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RELATING AFFECT VARIABILITY TO COMPLEX SKILL ACQUISITION AND ADAPTIVE PERFORMANCE: THE ROLE OF OFF-TASK ATTENTION

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RELATING AFFECT VARIABILITY TO COMPLEX SKILL ACQUISITION AND ADAPTIVE PERFORMANCE: THE ROLE OF OFF-TASK ATTENTION

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Abstract

Individuals with high affect variability—fluctuations in emotions—tend to react with greater intensity to emotional events and have a more difficult time adjusting to change (Beal & Ghandour, 2011). Although high affect variability has been linked to heightened reactivity to emotionally charged events and poor adjustment, limited research has examined its relationship with skilled performance. Therefore, the purpose of this lab study was to replicate Richels et al. (2020), which was the first empirical study to show how affect variability, specifically affect spin and pulse, undermines complex task performance, and extend Richels et al. (2020) by (1) examining off-task attention as a key explanatory mechanism and (2) including dimensions of affect flux in a relative importance analysis of affect variability scores. Specifically, using a lab sample of 253 undergraduate students (65% male) learning how to play a complex video game, I examined and compared how spin, pulse, and flux in positive activating, positive deactivating, negative activating, and negative deactivating emotions explained variance in skill acquisition and adaptive performance via self-report scores of off-task attention. Spin refers to within-person variability in pleasantness and arousal. Pulse refers to within-person fluctuations in intensity. Flux refers to within-person fluctuations in a particular emotion dimension. Per Nathans et al. (2012), I first examined the relative importance of the different affect variability scores. Then, discontinuous growth modeling was used to disentangle adaptation from acquisition when examining the effects of affect variability on performance. Results indicated the importance of flux indices and suggest that affect variability research has overlooked these indices. In addition, harmful, incremental effects beyond Big Five personality scores for affect variability were found through two mechanisms: primarily (1) via off-task attention (with respect to negative deactivating flux in particular), as well as (2) through moderating the off-task attention-adaptive performance relationship in the case of spin. More simply put, affect variability was found to be detrimental towards complex task learning. Results are further discussed in comparison to Richels et al. (2020), and in terms of the need for adaptability in today's increasingly uncertain, dynamic world.

Relating Affect Variability to Complex Skill Acquisition and Adaptive Performance: The Role of Off-Task Attention

A constant of the human experience is that change will occur within the spheres of our professional and personal lives (Elrod & Tippett, 2002). Success in a dynamic world depends on adaptability, which generally refers to an individual's capacity to effectively learn complex tasks and adjust to any changes in the environment (Bell et al., 2017). When change or complication occurs, it is critical that individuals have the capacity to adjust and respond to change (Baird & Griffin, 2006; Ployhart & Bliese, 2006; Pulakos et al., 2000). As adaptability has increasingly become recognized as necessary for workplace success and life in general, it is important to consider what individual differences make individuals more or less adaptable. Although different conceptualizations of adaptability exist, when viewed as "a relatively stable, higher-order individual difference construct" (Ployhart & Bliese, 2006, p.25), research suggests that there is more to the capacity to learn and adjust to change beyond cognitive abilities and previously learned skills, such as non-cognitive traits like personality. In general, the extant literature shows relatively weak relationships between personality variables and complex task learning, both in acquisition and adaptive performance (Huang et al., 2014; Ackerman et al., 1995; LePine et al., 2000). However, it is likely that the extant empirical research has underestimated the role of personality as a component of adaptability due to a failure to take into account the fundamentally dynamic nature of acquisition and adaptive performance, and human phenomena more generally (Baard et al., 2014; Jundt et al., 2015; Huang et al., 2014). Given the emotional nature inherent in complex task learning and adaptive performance, the present study focused on affect variability as a key to understanding personality-skilled performance relationships.

Although a range of emotions are felt daily (Barford et al., 2020), the experience of a range of emotions is particularly true when learning new and complex tasks and adapting to changes in the task environment (Kiefer, 2002). New tasks and changes in task demands can incite intense emotions as individuals both succeed and struggle in making progress while being forced to challenge their prior assumptions and face the potential degradation of their capabilities and normative position (Elrod & Tippett, 2002; Huy, 1999). Although personality is an important factor when trying to explain the emotional experiences that accompany dealing with change, common measures of personality, the Big Five and even emotional stability (i.e., neuroticism) in particular, are quite limited in how well they capture actual change in emotions (Huang et al., 2014). Consistent with Whole Trait Theory, the present research was based on the premise that fluctuations in the expressions of traits are crucial to understanding human phenomena and the individual expression of personality is dynamic despite stable between-person differences (Beckmann & Wood, 2017; Fleeson & Jayawickreme, 2015). In this respect, affect variability scores hold promise for reflecting personality constructs that are meaningfully distinct from common conceptualizations and operationalizations of personality (Moskowitz & Zuroff, 2004). Although the burgeoning literature on affect variability shows its importance to strain and coping (Beal et al., 2013; Shapiro, 2015), with the exception of Richels et al. (2020), there is a conspicuous lack of theory and empirical research addressing how affect variability is linked to task performance.

Therefore, the purpose of the current study was to replicate and extend Richels et al.'s (2020) lab study, which demonstrated how affect variability may be detrimental to task performance. Specifically, Richels et al. (2020) showed that over the course of skill acquisition and adaptation to changes in task demands on a complex first-person shooter computer game, affect variability was negatively related to both effort and performance, and affect variability also moderated effort-performance relationships such that the effort put forth by those higher in affect variability was less beneficial to performance compared to the effort of those lower in affect variability. In terms of replication, the present study examined the incremental relationships beyond the Big Five between two aspects of affect variability—spin and pulse—and task performance. The present study extended Richels et al. (2020) in two respects. First, it answered Richels et al.'s (2020) call to examine attention, off-task attention specifically, as a key explanatory mechanism. Second, it added dimensions of affect flux to the empirical investigation and per Nathans et al. (2012) examined the relative importance of spin, pulse, and flux in positive activating, positive deactivating, negative activating, and negative deactivating emotions. It was expected that indices of affect variability would differ in their relative importance but in general would yield harmful, incremental effects beyond the Big Five. Similar to Richels et al. (2020), two mechanisms for these harmful effects were examined: (1) positive relationships with off-task attention and (2) intensifying the off-task attention-performance relationship.

Skill Acquisition and Adaptive Performance

Skill acquisition commonly refers to the process whereby individuals learn the required skills to perform a certain task and achieve a desired result. Adaptive performance is commonly thought of as reactive in nature, referring to the relearning individuals engage in when faced with changes in the task environment (Jundt et al., 2015; Niessen & Jimmieson, 2016). However, adaptation can also be proactive in nature when individuals choose to make their own changes, for example in their performance strategies, despite an absence of change in task demands. Such proactive adaptation is relevant to individuals striving for performance gains after already reaching high levels of performance (Ployhart & Bliese, 2006) versus performing and even making gains with little or no attentional effort (i.e., autonomous phase of skill acquisition; Kanfer & Ackerman, 1989). As workplaces and the everyday world continually evolve and become more complex, it is necessary to understand both reactive and proactive forms of adaptive performance in relation to each other by conceptualizing both as part of the broader learning process (Ployhart & Bliese, 2006; Huang et al., 2014). Accordingly, to fully understand adaptive performance and its determinants, it is important to empirically examine and disentangle initial performance and gains in performance prior to changes in task demands (i.e., skill acquisition), the initial difficulties they experience with task changes (i.e., transition adaptation), and the process of relearning or again making gains in performance after changes in task demands (i.e., reacquisition adaptation; Lang & Bliese, 2009).

As adaptive performance becomes recognized as critical for the workplace and everyday living, it is theoretically and practically important to consider the constellation of individual differences underlying adaptive performance, namely adaptability. Adaptability, distinguished from adaptive performance per se, is a broad individual difference that can be activated in any complex performance environment, and the more dynamic the environment, the stronger the effect of adaptability (Ployhart & Bliese, 2006). Although cognitive abilities have garnered a lot of attention in the scholarly literature on adaptive performance, better understanding the specific non-cognitive individual differences comprising the broader construct of adaptability, personality especially, is key to better understanding performance in increasingly dynamic environments (Baard et al., 2014; Huang et al., 2014; Jundt et al., 2015; Ployhart & Bliese, 2006).

The ability to commit attentional resources to performance demands is central to adaptability. Learning and relearning after task changes is facilitated when employees are able to avoid distractions and focus their attentional resources on the task at hand (Kanfer & Ackerman, 1989; Jundt et al., 2015; Niessen & Jimmieson, 2016; Randall et al., 2014), but in new and dynamic performance environments emotions can play a strong role in the effective allocation of attentional resources (Jorgensen et al., 2020). Those whose emotions typically run wild would not be expected to be among the top performers. With respect to personality, it would thus seem that emotional stability should be an important determinant of adaptive performance. Although meta-analyses consistently demonstrate positive relationships between emotional stability and adaptive performance (Huang et al., 2014) and task performance in general (Hurtz & Donovan, 2000; Barrick et al., 2005), the magnitude of such relationships are modest at best and warrant pause to any conclusions about emotional stability as an important component of adaptability.

Affect Variability

In response to the modest effects observed by personality scores, affect variability holds considerable potential as a meaningfully distinct aspect of personality that better captures differences in the emotional side to how people react across a range of situations, performance contexts, and life events (Eid & Diener, 1999; Kuppens et al., 2007; Beal et al., 2013; Richels et al., 2020). Although personality constructs have long been conceptualized as relatively stable, research spawning affect variability conceptualizes personality constructs as fluctuating traits that nevertheless reflect relatively stable between-person differences (Fleeson, 2001). Affect variability speaks to how emotions fluctuate differently across individuals despite these individuals experiencing a common environment or situation. In this way, affect variability scores directly capture the dynamic nature to the experience of emotions, and thus are able to explain behavior and outcomes, which are also inherently dynamic, beyond what is explained by traditional personality scores (Richels et al., 2020). However, the potential in affect variability as an important component to personality likely lies in its different conceptualizations and operationalizations. While the literature on affect is replete with different theories, conceptualizations, and measures, the same is true with respect to how to best think about and measure between-person differences in affect fluctuations. The empirical literature on affect variability is relatively new, arguably still in its infancy, and thus the literature is limited in terms of how different aspects of affect variability compare in how well they explain behavior and outcomes, especially task performance.

An individual tends to have a general emotional state within which they are predisposed to reside, but it is important to recognize that affect is not static as it varies and fluctuates across time (Polk et al., 2005). Although mood changes and emotions fluctuate over time and events, affective states are not random and tend to follow a pattern that can be predicted within an individual (Larsen, 1987). Affective events, or emotional incidents, may cause disruptions in the pattern, but affect tends to return to its predictive state relatively quickly (Beal & Ghandour, 2011). Affect variability—between-person differences in affect fluctuations—is a reliable multidimensional construct, separate from other personality traits, that is predictive of future states and behaviors (Eid & Diener, 1999; Kuppens et al., 2010; Moskowitz & Zuroff, 2004, 2005; Richels et al., 2020). Neuroticism, which generally refers to a lack of emotional stability (Judge et al., 1999), is ostensibly similar to affect variability due to similar elements in their definitions. However, although affect variability scores are correlated with neuroticism as well as other Big Five personality traits, the correlations are moderate in magnitude, and affect variability incrementally explains variance in other variables of interest (Kuppens et al., 2007; Richels et al., 2020). Accordingly, affect variability is meaningfully distinct from neuroticism as well as the Big Five personality traits in general and holds considerable promise for extending theory on how personality plays a role in behavioral phenomena.

With respect to complex task learning, the role of affective variability may be best understood in terms of explaining differences in stress-attention-performance relationships and by undermining task enjoyment. Attention is often distracted or erratically focused when individuals feel stress. Those high in affect variability are more likely to view complex, dynamic task environments as overwhelming if not threatening, which creates hindrance stress (Beal & Ghandour, 2011). Hindrance stress (i.e., distress) is associated with self-doubt, worry, and mind wandering, all of which are aspects of off-task attention and undermine performance (Gopher et al., 2000; Randall et al., 2014). An individual's affective reaction to a task—enjoyment—can have a strong influence over affective outcomes such as motivation and self-efficacy, which in turn can spur future task engagement and learning outcomes (Sitzmann et al., 2008). Task enjoyment is typically associated with continued interest and informal learning (Brown, 2005; Tews & Noe, 2019). The stress and erratic attention individuals with greater affect variability feel when viewing a complex task may prevent them from enjoying the task and thus undermine long-term engagement with the task, impacting overall learning and performance. More generally, those high in affect variability have more complex mental lives due to the inherent unpredictability in their emotions and consequently greater need to focus their attentional resources on managing their emotions (Beal et al., 2013). In this way, high affect variability puts individuals at greater risk of distraction and slower reaction times, which ultimately undermines task performance (Smallwood, 2011).

Indices of Affect Variability: Spin, Pulse, and Flux

When conceptualizing and operationalizing affect variability, it is important to consider first the nuances to conceptualizing and operationalizing affective states. In particular, emotions are commonly conceptualized as residing on a circumplex involving two dimensions: valence (pleasure-displeasure or pleasant-unpleasant) and arousal (activation-deactivation potential) (cf.

Scherer, 1984; Smith & Ellsworth, 1985; Roseman, 1984). Emotions described as high in pleasure and high in arousal (e.g., excited, happy) are defined as positive activating, whereas emotions described as high in pleasure but low in arousal (e.g., calm, relaxed) are defined as positive deactivating. Emotions high in displeasure and high in arousal (e.g., angry, anxious) are defined as negative activating, whereas negative deactivating emotions are high in displeasure but low in arousal (e.g., bored, disappointed). Within this circumplex, an individual has a core affect space that falls within those dimensions, but those with greater affect variability experience more fluctuations across and within the dimensions (Kuppens et al., 2007). Those with greater affect variability have mood changes that occur more often and more rapidly, and such mood swings are associated with poor psychological outcomes (Hardy & Segerstrom, 2017). In general, affect variability has been largely viewed as maladaptive due to its association with lower well-being, life satisfaction, daily satisfaction, happiness, and greater depression and anxiety (Gruber et al., 2013; cf. Klein, 2020; Kuppens et al., 2010; Shapiro, 2015). Likewise, affect variability is associated with physical health concerns, such that greater affect variability is toxic for individuals due to its connection with systemic inflammation (Jones et al., 2020). However, the extent to which affect variability scores explain variance in various outcomes depends on how affect variability is indexed (calculated) from the same set of emotion scores from repeated measurements.

The scholarly literature points to several different but related aspects of affective variability, namely spin, pulse, and flux, with spin being the most commonly examined (e.g., Beal & Ghandour, 2011; Beal et al., 2013; Jung et al., 2015; Park, 2015). Along dimensions of valence and arousal, every individual has a core affect space in which the direction and intensity of their emotion fluctuations generally reside. This combination of direction and intensity is sometimes referred to as the core affect trajectory (Kuppens et al., 2007). In terms of direction, affect spin refers to an individual's variability in affect pleasantness and activation potential, reflecting how an individual's emotions fluctuate across the broader affect circumplex over time and events (Kuppens et al., 2007; Moskowitz & Zuroff, 2004). Affect pulse refers to fluctuations in the intensity of emotions felt, regardless of pleasantness or activation potential, such that higher pulse reflects a greater mix of low and high intensity in emotions over time and events (Kuppens et al., 2007; Moskowitz & Zuroff, 2004). Flux refers to fluctuations along a particular dimension (i.e., poles/axes) of the affect circumplex (Kuppens et al., 2007). As such, and in contrast to how affect spin covers the circumplex via a single index, multiple flux indices (e.g., positive activating, positive deactivating, negative activating, and negative deactivating) could be used together to cover the circumplex.

Early research on affect variability focused on spin and pulse with researchers concluding that spin is more stable and better captures affect variability as a personality variable related to well-being (Kuppens et al., 2007, Moskowitz & Zuroff, 2004). Subsequent research showed how high-spin individuals typically react more strongly to emotional events (Moskowitz & Zuroff, 2005; Beal & Ghandour, 2011; Clegg et al., 2020) regardless of whether they are distressing or not (Beal & Ghandour, 2011), which is problematic as more reactivity is related to less well-being (Grosse Rueschkamp et al., 2020). For example, research showed higher spin was related to poor goal progress (Uy et al., 2017); more emotional exhaustion, fatigue, and strain (Niven et al., 2012; Beal et al., 2013); less positive moods and relationship closeness (Niven et al., 2012; Côté et al., 2012); less citizenship behaviors at work (Clark et al., 2018); more career anxiety and indecision (Jung et al., 2015; Park, 2015); and greater work-life imbalance from poor child adjustment via parental spin (Yang & Dahm, 2020).

As the empirical literature on spin grew and pulse waned, interest in affect flux emerged similarly showing adverse effects (Chandler, 2012; Chester et al., 2012; Timmermans et al., 2010). While some researchers still maintained that spin is better suited than pulse and flux for explaining variance in behavioral outcomes (e.g., Chandler, 2012), others asserted that spin, pulse, and flux are all worthwhile to examine (e.g., Chester et al., 2020). I agree with this assertion for two reasons, both of which reflect how nascent the empirical literature on affect variability is. One, it seems renewed attention to pulse is warranted given Richels et al.'s (2020) recent findings showing how both spin and pulse undermined effort and complex skill learning and not necessarily through similar causal mechanisms. Second, the extant empirical literature is limited in terms of empirical studies that have comparatively examined spin, pulse, and flux. In my search of the literature, I only found two studies that examined all three indices (i.e., Chandler, 2012; Russell et al., 2007), and with respect to flux these studies only examined positive and negative valence dimensions without distinguishing high versus low activation potential. Thus, the present study makes an important contribution to the literature by comparatively examining spin, pulse, and four dimensions of flux that disentangle the valence and activation dimensions (i.e., positive activating, positive deactivating, negative activating, and negative deactivating flux). In particular, by disentangling the valence and activation dimensions in flux scores, compared to previous research the present study more carefully examined the validity of spin and pulse as single indices of affective variability versus the validity of a combination of flux indices.

Relative Importance of Different Aspect of Affect Variability

The relative importance of different predictor variables is important to consider when several or more predictors covary and there is little theoretical guidance as to how uniquely and together the predictors explain variance in outcomes of interest. Although linear multiple regression is the most commonly used statistical technique for examining how a set of predictors explains variance in outcomes, the regression weights for each predictor variable do not lend themselves to understanding how their common associations as a whole or as subsets contribute to the variance explained in an outcome. As such, the regression weights themselves do not adequately reflect how large a role any predictor plays. This is especially problematic in the case of suppression, which occurs when the association of one predictor (X_1) with an outcome is masked or underestimated when another predictor (X_2) is not included in the model. In such cases, the later variable (X_2), the suppressor, does not itself directly explain variance in the outcome but rather it purges the shared construct irrelevance from the first predictor (X_1) allowing its association to be better estimated. This suppression effect often leads to stronger estimates for the first predictor as well as for the total set of predictors.

Covariation among different indices of affect variability should be expected because they all (a) conceptually speak to fluctuations in emotions and (b) operationally are calculated using the same set of scores. Without properly accounting for the covariation, it is not only difficult to determine which index and subset of indices best explains variance in outcomes, but it also makes it difficult to understand the potential suppression one or more indices might have. Accordingly, relative importance analysis involving a combination of relative importance metrics (Nathans et al. 2012) is needed to inform theory on how affective variability contributes to outcomes of interest. There may be some aspects of emotion fluctuations that are not directly related to an outcome, but accounting for their covariance leads to better estimates for other aspects of emotion fluctuations. Relative importance analysis can also shed light on whether any index is dominant in their contribution—always explaining more unique variance in an outcome regardless of which other predictors are included in a regression model (Azen & Budescu, 2003).

Conceptually, by disentangling valence and activation in flux indices, relative importance analysis provides a more targeted examination of the contributions played by fluctuations in different dimensions of the affect circumplex in relation to fluctuations more broadly. Accordingly, following the recommendations of Nathans et al. (2012) and Nimon and Oswald (2013), I conducted a relative importance analysis of spin, pulse, positive activating flux, positive deactivating flux, negative activating flux, and negative deactivating flux in explaining variance in off-task attention and task performance during periods of skill acquisition adaptation. In particular, I examined the following research questions.

> *Research Question 1:* Does any index of affect variability show complete dominance over the others in explaining variance in (a) off-task attention, (b) task enjoyment, or (c) performance?
> *Research Question 2:* Are there any indices of affect variability that act as a suppressor for other indices in explaining variance in (a) off-task attention, (b) task enjoyment, or (c) performance?

I used average off-task attention and performance scores in pre-change (acquisition) and post-change (adaptation) sessions to answer these research questions. Then, the results of the relative importance analysis subsequently informed the choice of indices to examine in the discontinuous growth analysis used to test the hypothesized mechanisms by which affective variability undermines complex task learning.

Mechanisms by which Affect Variability Undermines Complex Task Learning

Not only is it likely that different indices of affect variability vary in their contributions to explaining variance in outcomes of interest, but it is also possible that they differ in terms of causal mechanisms—direct, mediating, and moderating effects (Richels et al, 2020). With respect to complex task learning, affect variability likely plays a role as a distal contributor to skill acquisition and adaptation via more proximal predictors, as is the case with mediation. In fact, Richels et al. (2020) found support for the distal role played by both spin and pulse, showing negative direct effects on self-reported learning effort, especially the sustainment of effort across acquisition and adaptation trials. Effort in turn was positively related to performance. In terms of moderation, affect variability may inhibit or exacerbate the effects of a more proximal predictor. In this respect, Richels et al. (2020) found support for an inhibiting role for spin but not pulse, such that effort helped adaptive performance (i.e., post-change performance) for those lower in spin but not for those higher in spin. Although not hypothesized, Richels et al. (2020) also found negative direct effects for pulse but not spin on performance that were stronger in adaptation compared to acquisition.

Although Richels et al. (2020) found support for both the mediation and moderation mechanisms, the differing effects for spin and pulse paint a fairly nuanced picture of affect variability's role in complex task learning. Given the nuanced results and that Richels et al. (2020) was the first empirical investigation of affect variability and task performance, replication is warranted. Moreover, Richels et al. (2020) conceded that a limitation of their study was that they did not directly test the underlying processes by which effort and performance may have been undermined by affect variability, and in this respect they emphasized that future research should examine task attention as a key underlying process. Richels et al.'s (2020) measure of learning effort focused on self-reports of effort toward exploring and exploiting new and existing task strategies and not attention per se. In fact, Richels et al. (2020) suggested that the observed direct effects of pulse on performance may be explained by task attention more so than effort put forth toward different learning strategies. Therefore, the present study examined off-task attention in lieu of learning effort. Figure 1 provides a model of the mechanisms tested.

Affect Variability → Off-Task Attention and Enjoyment

The overall greater reactivity to events and specifically distress from the demands of new and complex tasks translates into more off-task attention and less enjoyment for individuals with greater affect variability. Those with greater affect variability face the distractions of regulating their emotions compounded by greater self-doubt and worry, which in turn creates more mental fatigue, disengagement, and mind wandering over the course of skill acquisition and adapting to unanticipated changes in task demands (Grillon et al., 2015; Hopstaken et al., 2015; Richards & Gross, 2000). Although increases in off-task attention should generally be expected over the course of learning as autonomous processing replaces controlled processing, greater increases should be expected with higher affect variability from greater cumulative emotion reactivity and mental fatigue from devoting attentional resources to both regulating emotions and developing effective learning strategies. Accordingly, I tested the following hypotheses.

> *Hypothesis 1:* Affect variability will be positively related to off-task attention.
>
> *Hypothesis 2:* Affect variability will be positively related to increases in off-task attention.
>
> *Hypothesis 3:* Affect variability will be negatively related to end-of-training task enjoyment.

Affect Variability Moderating the Off-Task Attention → Performance Relationship

In addition to the direct effects on overall and changes in off-task attention, there is reason to examine the potential of affect variability moderating the relationship between off-task attention and performance. Specifically, affect variability might exacerbate the detrimental effects of off-task attention inasmuch as affect variability inhibits implicit learning. Although attention is crucial for learning and improved performance, research also suggests that it may be possible for learning to occur implicitly without attention to learning strategies (Shanks, 2003; Stadler, 1995). General awareness and attention to stimuli may be required for learning, but full attention to decisions about the learning process may not be. Implicit learning is learning that occurs without individuals being consciously aware that learning is taking place. In this vein, learning can occur through efficient associative processing just by engaging task stimuli (Stadler, 1995)—incidental processing rather than intentional processing—even when the information is complex in nature (Lewicki et al., 1992) and especially fast-paced tasks with strong perceptual-motor demands (Lewicki et al., 1992; DeShon and Alexander, 1996) such as the one involved in Richels et al. (2020) and the present study. This may be particularly true if the individual enjoys the task, as enjoyment has been shown to improve implicit learning (Tews et al., 2019). However, similar to secondary-task interference, implicit learning can be impeded by emotion reactivity and perceptions of threat, producing slower response times as individuals generally become less aware of the task environment while attending to their emotions (Estes & Verges, 2008; Ochs & Frasson, 2004; Richards & Milkwood, 1989; Yiend & Mathews, 2001). Thus, individuals can be overwhelmed by emotions as elicited emotional responses take precedence and draw resources away from general task awareness and incidental processing (Chaffar & Frasson, 2004; McVay & Kane, 2010; Vuilleumier, 2005). More simply put, those with greater affect variability are more likely to give up in difficult situations. In this way, performance suffers more from off-task attention for individuals with greater affect variability than for those who engage in general mind wandering but are still able to incidentally process the stimuli effectively. Accordingly, I tested the following hypothesis.

> *Hypothesis 4:* Affect variability will moderate the effects of off-task attention on performance such that the negative effects of off-task attention will be stronger for individuals with greater affect variability.

Affect Variability in Adaptation versus Acquisition

Although previous research has shown a link between affect variability, spin in particular, and maladjustment to emotionally charged events and change (e.g., Beal & Ghandour, 2011), with the exception of Richels et al. (2020) there is no empirical research addressing how affect variability plays a role in adapting task performance to changes. When task demands change unexpectedly and become more difficult, poor adjustment is more likely for those with greater affect variability as greater emotion reactivity and need to regulate emotions distract from the process of discovering and understanding the new task demands and refining previously learned strategies (Richels et al., 2020). Handling sudden and unexpected changes is especially taxing and fatiguing cognitively for those with greater affect variability. Cognitive resources are more likely to be depleted by emotion regulation, and implicit learning is also hindered as those with greater affect variability are more likely and quicker to give up on trying to meet the changes in task demands. Accordingly, I tested the following hypotheses.

> *Hypothesis 5:* The positive relationship between affect variability and off-task attention will be stronger in adaptation versus acquisition.
>
> *Hypothesis 6:* The positive relationship between affect variability and increases in off-task attention will be stronger in adaptation versus acquisition.
>
> *Hypothesis 7*: The moderation of affective variability on the off-task attention-performance relationship will be stronger in adaptation versus acquisition.

In addition to testing the specific hypotheses regarding how affective variability undermines skilled performance vis-à-vis off-task attention, the analyses speak to whether there might be any negative direct effects of affective variability on performance, and whether the magnitude of such direct effects differs in adaptation versus acquisition.

Method

Participants

Data from Huck (2018) was used to examine this study's research questions and hypotheses. Data were collected from 288 undergraduate students in the Department of Psychology participant pool at the University of Oklahoma. Participants were told that they would be playing a computer-based first-person-shooter video game in exchange for research credit in a psychology course and entry into a gift card drawing. No restrictions were placed on participants beyond being 18 or older (or obtaining parental permission if under 18) and being proficient in English. Data were excluded for 12 participants who experienced technical difficulties and 6 who failed to follow instructions. An additional 17 participants were removed for careless responding, which was detected via long string analysis (Meade & Craig, 2012). The final sample consisted of 253 students, 85 of which identified as female. Participants ranged in age from 18 to 30 years (M = 19, SD = 1.55). One hundred sixty-nine participants reported their ethnicity as Caucasian (66.8%), 25 as Asian (9.9%), 16 as Hispanic/Latino (6.3%), 14 as African American (5.5%), 11 as Multiple (two or more ethnicities) (4.4%), 8 as Native American (3.2%), 4 as Middle Eastern (1.6%), and 6 as other (2.4%).

Performance Task

The performance task used in this study was Unreal Tournament 2004 (UT2004; Epic Games, 2004), which is a commercially available first-person shooter computer game used in previous research on complex skill acquisition and adaptive performance (e.g., Hardy et al., 2014; Hughes et al., 2013). UT2004 was selected as the performance task because it reflects the demands of a complex and fast-paced environment. It is also relatively easy to learn yet difficult to master, which allows a skill acquisition curve to be observed.

The objective of UT2004 is to destroy computer-controlled opponents (i.e., bots), while minimizing the damage to one's own character. While completing this objective each game, participants also have the opportunity to collect new weapons or resources (i.e., power-ups) to increase their character's health or offensive or defensive capabilities. When a participant's character is destroyed, the character reappears in a random location with the default weapons and capabilities. The game is designed as "every character for them self," which means that the computer-controlled bots were competing against each other, as well as the participant's character. Performance on UT2004 involves strong cognitive and perceptual-motor demands. Participants used a keyboard and mouse simultaneously to control their character, while also learning the strengths and weaknesses of different strategies and weapons, and quickly deciding which to use in different circumstances.

Procedure

Upon entry to the lab, participants were told that the purpose of the study was to investigate how people learn to play a dynamic and complex video game. Participants completed the study at individual computer stations and no more than six individuals participated at the same time. Participants completed an informed consent form, followed by a battery of self-report individual difference measures to serve as control variables. Participants were told they would be entered into a performance-based lottery to win one of five, $25 gift cards for each trial in which their score was in the top 50% of all study participants for that specific trial. Participants next watched a 15-minute training presentation on UT2004 which explained the game's basic controls, rules, and power-ups. This was followed by a 1-minute practice trial that was free of competing bots so that participants could become familiar with the controls, display, and game environment without having to face any opponents.

Participants completed 14 training sessions, each consisting of two 4-minute trials (i.e., 28 trials total). The length of the trials was chosen based on previous research using UT2004 (Hardy et al., 2014, 2019). Performance across the trials was collapsed into 14 measurement sessions (i.e., an average of the performance across each pair of two trials), as is consistent with previous studies using discontinuous growth curve modeling (e.g., Lang & Bliese, 2009; Niessen & Jimmieson, 2016).

To track fluctuations across time, participants completed self-report measures of state-based affect (PANAS) and attention following each session. Since the same self-report measures were used throughout the study, the breaks between sessions were similar in length at approximately 2 minutes. There were two additional 4-minute breaks before Sessions 4 and 11.

For the first seven sessions, participants competed against two bots which were set to a difficulty level of 5 on a 1-to-8 scale. After the 7th session (i.e., the halfway point), several task demands changed without any warning, designed to prompt reactive adaptation due to an increasing task complexity (Hughes et al., 2013). Participants had to compete against nine bots at a difficulty setting of 6. In addition, the game environment (i.e., the game map) was much larger, with more open spaces, multiple levels of platforms, and edges that could lead to player character destruction if they were to fall. Task characteristics for the pre- and post-change trials were similar to those used by Hardy et al. (2014). Participants were debriefed following the 14th session.

Measures

Control Variables

Self-reported ACT scores (*M* = 26.91, *SD* = 4.25) were used as a measure of general mental ability (GMA). Gender was measured using a self-report. I chose to control for gender and video game experience as previous research (Hopp & Fisher, 2017) has demonstrated that first-person shooter games yield gender differences regarding performance, enjoyment levels, and history of playing these types of games. Prior video game experience was measured using a 4-item scale to gather information about participants pre-training video game knowledge. Utilizing a 5-point Likert scale (1 = not at all, 2 = rarely, just a few times, 3 = monthly, 4 = weekly, 5 = daily) for the first two items, participants responded to: (a) "Over the last 12 months, how frequently have you typically played video/computer games?" (*M* = 2.97, *SD* = 1.40) and "Over the last 12 months, how frequently have you typically played first-person shooter video/computer games (e.g., Call of Duty, Half-Life, Halo, Unreal Tournament, etc.)?" (*M* = 2.26, *SD* = 1.25). The following two items asked participants how many hours per week they play (a) video/computer games (*M* = 4.37, *SD* = 6.89, min. = 0.00, max. = 50) and (b) specifically first-person shooter video/computer games (*M* = 1.74, *SD* = 3.76, min. = 0.00, max. = 30). The scores for these items were standardized and averaged into a prior videogame experience score.

Additional control variables used in this study were the Big Five personality dimensions to examine the independent effects of affect variability. The Big Five personality dimensions were measured using Goldberg's 100 Unipolar Markers (Goldberg, 1992). Participants rated a list of 100 common human traits as to how accurately they describe the participant using a 9-point Likert scale, with anchors at (1) *Extremely inaccurate* and (9) *Extremely accurate.* Twenty items were used for each of the five factors, with a scale score consisting of the average of their corresponding item scores.

Affect Variability

To calculate spin, pulse, and flux, I used a 16-item version of the Positive and Negative Affect Schedule which was adapted for this study (PANAS; Watson et al., 1988). After each session of gameplay, participants were asked to respond in regard to how they felt during the previous two trials. Using 16 different emotions that varied in valence and arousal/activation, the scale measured four different areas of affect. Positive activating (PA) emotions were described with the words enthusiastic, excited, and happy. Positive deactivating (PD) emotions were assessed with the words ease, calm, and relaxed. Adjectives angry, anxious, frustrated, irritated, tense, and uneasy were used to assess negative activating (NA) emotions. Negative deactivating (ND) emotions were assessed with the adjectives bored, disappointed, discouraged, and fatigued. Participants responded to each word on a 9-point Likert scale (1 = very slight/not at all, 3 = a little, 5 = moderately, 7 = quite a bit, 9 = extremely).

Before calculating spin, pulse, and flux, valence and activation scores must be calculated for each participant across the 14 sessions. Following the procedures of Kuppens et al. (2007), valence was calculated as (PA + PD) − (NA + ND), and activation was calculated as (PA + NA) − (PD + ND). Next, the mean scores for valence and activation were calculated, in addition to their standard deviations. Standard deviations of the repeated scores were used to calculate valence variability (i.e., the standard deviation of pleasure-displeasure that occurs within person) and activation variability (i.e., the standard deviation of activation-deactivation that occurs within person). Although valence variability and activation variability can describe emotions over time, this description is uni-dimensional (Park, 2015). In comparison, affect spin and pulse are more reflective of affective changes and the measure captures both valence and activation (Beal et al., 2013).

Affect Spin. To calculate affect spin, I followed the framework provided by Moskowitz and Zuroff (2004) and the procedures by Kuppens et al. (2007). Spin describes how affect moves within the core affect space (Kuppens et al., 2007). First, the unit vector must be calculated for each session.

$$\left(\frac{valence_t}{\sqrt{valence_t^2 + activation_t^2}}, \frac{activation_t}{\sqrt{valence_t^2 + activation_t^2}}\right)$$

Next, the vector of all observations for one given participant, *R*, was calculated as follows.

$$\left(\sum_{t=1}^{n} \frac{valence_t}{\sqrt{valence_t^2 + activation_t^2}}, \sum_{t=1}^{n} \frac{activation_t}{\sqrt{valence_t^2 + activation_t^2}}\right)$$

The length of R was then calculated as

$$\sqrt{\frac{\sum_{t=1}^{n} \frac{valence_t}{\sqrt{valence_t^2 + activation_t^2}} + \sum_{t=1}^{n} \frac{activation_t}{\sqrt{valence_t^2 + activation_t^2}}}{n}}$$

The length of R $\left(\frac{||\vec{R}||}{n}\right)$ can range from 0 to 1. If there is no variability in the angles, then $\left(\frac{||\vec{R}||}{n}\right)$ will equal 1. If the angles are dispersed widely enough to cancel each other out, then $\left(\frac{||\vec{R}||}{n}\right)$ approaches 0 (Kuppens et al., 2007). The final calculation of spin involves the standard deviation of the angles of the unit vectors, which is calculated as

$$\sqrt{-2ln\left(\frac{||\vec{R}||}{n}\right)}$$

This final calculation of affect spin may range from 0 to infinity (Kuppens et al., 2007).

Affect Pulse. Again, following the framework by Moskowitz and Zuroff (2004) and procedures of Kuppens et al. (2007), affect pulse was calculated. Pulse, which examines the severity or intensity between reports of emotion (Kuppens et al., 2007), was calculated as

$$\sqrt{valence_t^2 + activation_t^2}$$

Affect Flux. Like Moskowitz and Zuroff (2004), flux was assessed for each emotion dimension (positive activating, positive deactivating, negative activating, negative deactivating) for each individual. This was done by calculating the standard deviation across all events for each of the emotion dimensions.

Off-Task Attention

Off-task attention was measured using a measure adapted from Kanfer et al. (1994). Example items that participants responded to include: “I lost interest in Unreal Tournament for short periods” and “I took ‘mental breaks’ during Unreal Tournament.” Answers were made on a 7-point Likert scale, with anchors at (1) *Never* and (7) *Constantly.* Across the 14 sessions, the mean alpha reliability was 0.90 (min. = 0.85, max. = 0.94).

Task Enjoyment

Task enjoyment was measured after participants completed the 14th and final training session. Utilizing the same measure as Hardy et al. (2014) participants responded to 11 items such as “I had fun learning UT2004”, “I enjoyed playing Unreal Tournament”, and “If I could, I would play Unreal Tournament at home” on a 5-point Likert scale (*1 = strongly disagree, 2 = agree, 3 = neither agree nor disagree, 4 = agree, 5 = strongly agree*).

Task Performance

Following the formula as described by Hardy et al. (2014) and Hardy et al. (2019), task performance scores were calculated by taking the number of kills (i.e., number of times a participant destroyed a bot), divided by the quantity of kills plus deaths (i.e., the number of times a participant themselves is destroyed), plus player rank (i.e., the participant’s rank relative to the bots within the trial). These scores were then multiplied by 100 to increase the ease of interpretability. A single performance score for each session was calculated by taking the average score for both trials in that session.

Results

Figures 2 and 3 show the trends in off-task attention and performance scores, respectively, across sessions. Descriptive statistics, including internal consistency reliabilities, correlations for study variables, and average performance and off-task attentions scores across sessions can be found in Table 4. Affect spin was not significantly correlated with off-task attention ($r = 0.07$, *ns*), but affect pulse was significantly correlated with off-task attention ($r = 0.21$, $p < 0.01$). Affect spin was not significantly correlated with performance ($r = -0.07$, *ns*) or enjoyment ($r = -0.06$, *ns*), but affect pulse was significantly, negatively correlated with performance ($r = -.18$, $p < 0.01$) and enjoyment ($r = -.19$, $p < 0.01$). Off-task attention was significantly, negatively correlated with performance ($r = -.47$, $p < 0.01$) and enjoyment ($r = -.40$, $p < 0.01$). Performance and enjoyment were significantly, positively correlated with each other ($r = .23$, $p < 0.01$). Affect pulse was not significantly correlated with emotional stability (*r*

= −0.05, *ns*). Divergent from Richels et al. (2020), affect spin was not significantly correlated with emotional stability ($r = -0.05$, *ns*). Each of the flux variables was significantly, positively correlated with affect spin, and affect pulse (mean $r = .48$; min $r = .38$, $p < 0.001$; max $r = .62$, $p < 0.01$). Neither positive activating nor positive deactivating flux were significantly correlated with off-task attention ($r = 0.02$ and 0.10, respectively, *ns*), performance ($r = -0.04$ and 0.00, respectively, *ns*), or enjoyment ($r = -0.04$ and 0.06, respectively, *ns*). However, negative activating and negative deactivating flux were significantly, positively correlated with off-task attention ($r = 0.28$ and 0.40, respectively, $p < 0.01$) and significantly, negatively correlated with performance ($r = -0.28$ and −0.24, respectively, $p < 0.01$) and enjoyment ($r = -0.22$ and −0.35, respectively, $p < 0.01$). None of the affect variability indices had a significant relationship with emotional stability except for negative activating flux ($r = -.17$, $p < 0.01$).

Relative Importance Analysis

To determine whether any of the affect variability indices was most dominant, or if one acted as a suppressor when explaining variance in off-task attention, enjoyment, and performance, I conducted a relative importance analysis by adapting publicly available code from Nimon and Oswald (2013). All indices of affect variability were compared for off-task attention, enjoyment, and performance. In addition to providing the full range of relative importance metrics reviewed by Nathans et al. (2012), relative weights, squared structure coefficients, and product measures for example, the relative importance analysis also examined measures of dominance and measures to identify suppressors. Specifically, dominance was determined by taking each pair of predictors and comparing their contributions across all models containing all possible combinations of all predictor variables (Azen & Budescu, 2003; Luchman, 2015). Although dominance can be established across three levels (complete, conditional, and general), I only focused on complete dominance, which denotes that a certain predictor contributed the highest amount of variance across all subsets of predictors (Azen & Budescu, 2003). By examining the dominance statistics, it was also possible to identify suppressors by seeing how unique variance contributions changed given the model's size. Typically, as a model's size increases (with added predictors) the unique variance contribution of a single predictor will decrease as the variance is shared among more predictors (Nathans et al., 2012; Azen & Budescu, 2003). However, a suppressor will work in the opposite way by contributing little variance on its own but contributing more variance overall as the number of predictors increases by suppressing variance in the other predictors.

Off-Task Attention

Prior to examining dominance, Hypothesis 1 predicted that affect variability would be positively related to off-task attention. As shown in Table 5, in support of Hypothesis 1, the structure coefficients and zero-order correlations (r_s and r, respectively) for all affect variability indices were positive for off-task attention.

A comparison across all statistics for off-task attention (Table 5) showed that negative deactivating flux (ND) was the strongest direct predictor across all the relative importance metrics. ND flux obtained the largest beta weight ($\beta = .53$, $p < .001$), demonstrating that it made the largest contribution to the regression equation, while holding all other predictor variables constant. The zero-order correlation of ND flux with off-task attention ($r = .40$), when squared, showed that ND flux shared the largest amount (16%) of its variance with off-task attention. The squared structure coefficient ($r_s^2 = .73$) demonstrated that ND flux explained the largest amount (73%) of the variance in y, the predicted values of off-task attention. Product measure results demonstrated that ND flux accounted for the largest partition of variance in off-task attention

(.213, 96.8% of the regression effect) when multiplying the beta weight (.53) by the zero-order correlation (.40). The results of the relative weights analysis demonstrated that ND flux explained a large portion of the overall regression effects, accounting for 12.8% of the variance in off-task attention which is 58% of the 22% variance in off-task attention accounted for by all the affect variability indices together. Negative activating (NA) flux emerged as the second strongest predictor of off-task attention. Its zero-order correlation (r = .28) was the second largest in the model and demonstrated that NA flux shared the second largest amount (7.8%) of its variance with off-task attention. The relative weights analysis showed that NA flux explained the second largest portion of the overall regression effects, accounting for 3.8% of the variance in off-task attention, which is 17.3% of the 22% variance in off-task attention accounted for by all the affect variability indices together.

With respect to Research Question 1a, dominance analysis (Table 6) showed complete dominance for ND flux over the other affect variability indices, as it contributed more unique variance in the regression results than all the other indices across all the multiple regression sub-models that included that variable. Table 7 shows the average incremental variance for each predictor's contributed variance to off-task attention. With respect to Research Question 2a, positive activating (PA) flux contributed more variance as the number of predictors increased, indicating that it acts as a suppressor. The average variance contributed with one other predictor was 1.4%, but this increased to 3.8% when all other predictors were included. Overall, these findings support ND flux as the dominant contributor to off-task attention and PA flux as an important suppressor. Consistent with mediation, the indirect effect of ND flux on performance via off-task attention, controlling for PA flux, was statistically significant (ab unstandardized = –3.54, [bootstrapped bias corrected CI_{99} = –6.72, –1.21], $p < .001$, $R^2 = .27$).

Enjoyment

Hypothesis 3 predicted that affect variability would be negatively related to end-of-training task enjoyment. As shown in Table 5, and in partial support of Hypothesis 3, the structure coefficients and zero-order correlations (r_s and r, respectively) for all affect variability indices except for positive deactivating (PD) flux were negative for enjoyment. Thus, with the exception of PD flux, Hypothesis 3 was supported.

Similar to off-task attention, a comparison across all statistics for enjoyment (Table 5) showed that negative deactivating (ND) flux was the strongest direct predictor across all the relative importance metrics. ND flux obtained the largest beta weight ($\beta = -.40$, $p < .001$), demonstrating that it made the largest contribution to the regression equation, while holding all other predictor variables constant. The zero-order correlation of ND flux with performance ($r = -.35$), when squared, showed that ND flux shared the largest amount (12.3%) of its variance with performance. The squared structure coefficient ($r_s^2 = .71$) demonstrated that ND flux explained the largest amount (71%) of the variance in y, the predicted values of performance. Product measure results demonstrated that ND flux accounted for the largest partition of variance in performance (.14, 79.5% of the regression effect) when multiplying the beta weight (−.40) by the zero-order correlation (−.35). Results of the relative weights analysis demonstrated that ND flux explained a large portion of the overall regression effects, accounting for 9.2% of the variance in task enjoyment which is 52% of the 17.6% variance in enjoyment accounted for by all the affect variability indices together. In a similar fashion to off-task attention, negative activating (NA) flux emerged as the second strongest predictor of enjoyment. Its zero-order correlation ($r = -.22$) was the second largest in the model and demonstrated that NA flux shared the second largest amount (4.8%) of its variance with enjoyment. The relative weights analysis showed that NA flux explained the second largest portion of the overall regression effects, accounting for 3% of the variance in enjoyment, which is 17.1% of the 17.6% variance in enjoyment accounted for by all the affect variability indices together.

With respect to Research Question 1b, like for off-task attention, dominance analysis for enjoyment (Table 6) showed complete dominance for ND flux over the other affect variability indices, as it contributed more unique variance in the regression effect than the other indices across all multiple regression sub-models that included that variable. Table 7 shows the average incremental variance for each predictor's contributed variance to enjoyment. With respect to Research Question 2b, none of the indices contributed more variance as the number of predictors increased, indicating no suppression effects for task enjoyment.

Performance

Relative importance comparisons across all statistics for performance (Table 5) showed that negative activating (NA) flux was the strongest direct predictor of performance. NA flux obtained the largest beta weight ($\beta = -.34$, $p < .001$), demonstrating that it made the largest contribution to the regression equation, while holding all other predictor variables constant. The zero-order correlation of NA flux with performance ($r = -.28$), when squared, showed that NA flux shared the largest amount (7.8%) of its variance with performance. The squared structure coefficient ($r_s^2 = .65$) demonstrated that NA flux explained the largest amount (65%) of the variance in y, the predicted values of performance. Product measure results demonstrated that NA flux accounted for the largest partition of variance in performance (.096, 76.8% of the regression effect) when multiplying the beta weight (−.34) by the zero-order correlation (−.28). Results of the relative weights analysis demonstrated that NA flux explained a large portion of the overall regression effects, accounting for 5.9% of the variance in performance which is 48%

of the 12.4% variance in performance accounted for by all the affect variability indices together. There was only one metric in which NA flux was not reported as the strongest direct predictor of performance. For the common metric, negative deactivating (ND) flux was found to be the strongest predictor (0.053, in comparison to NA flux's 0.033). ND flux was the second strongest predictor of performance. Its zero-order correlation ($r = -.24$) was the second largest in the model and demonstrated that ND flux shared the second largest amount (5.8%) of its variance with performance. The relative weights analysis showed that ND flux explained the second largest portion of the overall regression effects, accounting for 2.9% of the variance in performance, or 23.4% of the 12.4% variance in performance accounted for by all the affect variability indices together.

With respect to Research Question 1c, dominance analysis (Table 6) showed complete dominance of NA flux over the other affect variability indices. With respect to Research Question 2c, Table 7 shows that positive deactivating (PD) flux contributed more variance as the number of predictors increased, indicating that it acts as a suppressor. The variance contributed with one other predictor was 0.9% but increased to 1.6% when all other predictors were included. Overall, these findings support NA flux as the dominant direct contributor to performance and PD flux as an important suppressor.

Growth Trends

Discontinuous growth curve modeling was used to model off-task attention and performance scores across skill acquisition (SA), transition adaptation (TA), and reacquisition adaptation (RA). This technique allowed for a comparison between scores prior to the task change to scores following the task change (i.e., post-change period; reacquisition) (Bliese & Lang, 2016). Following the recommendation of Bliese and Lang (2016) and taking similar steps as Richels et al. (2020), I examined a series of growth models. The first step was to test a basic growth model with each time variable included in the equation below:

$$Y_{ij} = \gamma_{00} + \gamma_{10}SA + \gamma_{20}TA + \gamma_{30}RA + \gamma_{40}SA^2 + \gamma_{50}RA^2 + \varepsilon_{ij}$$

Defining the terms in the equation, SA refers to the linear growth trend across sessions. TA, or transition adaptation, is the change in scores following the change in task demands, which occurred between Session 7 and 8. RA refers to reacquisition adaptation, which is the difference in the linear growth trend post-change in comparison to the linear growth trend pre-change. SA^2 and RA^2 account for any curvilinear growth trends. Prior to building the models as described in Table 2, the random intercept model was tested to estimate the intraclass correlation coefficient (ICC), which indicates the proportion of variance that resides within- and between-persons. The ICC for off-task attention indicated that differences existed within participants.

Off-Task Attention

The ICC for off-task attention indicated that differences existed within participants (37%). When testing the basic growth model from Step 1, I built the model by including each time variable (SA, TA, RA, etc.) one by one and examined the AIC to determine the best model fit. The final growth model only included SA (see Model 1 of Table 8), and showed that off-task attention scores increased at a linear rate across sessions ($t[3288] = 9.11$, $B = 0.07$, $p < 0.01$) without any curvilinear or discontinuous effects.

I included the covariates in the next model (see Model 2 of Table 8). There was a significant gender effect ($t[244] = 3.41$, $B = 0.54$, $p < 0.01$), which showed that females had more off-task attention. General mental ability ($t[244] = -2.37$, $B = -0.04$, $p < 0.05$) and agreeableness ($t[244] = -2.34$, $B = -0.19$, $p < 0.05$) both showed significant negative effects. Higher levels of general mental ability and agreeableness were associated with lower levels of off-task attention. No other covariate yielded a statistically significant effect.

Effects of Dominant and Suppressor Affect Variability Indices. In Step 3, the main effects of the dominant and suppressor variables (i.e., ND flux and PA flux, respectively) were included (see Model 3 of Table 8). Hypothesis 1 predicted that affect variability would be positively related to off-task attention. Consistent with the findings from the relative importance analysis, and in support of Hypothesis 1, ND flux ($t[242] = 5.77$, $B = 0.72$, $p < 0.01$) yielded a positive, significant effect. PA flux as a suppressor yielded a smaller negative effect ($t[242] = -2.99$, $B = -0.33$, $p < 0.01$).

In Step 4, I added the interaction between the dominant variable, ND flux, with the linear trend (SA) for off-task attention (see Model 4 of Table 8). Hypothesis 2 proposed that affect variability would be positively related to increases in off-task attention. In support of Hypothesis 2, there was a statistically significant, positive interaction between ND flux and the SA off-task attention trend ($t[3287] = 4.46$, $B = 0.06$, $p < 0.01$), which indicated a greater increase in off-task attention for individuals higher in ND flux. Results of the AIC values showed better fit for this model relative to previous models. Since this step did not include TA or RA interactions with ND flux, this increasing off-task attention occurred for those higher in ND flux regardless of the changes in task demand. Figure 4 illustrates the trend for ND flux, showing substantial growth in off-task attention for those higher in ND flux versus virtually no growth for those lower in ND flux.

Hypotheses 5 and 6 proposed stronger positive relationships overall and with respect to growth, respectively, between affect variability and off-task attention in adaptation versus acquisition. Although I planned an additional step (as shown in Model 5 of Table 2) that examined the interactions involving ND flux with TA and RA, the aforementioned lack of TA and RA effects for off-task attention indicated such a step was not appropriate. Thus, the results did not support Hypotheses 5 and 6, and instead showed similar relationships between affect variability and off-task attention in adaptation and acquisition.

Performance

Prior to building the models as described in Table 3, the random intercept model was tested to estimate the intraclass correlation coefficient (ICC). The ICC for performance indicated that differences existed within participants (29%). Similar to off-task attention, I began building the models for performance by including each time variable (SA, TA, RA, etc.) individually and examining the AIC to determine the best model fit. This indicated that all time variables should be included when building the growth models. As shown in Model 1 of Table 9, there was a statistically significant positive SA effect ($t[3284] = 14.19$, $B = 5.28$, $p < 0.01$), a statistically significant, negative TA effect ($t[3284] = -21.79$, $B = -18.45$, $p < 0.01$), and a statistically significant, negative RA effect ($t[3284] = -8.09$, $B = -4.18$, $p < 0.01$). These effects indicated that performance levels increased across pre-change sessions, but then dropped after the task change. After the change, performance began to increase, but at a slower rate than the pre-change rate. SA^2 was significant ($t[3284] = -9.14$, $B = -0.54$, $p < 0.01$) which indicated that increases in performance decelerated across sessions. RA^2 was not significant and was removed from further model tests.

I included the covariates in the next model (see Model 2 of Table 9). There was a significant gender effect ($t[244] = -7.85$, $B = -12.45$, $p < 0.01$), which indicated that females had lower performance levels than males. General mental ability ($t[244] = 3.43$, $B = 0.53$, $p < 0.01$) and video game experience ($t[244] = 9.61$, $B = 7.04$, $p < 0.01$) were both positive and statistically significant, which meant that higher ACT scores and prior video game experience were associated with higher performance scores. No other covariate yielded a statistically significant effect. The results from Models 1 and 2 align well with the findings from Richels et al. (2020). A divergent finding was that extraversion was not found to be significant in my model ($t[244] = -1.64$, $B = -0.99$, *ns*).

Effects of Affect Variability Indices. In Step 3, the main effects of each affect variability index and the suppressor variable (PD flux) were included (following the steps displayed in Table 3). Each affect variability index was examined independently of each other in separate models. A statistically significant, negative effect was found for NA flux (the dominant variable; $t[242] = -3.07$, $B = -3.81$, $p < 0.01$), ND flux ($t[242] = -2.30$, $B = -2.68$, $p < 0.05$), PA flux ($t[242] = -2.04$, $B = -2.39$, $p < 0.05$), and spin ($t[242] = -2.40$, $B = -4.10$, $p < 0.05$). This indicated that those with higher NA flux, ND flux, PA flux, and spin had lower performance scores. Although the results for spin align with what was found by Richels et al. (2020), my findings differ in that pulse was not a significant predictor.

Next, I included the main effect of off-task attention in Step 4 (Model 4 of Tables 10-15), which showed an improvement in model fit for all indices. As expected, off-task attention was negatively related to performance (NA flux, $t[241] = -5.40$, $B = -2.88$, $p < 0.01$; PD flux, t[242] = −5.80, B = −3.08, p < 0.01; ND flux, $t[241] = -5.21$, $B = -2.96$, $p < 0.01$; PA flux, $t[241] = -5.84$, $B = -3.08$, $p < 0.01$; spin, $t[241] = -5.73$, $B = -3.02$, $p < 0.01$; pulse, $t[241] = -5.70$, $B = -3.06$, $p < 0.01$). After adding off-task attention, the model examining ND flux indicated that ND flux no longer had a statistically significant effect on performance (see Table 12). Consistent with the mediation analysis in the relative importance analysis, ND flux is a distal predictor of off-task attention, which may be why its effect disappears when adding off-task attention. Based on the AIC, Model 4 was the best fit for PD flux (Table 11), PA flux (Table 13), and pulse (Table 15).

In Step 5, all two-way interactions were included. This step was used to test Hypothesis 4, which proposed that affect variability would moderate the effects of off-task attention on performance such that the negative effects of off-task attention would be stronger for individuals with greater affect variability. As shown in Model 5 of Tables 10-15, the interaction between off-task attention and the affect variability indices were not statistically significant. Thus, the results did not support Hypothesis 4. Model 5 also included two-way interactions between each affect variability index and off-task attention with SA, TA, and RA. For off-task attention, there was a statistically significant, negative interaction with SA in the models that examined NA flux (Table 10; $t[3279] = -2.27$, $B = -1.24$, $p < 0.05$), ND flux (Table 12; $t[3279] = -2.09$, $B = -0.23$, $p < 0.05$), and spin (Table 14; $t[3279] = -2.86$, $B = -0.29$, $p < 0.01$). Excluding spin, this finding indicated that the negative effect of off-task attention was stronger across later sessions.

There was a statistically significant, positive interaction between off-task attention and TA ($t[3279] = 2.58$, $B = 1.68$, $p < 0.05$) in the model that examined spin (Table 14), which indicated that the drop in performance was less severe for individuals with increased off-task attention, which may be due to these individuals having less to lose (i.e., performance scores were already lowered in comparison to those with decreased off-task attention). For NA flux (dominant variable), there was also a statistically significant, positive TA interaction ($t[3279] = 2.28$, $B = 3.01$, $p < 0.05$), which indicated that the drop in performance was less severe for individuals with increased NA flux, which again, may be due to these individuals having less to lose (i.e., performance scores were already lowered in comparison to those with decreased NA flux). Figure 5 shows this interaction involving NA flux and TA. It is important to acknowledge that the results of the AIC values showed improved fit for certain indices, with this model found to be the best fit for NA flux (Table 10) and ND flux (Table 12).

In the final step, I included three-way interactions between (1) the affect variability index, (2) off-task attention, and (3) SA, TA, and RA. This model tested Hypothesis 7, which proposed that the moderation effect of affect variability on the off-task attention-performance relationship would be stronger in adaptation versus acquisition. None of the interactions were found to be significant except with spin. A statistically significant, negative interaction (Model 6 of Table 14) was found between spin, off-task attention, and TA ($t[3276] = -2.53$, $B = -4.49$, $p < 0.05$) such that affect spin accentuated the negative effect of off-task attention in adaptation (i.e., post-change sessions) but not in acquisition (i.e., pre-change sessions). As shown in Figure 6, after the task changes, there was a negative effect of off-task attention for individuals high in affect spin, but there was not a negative effect of off-task attention for individuals low in affect spin. In other words, off-task attention was particularly detrimental to performance in individuals high in affect spin after a change in task demands. The results of the AIC values showed improved fit for this model relative to previous models for affect spin but not for any other affect variability indices. Thus, the results partially supported Hypothesis 7. Hypothesis 7 was supported with respect to spin but not for any other indices of affect variability.

Discussion

The broad aim of this lab study was to replicate Richels et al. (2020), which was the first empirical study to show how affect variability, specifically affect spin and pulse, undermines complex task performance, and extend Richels et al. (2020) by (1) examining off-task attention as a key explanatory mechanism and (2) including dimensions of affect flux in a relative importance analysis of affect variability scores. Using a repeated measures design, the present study examined affect variability—spin, pulse, negative activating (NA) flux, negative deactivating (ND) flux, positive activating (PA) flux, positive deactivating (PD) flux—in the context of complex task learning with the aim of better understanding the non-cognitive traits that impact an individual's capacity to be successful when learning new tasks and adapting to changes in task demands.

Several hypotheses regarding affect variability were supported. Indices of affect variability were found to be harmful towards attention, and even exacerbated off-task attention over time. Nearly all indices of affect variability were also found to be detrimental towards task enjoyment. Although affect variability indices in general did not moderate the effects of off-task attention on performance, affect spin was found to negatively moderate the off-task attention-performance relationship after the task change such that off-task attention was especially harmful for individuals higher in affect spin. All these relationships were observed after controlling for the Big Five personality variables, including emotional stability, demonstrating that affect variability indices represent distinct aspects of personality that can provide additional insight to behavioral outcomes.

Relative Importance of Affect Variability Indices

When examining the relative importance of affect variability—spin, pulse, NA flux, ND flux, PA flux, PD flux—in relation to off-task attention, task enjoyment, and performance, two research questions were asked. First, it was queried whether any index of affect variability showed complete dominance over the others in explaining variance in off-task attention, task enjoyment, and performance. Results indicate that negative flux variables were dominant contributors. Specifically, ND flux was the dominant contributor for both off-task attention and enjoyment. NA flux was the dominant predictor for performance. The second research question sought to determine whether any indices of affect variability acted as a suppressor for other indices in explaining variance in off-task attention, task enjoyment, and performance. Although there was no suppressor found for task enjoyment, PA flux and PD flux were found to be important suppressors for off-task attention and performance, respectively. Of note, the dominant and suppressor flux variables for off-task attention and performance were in opposite quadrants or opposing ends of the same pole in the circumplex (Kuppens et al., 2007).

The majority of research on affect variability has focused on spin and pulse. Although flux is not new to dynamic theories of personality (e.g., Moskowitz & Zuroff, 2004), my search of the literature revealed only two studies that examined affect spin, pulse, and flux together (i.e., Chandler, 2012; Russell et al., 2007), with flux scores capturing valence without activation distinguished. The relative importance of flux variables over the traditionally used spin and pulse variables is an important finding. Neither spin nor pulse were found to be dominant or even modest contributors, as might have been expected, especially for spin. Thus, the findings from the present study suggest that flux should be given more empirical attention in research on affect variability, and that flux variables that disentangle valence and activation dimensions have potential to better explain behavioral outcomes compared to single indices like spin and pulse. Put another way, a combination of flux variables likely better covers the core affect space than indices like spin and pulse. For example, a close look at the formula for calculating spin shows that two individuals can receive the same spin scores despite having different patterns across the circumplex (e.g., one varying across PA and ND and the other varying across PD and NA). Altogether, our findings point to the need for future research to include spin, pulse, and flux variables to expand theory on how affect variability contributes to behavioral phenomena.

Direct Effect on Off-Task Attention and Enjoyment

When examining the effects of affect variability, two theoretical mechanisms were tested. First, it was proposed that affect variability would strengthen off-task attention, with those higher in affect variability reporting more off-task attention and increases in off-task attention over time. Results showed that the dominant variable, ND flux, had a positive effect on off-task attention and increases in off-task attention. These results provide support for the first theoretical mechanism proposed, indicating that those high in ND flux are more likely to direct their attention elsewhere, rather than towards the task at hand. Taking into consideration previous research on affect variability, there are several potential explanations for these results. Although research on affect flux is limited, research on affect variability generally indicates that individuals with increased affect variability face greater distress, self-doubt, worry, and emotion reactivity when faced with new and complex demands. These characteristics can cause distraction as the individual works to regulate their emotions, further leading to fatigue, disengagement, and mind wandering, all which may contribute towards heightened off-task attention over the course of skill acquisition and adaptation (Grillon et al., 2015; Hopstaken et al., 2015; Richards & Gross, 2000).

The finding that ND flux yielded a positive interaction with the linear growth term (i.e., SA) with respect to off-task attention suggests that individuals with high affect variability struggled to maintain the necessary levels of attention needed to improve performance, regardless of any changes in task demands. This speaks to proactive adaptation or one’s capacity to take initiative to improve performance regardless of changes in task demands (Ployhart & Bliese, 2006). This interaction involving ND flux and greater linear growth in off-task attention suggests that those high in affect variability are less likely to focus their attention to recognize the subtle differences in various performance strategies, find more effective strategies, and make the adjustments needed to reach higher levels of performance even in stable performance environments. ND flux also had a negative relationship with enjoyment, which can strongly influence task engagement, sustained interest, informal learning, and long-term progress (Sitzmann et al., 2008; Tews et al., 2017). Beyond finding that individuals with greater affect variability may struggle to devote attention to a task, it may also be difficult to engage due to impeded enjoyment from heightened distress, self-doubt, worry, and emotion reactivity resulting from complex or changing demands. Put another way, affect variability is detrimental to task learning.

Moderation of the Off-Task Attention-Performance Relationship

The second theoretical mechanism proposed that affect variability would moderate the off-task attention performance relationship. Support for this mechanism was only found for affect spin and with respect to transition adaptation. Specifically, after the task change, off-task attention was particularly detrimental for individuals high in affect spin. Experiencing shifting emotions, which would be particularly heightened after a change in task demands, likely makes adjusting to change difficult as the individual has less cognitive resources to dedicate towards discovering or altering performance strategies. It is important to mention that although the aforementioned results emphasize the importance of flux, these findings exhibit that spin is still distinctly important and affirm the value of prior literature studying spin. Ultimately this suggests that different indices may be more relevant depending on the outcome of interest.

Combined with the previously mentioned negative impact of off-task attention levels (regardless of task change), and alongside findings from Richels et al. (2020), these results indicate that high affect variability is a hindrance to learning in fast-paced, complex performance contexts, in terms of both acquisition and adaptation. Low levels of affect variability are important aspects of adaptability and are particularly important for occupation and performance environments that are fast-paced, emphasize continuous learning, or involve unpredictable changes. Environments that require a lot of autonomous and informal learning may not be suitable for those high in affect variability because these environments require the individual to control their emotions and sustain attention (Kanfer & Ackerman, 1989).

Distinctiveness of Affect Variability

Like Richels et al. (2020), the present study advances theory in terms of how affect variability indices act as important non-cognitive traits that help comprise the construct of adaptability (Baard et al., 2014). Affect variability indices uniquely address aspects of personality that are not captured by traditional measures of the Big Five—specifically that fluctuations in the expressions of traits should be expected across time (Fleeson and Jayawickreme, 2015). Although personality is an important factor when considering the emotional experiences that accompany change, common measures of personality like the Big Five can be limited in how well they capture the dynamic experience of emotions. My findings support Whole Trait Theory and dynamic approaches to measuring personality (Beckmann & Wood, 2017; Fleeson & Jayawickreme, 2015) and reinforce how affect variability better captures between-person differences in emotion fluctuations and thus are better suited to explaining behavioral phenomena than traditional Big Five measures, even emotional stability (neuroticism).

The repeated-measured structure used to measure affect variability captures individual differences in within-person fluctuations in affect expression, leading to a more comprehensive understanding of emotion reactivity and personality more generally. Affect variability scores are suited for understanding complex or inherently emotional contexts. In this respect, while prior research has found weak relationships between personality variables and task performance, the present study advances theory by demonstrating how affect variability indices capture important non-cognitive traits predictive of off-task attention and performance. With the exception of Richels et al. (2020), there has been a lack of theory and empirical research addressing the relationship between affect variability and complex task learning, and together with Richels et al. (2020), the present study contributes to theory regarding how personality plays a role in complex task learning via the lens of stress-attention-performance relationships and advances our understanding of affect variability indices as important contributors to skill acquisition and adaptation.

Limitations and Future Research

There are several limitations that should be considered when interpreting and generalizing the results found here. First, it is critical to scrutinize the performance task. The nature of the task may differentially impact individuals high in affect variability and findings may be most applicable to specific contexts that rely on complex, fast-paced performance. Considering that individuals with increased affect variability are likely to have a greater reaction to stressful or emotionally charged events (Beal & Ghandour, 2011), the task in this study may have elicited a stronger effect. There also may have been added pressure due to the chance for monetary reward in exchange for high performance that could have exacerbated the effects of greater affect variability. This study repeats the limitation given by Richels et al (2020) in that the performance context was not a proceduralized learning environment, meaning that the results may not be generalizable to proceduralized training contexts. Individuals did not have time to reflect on or explore different strategies to improve performance, resembling a more active learning environment. Thus, future research should examine different learning environments as these different environments may alter the effects of an individual's affect variability. Similar to Richels et al. (2020), my results showed a performance difference between males and females. Although these differences might be expected as males typically report engaging more in video games and a higher degree of interest than females (Ogletree & Drake, 2007), it may be possible that gender is an additional factor that must be considered when trying to determine the effect of affect variability in particular performance contexts. Future research should seek replicate the current findings under various performance contexts, keeping in mind that there may be gender-based differences.

It should also be noted the self-report nature of the study which may fail to fully encompass all aspects of off-task attention. Participants may have struggled to fully monitor how much attention they directed to the task and may thus over- or underestimate the true amount of attention directed towards the task. Some participants may also be hesitant to report that they were not paying attention to the task. Future research could utilize physiological measures such as eye-tracker technology, which has been used in the past to measure on-task attention or attentional shifts (Maclin et al., 2011), under the assumption that participants are focused on what they fixate upon visually (Duchowksi, 2002; Moran et al., 2016). Prior complex skill research has found it possible to utilize other technology, such as electroencephalogram (EEG; Bakaoukas et al., 2016; Maclin et al., 2011) and functional magnetic resonance imaging (fMRI; Prakash et al., 2012), to monitor brain states that reflect attention. As individuals acquire skills, there will be a reduction in the amount of attentional resources devoted to task performance as the execution of performance strategies become automated (Kanfer & Ackerman, 1989; Kanfer et al., 1994; Prakash et al., 2012). As such, neuroimaging and EEG could be better leveraged to capture changes and differences in attention, rather than relying on self-reports, to indicate if (1) participants are actually putting resources towards on-task attention and (2) they are activating attentional control areas but failing to succeed in acquiring the skills necessary to perform the task. This may enable a more nuanced examination of the mechanisms tested in the present study. Another strategy that may be effective in gauging attention is to utilize think aloud protocols (Ericsson & Simon, 1980). Think aloud protocols refer to the process whereby a participant verbalizes all their thoughts as they engage with a task (Ericsson & Fox, 2011). With proper standardized procedures, valid measurement of attention control and specific cognitive process can be attained without unduly disrupting performance (Kircher & Ahlstrom, 2018; Oliver et al., 2021). Indeed, think aloud protocols have been shown to yield verbalizations that are consistent with behavioral performance (Ericsson & Simon, 1980).

Although this research answers a call by Richels et al. (2020) to explain the underlying mechanisms of affect variability that may undermine performance (i.e., via off-task attention), there are other mechanisms that should be examined, emotion regulation and strain for instance. Understanding these underlying processes could lead to the development of interventions that could foster learning and adaptive performance for those higher in affect variability and help mitigate the detrimental effects of affect variability. This may be particularly relevant as there is currently no single intervention that has been found to be effective for managing personality traits that are viewed as maladaptive (Livesley, 2005). Research in this area is lacking (Bateman et al., 2015), but it is likely that individually tailored approaches that comprehensively target thoughts, emotions, and behaviors are the best solution (Livesley, 2005; Gibbon et al., 2020). One weakness that many individuals with maladaptive personality traits face is the use of ineffective emotion regulation strategies for handling negative affect (Daros & Williams, 2019).

Recent research has found that targeting or eliciting specific emotions, specifically positive deactivating emotions, while engaging with a complex task may help performance (Jorgensen, 2020). This is a preliminary line of research that should be pursued further.

A common limitation to studies of affect variability repeated here was that the measurement of emotions occurred concurrently with the measurement of the outcome variables. Predictive designs that measure affect variability prior to the measurement of outcomes (e.g., task performance) are needed to provide stronger evidence that affect variability scores reflect personality broadly rather than as situationally-specific predictors. Additionally, given the practical constraints to measuring affect variability via repeated measures, I believe future research should examine the extent to which one-time measures of emotion reactivity (e.g., Becerra et al., 2019) might be viable substitutes for capturing affect variability. Emotion reactivity is similar to affect variability in that it seeks to uncover the intensity with which an individual experiences emotion. It differs in that it also takes into consideration the individual's sensitivity to various stimuli and the duration or period of time it takes to return to baseline (Nock et al., 2008). Becerra et al. (2019) Perth Emotional Reactivity Scale (PERS) looks at these aspects of emotion reactivity (intensity, sensitivity, duration) while also accounting for the valence of the emotion (positive or negative). This measure may be a more feasible option to use as it may be taken just once and is less cognitively taxing. However, it may fail to uncover the nuances of emotional arousal or activation (activated or deactivated), which may be a weakness as the results of the present study showed the importance of disentangling activation and valence when examining flux.

Divergent from foundational research suggesting that affect spin is the central contributor to psychological well-being (Kuppens et al., 2007), the results of the current study highlight other indices of affect variability as meaningful contributors to behavioral outcomes, specifically performance in fast-paced, complex performance environments. It would be beneficial for future empirical research on affect variability to include all indices of affect variability in relation to behavioral outcomes to better understand how personality contributes to adjustment and psychological well-being.

Conclusion

In summary, the current study furthers our understanding of the non-cognitive aspects of adaptability by demonstrating that affect variability indices are related, yet meaningfully distinct aspects of personality that differentially predict off-task attention and performance. In this way, my results indicate that consistency in emotion is important for limiting off-task attention, spurring task enjoyment and learning, and enabling adapting to unexpected changes. Further, measurement approaches that account for the dynamic nature of personality not captured by traditional measures are crucial for understanding human performance, especially when the task setting is fast-paced and complex. In accordance with Richels et al. (2020), future research should involve different tasks and learning contexts to further examine the mechanisms by which affect variability indices together and distinctly explain variance in learning and performance outcomes. Pursuing this research may provide recommendations to mitigate the detrimental effects of higher affect variability on behavioral outcomes.

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Table 1

Coding scheme of change variables in discontinuous mixed-effects growth models.

Variable	**Pre-change period**							**Post-change period**						
Measurement occasion (Session)	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Skill acquisition (SA)	0	1	2	3	4	5	6	7	8	9	10	11	12	13
Transition adaptation (TA)	0	0	0	0	0	0	0	1	1	1	1	1	1	1
Reacquisition adaptation (RA)	0	0	0	0	0	0	0	0	1	2	3	4	5	6
Quadratic skill acquisition (SA^2)	0	1	4	9	16	25	36	36	36	36	36	36	36	36
Quadratic reacquisition adaptation (RA^2)	0	0	0	0	0	0	0	0	1	4	9	16	25	36

Table 2

Discontinuous growth model building of off-task attention as a function of affect variability.

Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Intercept	X	X	X	X	X
Skill acquisition (SA)	X	X	X	X	X
Transition adaptation (TA)	X	X	X	X	X
Reacquisition adaptation (RA)	X	X	X	X	X
Quadratic skill acquisition (SA^2)	X	X	X	X	X
Quadratic skill reacquisition (RA^2)	X	X	X	X	X
Gender		X	X	X	X
GMA		X	X	X	X
Video game experience (VGE)		X	X	X	X
Openness		X	X	X	X
Conscientiousness		X	X	X	X
Extraversion		X	X	X	X
Agreeableness		X	X	X	X
Emotional Stability		X	X	X	X
Spin/Pulse/Flux Index			X	X	X
SA × Spin/Pulse/Flux Index				X	X
TA × Spin/Pulse/Flux Index					X
RA × Spin/Pulse/Flux Index					X

Table 3

Discontinuous growth model building of performance as a function of affect variability.

Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Intercept	X	X	X	X	X	X
Skill acquisition (SA)	X	X	X	X	X	X
Transition adaptation (TA)	X	X	X	X	X	X
Reacquisition adaptation (RA)	X	X	X	X	X	X
Quadratic skill acquisition (SA^2)	X	X	X	X	X	X
Quadratic skill reacquisition (RA^2)	X	X	X	X	X	X
Gender		X	X	X	X	X
GMA		X	X	X	X	X
Video game experience (VGE)		X	X	X	X	X
Openness		X	X	X	X	X
Conscientiousness		X	X	X	X	X
Extraversion		X	X	X	X	X
Agreeableness		X	X	X	X	X
Emotional Stability		X	X	X	X	X
Spin/Pulse/Flux Index			X	X	X	X
Off-Task Attention (OTA)				X	X	X
Spin/Pulse/Flux Index × OTA					X	X
SA × Spin/Pulse/Flux Index					X	X
SA × OTA					X	X
TA × Spin/Pulse/Flux Index					X	X
TA × OTA					X	X
RA × Spin/Pulse/Flux Index					X	X
RA × OTA					X	X
SA × Spin/Pulse/Flux Index x OTA						X
TA × Spin/Pulse/Flux Index x OTA						X
RA × Spin/Pulse/Flux Index x OTA						X

Table 4

Means, Standard Deviations, and Correlations

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10
1.Gender	–	–										
2.ACT	26.91	4.25	−.21**									
3.Vid. game exp.	0.08	1.02	−.54**	.20**	(.68)							
4.Openness	6.39	0.89	−.02	.04	.12	(.83)						
5.Conscientiousness	6.29	0.89	.08	−.05	−.06	.37**	(.84)					
6.Extraversion	5.56	1.06	−.02	−.13*	−.08	.23**	.12*	(.87)				
7.Agreeableness	6.82	0.86	.05	−.17**	.03	.28**	.29**	.15*	(.88)			
8.Emotional stability	5.10	0.98	−.22**	.13*	.12*	−.07	.18**	.10	.25**	(.81)		
9.Spin	1.25	0.40	−.12	−.11	−.03	.06	.02	.11	−.11	−.05		
10.Pulse	2.22	0.97	.15*	−.15*	−.14*	.10	.12	.11	.07	−.05	.13*	
11.PA flux	1.28	0.62	−.10	−.03	.00	.14*	.11	.15*	.05	.02	.46**	.48**
12.PD flux	1.25	0.61	−.03	−.12*	.06	.17**	.14*	.16*	.04	.03	.38**	.46**
13.NA flux	1.08	0.62	.21**	−.19**	−.11	.12*	.13*	.18**	−.06	−.17**	.47**	.59**
14.ND flux	1.13	0.56	.12	−.16**	−.11	.13*	.04	.15*	−.01	−.12	.41**	.62**
15.Off-task attention	2.40	1.20	.33**	−.21**	−.22**	−.10	−.08	.11	−.12	−.15*	.07	.21**
16.Enjoyment	2.03	0.81	−.15*	.07	.09	−.06	.06	.04	.06	.07	−.06	−.19**
17.Performance	33.83	16.86	−.66**	.31**	.69**	.08	−.01	−.11	.01	.18**	−.07	−.18**

Variable	11	12	13	14	15	16
12.PD flux	.53**					
13.NA flux	.47**	.53**				
14.ND flux	.51**	.31**	.65**			
15.Off-task attention	.02	.10	.28**	.40**	(.90)[a]	
16. Enjoyment	−.04	.06	−.22**	−.35**	−.40**	(.90)
17.Performance	−.04	.00	−.28**	−.24**	−.47**	.23**

Note. Diagonal values are coefficient alpha reliabilities. Gender is a dichotomous variable: 0 = male, 1 = female. Video game experience was a standardized composite. Mean alpha across 14 sessions for off-task attention and performance. [a]Mean alpha across 14 sessions. *N* = 253. *p < .05, **p < .01, two-tailed

Table 5

Summary of Statistics Determining Independent Variable Contributions to Regression Effects

Variable	β	r_s	r_s^2	r	Pratt	Unique	Common	GenDom	RWI	RWI %
Off-Task Attention										
Spin	−0.101	0.154	0.024	0.072	−0.007	0.006	−0.001	0.006	0.007	3.18
Pulse	−0.086	0.452	0.205	0.212	−0.018	0.003	0.042	0.018	0.020	9.09
PA Flux	−0.265	0.047	0.002	0.022	−0.006	0.038	−0.037	0.024	0.021	9.54
PD Flux	0.101	0.216	0.046	0.101	0.010	0.006	0.005	0.005	0.006	2.72
NA Flux	0.101	0.589	0.347	0.276	0.028	0.004	0.072	0.034	0.038	17.27
ND Flux	0.534	0.851	0.725	0.399	0.213	0.117	0.042	0.133	0.128	58.18
Total	N/A	N/A	1.349	N/A	0.220	0.174	0.123	0.220	0.220	100
Enjoyment										
Spin	0.050	−0.131	0.017	−0.055	−0.003	0.001	0.002	0.003	0.005	2.84
Pulse	−0.017	−0.463	0.214	−0.194	0.003	0.000	0.038	0.017	0.021	11.93
PA Flux	0.109	−0.095	0.009	−0.040	−0.004	0.006	−0.005	0.008	0.009	5.11
PD Flux	0.185	0.153	0.023	0.064	0.012	0.019	−0.015	0.023	0.019	10.80
NA Flux	−0.128	−0.522	0.273	−0.219	0.028	0.007	0.041	0.026	0.030	17.05
ND Flux	−0.395	−0.844	0.713	−0.354	0.140	0.064	0.061	0.098	0.092	52.27
Total	N/A	N/A	1.249	N/A	0.176	0.097	0.122	0.175	0.176	100

Performance										
Spin	0.038	−0.188	0.035	−0.066	−0.002	0.001	0.004	0.003	0.004	3.22
Pulse	−0.039	−0.514	0.264	−0.181	0.007	0.001	0.032	0.013	0.016	12.90
PA Flux	0.091	−0.108	0.012	−0.038	−0.003	0.004	−0.003	0.006	0.005	4.03
PD Flux	0.169	−0.003	0.000	−0.001	0.000	0.016	−0.016	0.012	0.011	8.87
NA Flux	−0.338	−0.804	0.646	−0.283	0.096	0.048	0.033	0.062	0.059	47.58
ND Flux	−0.113	−0.685	0.469	−0.241	0.027	0.005	0.053	0.028	0.029	23.39
Total	N/A	N/A	1.426	N/A	0.125	0.075	0.103	0.124	0.124	100

Note. PA = positive activating. PD = positive deactivating. NA = negative activating. ND = negative deactivating. RWI = relative weight importance; percentage of the total variance explained in *y* by the given index. RWI% = percentage of the total variance explained in *y* by all the indices attributed to the given index.

Table 6

Paired Dominance Metrics

	Off-Task Attention			Enjoyment		
	Complete	Conditional	General	Complete	Conditional	General
Spin>Pulse	0.5	0.5	0.0	0.5	0.5	0.0
Spin>PA Flux	0.5	0.5	0.0	0.5	0.5	0.0
Spin>PD Flux	0.5	0.5	1.0	0.0	0.0	0.0
Spin>NA Flux	0.5	0.5	0.0	0.5	0.0	0.0
Spin>ND Flux	0.0	0.0	0.0	0.0	0.0	0.0
Pulse>PA Flux	0.5	0.5	0.0	0.5	0.5	1.0
Pulse>PD Flux	0.5	0.5	1.0	0.5	0.5	0.0
Pulse>NA Flux	0.5	0.0	0.0	0.5	0.0	0.0
Pulse>ND Flux	0.0	0.0	0.0	0.0	0.0	0.0
PA Flux>PD Flux	0.5	0.5	1.0	0.0	0.0	0.0
PA Flux>NA Flux	0.5	0.5	0.0	0.5	0.0	0.0
PA Flux>ND Flux	0.0	0.0	0.0	0.0	0.0	0.0
PD Flux>NA Flux	0.5	0.5	0.0	0.5	0.5	0.0
PD Flux>ND Flux	0.0	0.0	0.0	0.0	0.0	0.0
NA Flux>ND Flux	0.0	0.0	0.0	0.0	0.0	0.0

	Performance		
	Complete	Conditional	General
Spin>Pulse	0.5	0.5	0.0
Spin>PA Flux	0.5	0.5	0.0
Spin>PD Flux	0.5	0.5	0.0
Spin>NA Flux	0.0	0.0	0.0
Spin>ND Flux	0.0	0.0	0.0
Pulse>PA Flux	0.5	0.5	1.0
Pulse>PD Flux	0.5	0.5	1.0
Pulse>NA Flux	0.0	0.0	0.0
Pulse>ND Flux	0.0	0.0	0.0
PA Flux>PD Flux	0.5	0.5	0.0
PA Flux>NA Flux	0.0	0.0	0.0
PA Flux>ND Flux	0.5	0.0	0.0
PD Flux>NA Flux	0.0	0.0	0.0
PD Flux>ND Flux	0.5	0.5	0.0
NA Flux>ND Flux	1.0	1.0	1.0

Note. PA = positive activating. PD = positive deactivating. NA = negative activating. ND = negative deactivating. 1.0 = first listed variable is dominant, 0.0 = second listed variable is dominant, 0.5 = dominance cannot be determined.

Table 7

Average Contributed Variance of Predictor

	Off-Task Attention						Enjoyment					
Subset Size	Spin	Pulse	PA Flux	PD Flux	NA Flux	ND Flux	Spin	Pulse	PA Flux	PD Flux	NA Flux	ND Flux
1	0.0044	0.0281	0.0138	0.0042	0.0542	0.1436	0.0046	0.0294	0.0088	0.0127	0.0412	0.1210
2	0.0059	0.0166	0.0255	0.0027	0.0374	0.1327	0.0047	0.0202	0.0105	0.0330	0.0305	0.1089
3	0.0062	0.0091	0.0326	0.0026	0.0230	0.1244	0.0037	0.0113	0.0098	0.0321	0.0199	0.0932
4	0.0060	0.0024	0.0362	0.0036	0.0116	0.1190	0.0022	0.0042	0.0080	0.0262	0.0114	0.0774
5	0.0060	0.0030	0.0380	0.0060	0.0040	0.1170	0.0010	0.0000	0.0060	0.0190	0.0070	0.0640

Note. Values are averages across subsets. Increasing values for a given predictor as subset size increases reflects the predictor is acting as a suppressor.PA = positive activating. PD = positive deactivating. NA = negative activating. ND = negative deactivating.

	Performance					
Subset Size	Spin	Pulse	PA Flux	PD Flux	NA Flux	ND Flux
1	0.0034	0.0214	0.0054	0.0096	0.0718	0.0438
2	0.0035	0.0137	0.0077	0.0151	0.0641	0.0311
3	0.0027	0.0073	0.0080	0.0170	0.0571	0.0200
4	0.0016	0.0026	0.0066	0.0168	0.0510	0.0112
5	0.0010	0.0010	0.0040	0.0160	0.0480	0.0050

Note. Values are averages across subsets. Increasing values for a given predictor as subset size increases reflects the predictor is acting as a suppressor.PA = positive activating. PD = positive deactivating. NA = negative activating. ND = negative deactivating.

Table 8

Discontinuous growth models of off-task attention as a function of affect variability.

	Model 1		Model 2		Model 3		**Model 4**	
Variable	*B*	*SE*	*B*	*SE*	*B*	*SE*	***B***	***SE***
Intercept, γ_{00}	1.96**	0.06	1.78**	0.08	1.81**	0.08	**1.81****	**0.08**
Skill acquisition (SA), γ_{10}	0.07**	0.01	0.07**	0.01	0.07**	0.01	**0.07****	**0.01**
Gender, γ_{01}			0.54**	0.16	0.45**	0.15	**0.45****	**0.15**
ACT/SAT, γ_{02}			−0.04**	0.02	−0.03	0.01	**−0.03†**	**0.01**
Video game experience (VGE), γ_{03}			−0.08	0.07	−0.07	0.07	**−0.07**	**0.07**
Openness, γ_{04}			−0.09	0.08	−0.13	0.08	**−0.13†**	**0.08**
Conscientiousness, γ_{05}			−0.06	0.08	−0.04	0.07	**−0.04**	**0.07**
Extraversion, γ_{06}			0.11†	0.06	0.10	0.06	**0.10†**	**0.06**
Agreeableness, γ_{07}			−0.19*	0.08	−0.16	0.08	**−0.16**	**0.08**
Emotional Stability, γ_{08}			−0.06	0.07	−0.03	0.07	**−0.03**	**0.07**
ND Flux, γ_{09}					0.72**	0.12	**0.55**	**0.13**
PA Flux, γ_{010}					−1.33**	0.11	**−0.33****	**0.11**
SA × ND Flux, γ_{111}							**0.06****	**0.01**
AIC	8685.35		8680.62		8659.78		**8649.46**	

Note. Results of the best fitting model per the AIC are bolded. SA = skill acquisition. ND = negative deactivating. PA = positive activating. Across Models 3–4, effects for the growth terms and covariates were substantively unchanged from Model 2. *N* = 253. †*p* <0.10 **p* < .05, ***p* < .01, two-tailed.

Table 9

Discontinuous growth models of performance as a function of affect variability.

	Model 1		Model 2	
Variable	*B*	*SE*	*B*	*SE*
Intercept, γ_{00}	28.69**	1.11	32.88**	0.92
Skill acquisition (SA), γ_{10}	5.28**	0.37	5.26**	0.37
Transition adaptation (TA), γ_{20}	−18.45**	0.85	−18.05**	0.80
Reacquisition adaptation (RA), γ_{30}	−4.18**	0.52	−4.67**	0.39
Quadratic skill acquisition (SA^2), γ_{40}	−0.54**	0.06	−0.53**	0.06
Quadratic skill reacquisition (RA^2), γ_{50}	−0.08	0.06		
Gender, γ_{01}			−12.45**	1.59
ACT/SAT, γ_{02}			0.53**	0.15
Video game experience (VGE), γ_{03}			7.04**	0.73
Openness, γ_{04}			0.05	0.81
Conscientiousness, γ_{05}			0.69	0.78
Extraversion, γ_{06}			−0.99†	0.61
Agreeableness, γ_{07}			−0.48	0.80
Emotional stability, γ_{08}			0.50	0.70
AIC	26432.26		26210.77	

Note. $N = 253$. †p <0.10 *p < .05, **p < .01, two-tailed.

Table 10

Discontinuous growth models of performance as a function of NA flux.

	Model 3		Model 4		**Model 5**		Model 6	
Variable	*B*	*SE*	*B*	*SE*	***B***	***SE***	*B*	*SE*
NA Flux, $\gamma_{0\,09}$	−3.81**	1.24	−2.84*	1.19	**−3.42****	**1.38**	−3.54**	1.39
PD Flux, $\gamma_{0\,10}$	1.81	1.21	1.87†	1.15	**1.90†**	**1.15**	1.90†	1.15
Off-task attention, $\gamma_{0\,11}$			−2.88**	0.53	**−2.54****	**0.65**	−2.68**	0.65
NA Flux × OTA, $\gamma_{0\,12}$					**0.92**	**0.80**	2.13*	0.97
SA × NA Flux, $\gamma_{1\,11}$					**−0.33**	**0.21**	−0.30	0.21
SA × OTA, $\gamma_{1\,12}$					**−1.24***	**0.11**	−0.21*	0.11
TA × NA Flux, $\gamma_{2\,11}$					**3.01***	**1.32**	2.97*	1.32
TA × OTA, $\gamma_{2\,12}$					**1.20†**	**0.67**	1.16†	0.69
RA × NA Flux, $\gamma_{3\,11}$					**0.19**	**0.30**	0.16	0.30
RA × OTA, $\gamma_{3\,12}$					**−0.01**	**0.16**	−0.04	0.16
SA × NA Flux × OTA, $\gamma_{1\,13}$							−0.30†	0.16
TA × NA Flux × OTA, $\gamma_{2\,13}$							0.35	1.04
RA × NA Flux × OTA, $\gamma_{3\,13}$							0.27	0.24
AIC	26201.49		26176.38		**26173.53**		26176.11	

Note. Results of the best fitting model per the AIC are bolded. SA = skill acquisition. TA = transition adaptation. RA = reacquisition adaptation. NA = negative activating. PD = positive deactivating. OTA = off-task attention. PD flux acts as a suppressor. Across Models 3–6, effects for the growth terms and covariates were substantively unchanged from Model 2 in Table 9. $N = 253$. †p <0.10 *p < .05, **p < .01, two-tailed.

Table 11

Discontinuous growth models of performance as a function of PD flux.

	Model 3		**Model 4**		Model 5		Model 6	
Variable	*B*	*SE*	***B***	***SE***	*B*	*SE*	*B*	*SE*
PD Flux, $\gamma_{0\,09}$	−0.12	1.04	**0.46**	**0.99**	0.52	1.20	0.45	1.20
Off-task attention, $\gamma_{0\,10}$			**−3.08****	**0.53**	−2.66**	0.63	−2.70**	0.63
PD Flux × OTA, $\gamma_{0\,11}$					−0.21	0.81	0.77	0.99
SA × PD Flux, $\gamma_{1\,11}$					−0.08	0.20	−0.07	0.21
SA × OTA, $\gamma_{1\,12}$					−0.28**	0.10	−0.28*	0.10
TA × PD Flux, $\gamma_{2\,11}$					0.55	1.30	0.58	1.30
TA × OTA, $\gamma_{2\,12}$					1.61**	0.66	1.62*	0.66
RA × PD Flux, $\gamma_{3\,11}$					0.03	0.30	0.00	0.30
RA × OTA, $\gamma_{3\,12}$					0.01	0.15	0.00	0.15
SA × PD Flux × OTA, $\gamma_{1\,13}$							−0.15	0.17
TA × PD Flux × OTA, $\gamma_{2\,13}$							−0.48	1.09
RA × PD Flux × OTA, $\gamma_{3\,13}$							0.32	0.25
AIC	26210.83		**26182.16**		26185.56		26190.47	

Note. Results of the best fitting model per the AIC are bolded. SA = skill acquisition. TA = transition adaptation. RA = reacquisition adaptation. PD = positive deactivating. OTA = off-task attention. Across Models 3–6, effects for the growth terms and covariates were substantively unchanged from Model 2 in Table 9. $N = 253$. †p <0.10 *p < .05, **p < .01, two-tailed.

Table 12

Discontinuous growth models of performance as a function of ND flux.

	Model 3		Model 4		**Model 5**		Model 6	
Variable	*B*	*SE*	*B*	*SE*	***B***	***SE***	*B*	*SE*
ND Flux, $\gamma_{0\ 09}$	−2.68*	1.16	−0.65	1.19	**−0.55**	**1.44**	−0.66	1.44
PD Flux, $\gamma_{0\ 10}$	0.57	1.08	0.61	1.03	**0.83**	**1.04**	0.84	1.04
Off-task attention, $\gamma_{0\ 11}$			−2.96**	0.57	**−2.80****	**0.69**	−2.89**	0.69
ND Flux × OTA, $\gamma_{0\ 12}$					**1.16**	**0.81**	1.79†	0.97
SA × ND Flux, $\gamma_{1\ 11}$					**−0.29**	**0.24**	−0.26	0.24
SA × OTA, $\gamma_{1\ 12}$					**−0.23***	**0.11**	−0.21†	0.11
TA × ND Flux, $\gamma_{2\ 11}$					**1.68**	**1.51**	1.61	1.53
TA × OTA, $\gamma_{2\ 12}$					**1.31†**	**0.71**	1.26†	0.72
RA × ND Flux, $\gamma_{3\ 11}$					**−0.06**	**0.35**	−0.10	0.35
RA × OTA, $\gamma_{3\ 12}$					**0.03**	**0.16**	0.00	0.17
SA × ND Flux × OTA, $\gamma_{1\ 13}$							−0.20	0.16
TA × ND Flux × OTA, $\gamma_{2\ 13}$							0.43	1.03
RA × ND Flux × OTA, $\gamma_{3\ 13}$							0.23	0.24
AIC	26205.65		26181.68		**26178.45**		26185.10	

Note. Results of the best fitting model per the AIC are bolded. SA = skill acquisition. TA = transition adaptation. RA = reacquisition adaptation. ND = negative deactivating. PD = positive deactivating. OTA = off-task attention. PD flux acts as a suppressor. Across Models 3–6, effects for the growth terms and covariates were substantively unchanged from Model 2 in Table 9. N = 253. †p <0.10 *p < .05, **p < .01, two-tailed.

Table 13

Discontinuous growth models of performance as a function of PA flux.

	Model 3		**Model 4**		Model 5		Model 6	
Variable	*B*	*SE*	***B***	***SE***	*B*	*SE*	*B*	*SE*
PA Flux, $\gamma_{0\ 09}$	−2.39*	1.17	**−2.47***	**1.10**	−1.86	1.28	−1.88	1.28
PD Flux, $\gamma_{0\ 10}$	1.18	1.22	**1.80**	**1.15**	1.80	1.15	1.80	1.15
Off-task attention, $\gamma_{0\ 11}$			**−3.08****	**0.53**	−2.69**	0.63	−2.63**	0.63
PA Flux × OTA, $\gamma_{0\ 12}$					0.60	0.83	1.99*	1.00
SA × PA Flux, $\gamma_{1\ 11}$					−0.07	0.20	−0.07	0.20
SA × OTA, $\gamma_{1\ 12}$					−0.29**	0.10	−0.30**	0.10
TA × PA Flux, $\gamma_{2\ 11}$					−0.30	1.26	−0.30	1.25
TA × OTA, $\gamma_{2\ 12}$					1.63**	0.65	1.64**	0.65
RA × PA Flux, $\gamma_{3\ 11}$					0.00	0.29	0.00	0.29
RA × OTA, $\gamma_{3\ 12}$					0.02	0.15	0.03	0.15
SA × PA Flux × OTA, $\gamma_{1\ 13}$							−0.29†	0.17
TA × PA Flux × OTA, $\gamma_{2\ 13}$							−0.02	1.09
RA × PA Flux × OTA, $\gamma_{3\ 13}$							0.33	0.25
AIC	26206.53		**26177.17**		26179.23		26181.36	

Note. Results of the best fitting model per the AIC are bolded. SA = skill acquisition. TA = transition adaptation. RA = reacquisition adaptation. PA = positive activating. PD = positive deactivating. OTA = off-task attention. PD flux acts as a suppressor. Across Models 3–6, effects for the growth terms and covariates were substantively unchanged from Model 2 in Table 9. $N = 253$. †p <0.10 *p < .05, **p < .01, two-tailed.

Table 14

Discontinuous growth models of performance as a function of spin.

	Model 3		Model 4		Model 5		**Model 6**	
Variable	*B*	*SE*	*B*	*SE*	*B*	*SE*	***B***	***SE***
Spin, $\gamma_{0\,09}$	−4.10*	1.71	−3.74*	1.61	−3.24†	1.91	**−3.28†**	**1.91**
PD Flux, $\gamma_{0\,10}$	0.86	1.11	1.35	1.0	1.40	1.05	**1.40**	**1.05**
Off-task attention, $\gamma_{0\,11}$			−3.02**	0.53	−2.61**	0.63	**−2.49****	**0.63**
Spin × OTA, $\gamma_{0\,12}$					1.27	1.40	**3.10†**	**1.68**
SA × Spin, $\gamma_{1\,11}$					0.19	0.31	**0.18**	**0.31**
SA × OTA, $\gamma_{1\,12}$					−0.29**	0.10	**−0.28****	**0.10**
TA × Spin, $\gamma_{2\,11}$					−2.08	1.98	**−1.98**	**1.96**
TA × OTA, $\gamma_{2\,12}$					1.68**	0.65	**1.40***	**0.65**
RA × Spin, $\gamma_{3\,11}$					−0.09	0.45	**−0.09**	**0.46**
RA × OTA, $\gamma_{3\,12}$					0.02	0.15	**0.02**	**0.15**
SA × Spin × OTA, $\gamma_{1\,13}$							**0.23**	**0.28**
TA × Spin × OTA, $\gamma_{2\,13}$							**−4.49****	**1.77**
RA × Spin × OTA, $\gamma_{3\,13}$							**0.03**	**0.41**
AIC	26204.25		26176.05		26174.18		**26171.01**	

Note. Results of the best fitting model per the AIC are bolded. SA = skill acquisition. TA = transition adaptation. RA = reacquisition adaptation. PD = positive deactivating. OTA = off-task attention. PD flux acts as a suppressor. Across Models 3–6, effects for the growth terms and covariates were substantively unchanged from Model 2 in Table 9. $N = 253$. †p <0.10 *p < .05, **p < .01, two-tailed.

Table 15

Discontinuous growth models of performance as a function of pulse.

	Model 3		**Model 4**		Model 5		Model 6	
Variable	*B*	*SE*	***B***	***SE***	*B*	*SE*	*B*	*SE*
Pulse, $\gamma_{0\,09}$	−0.66	0.73	**−0.14**	**0.69**	−0.37	0.83	−0.50	0.84
PD Flux, $\gamma_{0\,10}$	0.36	1.17	**0.56**	**1.11**	0.67	1.11	0.66	1.11
Off-task attention, $\gamma_{0\,11}$			**−3.06****	**0.54**	−2.74**	0.65	−2.83**	0.65
Pulse × OTA, $\gamma_{0\,12}$					0.37	0.46	0.86	0.55
SA × Pulse, $\gamma_{1\,11}$					−0.20	0.13	−0.15	0.13
SA × OTA, $\gamma_{1\,12}$					−0.25*	0.10	−0.21*	0.11
TA × Pulse, $\gamma_{2\,11}$					1.54†	0.82	1.33	0.84
TA × OTA, $\gamma_{2\,12}$					1.37*	0.66	1.23†	0.67
RA × Pulse, $\gamma_{3\,11}$					0.22	0.19	0.17	0.19
RA × OTA, $\gamma_{3\,12}$					−0.02	0.15	−0.06	0.15
SA × Pulse × OTA, $\gamma_{1\,13}$							−0.21*	0.09
TA × Pulse × OTA, $\gamma_{2\,13}$							0.74	0.59
RA × Pulse × OTA, $\gamma_{3\,13}$							0.18	0.14
AIC	26210.81		**26183.00**		26186.16		26192.38	

Note. Results of the best fitting model per the AIC are bolded. SA = skill acquisition. TA = transition adaptation. RA = reacquisition adaptation. PD = positive deactivating. OTA = off-task attention. PD flux acts as a suppressor. Across Models 3–6, effects for the growth terms and covariates were substantively unchanged from Model 2 in Table 9. $N = 253$. †p <0.10 *p < .05, **p < .01, two-tailed.

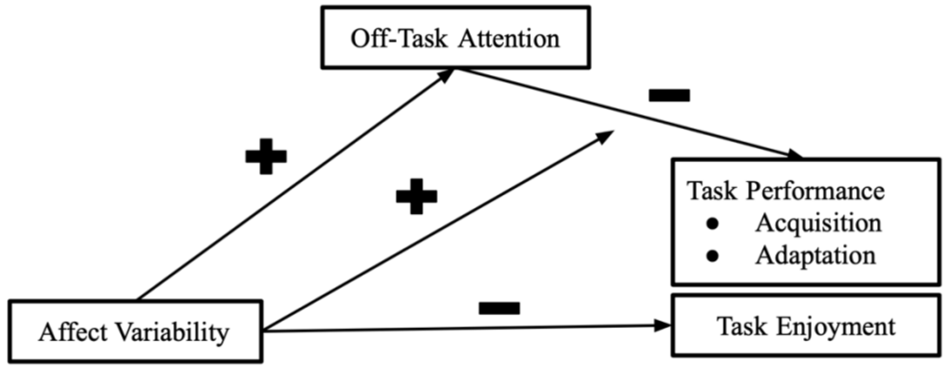

Figure 1. Proposed model of relationship between off-task attention, enjoyment, and task performance, moderated by affect variability.

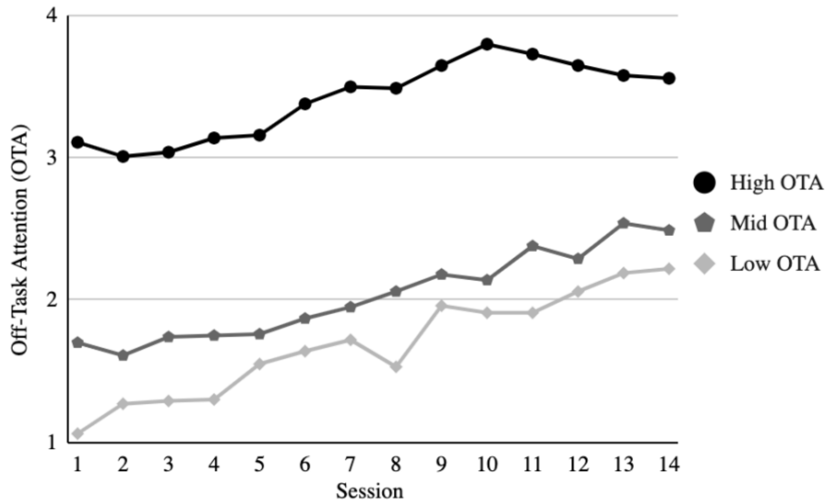

Figure 2. Off-task attention trends across sessions by Session 1 tertiles. Sessions 1-7 = pre-change. Sessions 8-14 = post-change. Off-task attention scores could range from 1.00 to 7.00.

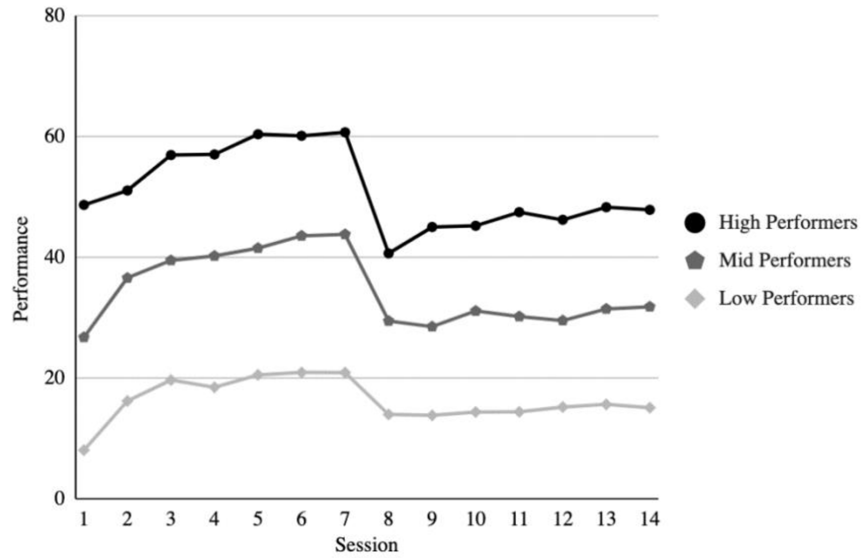

Figure 3. Performance trends across sessions by Session 1 tertiles. Sessions 1-7 = pre-change. Sessions 8-14 = post-change. Performance scores could range from 0.00 to 1.00.

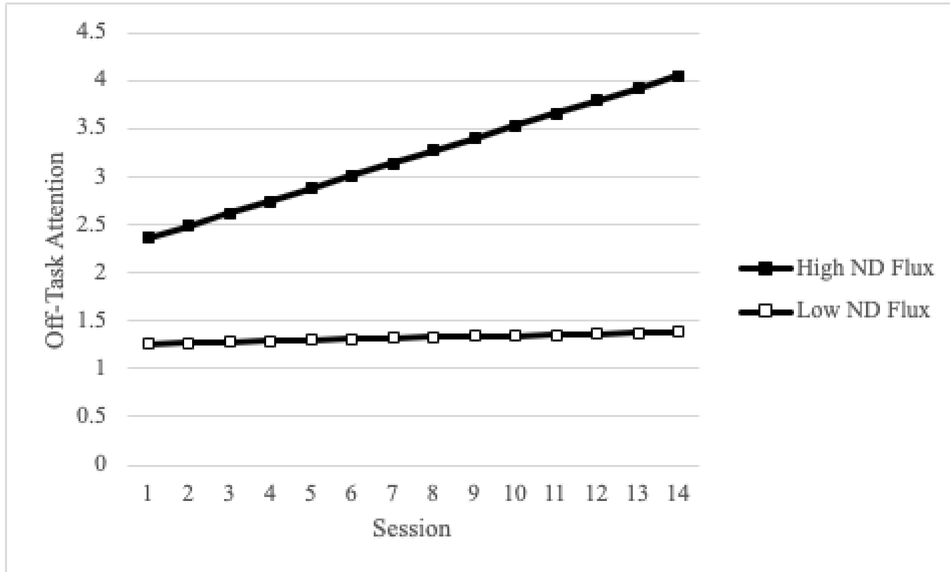

Figure 4. Effect of ND Flux on off-task attention across sessions. Values are predicted scores from model estimates. High/low affect pulse = ±1 standard deviation. Off-task attention scores could range from 1.00 to 7.00. ND = negative deactivating.

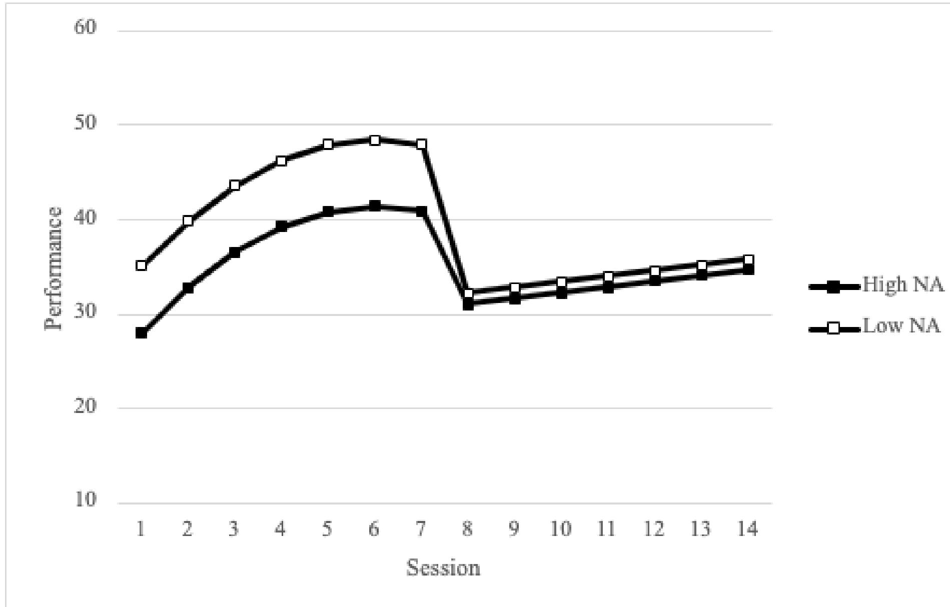

Figure 5. Effect of NA Flux on performance across sessions. Values are predicted scores from model estimates. High/low affect pulse = ±1 standard deviation. NA = negative activating.

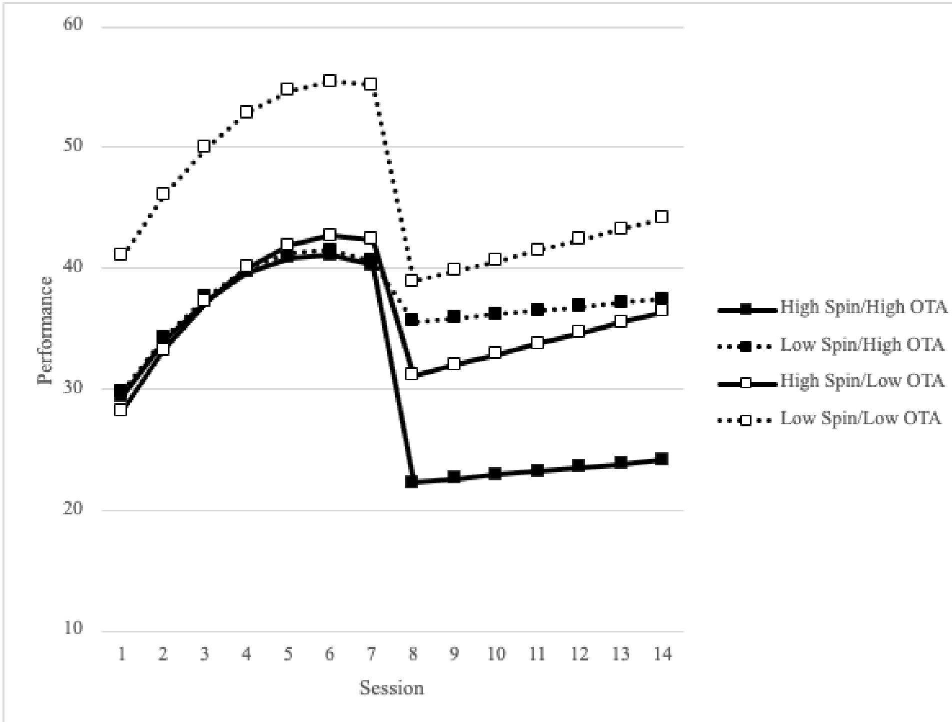

Figure 6. Effect of affect spin on performance across sessions. Values are predicted scores from model estimates. High/low affect pulse = ±1 standard deviation. OTA = off-task attention.