeared and the dot remained on-screen for 5 s. The screen then told participants, "Click the dot to begin the trial." The black circle then began to move around the screen. The circle moved in a pseudorandom fashion within a 400 × 440 pixel region centered on the screen (the borders of which were invisible). The circle moved at a constant speed in vertical, horizontal, and diagonal directions. Trials lasted for 30, 60, 90, or 120 s. Participants first completed one 30-s trial as practice, after which they were encouraged to seek clarification from the experimenter if necessary. Participants then completed one 30 s and one 120 trial and two 60 and two 90 s trials, which occurred in a random order for each participant. The main dependent measure was the number of flat spots—periods in which tracking completely stopped for a period of at least 1.5 s. The measurement of flat spots as a stoppage of at least 1.5 s was based on prior research using tracking tasks (Peiris et al., 2006). The duration of 1.5 s is somewhat arbitrarily defined given that other research with this task has used a larger range of values (e.g., Buckley et al., 2016; Jones et al., 2010; Poudel et al., 2009). Prior research on flat spots has found that they are sensitive to fatigue, time-on-task, instructions to stay focused, and are related to TUTs (Buckley et al., 2016; Jones et al., 2010; Peiris et al., 2006; Robison et al., 2019). We also examined overall tracking error as a measure of lapses (see Appendix A).

Whole Report Visual Working Memory. The participants' task was to remember the colors of squares over brief delays and to report the colors of these squares on a testing screen (Adam et al., 2015, 2018; Adam & Vogel, 2016, 2017; Robison & Unsworth, 2019). Each trial began with a 1-s fixation screen on which a black fixation crossed appeared on a gray background, followed by a 100-ms blank screen. Then, a pattern of six colored squares appeared and remained on screen for 250 ms. The squares (60 × 60 pixels; 3° visual angle) appeared within a 540 × 402-pixel region centered on the screen. The locations were random with the restriction that no items appeared within a 100-pixel vector distance of each other (measured from each item's top-left starting point). Colors were randomly sampled from a set of nine discrete colors (white, black, red, blue, lime green, magenta, green, cyan, and yellow). Colors did not repeat within a trial (i.e., all six items were different colors). After a 1,000-ms blank delay screen, the color response grids appeared in the locations where the six items had appeared previously. The participants' task was to report the color of the square in each location by clicking the appropriate color in the grid. After the participant responded to all six items, the next trial immediately started. Participants first read through a series of instruction screens followed by five practice trials. If participants were confused during the practice trials, they were encouraged to seek clarification from the experimenter. They then completed 68 experimental trials. The main dependent variable was the number of trials where participants recalled only 0 or 1 items correctly (Adam et al., 2015). Thought probes were randomly presented after eight trials.

Motivation and Alertness

Following the psychomotor vigilance, choice RT, continuous tracking, and antisaccade tasks participants were asked how motivated they felt to perform and how alert they were during the task (Robison & Unsworth, 2018; Robison et al., in press; Unsworth & McMillan, 2013). Specifically, participants were asked, "How motivated were you to perform well on the task?" and "How alert do you feel right now?" Participants responded on a 1 to 6 scale.

Thought Probes

During the psychomotor vigilance, whole report working memory, Stroop, and sustained attention to response tasks participants were periodically presented with thought probes asking them to classify their immediately preceding thoughts. The response options for the thought probes were based on prior investigations of mind-wandering and other thought content (i.e., external distraction, task-related interference; mind-blanking; Robison & Unsworth, 2018; Stawarczyk et al., 2011; Unsworth & Robison, 2016b; Ward & Wegner, 2013). Probes asked participants to report the current contents of their consciousness. Specifically, they saw a screen that said

> Please characterize your current conscious experience.
>
> 1) I am totally focused on the current task
>
> 2) I am thinking about my performance on the task
>
> 3) I am distracted by sights/sounds/physical sensations
>
> 4) I am daydreaming/my mind is wandering about things unrelated to the task
>
> 5) My mind is blank.

Responses 3–5 were taken as the measure of TUTs in each task.

Questionnaires

Participants completed a set of questionnaires to assess various trait characteristics. The questionnaires were delivered in the following order for all participants: Big Five Inventory, Boredom Proneness Scale, cognitive failures-memory and attention lapses (CFQ-MAL), sleep, and Mindful Attention Awareness Scale. Because of the large degree of overlap between the CFQ-MAL and the Mindful Attention Awareness Scale we do not discuss it further.

Big Five Inventory (BFI). Participants completed the 44-item Big Five Inventory (John et al., 2008). The BFI contains eight items to measure extraversion, nine items to measure agreeableness, nine items to measure conscientiousness, eight items to measure neuroticism, and 10 items to measure openness. Participants rated how well each item (e.g., "I see myself as someone who is talkative") described them on a 5-point scale (1 = *disagree strongly*, 5 = *agree strongly*).

Boredom Proneness. The 28-item Boredom Proneness Scale (Vodanovich & Kass, 1990) asks participants to rate how a variety of traits (e.g., "It is easy for me to concentrate on my activities") describe them. Participants responded on a 7-point scale (1 = *not at all*, 7 = *extremely well*).

CFQ–Memory and Attention Lapses (CFQ-MAL). This is a modified version of the CFQ from McVay and Kane (2009) that presents only items about memory and attention lapses. This computerized CFQ-MAL presented 40 questions (with responses on a 1–5 scale: 1 = *never*, 2 = *rarely*, 3 = *once in a while*, 4 = *often*, 5 = *very often*); subjects responded via keypress. Total score reflected the item sum.

Sleep. Participants were asked four questions regarding their previous night's sleep. The first question asked, "How many hours of sleep did you get last night?" Response options were 0–5 hr, 5–6 hr, 6–7 hr, 7–8 hr, or 8+ hr. The second question asked "How much does this compare to how much you typically sleep?" Response options were "much less than normal," "slightly less than normal," "about normal," "slightly more than normal," and "much more than normal." The third question asked "How awake/alert do you feel right now?" Response options were on a 9-point scale (1 = *extremely alert*, 9 = *extremely sleepy/fighting sleep*). The fourth question asked "How awake/alert do you typically feel at this time of day?" The response options were the same as the previous question. We used responses to the first question as our measure of sleep quantity (Robison et al., in press).

Results

Descriptive Statistics and Bivariate Correlations

Descriptive statistics for all of the measures are shown in Table 1. As can be seen, the measures had generally acceptable values of reliability (except for Stroop) and most of the measures were approximately normally distributed. However, several of the behavioral lapse measures tended to be positively skewed given low overall numbers of lapses. Next, we checked to see if these measures were zero-inflated with a preponderance of zero counts. The only measure that demonstrated a high percentage of zeros was the flat spot measure with 76% of participants having zero flat spots (median = 0.0 flat spots). Given that this measure correlated reasonably well with the other lapse measures (see below) we retained it for all subsequent analyses (see General Discussion for an alternative measure from the continuous tracking task). The other behavioral lapses measures had much smaller percentages of zeros (PVT lapses = 17.9% zeros, median = 2.0 lapses; whole report lapses = 0.3% zeros, median = 9.0 lapses; blocks = 32.7% zeros, median = 1.0 blocks; SART anticipations = 36.8% zeros, median = 2.00 anticipations; SART omissions = 1.2% zeros; median = 16 omissions). Frequency distributions for all of the behavioral lapse measures can be found in the online supplemental materials.

Correlations, shown in Table 2, were weak to moderate in magnitude with measures of the same construct generally correlating stronger with one another than with measures of other constructs, indicating both convergent and discriminant validity within the data. Importantly, all of the behavioral lapse indicators were positively correlated with one another.[1] Similarly, the TUTs measures were all positively intercorrelated and the bivariate relations between the behavioral lapses and TUTs were also positive. Generally similar results were obtained when examining Spearman's rho instead of Pearson correlations and when transforming the skewed behavioral lapse measures (see Appendix A for alternative models using Spearman's rho and the transformed variables as well as models using the Satorra-Bentler scaled test statistic which is robust to non-normality).

Confirmatory Factor Analyses

Next, we used latent variable techniques to test our main questions of interest. Specifically, our first analysis was to examine whether all of the behavioral indicators of lapses would load on the same general lapse factor. Therefore, we specified a confirmatory factor analysis with all seven behavioral indicators of lapses loading onto a single factor. Given that three measures come from the SART task, we allowed the residuals for those three measures to correlate. To fit the models we used the sample correlation matrix using all available data (pairwise correlations; see the Appendix A for similar results when using full information maximum likelihood). For all model testing (using Lisrel 8.80; similar results were found when using R), we report several fit statistics. Nonsignificant chi-square tests indicate adequate model fit; with large samples like ours, however, they are nearly always significant. Comparative fit indices (CFI) and non-normed fit index (NNFI) of $\geq$.90 indicate adequate fit, whereas the root mean square error of approximation (RMSEA) and standardized root mean square residual (SRMR) values of $\leq$.08 indicate adequate fit (e.g., Schermelleh-Engel et al., 2003). The overall fit of the model was good, $\chi^2(11) = 24.60$, $p = .010$, RMSEA = .06, 90% CI [.027, .090], NNFI = .97, CFI = .99, SRMR = .05. Shown in Figure 1a is the model. As can be seen, all of the measures loaded significantly and moderately on the overall lapse factor suggesting that the measures shared quite a bit of variance. Next, we tested a two-factor lapse model in which one lapse factor was composed of all of the RT measures (e.g., PVT lapses, blocks, coefficient of variation on the SART, and anticipations on the SART) and the other lapse factor was composed of performance failures (e.g., flat spots, lapses on whole report working memory, and omissions on SART). Thus, this model tests whether lapses can be differentiated

[1] The finding that all three SART measures were positively correlated with one another replicates Cheyne et al. (2009). Furthermore, Cheyne et al. (2009) suggested that the three SART measures were somewhat independent in that they accounted for unique variance in no go accuracy. We also replicated this finding in the current dataset in which coefficient of variation of RTs, anticipations, and omissions all accounted for unique variance in no go accuracy. In a prior article we (Unsworth & Robison, 2017b) noted that a reanalysis of Cheyne et al.'s (2009) data suggested that the majority of the variance was actually shared by the three predictors. Specifically, the three predictors accounted for 32% of the variance in no go accuracy. The shared variance between the three predictors accounted for 14% of the variance (or 44% of the total variance accounted for). Similarly, in the current data set we accounted for 44% of the variance in no go accuracy and the common variance shared by the three predictors accounted for 13% of the variance (or 30% of the total variance accounted for). Thus, although each measure accounted for unique variance suggesting some independence, there was also substantial shared variance across the three SART measures.

Table 1
Descriptive Statistics for All Measures

Measure	*M*	*SD*	Skew	Kurtosis	Reliability	*N*
Ospan	37.93	8.08	−.69	.09	.72	357
Symspan	18.82	5.21	−.48	−.10	.64	358
Rspan	37.25	8.60	−1.05	1.36	.76	358
Anti	.60	.15	.04	−.62	.83	349
Stroop	149.31	98.60	.61	1.12	.48	353
Cued	1279.87	290.54	.61	.36	.87	356
PVTLap	4.71	6.59	3.21	14.14	.83	351
FlatSpot	1.43	4.28	4.60	25.41	.81	335
WRLap	11.06	8.58	1.54	2.13	.91	290
Blocks	2.01	2.59	2.61	10.22	.77	349
SaCoV	.32	.11	1.04	1.36	.79	338
SaAntic	5.30	10.21	3.56	15.67	.88	337
SaOm	19.79	16.44	1.75	4.13	.98	338
ContAl	2.30	1.43	.80	−.45	—	326
AntiAl	3.65	1.31	−.03	−.77	—	349
CRTAl	3.32	1.33	.05	−.73	—	350
PVTAl	3.30	1.28	.13	−.52	—	353
ContMo	2.68	1.60	.42	−1.12	—	326
AntiMo	3.99	1.36	−.43	−.58	—	349
CRTMo	4.03	1.38	−.56	−.34	—	350
PVTMo	4.01	1.31	−.41	−.54	—	353
WRTUT	.55	.38	−.18	−1.45	.64	311
PVTTUT	.44	.30	.24	−.95	.60	353
StTUT	.22	.29	1.39	.87	.71	354
SaTUT	.45	.33	.23	−1.24	.89	354
PVTRT1	283.10	26.07	1.23	3.45	.97	351
CRTRT1	293.60	39.86	.33	4.72	.96	347
StRT1	439.49	67.73	1.19	2.38	.97	354
CFQ-MAL	111.39	25.88	.23	−.11	.95	285
Boredom	3.82	.53	.18	−.22	.72	285
Sleep	3.14	1.14	−.27	−.66	—	285
Extraversion	3.21	.86	−.35	−.76	.84	285
Agreeableness	3.90	.67	−.81	.90	.75	285
Conscientiousness	3.61	.63	−.46	.47	.77	285
Neuroticism	3.14	.86	.01	−.73	.85	285
Openness	3.57	.58	−.13	−.07	.73	285

Note. Ospan = operation span; Symspan = symmetry span; Rspan = reading span; Anti = antisaccade; Cued = cued visual search; PVTLap = lapses in psychomotor vigilance task; Flat Spots = flat spots in continuous tracking; WRLap = lapses in whole report working memory; Blocks = blocks in choice reaction time; SaCoV = coefficient of variation in sustained attention to response task; SaAntic = anticipations in sustained attention to response task; SaOm = omission errors in sustained attention to response task; ContAl = alertness in continuous tracking; AntiAl = alertness in antisaccade; CRTAl = alertness in choice reaction time; PVTAl = alertness in psychomotor vigilance task; ContMo = motivation in continuous tracking; AntiMo = motivation in antisaccade; CRTMo = motivation in choice reaction time; PVTMo = motivation in psychomotor vigilance task; WRTUT = task-unrelated thoughts in whole report working memory; PVTTUT = task-unrelated thoughts in psychomotor vigilance task; StTUT = task-unrelated thoughts in Stroop; SaTUT = task-unrelated thoughts in sustained attention to response task; PVTRT1 = fastest 20% of reaction times in the psychomotor vigilance task; CRTRT1 = fastest 20% of reaction times in choice reaction time; StRT1 = fastest 20% of reaction times on congruent trials in the Stroop; CFQ-MAL = cognitive failures—memory and attention lapses; Boredom = Boredom Proneness Scale; Sleep = sleep quantity. Reliabilities represent split-half reliabilities for all measures except the questionnaires where reliability represents alphas.

based on RT versus non-RT measures. The same residuals as the prior model were allowed to correlate. The overall fit of the model was good, $\chi^2(10) = 23.64$, $p = .009$, RMSEA = .06, 90% CI [.030, .094], NNFI = .97, CFI = .99, SRMR = .05. All measures loaded on their respective factors, and the correlation between the two factors was .94 ($SE = .05$). Critically, the two-factor model did not fit significantly better than the one-factor model, $\Delta\chi^2(1) = 0.96$, $p = .33$, suggesting that the one-factor model provided the best-fitting, most parsimonious account of the data. Thus, the one-factor lapse model was retained for all subsequent analyses.

Next, we examined whether behavioral lapses and TUTs were best considered as one overall factor, or as separate but related factors. To test this, we specified a confirmatory factor analysis with all of the behavioral lapse indicators and all of the TUTs measures loading onto a single common factor. The residuals for SART were allowed to correlate. The overall fit of the model was poor, $\chi^2(41) = 398.59$, $p < .001$, RMSEA = .16, 90% CI [.14, .17], NNFI = .76, CFI = .82, SRMR = .11. We contrasted the one-factor model with a two-factor model in which the behavioral lapse indicators loaded onto one factor as before, and now the

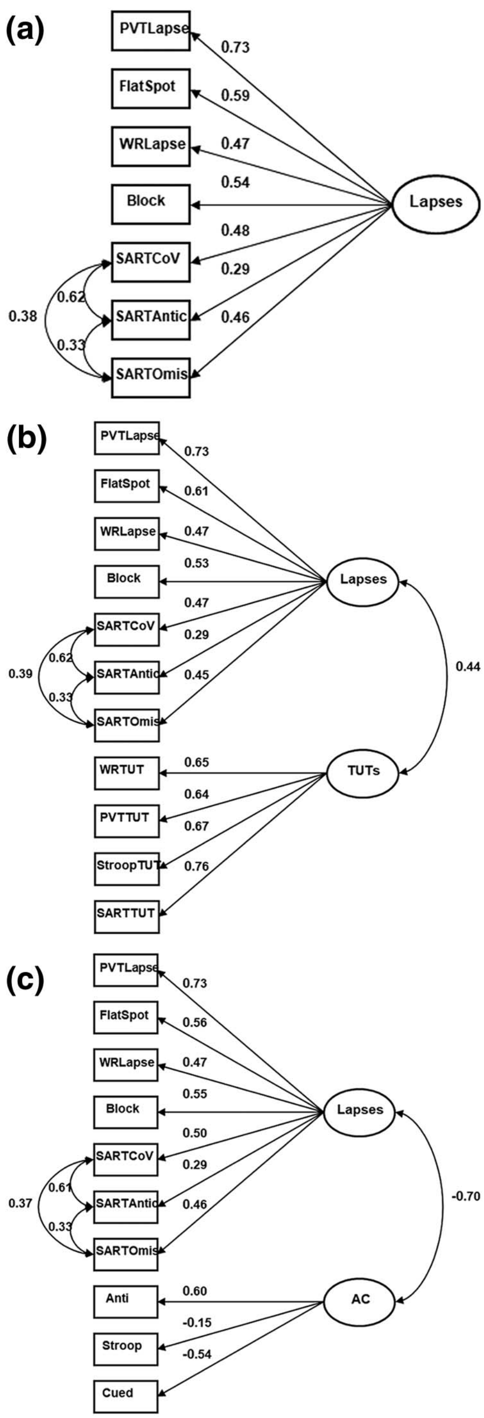
Table 2
Correlations Among the Measures

Measure	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
1. Ospan	—																																			
2. Symspan	0.41	—																																		
3. Rspan	0.51	0.35	—																																	
4. Anti	0.18	0.24	0.14	—																																
5. Stroop	−0.21	−0.1	−0.16	−0.15	—																															
6. Cued	−0.19	−0.23	−0.06	−0.31	0.1	−-																														
7. PVTLap	−0.06	−0.15	−0.17	−0.32	0.04	0.27	—																													
8. FlatSpot	−0.06	−0.15	0.02	−0.16	−0.02	0.17	0.45	—																												
9. WRLap	−0.23	−0.31	−0.26	−0.16	0.07	0.24	0.33	0.29	—																											
10. Block	−0.06	−0.09	−0.08	−0.24	−0.08	0.27	0.43	0.28	0.21	—																										
11. SaCoV	−0.15	−0.16	−0.2	−0.3	0.05	0.2	0.33	0.25	0.35	0.27	—																									
12. SaAnti	−0.07	−0.1	−0.16	−0.12	0.01	0.08	0.18	0.13	0.31	0.14	0.76	—																								
13. SaOm	−0.16	−0.14	−0.18	−0.23	0	0.15	0.3	0.3	0.25	0.27	0.6	0.46	—																							
14. ContA1	0.08	0.15	−0.01	0.11	0.04	−0.18	−0.09	−0.17	−0.04	−0.09	−0.12	−0.03	−0.06	—																						
15. AntiA1	0.06	0.13	0.09	0.3	−0.07	−0.14	−0.18	−0.1	−0.14	−0.1	−0.07	−0.06	−0.07	0.28	—																					
16. CRTA1	0.07	0.15	0.07	0.07	−0.04	−0.07	−0.18	−0.16	−0.14	−0.18	−0.15	−0.07	−0.09	0.48	0.3	—																				
17. PVTA1	0.03	0.17	0.12	0.23	−0.07	−0.17	−0.34	−0.21	−0.16	−0.2	−0.21	−0.16	−0.15	0.43	0.51	0.52	—																			
18. ContMo	0.05	0.16	0.01	0.05	0.03	−0.16	−0.09	−0.23	−0.11	−0.04	−0.17	−0.11	−0.14	0.78	0.19	0.36	0.34	—																		
19. AntiMo	0.05	0.14	0.04	0.29	−0.11	−0.14	−0.24	−0.07	−0.2	−0.05	−0.19	−0.11	−0.12	0.22	0.59	0.26	0.39	0.23	—																	
20. CRTMo	0.13	0.17	0.14	0.09	−0.08	−0.06	−0.22	−0.16	−0.19	−0.23	−0.17	−0.14	−0.16	0.33	0.25	0.68	0.37	0.38	0.32	—																
21. PVTMo	0.01	0.14	0.1	0.12	−0.01	−0.11	−0.3	−0.18	−0.23	−0.18	−0.14	−0.15	−0.12	0.32	0.39	0.38	0.62	0.42	0.46	0.56	—															
22. WRTUT	−0.03	−0.07	−0.11	0	−0.08	−0.01	0.14	0.13	0.19	0.03	0.09	0.14	0.07	−0.27	−0.26	−0.34	−0.39	−0.27	−0.25	−0.33	−0.31	—														
23. PVTTUT	−0.07	−0.14	−0.08	−0.13	−0.03	0.1	0.33	0.22	0.11	0.14	0.02	−0.04	−0.01	−0.33	−0.32	−0.4	−0.56	−0.24	−0.29	−0.3	−0.47	0.38	—													
24. StTUT	−0.11	−0.17	−0.08	−0.11	0.01	0.17	0.28	0.28	0.23	0.22	0.08	0.02	0.04	−0.22	−0.24	−0.35	−0.39	−0.17	−0.22	−0.29	−0.28	0.35	0.53	—												
25. SaTUT	−0.05	−0.16	−0.04	−0.08	−0.08	0.1	0.16	0.26	0.14	0.16	0.22	0.17	0.22	−0.31	−0.24	−0.34	−0.4	−0.27	−0.28	−0.25	−0.33	0.59	0.42	0.48	—											
26. PVTRT1	−0.06	−0.17	−0.1	−0.29	0.09	0.19	0.6	0.18	0.12	0.23	0.13	0	0.08	−0.03	−0.11	−0.11	−0.23	−0.01	−0.1	−0.09	−0.16	0.09	0.35	0.16	0.03	—										
27. CRTRT1	−0.07	−0.18	−0.05	−0.18	0.02	0.25	0.15	0.09	0.04	0.17	−0.08	−0.15	0.11	0	−0.03	−0.06	−0.01	0.01	−0.1	−0.04	0.01	0.07	0.09	0.13	0.01	0.32	—									
28. StRT1	−0.19	−0.23	−0.2	−0.28	0.17	0.34	0.33	0.13	0.29	0.21	0.07	−0.03	0.16	0.01	−0.07	−0.11	−0.11	−0	−0.09	−0.12	−0.09	0.06	0.15	0.25	0.05	0.44	0.55	—								
29. CFQMAL	−0.01	−0.01	−0.05	−0.04	−0.03	0.07	0.08	0.12	0.12	0.02	0.06	0.04	0.1	−0.09	−0.06	−0.08	−0.1	−0.15	−0.03	−0.09	0.01	0.12	0.2	0.11	0.17	−0	−0.03	0.02	—							
30. Boredom	0.12	0.16	0.02	0.01	−0.11	0.03	0.07	0.13	0.1	0.12	0.15	0.18	0.15	0.02	0.01	0	0.01	−0.03	−0.01	−0.04	0.03	0.08	0	0.05	0.11	−0.16	−0.01	−0.1	0.4	—						
31. Sleep	0.04	−0.03	0.07	−0	−0.05	−0.11	−0.08	−0.07	0.02	−0.13	−0.02	0.03	−0.06	−0.04	0.09	0.09	0.1	0	−0.01	0.12	0.06	−0.06	−0.06	−0.12	−0.13	−0.1	−0.06	−0.06	−0.11	0.01	—					
32. Extra	−0.01	−0.02	0.04	−0.03	−0.13	−0.03	0.04	0.01	0.02	0.13	0.08	0.06	0.1	0.09	0.02	0.09	0.01	0.1	0.08	0.03	−0	0.05	−0.04	−0.04	0.04	0.04	−0.05	−0.02	−0.05	−0.06	0.06	—				
33. Agree	−0.05	0.05	0.04	−0.06	0.04	0.01	−0.02	−0.04	0	0.05	0.08	0.07	0.08	0.11	0.11	0.22	0.16	0.07	0.08	0.15	0.08	−0.08	−0.15	−0.12	−0.08	0.11	−0.06	−0.03	−0.18	−0.22	0.05	0.12	—			
34. Consc	−0.09	−0.02	0.01	−0.05	0.05	−0.07	−0.05	−0.06	−0.03	−0.08	0.01	−0.01	−0.03	0.09	0.09	0.12	0.13	0.13	0.04	0.15	0.08	−0.11	−0.18	−0.22	−0.15	0.03	−0.05	−0	−0.39	−0.24	0.14	0.09	0.22	—		
35. Neurot	−0.07	−0.18	−0.08	−0.09	0.06	0.18	−0.02	0.03	−0.03	0.01	−0.03	−0.11	−0.01	−0.06	−0.12	−0.07	−0.1	−0.04	−0.08	−0.01	−0.04	−0	0. 2	0.13	0.08	−0.02	−0.02	0.05	0.38	0.15	−0.13	−0.24	−0.31	−0.19	—	
36. Open	−0.01	0	0.03	0.04	0.01	0.03	−0.06	−0.08	0.04	0.05	−0.02	0.01	0.03	0.09	0.03	0.12	0.09	0.05	0.01	0.03	0.02	−0.02	−0.11	−0.08	−0.05	−0.05	−0.05	−0.04	0.01	0.24	0	0.14	−0.05	−0.03	−0.02	—

Note. Correlations > .10 are significant at the $p < .05$ level. Ospan = operation span; Symspan = symmetry span; Rspan = reading span; Anti = antisaccade; Cued = cued visual search; PVTLap = lapses in psychomotor vigilance task; Flat Spots = flat spots in continuous tracking; WRLap = lapses in whole report working memory; Blocks = blocks in choice reaction time; SaCoV = coefficient of variation in sustained attention to response task; SaAntic = anticipations in sustained attention to response task; SaOm = omission errors in sustained attention to response task; ContAl = alertness in continuous tracking; AntiAl = alertness in antisaccade; CRTAl = alertness in choice reaction time; PVTAl = alertness in psychomotor vigilance task; ContMo = motivation in continuous tracking; AntiMo = motivation in antisaccade; CRTMo = motivation in choice reaction time; PVTMo = motivation in psychomotor vigilance task; WRTUT = task-unrelated thoughts in whole report working memory; PVTTUT = task-unrelated thoughts in psychomotor vigilance task; StTUT = task-unrelated thoughts in Stroop; SaTUT = task-unrelated thoughts in sustained attention to response task; PVTRT1 = fastest 20% of reaction times in the psychomotor vigilance task; CRTRT1 = fastest 20% of reaction times in choice reaction time; StRT1 = fastest 20% of reaction times on congruent trials in the Stroop; CFQ-MAL = cognitive failures—memory and attention lapses; Boredom = Boredom Proneness Scale; Sleep = sleep quantity; Extra = extraversion; Agree = agreeableness; Consc = conscientiousness; Neurot = neuroticism; Open = openness.

Figure 1

(a) Confirmatory Factor Analysis Model for Behavioral Lapses of Attention. (b) Confirmatory Factor Analysis Model for Behavioral Lapses of Attention and Task-Unrelated Thoughts (TUTs). (c) Confirmatory Factor Analysis Model for Behavioral Lapses of Attention and Attention Control (AC)



TUTs measures loaded onto a separate factor. The two factors were allowed to correlate. The overall fit of the model was acceptable, $\chi^2(40) = 166.96$, $p < .001$, RMSEA = .09, 90% CI [.08, .11], NNFI = .90, CFI = .93, SRMR = .06. Importantly, the two-factor model fit significantly better than the one factor model, $\Delta\chi^2(1) = 231.63$, $p < .001$, suggesting that a two-factor model with separate lapse and TUT factors best accounted for the data. Shown in Figure 1b is the model. As can be seen, the behavioral lapse measures all loaded onto the lapse factor and the TUT measures all loaded onto the TUT factor and these two factors were moderately correlated (.44), suggesting that they are related, but clearly distinct factors.

We also examined whether behavioral lapses and attention control (based on restraint and constraint tasks) were best considered as one overall factor, or as separate but related factors. To test this, we specified a confirmatory factor analysis with all of the behavioral lapse indicators and all of the attention control measures loading onto a single common factor. The residuals for SART were allowed to correlate. The overall fit of the model was acceptable, $\chi^2(32) = 77.33$, $p < .001$, RMSEA = .06, 90% CI [.045, .081], NNFI = .95, CFI = .96, SRMR = .05. We contrasted the one-factor model with a two-factor model in which the behavioral lapse indicators loaded onto one factor and the attention control measures loaded onto a separate factor. The two factors were allowed to correlate. The overall fit of the model was acceptable, $\chi^2(31) = 61.33$, $p < .001$, RMSEA = .05, 90% CI [.033, .072], NNFI = .96, CFI = .97, SRMR = .05. Importantly, the two-factor model fit significantly better than the one factor model, $\Delta\chi^2(1) = 16.00$, $p < .001$, suggesting that the two-factor model with separate lapse and attention control factors best accounted for the data. Shown in Figure 1c is the model. As can be seen, the behavioral lapse measures all loaded onto the lapse factor and the attention control measures all loaded onto the attention control factor (although the loading for Stroop was weak) and these two factors were strongly correlated (−.70), suggesting that they are strongly related, but distinct factors.

For our final confirmatory factor analysis we examined how all of the different constructs related to one another. Specifically, we specified a model in which there were separate factors for behavioral lapses, TUTs, attention control, working memory capacity, speed of processing (based on the fastest 20% of accurate congruent Stroop trials, fastest 20% of psychomotor vigilance trials, and fastest 20% of accurate choice RT trials), alertness, and motivation. All of the variables were allowed to load only on their

Figure 1 (*Continued*) *Note*. Paths connecting latent variables (circles) to each other represent the correlations between the constructs and the numbers from the latent variables to the manifest variables (squares) represent the loadings of each task onto the latent variable. Solid paths are significant at the $p < .05$ level, whereas dashed paths are not significant. PVTLapse = lapses on psychomotor vigilance task; FlatSpot = flat spots in continuous tracking; WRLapse = lapses on whole report working memory task; Block = blocks in choice reaction time; SARTCoV = coefficient of variation in sustained attention to response task; SARTAntic = anticipatory response in the sustained attention to response task; SARTOmis = omission errors on the sustained attention to response task; Anti = antisaccade; Cued = cued visual search.

respective factor. As before we allowed all of the SART residual variances to correlate with one another. Additionally, we a priori specified residual variances for alertness and motivation within each task (i.e., alertness in continuous tracking and motivation in continuous tracking) to correlate given that these questions came right after one another on the same task. We post hoc allowed residual variances for psychomotor vigilance lapses and psychomotor vigilance fastest 20% of RTs to correlate based on modification indices. We also included manifest variables for boredom proneness, sleep, extraversion, agreeableness, conscientiousness, neuroticism, openness, and cognitive failures. Loadings for each of the questionnaire variables were set equal to one. All of the factors and manifest variables for the questionnaires were allowed to correlate. The overall fit of the model was acceptable, $\chi^2(489) = 972.52$, $p < .001$, RMSEA = .05, 90% CI [.048, .057], NNFI = .91, CFI = .93, SRMR = .06. Shown in Table 3 are the factor loadings. As can be seen, all of the measures loaded onto their respective constructs with the loadings typically being moderate to strong (with the exception of the Stroop which was weaker). Shown in Table 4 are the latent variable correlations. There are a number of notable relations. Specifically, as noted above, the behavioral lapse factor was related to both TUTs and attention control, suggesting that individuals who experience many lapses of attention tend to have reduced attention control abilities and tend to have many TUTs. Additionally, lapses were related to working memory capacity consistent with prior research which examined relations at the task level (e.g., Unsworth et al., 2010; Unsworth & Robison, 2020). Lapses were also related to the speed of processing factor.[2] In terms of contextual variables, lapses were related to both alertness and motivation levels, suggesting that individuals who are not alert or not motivated to perform the current task are more likely to experience lapses. In terms of the trait measures, only boredom proneness was associated to lapses. Finally, lapses were related to everyday cognitive failures suggesting that individuals who experience lapses of attention on the laboratory tasks also tend to experience lapses and cognitive failures in the everyday life. To estimate our power to detect specific relations between the behavioral lapse factor and the other factors we used Wang and Rhemtulla's (in press) pwrSEM app. We specified the factor loadings for the behavioral lapse factor to be .50, with an N of 358, and we estimated factor correlations ranging from .10–.70 with 1,000 samples. The pwrSEM results suggested that we had sufficient power (power > .90) to detect correlation greater than .19. However, we had much less power (power < .40) to detect smaller correlations ≤ .10. Thus, we were sufficiently powered to detect most of the factor correlations, but

Table 3
Standardized Factor Loadings for Confirmatory Factor Analysis

Measure	Lapse	TUT	AC	WMC	Speed	Alertness	Motivation
PVTLap	.67						
FlatSpot	.55						
WRLap	.53						
Blocks	.53						
SaCoV	.49						
SaAntic	.32						
SaOm	.48						
WRTUT		.62					
PVTTUT		.73					
StTUT		.66					
SaTUT		.68					
Anti			.55				
Stroop			−.23				
Cued			−.57				
Ospan				.72			
Symspan				.61			
Rspan				.63			
PVTRT1					.49		
CRTRT1					.62		
StRT1					.85		
ContAl						.53	
AntiAl						.53	
CRTAl						.68	
PVTAl						.83	
ContMo							.50
AntiMo							.52
CRTMo							.68
PVTMo							.83

Note. All loadings are significant at the $p < .05$ level. PVTLap = lapses in psychomotor vigilance task; Flat Spots = flat spots in continuous tracking; WRLap = lapses in whole report working memory; Blocks = blocks in choice reaction time; SaCoV = coefficient of variation in sustained attention to response task; SaAntic = anticipations in sustained attention to response task; SaOm = omission errors in sustained attention to response task; WRTUT = task-unrelated thoughts in whole report working memory; PVTTUT = task-unrelated thoughts in psychomotor vigilance task; StTUT = task-unrelated thoughts in Stroop; SaTUT = task-unrelated thoughts in sustained attention to response task; Anti = antisaccade; Cued = cued visual search; Ospan = operation span; Symspan = symmetry span; Rspan = reading span; PVTRT1 = fastest 20% of reaction times in the psychomotor vigilance task; CRTRT1 = fastest 20% of reaction times in choice reaction time; StRT1 = fastest 20% of reaction times on congruent trials in the Stroop; ContAl = alertness in continuous tracking; AntiAl = alertness in antisaccade; CRTAl = alertness in choice reaction time; PVTAl = alertness in psychomotor vigilance task; ContMo = motivation in continuous tracking; AntiMo = motivation in antisaccade; CRTMo = motivation in choice reaction time; PVTMo = motivation in psychomotor vigilance task.

[2] Given the strong relations among the behavioral lapse factor, attention control, and the speed of processing factor, a concern is that the relation between the behavioral lapse factor and attention control could simply be due to shared variance with speed. That is, once speed of processing is taken into account there may no longer be a relation between lapses and attention control. To examine this, we tested a structural equation model in which both attention control and speed of processing were allowed to predict the behavioral lapse factor. The fit of the model was acceptable, $\chi^2(58) = 157.48$, $p < .001$, RMSEA = .07, 90% CI [.056, .082], NNFI = .93, CFI = .94, SRMR = .06. Importantly, the model demonstrated that attention control predicted unique variance in lapses (path coefficient = −.67), but speed did not (path coefficient = .03). We also tested a bifactor model in which we allowed all of the attention control and speed of processing measures to load onto a common factor, and the three attention control tasks also loaded on a residual attention control factor. Both factors were allowed to correlate with the behavioral lapse factor. The fit of the model was acceptable, $\chi^2(56) = 155.87$, $p < .001$, RMSEA = .07, 90% CI [.058, .084], NNFI = .93, CFI = .94, SRMR = .06. All measures loaded on their respective factors, except Stroop which did not have a significant loading on the residual attention control factor. Importantly, both the common factor (.47) and the residual attention control factor (−.52) correlated with the behavioral lapse factor. Thus, although attention control and speed of processing were strongly correlated, attention control consistently accounted for unique variance in lapses of attention even when taking speed into account. Similar results were obtained when examining the relation between attention control and working memory capacity, suggesting that the relation was not due to variation in speed of processing.

Table 4
Latent Variable Correlations From the Confirmatory Factor Analysis

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Lapse	—														
2. TUT	**0.42**	—													
3. AC	**−0.69**	**−0.21**	—												
4. WMC	**−0.34**	**−0.20**	**0.50**	—											
5. Speed	**0.47**	**0.24**	**−0.67**	**−0.34**	—										
6. Alertness	**−0.40**	**−0.78**	**0.40**	**0.18**	**−0.15**	—									
7. Motivation	**−0.46**	**−0.65**	**0.30**	**0.19**	**−0.15**	**0.75**	—								
8. Bored	**0.20**	0.08	0.01	**0.15**	−0.11	0.02	−0.01	—							
9. Sleep	−0.10	**−0.14**	0.11	0.05	**−0.09**	0.09	0.09	0.01	—						
10. Extra	0.08	0.00	0.04	0.01	−0.02	0.05	0.03	−0.06	0.06	—					
11. Agree	−0.03	**−0.16**	−0.06	0.00	−0.01	**0.22**	**0.13**	**−0.22**	0.05	**0.12**	—				
12. Consc	−0.09	**−0.25**	0.01	−0.07	−0.01	**0.15**	**0.14**	**−0.24**	**0.14**	0.09	**0.22**	—			
13. Neurot	0.01	**0.16**	**−0.24**	**−0.16**	0.03	**−0.13**	−0.05	**0.15**	**−0.13**	**−0.24**	**−0.31**	**−0.19**	—		
14. Open	−0.04	−0.10	0.00	0.01	−0.05	**0.12**	0.03	**0.24**	0.00	**0.14**	−0.05	−0.03	−0.02	—	
15. CFQ	**0.15**	**0.23**	−0.09	−0.03	0.01	−0.10	−0.06	**0.40**	**−0.11**	−0.05	**−0.17**	**−0.39**	**0.38**	0.01	—

Note. Significant correlations are in bold. Lapse = behavioral lapse factor; TUT = task-unrelated thoughts factor; AC = attention control factor; WMC = working memory capacity factor; Speed = speed of processing factor; Alertness = alertness factor; Motivation = motivation factor; Bored = boredom proneness manifest variable; Sleep = sleep quantity; Extra = extraversion manifest variable; Agree = agreeableness manifest variable; Consc = conscientiousness manifest variable; Neurot = neuroticism manifest variable; Open = openness manifest variable; CFQ = cognitive failures manifest variable.

were generally underpowered to detect correlations relating to the personality traits.

TUTs were weakly and negatively related to both attention control and working memory capacity, consistent with prior research (e.g., McVay & Kane, 2012b; Kane et al., 2016; Robison & Unsworth, 2018; Unsworth & McMillan, 2014). TUTs were also strongly related to alertness and motivation levels consistent with prior research (Robison & Unsworth, 2018; Robison et al., in press; Unsworth & McMillan, 2013). Sleep quantity was also weakly related to TUTs consistent with prior research (Robison et al., in press; Stawarczyk & D'Argembeau, 2016). In terms of traits, agreeableness and conscientiousness were negatively related to TUTs (e.g., Robison et al., in press), while neuroticism was positively related to TUTs (Jackson et al., 2012; Kane et al., 2017; Robison et al., 2017). Similar to behavioral lapses, TUTs were related to cognitive failures in everyday life. Thus, although lapses and TUTs were correlated and demonstrated many similar relations, they also demonstrated differential relations. Behavioral lapses tended to demonstrate numerically larger relations with the cognitive measures, whereas TUTs tended to demonstrate numerically larger relations with the contextual and trait measures. To examine whether these relations were in fact significantly different, we constrained the relations to be equal between behavioral lapses and TUTs and examined the change in model fit. Constraining the relations to be equal suggested that behavioral lapses were more strongly related with attention control and speed of processing (both $\Delta\ \chi^2$'s > 7.2, p's $< .01$; the change in model fit for working memory capacity was not significant $p = .07$). TUTs, however, were more strongly related to alertness and motivation (both $\Delta\ \chi^2$'s > 9.6, p's $< .01$; the change in model fit for sleep was not significant $p = .63$). Constraining the correlations to be equal for the trait measures suggested that the relations with TUTs and behavioral lapses were roughly equal (all $\Delta\ \chi^2$'s < 3.49, p's $>$ .06). These relations will be examined more thoroughly next via structural equation modeling.

Other notable relations include the consistent finding that attention control and working memory capacity were related and both were related to the speed of processing factor as well as to alertness, motivation, and neuroticism. Alertness and motivation were strongly related suggesting possible multicollinearity. Finally, the cognitive failures questionnaire was not only related to lapses and TUTs, but was also related to several of the other measures including boredom proneness, sleep quantity, agreeableness, conscientiousness, and neuroticism, suggesting that self-reports of cognitive failures are related to a number of personality traits (e.g., Könen & Karbach, 2018; Wallace, 2004; Wilhelm et al., 2010).

Structural Equation Modeling

We next used structural equation modeling (SEM) to assess how the different factors uniquely accounted for variance in lapses, TUTs, and cognitive failures. Similar to simultaneous regressions, SEMs allow for an assessment of how a number of predictors account for unique variance (path coefficients) in a construct. Thus, we were interested in examining which factors have more direct relations to lapses after accounting for shared variance with the other factors. This should tell us which of the various factors are important in accounting for unique variance in lapses of attention. For our first model, we examined which of the factors that were shown to correlate with the behavioral lapse factor would account for unique variances in lapses. Therefore, we specified a model in which the behavioral lapse factor was predicted by working memory capacity, attention control, TUTs, motivation, alertness, speed of processing, and boredom proneness. The exogenous factors were all allowed to correlate with one another and the same residuals as in the confirmatory factor analyses were freed. The overall fit of the model was acceptable, $\chi^2(342) = 778.04$, $p < .001$, RMSEA = .06, 90% CI [.054, .065], NNFI = .92, CFI = .93, SRMR = .06. Overall, 65% of the variance in the lapse factor was accounted for by the different predictors. Shown in Figure 2a is the resulting model. Note, for simplicity, correlations among the exogenous factors are not shown. The correlations among the factors remained the same as shown in Table 4. As can be seen, only attention control and motivation accounted for unique variance in lapses. Thus, while the other factors were related to lapses, only variation in attention control and motivation were uniquely related to lapses. This suggests that variation in attention control and motivation are two critical factors for variation in lapses of attention. However, there were some potential issues with the model. As can be seen in Figure 2a, the path coefficients for TUTs and alertness were large, but not significant due to large standard errors (.32 and .38, respectively). Furthermore, alertness was now positively related to lapses. Given that TUTs, motivation, and alertness were all strongly correlated, it is likely that multicollinearity among these factors is influencing the resulting path coefficients. To deal with this multicollinearity, we next specified a bifactor model in which we modeled the common variance among TUTs, motivation, and alertness and specified residual factors for TUTs, motivation, and alertness. In this way, we can assess whether the common variance among the factors is important, as well as whether there is any specific variance associated with each factor that is important for predicting lapses. Correlations between the common factor and the residual factors was set to zero and the residual factors were allowed to correlate. All of relations remained the same as the prior structural equation model. The overall fit of the model was generally acceptable, $\chi^2(329) = 939.45$, $p < .001$, RMSEA = .07, 90% CI [.067, .078], NNFI = .88, CFI = .90, SRMR = .06. Shown in Table 5 are the factor loadings for the common factor as well as for the residual TUTs, alertness, and motivation factors. As can be seen, all measures loaded significantly on the common factor. The TUT measures also loaded on the TUTs factor. Most of the alertness measures also loaded weakly on the alertness factor (the loading for antisaccade was not significant) except for continuous tracking which had a very strong loading on the residual factor. Similarly, most of the motivation measures loaded weakly on the motivation factor (the loading for antisaccade was not significant) except for continuous tracking which had a very strong loading on the residual factor. This suggests that the residual alertness and motivation factors are largely driven by variance in the continuous tracking task. Thus, there was considerable shared variance among the measures and some of the measures had additional unique variance shared only with their specific factor. Shown in Figure 2b is the resulting structural equation model. As can be seen, attention control still predicted lapses. Additionally, the residual TUTs factor, boredom proneness, and the common factor predicted unique variance in lapses. The common factor likely reflects overall task disengagement whereby participants are not engaged with the task resulting in overall lower alertness, lower motivation, and an increased likelihood of TUTs. The residual TUTs factor likely represent more specific variation in who is likely to experience TUTs regardless of current alertness and motivation levels. None of the other factors accounted for unique variance. Overall, 60% of the variance in lapses was accounted for by both shared variance among the factors as well as unique variance from atten-

Figure 2

(a) Structural Equation Model in Which the Behavioral Lapse Factor Was Predicted by Working Memory Capacity (WMC), Attention Control (AC), Task-Unrelated Thoughts (TUTs), Motivation, Alertness, Speed of Processing (Speed), And Boredom Proneness (Bored). (b) Structural Equation Model in Which the Behavioral Lapse Factor Was Predicted by Working Memory Capacity (WMC), Attention Control (AC), Task-Unrelated Thoughts (TUTs), Motivation, Alertness, Speed of Processing (Speed), Common Variance Shared by Task-Unrelated Thoughts, Alertness, and Motivation (Common), and Boredom Proneness (Bored)

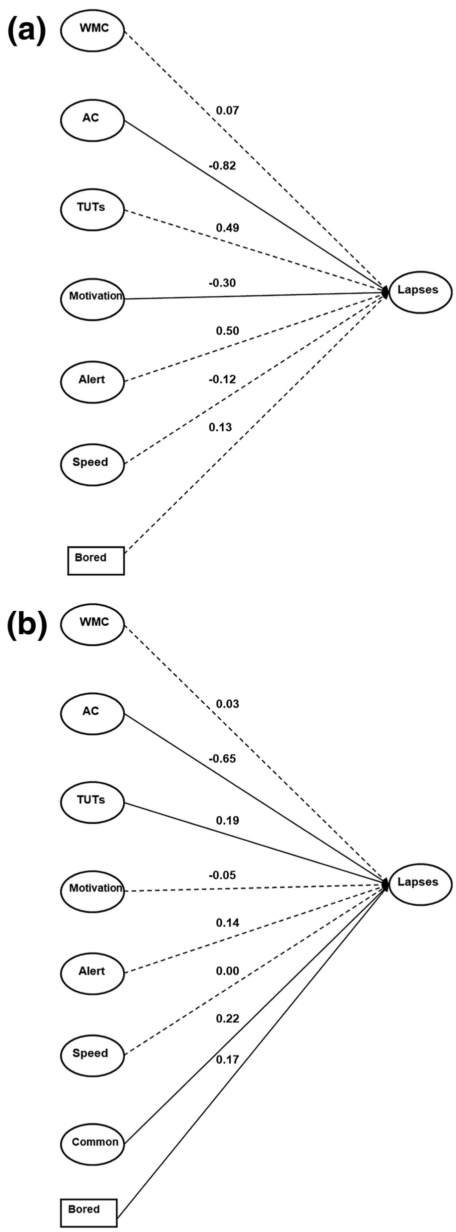


Figure 2 (*Continued*) *Note*. Solid paths are significant at the $p < .05$ level, whereas dashed paths are not significant. See Table 4 for correlations among the exogenous factors.

Table 5
Standardized Factor Loadings for Bifactor Structural Equation Model

Measure	Common	TUT	Alertness	Motivation
WRTUT	.43	.54		
PVTTUT	.61	.27		
StTUT	.47	.39		
SaTUT	.44	.69		
ContAl	−.34		.99	
AntiAl	−.58		*.08*	
CRTAl	−.61		.28	
PVTAl	−.78		.16	
ContMo	−.27			.99
AntiMo	−.57			*.06*
CRTMo	−.60			.16
PVTMo	−.74			.19

Note. Italicized loadings are not significant at the $p < .05$ level. All other loadings are significant. WRTUT = task-unrelated thoughts in whole report working memory; PVTTUT = task-unrelated thoughts in psychomotor vigilance task; StTUT = task-unrelated thoughts in Stroop; SaTUT = task-unrelated thoughts in sustained attention to response task; ContAl = alertness in continuous tracking; AntiAl = alertness in antisaccade; CRTAl = alertness in choice reaction time; PVTAl = alertness in psychomotor vigilance task; ContMo = motivation in continuous tracking; AntiMo = motivation in antisaccade; CRTMo = motivation in choice reaction time; PVTMo = motivation in psychomotor vigilance task.

tion control, TUTs, boredom proneness, and the common variance shared across TUTs, alertness, and motivation. As such these results suggest that a number of factors are important in predicting who is likely to experience frequent lapses of attention.

In the next SEM we specified a model in which TUTs were predicted by working memory capacity, attention control, lapses, motivation, alertness, sleep quantity, agreeableness, conscientiousness, and neuroticism based on the correlations from the prior confirmatory factor analysis. The exogenous factors were all allowed to correlate with one another and the same residuals as in the confirmatory factor analyses were freed. The overall fit of the model was acceptable, $\chi^2(329) = 699.20$, $p < .001$, RMSEA = .06, 90% CI [.050, .062], NNFI = .93, CFI = .94, SRMR = .06. Overall, 74% of the variance in the TUTs factor was accounted for by the different predictors. Shown in Figure 3 is the resulting model. Note, for simplicity correlations among the exogenous factors are not shown. The correlations among the factors remained the same as shown in Table 4. As can be seen, lapses, attention control, and alertness all predicted unique variance in TUTs. None of the other factors accounted for unique variance in TUTs. One interesting thing to note, however, is that in this model attention control was positively related to TUTs, whereas the latent variable correlation (see Table 4) was negative. This suggests that once variance in the other constructs (in particular lapses and perhaps working memory capacity) is accounted for, attention control is now positively related to TUTs. This suggests that some of the attention control to TUTs relation is suppressed by the other variables. This pattern of results is consistent with prior research suggesting that once common variance associated with a general tendency to experience TUTs is accounted for, there is a residual positive relation between attention control abilities and TUTs (e.g., Robison et al., in press). Similar positive relations between TUTs and cognitive abilities due to suppression have been found for working memory capacity and even fluid intelligence (Robison et al., in press; Rummel & Boywitt, 2014; Unsworth & McMillan, 2014). These results suggest that for the most part low ability participants are more likely to experience TUTs, but there are also important positive relations between abilities and TUTs such that in some situations (and perhaps for some individuals), high cognitive ability participants are more likely to experience TUTs. Collectively, these results suggest that several factors are important in accounting for individual differences in TUTs.

Our final SEM examined what factors are important for accounting for variation in everyday cognitive failures. Therefore, we specified a model in which CFQ was predicted by TUTs, behavioral lapses, boredom proneness, sleep quantity, agreeableness, conscientiousness, and neuroticism based on the prior confirmatory factor analysis. The overall fit of the model was acceptable, $\chi^2(94) = 250.84$, $p < .001$, RMSEA = .07, 90% CI [.058, .079], NNFI = .90, CFI = .93, SRMR = .05. Overall, 34% of the variance in everyday cognitive failures was accounted for by the different predictors. Shown in Figure 4 is the resulting model. Note, for simplicity correlations among the exogenous factors are not shown. The correlations among the factors remained the same as shown in Table 4. As can be seen, neither TUTs nor behavioral lapses accounted for unique variance in CFQ scores. Rather, boredom proneness, conscientiousness, and neuroticism all accounted for unique variance in CFQ. Thus, in the current data behavioral lapses and TUTs did not have any unique relations with everyday cognitive failures.[3] Rather cognitive failures seemed to be predominantly driven by various personality traits.

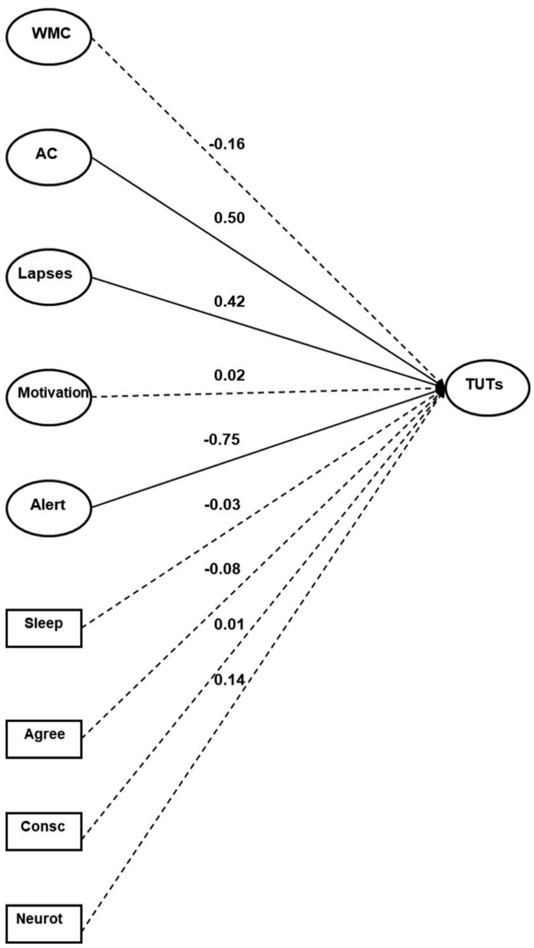
General Discussion

In a novel latent variable study, we investigated individual differences in lapses of attention. As noted in the introduction we had three main goals: (a) examine whether different behavioral indicators of lapses are related enough to be accounted for by a single latent factor; additionally we wanted to examine whether a general behavioral lapse factor was the same or different from TUTs and attention control abilities (indexed with restraint and constraint type tasks); (b) examine how various cognitive, contextual, and trait factors are associated with lapses of attention in order to better understand what factors are important for susceptibility to lapses of attention; (c) examine how lapses of attention

[3] The lack of a relation between some of the cognitive ability measures (working memory capacity and attention control) with the cognitive failures questionnaire and the lack of direct relations between behavioral lapses and TUTs with the cognitive failure questionnaire in the SEMs at first glance seems inconsistent with prior research which has found these factors to correlate with reports of various attentional failures in the real-world (e.g., Kane et al., 2007; Kane et al., 2017; Unsworth, McMillan, et al., 2012; Unsworth & McMillan, 2017). However, it is important to note that those prior studies utilized experience sampling methods (PDAs and diaries) to estimate how frequently attentional failures occurred in daily life. The cognitive failures questionnaire, however, asks how often individuals experience various cognitive failures. This has led some researchers to argue that self-report questionnaires are more likely to index subjective beliefs about the cognitive system rather than how the system actually operates (Herrmann, 1982), as well as possibly providing an index of neuroticism and overall subjective complaints about the cognitive system (e.g., Wilhelm et al., 2010). Thus, it is possible that experience sampling methods and self-report questionnaires are measuring different aspects of everyday attentional failures.

Figure 3

Structural Equation Model in Which theTask-Unrelated Thoughts (TUTs) Factor was Predicted by Working Memory Capacity (WMC), Attention Control (AC), Behavioral Lapses (Lapses), Motivation, Alertness, Sleep Quantity (Sleep), Agreeableness (Agree), Conscientiousness (Consc), and Neuroticism (Neurot)



Note. Solid paths are significant at the $p < .05$ level, whereas dashed paths are not significant.

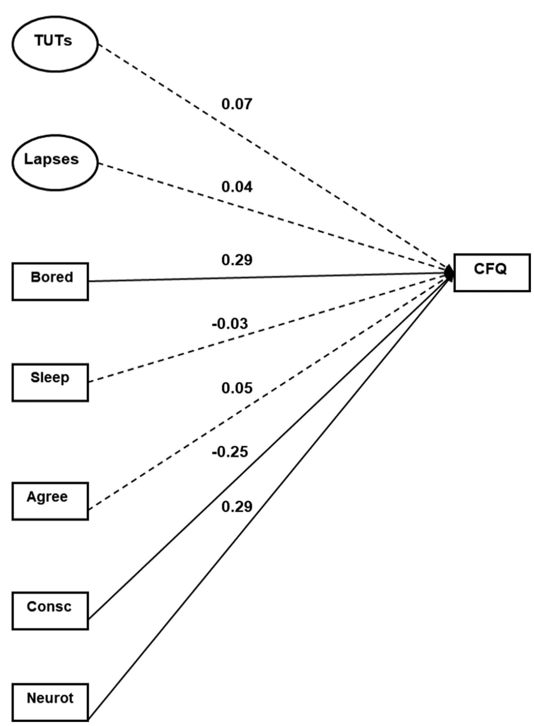
assessed in the laboratory are associated with self-reports of cognitive failures in everyday life.

In terms of our first goal, the results suggested that (a) all of the different behavioral lapse indicators were positively correlated and loaded onto a general lapse factor. Testing a two-factor lapse model in which one lapse factor was composed of RT measures and the other lapse factor was composed of non-RT measures suggested a good fit to the data, but the fit was significantly worse than the one factor lapse model. These results provide novel evidence for the notion that there is a general propensity to experience lapses of attention and this is not simply driven by the type of dependent measure used to measure lapses. The results also suggested that (b) the behavioral lapse factor was correlated with a TUTs factor, but these factors were clearly separable. Likewise the results suggested that (c) the behavioral lapse factor was strongly correlated with attention control abilities, but again the factors were clearly separable. Thus, the results from the current latent variable analyses suggest that different behavioral indicators of lapses of attention largely measure the same overall susceptibility and this variation is related to, but distinct, from variation in TUTs and attention control abilities. This is the first study, to our knowledge, to directly compare and disambiguate individual differences in these constructs at the latent factor level.

In terms of our second goal, the results suggested that (a) in addition to being related to TUTs and attention control, lapses were related to working memory capacity and our measure of speed of processing; (b) lapses were also related to overall alertness levels during the tasks and to task-specific motivation; (c) the only trait measure related to lapses was boredom proneness. SEM further suggested that (d) attention control, TUTs, boredom proneness, and the common variance shared by alertness, motivation, and TUTs all accounted for unique variance in lapses with roughly 60% of the variance in lapses being accounted for by the various factors. Similarly, TUTs were related to (e) attention control, working memory capacity, and speed of processing; (f) TUTs were also

Figure 4

Structural Equation Model in Which Everyday Cognitive Failures (CFQ) Were Predicted by Working Memory Capacity Task-Unrelated Thoughts (TUTS), Behavioral Lapses (Lapses), Boredom Proneness (Bored), Sleep Quantity (Sleep), Agreeableness (Agree), Conscientiousness (Consc), and Neuroticism (Neurot)



Note. Solid paths are significant at the $p < .05$ level, whereas dashed paths are not significant.

related to alertness, motivation, and sleep quantity; and (g) unlike behavioral lapses TUTs were related to several trait measures including agreeableness, conscientiousness, and neuroticism (but not to boredom proneness). Although, it should be emphasized that differences in the correlations were not significant. SEM further suggested that (h) behavioral lapses, attention control (positively), and alertness all accounted for unique variance in TUTs with roughly 74% of the variance in TUTs being accounted for by the various factors. Collectively, these results suggest that a number of factors are important in accounting for lapses of attention and TUTs and that lapses and TUTs demonstrate similarities and differences in terms of their relations with other constructs (see below).

In terms of our final goal, the results suggested that (a) both behavioral lapses and TUTs were related to self-reports of everyday cognitive failures assessed with the CFQ; and (b) self-reports of everyday cognitive failures were related to various personality traits including boredom proneness, agreeableness, conscientiousness, and neuroticism as well as sleep quantity. SEM further suggested that (c) boredom proneness, conscientiousness, and neuroticism all accounted for unique variance in self-reported cognitive failures with roughly 34% of the variance in everyday cognitive failures being accounted for by the various factors. Collectively, these results suggest that lapses of attention assessed in laboratory settings have some ecological validity in terms of being related to everyday cognitive failures, but at the same time, self-reports of everyday cognitive failures seem to be driven more by various personality traits and are more indirectly related to lapses of attention (e.g., Könen & Karbach, 2018; Wilhelm et al., 2010).

Similarities and Differences Between Behavioral Lapses and Task-Unrelated Thoughts

The current analyses suggested that behavioral indicators of lapses of attention and TUTs, although related (.44), were clearly distinct constructs. These results are consistent with recent research which suggested that variability in RTs (using coefficient of variation of RTs) are related to TUTs, but are also separable. For example, both Unsworth (2015) and Kane et al. (2016) found that a coefficient of variability of RT factor was related to a TUTs factor (.40 and .54, respectively). The results are also consistent with recent neuroimaging work suggesting that RT variability and TUTs account for separate variance in default mode activity during a sustained attention task (Kucyi et al., 2016). The current results extend this prior work by more specifically demonstrating important ways in which behavioral lapses and TUTs are similar yet distinct. For instance, in the current results it was found that behavioral lapses were more strongly related to other task performance measures such as cognitive abilities (attention control, speed of processing) than TUTs, whereas TUTs were more strongly related to other self-report measures such as alertness and motivation. Thus, behavioral lapses and TUTs were influenced by variation in attention control, contextual factors such as alertness and motivation, but to differing degrees and in different ways. Thus, the current results extend prior research in suggesting that individual differences in behavioral lapses of attention and TUTs are related, but separable constructs.

There are a number of possible reasons for similarities and differences between behavioral lapses and TUTs. For example, there are clear method differences for how these two are being assessed. Behavioral lapses are assessed via changes in task performance, whereas TUTs are assessed via self-reports during task performance. Thus, shared method variance (performance vs. self-report) could be influencing some of the relations seen in the current dataset. An additional reason for differences between these two constructs is that TUTs likely reflect variation in things other than just lapses of attention. For example, as noted previously, some prior research suggests that high ability participants report more mind-wandering than low ability participants in certain situations (e.g., Levinson et al., 2012; Robison et al., in press; Rummel & Boywitt, 2014; but see Meier, 2019). This may represent intentional forms of mind-wandering, rather than unintentional/spontaneous mind-wandering (Seli et al., 2015; Seli et al., 2016; Robison & Unsworth, 2018; Robison et al., in press) in that high ability participants might be engaging in mind-wandering in some situations where not all of their capacity is needed to perform a task (Rummel & Boywitt, 2014; Smallwood & Andrews-Hanna, 2013). Yet, these same participants might demonstrate few behavioral lapses of attention compared with low ability participants. Indeed, as noted previously, attention control abilities were positively correlated with TUTs once the shared variability with behavioral lapses was accounted for, suggesting that some high attention control participants were engaging in more mind-wandering than low attention control participants. This same finding of cognitive abilities positively predicting TUTs once shared variance is accounted for has been reported in several prior studies (Robison et al., in press; Rummel & Boywitt, 2014; Unsworth & McMillan, 2014) suggesting that in some situations and/or for some individuals, high ability participants are actually reporting more TUTs than low ability participants.

Additionally, it is likely that TUTs reflect how participants are responding to the thought probes based on personality characteristics. For example, individuals high in neuroticism are more likely to have a negative bias in responding, and thus may not only have more current concerns than individuals low in neuroticism, but may also worry/think that they mind-wander more leading to a negative bias in responding to the thought probes. Conversely, individuals high in conscientiousness are more likely to be achievement oriented and self-disciplined than individuals low in conscientiousness, resulting in reports of more on-task focus and less mind-wandering (Jackson et al., 2010). In both cases this could lead to biases in how participants are responding to the thought probes, but may not reflect differences in performance associated to behavioral lapses. Thus, variation in TUTs can arise not only due to variation in lapses, but also variation in the amount of current concerns an individual has as well as any biases an individual has in responding to the thought probes (see Kane et al., 2016 for similar arguments).

In a similar vein, the behavioral lapse measures that we used are likely not process pure indicators of lapses. Rather, as noted previously, participants could have particularly long RTs simply because they have overall slower speed of processing leading to a shift in the RT distribution. Thus, many long RTs could result from lapses as well as speed of processing. Indeed, the current results suggested that our speed of processing factor (the fastest RTs in several tasks) was positively correlated with the behavioral lapse factor. Thus, when assessing behavioral lapses of attention based on RT measures it is critical to have some assessment of speed of processing to examine to what extent the results are driven by differences in speed rather than lapses per se. Despite some of the variability in the behavioral lapse factor being associated with speed of processing, it is important to note that many relations held even when taking speed into account, suggesting that much of the variability in the behavioral lapse factor was due to lapses rather than just speed. In addition to basic speed differences, the behavioral lapse factor is also likely associated with variation in speed–accuracy trade-offs whereby some participants will be slower to ensure that they are responding more accurately. Again this would result in a shift in the distribution whereby some participants are sacrificing speed for accuracy. Long RTs could arise not only because of differences in overall speed-accuracy settings, but also in more local speed–accuracy trade-offs associated with errors. That is, some of the slow RTs could be due to posterror slowing, whereby following an error participants slow down to ensure that the next trial is accurate (e.g., Rabbitt, 1966). Thus, when examining variation in lapses of attention it is important not only to take basic differences in speed of processing into account, but it is also important to ensure that not all of the lapse measures are based solely on RTs or variability in RTs.

Collectively, the current results suggest that behavioral lapses and TUTs are not isomorphic constructs and should not be used interchangeably. Rather, there are distinct factors that influence individual differences in each. Furthermore, these two constructs may be getting at different aspects of overall task disengagement (Cheyne et al., 2009). In many situations it will be important to examine both behavioral lapses and TUTs, and in other situations it may be more appropriate to assess only one or the other. Careful consideration is needed to determine which measures are appropriate for a given study when attempting to assess variation in overall lapses of attention. Furthermore, future research is needed to better examine similarities and differences between behavioral lapses of attention and TUTs.

Similarities and Differences Between Behavioral Lapses and Other Attention Control Constructs

The current results further increased our understanding of lapses of attention by demonstrating that behavioral lapses and our attention control factor were strongly correlated (−.70), yet distinct. This is consistent with prior research which has suggested that there are different subcomponents of attention control (e.g., Friedman & Miyake, 2004; Kane et al., 2016; Poole & Kane, 2009; Unsworth & Robison, 2020; Unsworth & Spillers, 2010). In particular, Kane and colleagues (Kane et al., 2016; Poole & Kane, 2009) have suggested that the attention control construct can be fractionated into separate restraint and constraint factors (see also Friedman & Miyake, 2004). Restraint refers to the ability to prevent prepotent responses from guiding behavior (e.g., preventing the flashing cue in the antisaccade task from capturing attention) while constraint refers to the ability to constrain attention to target items among distractors (e.g., to zoom attention in on target items in the flanker task). Additional research has suggested a third subcomponent of attention control abilities in terms of the ability to sustain attention across both short and long intervals and prevent lapses of attention (Kane et al., 2016; Unsworth, 2015; Unsworth & Robison, 2020; Unsworth & Spillers, 2010). This ability is seen as important even in situations and tasks were there are really no strong task-relevant distractors (i.e., no flashing cues, no flankers), but where it is critical to keep attention focused on the current task to prevent off-task distractors (mind-wandering) from hijacking attention away. In our view, these are precisely the abilities that are being accounted for by the behavioral lapse factor in the current study. Those individuals who can maintain and sustain attentional focus on the current task at hand are less likely to experience lapses of attention resulting in better overall performance. Thus, by this account we would expect attention control abilities indexed by restraint and constraint tasks to be highly correlated with lapses of attention (sustained attention abilities), but to also be clearly distinct as demonstrated in the current study. Furthermore, we would expect that variation in TUTs should be more strongly related to lapses of attention than to attention control abilities indexed by restraint and constraint abilities. As shown in Table 4, this was exactly the case as lapses and TUTs were more strongly correlated (.42) than TUTs and attention control abilities (−.21).

These results are also consistent with prior research which has examined variability in RTs on attention control tasks (assuming this provides some assessment of lapses of attention) and found that variability in RTs are related to attentional restraint and constraint factors. For example, Unsworth (2015) found that a variability in RT factor composed of the psychomotor vigilance task and the SART was strongly (−.93) related to an attention control factor composed of restraint and constraint tasks (i.e., antisaccade, flankers, Stroop). Furthermore, the variability in RT factor was more strongly related to TUTs (.51; mind-wandering) than the attention control factor based on restraint and constraint tasks (−.23). Similarly, Kane et al. (2016) found that both restraint (.48) and constraint (.24) factors correlated with variability in RTs. Note here that these correlations are positive because Kane et al. (2016) relied on total number of errors rather than accuracy as the main dependent measure for several tasks. Reanalyzing their data and creating a single restraint/constraint attention control factor similar to the current study suggests that the variability in RT factor was strongly related to the combined restraint/constraint factor (.56), and that the variability in RT factor was more strongly correlated with TUTs (.52) than the combined restraint/constraint factor (.34).

Collectively, the current results provide important information suggesting that individual differences in lapses of attention are strongly related to, but distinct, from other forms of attention control (such as constraint and restraint). We argue that variation in behavioral lapses of attention reflect differences in the ability to sustain attention on task both moment-to-moment and over the long-term, and this ability is related to, but distinct from other forms of attention control (e.g., Langner & Eickhoff, 2013; Posner & Petersen, 1990; Robertson & O'Connell, 2010; Sturm & Willmes, 2001; Stuss et al., 1995; Unsworth & Robison, 2020; van Zomeren & Brouwer, 1994). Future research is better needed to examine similarities and differences between different subcomponents of attention control and the extent to which they can be accounted for by a higher-order attention control factor.

Multiple Factors Influence Lapses of Attention

As noted previously, one of the main goals of the current study was to examine what factors are important in accounting for variation in lapses of attention. The current results provide important novel information that variation in lapses of attention arise due to multiple factors. One main factor was variation in overall attention control abilities. Typically, those individuals high in attention control will be better able to sustain attention on task and prevent lapses of attention than individuals low in attention control. In addition to overall attention control abilities, a number of other factors also seem to be important. For example, individuals who are prone to mind-wandering and TUTs are more likely to experience lapses of attention and some of this variation is independent of variation in attention control abilities. Thus, regardless of attention control abilities, some individuals are more likely to experience frequent lapses of attention due to higher rate of mind-wandering. Furthermore, contextual factors such as current alertness levels and task-specific motivation will be important in determining susceptibility to lapses of attention. Individuals who are low in alertness or arousal (due to a variety of factors) are more likely to experience lapses of attention than individuals who are currently alert. Additionally, individuals who are more motivated to perform the current task will experience fewer lapses of attention than individuals who are less motivated to perform the current task. Finally, the current results suggested that trait levels of boredom proneness are also associated with variation in lapses of attention whereby individuals are more prone to get bored with a task are more likely to experience lapses of attention on a variety of tasks. Collectively, the current results suggest that a number of cognitive, contextual, and trait factors are important sources of variation in determining who is likely to experience frequent lapses of attention. At the same time, it is important to note that in the current models only 60% of the variance was accounted for in the behavioral lapse factor. While this amount is impressive, it also suggests that there are other sources of variance that are important in determining variation in lapses of attention. These other factors could include additional state level variables like stress and anxiety (see below) as well as other cognitive, contextual, and trait factors not assessed in the current study. Future research is needed to better examine the nature of individual differences in lapses of attention and what additional factors may be important in driving variation in lapses of attention.

While our models provide information on what factors are essential for accounting for variance in lapses of attention, it is important to also note the bidirectional nature of many of these relations. That is, in our models we had several factors predicting variation in lapses of attention in order to better understand how these factors account for shared and unique variance in lapses. But, it is also the case that variation in lapses can influence those factors as well. For example, as noted in the Introduction, lapses of attention in the Stroop and antisaccade task can result in temporary failures in goal-maintenance (goal neglect) and reductions in overall performance (e.g., Balota & Duchek, 2015; Hutchison et al., 2010; Kane & Engle, 2003; Unsworth et al., 2004). Thus, variation in lapses of attention can result in variation in performance on our attention control measures. Similarly, variation in lapses of attention are also likely influencing overall RTs in the attention control tasks resulting in more variability in RTs, and thereby influencing the measures of speed of processing. Thus, just as variation in speed of processing could influence our lapse measures, variation in lapses could influence the speed measures themselves. Furthermore, as noted in the Introduction (and see below), variation in lapses of attention can also influence performance on working memory measures (Adam et al., 2015; Adam & Vogel, 2017; Mrazek et al., 2012; Robison & Unsworth, 2019; Unsworth & Robison, 2016b). Thus some of the variation in working memory measures is likely due to variation in lapses of attention. These notions highlight the importance of recognizing that measures, and factors made from those measures, are multidimensional and likely include bidirectional relations.

Limitations and Alternative Measures

As noted above, one limitation of the current study was that we did not examine more state dependent variables such as mood, anxiety, and current stress levels. Prior research has suggested that lapses of attention tend to be more frequent when participants are stressed (Broadbent, 1971; Hockey, 1986; Reason, 1983). For example, recent research has found that daily life stressors lead to an increase in very slow RTs, rather than a shift in the overall distribution (Sliwinski et al., 2006), consistent with the notion that stress can lead to an increase in lapses of attention. Similarly, anxiety and negative mood have been suggested to increase lapses of attention and be related to TUTs (e.g., Forster et al., 2015; Killingsworth & Gilbert, 2010; Poerio et al., 2013; Robison et al., in press; Smallwood et al., 2009) consistent with the notion that lapses and TUTs are related to a participant's current concerns (e.g., Klinger, 1999; McVay & Kane, 2010). For example, Robison et al. (in press) found that a negative mood factor (based on positive affect, negative affect, and state anxiety) was positively related to TUTs consistent with prior research. Thus, it is very likely that current state variables like stress, mood, and anxiety are important factors in variation in lapses of attention and could likely account for additional unique variance in predicting individual differences in lapses of attention. Future research should include measures of negative affective state as an additional important source of variance in lapses of attention.

Another limitation of the current study was our sleep quantity variable in which we simply asked participants how much sleep they got the night before. While this is a straightforward measure that should index sleepiness, it tended to correlate weakly with the other variables. For example, sleep quantity correlated weakly with TUTs, conscientiousness, and neuroticism, but none of the other correlations were significant. These results are consistent with recent research from our laboratory using the same measure suggesting significant, but weak relations with TUTs, conscientiousness, and alertness (Robison et al., in press). With only a single measure it is difficult to know whether these relations are simply weak overall, or whether the measure is unreliable or lacking in validity. Furthermore, our sleep quantity variable is problematic given that same response shared across mutually exclusive response options. Stawarczyk and D'Argembeau (2016) used a variant of the Karolinska Sleepiness Scale (Akerstedt & Gillberg, 1990) embedded in the SART and found that this measure correlated with task performance (accuracy and variability in RTs) and with TUTs. Thus, it may be necessary for future research to use additional sleep measures to better examine how sleep quantity and subjective sleepiness are related to variation in lapses of attention.

Additional problems with some of the behavioral lapse measures should also be noted. For example, as noted previously, most participants did not demonstrate any flat spots in the continuous tracking task (only 24% of participants demonstrated at least one flat spot). Thus, the distribution for flat spots was positively skewed and leptokurtic. Although the flat spots measure correlated well with the other lapse measures, it might not be the best measure to use to examine variation in lapses of attention given how rare the flat spots are. Another possibility to examine fluctuations in sustained attention on the continuous tracking task is to simply use overall tracking error (i.e., the difference between the object and the cursor; Kam et al., 2012; Peiris et al., 2006; Robison et al., 2019). In the current dataset overall tracking error was reliable (split-half = .98) and overall tracking error and flat spots were correlated (r = .77). Overall tracking error also demonstrated positive correlations with the other behavior lapses measures of a similar magnitude as flat spots (see Appendix A for an alternative model that uses this measure). Thus, examining both overall tracking error and flat spots may be necessary in future research.

Furthermore, although some of the other count measures (lapses in psychomotor vigilance and blocks in choice RT) were not as rare as flat spots, the average number of each was still fairly low. Rather than simply counting the number of lapses or blocks, in prior research we have examined the full RT distributions in these tasks and typically utilized the slowest 20% of trials as our measure of lapses (e.g., Unsworth et al., 2010; see the Appendix E for correlations between the RT quintiles in each task and the various cognitive and contextual factors).[4] The slowest 20% of trials in each task tends to be strongly correlated with the different count measures (psychomotor vigilance lapses—slowest 20% of RTs r = .79; blocks—slowest 20% of RTs r = .78) and demonstrate similar positive relations with the other lapse measures. Using the slowest 20% of RTs in both tasks resulted in very similar results (see Appendices A-D for an alternative model that uses these measures). Thus, examining the full RT distribution and using the slowest RTs should provide overall similar information as when using counts for particularly slow RTs.

An additional issue that should be recognized is that in the whole report visual working memory task the measure of lapses is strongly negatively correlated with estimates of overall capacity (r = −.90; see also Robison & Unsworth, 2019). Thus, those individuals who experience many lapses of attention tend to have lower estimates of capacity (Adam et al., 2015). Because of this strong negative correlation, it is difficult to know whether the measure is correlating with other measures because of variation in lapses or variation in working memory capacity (see Appendices A-D for a model which whole report lapses are excluded). To assess this, we computed a new estimate of capacity after excluding any lapse trials and examined how this measure was related to the lapse measure and to other measures of working memory capacity from the complex span tasks. On average participants recalled 2.93 (SD = .32) items correctly across nonlapse trials and this measure of capacity was related to both the lapse measure (r = −.62) and to the working memory capacity composite (r = .35). Lapses and the working memory capacity composite were also related (r = −.32). Importantly, both the lapse measure and the capacity measure accounted for unique variance in the working memory capacity composite (lapse $\beta = -.17$, $p = .019$; capacity $\beta = .25$, $p = .001$). Thus, this suggests that although the lapse measure and capacity are strongly negatively related in this task, they represent distinct sources of individual differences which contribute to variation in performance on working memory measures. Future research is needed to further examine the extent to which lapses and capacity measures from this task represent distinct sources of variance.

Conclusions

Collectively, the current results suggest that there is a general tendency to experience lapses of attention in a variety of tasks. Variation in lapses of attention were found to be related to, but distinct from, variation in TUTs and attention control from constraint and restraint type tasks. Other important factors to lapses of attention were variance shared across TUTs, motivation, and alertness, and boredom proneness. Lapses of attention were weakly related to self-reports of everyday cognitive failures suggesting some ecological validity to lapses assessed in the laboratory. These results extended prior research in suggesting that there are robust and stable individual differences in lapses of attention and that a number of factors are important in contributing to variation in lapses of attention. Understanding lapses of attention will provide valuable information in terms of predicting for whom and under what conditions failures of attention are most likely and potentially developing interventions to reduce lapses and increase overall task performance in a variety of situations.

[4] Another potential indicator of lapses on the psychomotor vigilance task are false alarms (i.e., pressing the space bar before the numbers begin counting up). In the current dataset we found that participants made 3.10 (SD = 3.56) false alarms on average. These false alarms were positively correlated with lapses on the psychomotor vigilance task (r = .20) and correlated positively with all of the other behavioral lapse measures (all r's > .15). The false alarm measure was only related to alertness (r = −.20) and task-specific motivation (r = −.25).

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Appendix A

Alternative Models and Measures

Alternative Confirmatory Factor Analyses

Given potential issues with missing data, skewed lapses measures, and the use of potential alternative measures of lapses, here we present several alternative confirmatory factor analyses. As will be seen, all of the models produced results very similar to those from the overall confirmatory factor analysis seen in Tables 3 and 4 suggesting that the presented results are fairly robust.

Full Information Maximum Likelihood Model

Given variation across tasks in the amount of missing data we tested a version of the main confirmatory factor analysis using full information maximum likelihood which uses all available information in the likelihood function by combining likelihood estimates from cases with different patterns of missingness (Enders, 2010). As shown in Appendix B, the fit of the model was acceptable with factor loadings of the lapse measures (Appendix C) and latent correlation between the lapse factor and other factors (Appendix D) being very similar to the main confirmatory factor analysis. Thus, using all available data with full information maximum likelihood estimation resulted in very similar overall results.

Model Using Spearman Rhos

Given potential issues with non-normal distributions and potential outliers with some of the lapse measures we tested a version of

(*Appendices continue*)

the main confirmatory factor analysis using Spearman rhos. We used Spearman rhos because they tend to be more robust to non-normal distributions and presence of outliers than typical Pearson correlations (de Winter et al., 2016). As shown in Appendix B, the fit of the model was acceptable with factor loadings of the lapse measures (Appendix C) and latent correlation between the lapse factor and other factors (Appendix D) being very similar to the main confirmatory factor analysis. Thus, using Spearman rhos rather than Pearson correlations resulted in very similar overall results.

Model Using Transformed Lapse Measures

Given potential issues with non-normal distributions with some of the lapse measures we also tested a version of the main confirmatory factor analysis after transforming (square root transformation) the skewed lapse measures. This resulted in overall more normal distributions for the measures. As shown in Appendix B, the fit of the model was acceptable with factor loadings of the lapse measures (Appendix C) and latent correlation between the lapse factor and other factors (Appendix D) being very similar to the main confirmatory factor analysis. Thus, using the transformed lapse measures resulted in very similar overall results.

Model Using Satorra-Bentler Scaled Test Statistic

Another way of dealing with non-normal data is to use the Satorra–Bentler scaled chi-squared test which is robust to nonnormality (Curran et al., 1996; Satorra & Bentler, 1994). Adjustments with the Satorra-Bentler test also leads to robust standard errors, *p*-values, and confidence intervals. Therefore, we also tested a version of the main confirmatory factor analysis using the Satorra-Bentler scaled chi-squared test. As shown in Appendix B, the fit of the model was acceptable with factor loadings of the lapse measures (Appendix C) and latent correlation between the lapse factor and other factors (Appendix D) being very similar to the main confirmatory factor analysis. Thus, using the Satorra–Bentler scaled test statistic resulted in very similar overall results.

Model Excluding the Whole Report Lapse Measure

Given concerns that the whole report lapse measure might not be the best measure of lapses and the fact that it is highly correlated with working memory, we excluded this measure and re-ran the primary confirmatory factor analysis. As shown in Appendix B, the fit of the model was acceptable with factor loadings of the lapse measures (Appendix C) and latent correlation between the lapse factor and other factors (Appendix D) being very similar to the main confirmatory factor analysis. Excluding the whole report measure resulted in very similar overall results, suggesting that this measure was not unduly influencing the results.

Model With Alternative Lapse Measures

In the General Discussion we noted some alternative measures from some of the tasks could be used. Therefore, we reran the primary confirmatory factor analysis with these alternative measures. Specifically, we examined a model in which the slowest 20% of reaction times in the psychomotor vigilance and choice reaction time tasks were used instead of the more conventional lapse and block measures. We also used the overall tracking error in the continuous tracking task rather than the flat spot measure from this task. The overall model was the same as the model reported in Tables 3 and 4, except that we also allowed the residual variance for the choice reaction time fastest 20% of RTs and choice reaction time slowest 20% of RTs to correlate based on modification indices. As shown in Appendix B, the fit of the model was acceptable with factor loadings of the lapse measures (Appendix C) and latent correlation between the lapse factor and other factors (Appendix D) being very similar to the main confirmatory factor analysis. Thus, using alternative measures such as the slowest 20% of trials as a measure of lapses similar to prior research (e.g., Unsworth et al., 2010) resulted in similar overall results suggesting that these measures can be used in place of the more standard count measures.

Relations With Reaction Time Distributions From Psychomotor Vigilance and Choice Reaction Time

To examine how different components of the reaction time distributions in the psychomotor vigilance task and the choice reaction time task relate to the different cognitive and contextual measures we rank ordered each individual's reaction times in each task from fastest to slowest and created five bins (quintiles) for each individual. Thus, the first quintile represents the fastest 20% of trials and the last quintile represents the slowest 20% of trials. These quintiles were then correlated with factor composites for working memory capacity, attention control, TUTs, alertness, and motivation. For the factor composites we entered the measures for each construct (e.g., operation span, symmetry span, and reading span for working memory capacity) into a separate factor analysis using principal axis factoring and saved the factor scores for each individual. These factor scores were then correlated with each quintile in each task. The results are shown in Appendix E.

(*Appendices continue*)

Appendix B

Alternative Models and Measures

Fit Indices for the Alternative Confirmatory Factor Analyses

Model	χ^2	*df*	RMSEA	NNFI	CFI	SRMR
FIML	886.16	489	.05 [.043, .053]	.87	.90	.05
Rhos	957.89	489	.05 [.047, .057]	.91	.93	.06
Transform	962.48	489	.05 [.047, .057]	.91	.93	.06
Satorra-Bentler	733.53	489	.05 [.042, .057]	.84	.87	.06
No WR	883.08	455	.05 [.046, .056]	.91	.93	.05
Alternative	989.17	488	.05 [.049, .058]	.91	.93	.06

Note. RMSEA = root mean square error of approximation; NNFI = non-normed fit index; CFI = comparative fit index; SRMR = standardized root mean square residual; FIML = Full Information Maximum Likelihood Model.

Appendix C

Alternative Models and Measures

Standardized Factor Loadings for Alternative Confirmatory Factor Analyses

Lapse measure	FIML	Rhos	Transform	Satorra-Bentler	No WR	Alternative
PVTLap/PVTRT5	.70	.57	.61	.68	.69	.67
FlatSpot/TrackErr	.56	.53	.55	.57	.56	.54
WRLap	.55	.52	.55	.57		.53
Blocks/CRTRT5	.55	.44	.46	.46	.55	.67
SaCoV	.49	.57	.53	.41	.46	.50
SaAntic	.32	.53	.47	.24	.27	.30
SaOm	.49	.55	.52	.37	.48	.51

Note. All loadings are significant at the $p < .05$ level. PVTLap = lapses in psychomotor vigilance task; PVTRT5 = slowest 20% of reaction times in the psychomotor vigilance task; Flat Spots = flat spots in continuous tracking; TrackErr = overall tracking error in the continuous tracking task; WRLap = lapses in whole report working memory; Blocks = blocks in choice reaction time; CRTRT5 = slowest 20% of reaction times in the choice reaction time task; SaCoV = coefficient of variation in sustained attention to response task; SaAntic = anticipations in sustained attention to response task; SaOm = omission errors in sustained attention to response task; FIML = Full Information Maximum Likelihood Model.

(*Appendices continue*)

Appendix D

Alternative Models and Measures

Latent Variable Correlations With the Lapse Factor From the Alternative Confirmatory Factor Analysis

Latent factor	FIML	Rhos	Transform	Satorra-Bentler	No WR	Alternative
TUT	**.43**	**.39**	**.43**	**.42**	**.42**	**.39**
AC	**−.69**	**−.73**	**−.74**	**−.68**	**−.68**	**−.69**
WMC	**−.32**	**−.41**	**−.39**	**−.36**	**−.27**	**−.39**
Speed	**.47**	**.32**	**.42**	**.45**	**.46**	**.54**
Alertness	**−.41**	**−.49**	**−.46**	**−.36**	**−.40**	**−.39**
Motivation	**−.47**	**−.53**	**−.52**	**−.35**	**−.44**	**−.43**
Bored	**.20**	**.21**	**.22**	.14	**.20**	**.15**
Sleep	−.10	−.11	−.10	−.06	−.12	−.10
Extra	.08	.10	.10	.03	.08	.11
Agree	−.04	.01	−.02	−.07	−.04	.04
Consc	−.09	−.09	−.08	−.14	−.09	−.04
Neurot	.03	.09	.04	.05	.02	.02
Open	−.04	−.10	−.06	−.05	−.05	.01
CFQ	**.15**	**.21**	**.20**	**.18**	**.13**	**.13**

Note. Significant correlations are in bold. TUT = task-unrelated thoughts factor; AC = attention control factor; WMC = working memory capacity factor; Speed = speed of processing factor; Alertness = alertness factor; Motivation = motivation factor; Bored = boredom proneness manifest variable; Sleep = sleep quantity; Extra = extraversion manifest variable; Agree = agreeableness manifest variable; Consc = conscientiousness manifest variable; Neurot = neuroticism manifest variable; Open = openness manifest variable; CFQ = cognitive failures manifest variable; FIML = Full Information Maximum Likelihood Model.

Appendix E

Alternative Models and Measures

Correlations for the Reaction Time Measures From the Psychomotor Vigilance Task and the Choice Reaction Time Task With the Cognitive and Contextual Measures

Measure	WMC	AC	TUTs	Alertness	Motivation
PVT Quintile 1	**−.12**	**−.29**	**.19**	**−.17**	**−.11**
PVT Quintile 2	**−.15**	**−.34**	**.25**	**−.24**	**−.19**
PVT Quintile 3	**−.16**	**−.36**	**.28**	**−.28**	**−.24**
PVT Quintile 4	**−.17**	**−.35**	**.30**	**−.28**	**−.27**
PVT Quintile 5	**−.16**	**−.28**	**.28**	**−.25**	**−.28**
CRT Quintile 1	**−.11**	**−.27**	**.12**	−.01	−.01
CRT Quintile 2	**−.19**	**−.36**	**.13**	−.08	−.06
CRT Quintile 3	**−.20**	**−.41**	**.15**	**−.12**	−.09
CRT Quintile 4	**−.20**	**−.44**	**.18**	**−.15**	**−.12**
CRT Quintile 5	**−.15**	**−.38**	**.19**	**−.19**	**−.15**

Note. Bold correlations are significant. Quintile = reaction time quintile; PVT = psychomotor vigilance task; CRT = choice reaction time task; WMC = factor composite for working memory capacity; AC = factor composite for attention control; TUTs = factor composite for task-unrelated thoughts; Alertness = factor composite for alertness; Motivation = factor composite for motivation.

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