ADAPTING FOR SUCCESS:
THE MODERATING EFFECT OF GOAL ORIENTATIONS ON WITHIN-PERSON EFFICACY

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ABSTRACT

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Social Cognitive Theory holds that the effects of self-efficacy have nearly uniformly positive relationships with important outcomes, such as performance. However, Control Theorists have recently challenged this notion, arguing that the relationship between self-efficacy and performance may be negative under some circumstances. Vancouver and colleagues (Vancouver, Moore, & Yoder, 2008) developed a Discontinuous Model of self-efficacy, where, within-individuals, people generally do not engage in tasks at low levels of efficacy, begin to engage and put forth maximal effort at moderate levels, and continue to engage but decrease effort at high levels of efficacy. This is an adaptive behavioral pattern. Building on that model, the present study examines the potential moderating effect of Goal Orientations on how individuals choose to engage in tasks across levels of efficacy by experimentally manipulating goal orientation in 312 university students. It was found that no difference between the orientations existed on what level of efficacy they would begin to engage in the task, but that differences do exist for how they allocate their resources once engaged. Specifically, learning oriented individuals conserve the greatest amount of resources as efficacy increases, and performance avoid the fewest. This helps show a further mechanism by which learning orientation leads to more adaptive behavioral patterns. However, it was also found that avoid individuals adopted a theoretically less adaptive behavioral when they were meeting their goals as opposed to failing them. This suggests avoid individuals may be better labelled as differentially adaptive instead of maladaptive. However, more research is needed to confirm these findings.

This thesis is dedicated to my son, Ronald, who was born during its completion.

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Introduction

Adapt or perish, now as ever, is nature's inexorable imperative. – H.G. Wells

The essence of strategy is choosing what not to do. – Michael Porter

As we go through our lives we encounter ever changing environments to which we must adapt our behaviors to fit the demands of that environment. Failure to adapt our behaviors accordingly could have dire consequences, from social embarrassment, to failure on an important task, or even death. To succeed and avoid negative consequences, and obtain more positive ones, we are likely to behave strategically, choosing our behaviors to achieve our respective goals which may be different from anyone else in that environment. Sometimes this may involve opting not to engage in a task at all if we do not view it as worth our effort. As we interact with our environment, we learn more about how our behaviors allow us to reach our goals and then make behavioral changes better reach them. This paper draws on motivational theories, specifically self-regulation and goal orientations, to shed light on how individuals make strategic choices regarding how to behave and engage in tasks to reach disparate goals which are activated by how we view our environments, and how those behaviors change over time.

Self-regulation represents the dominant view of motivation in Organizational Psychology today (Vancouver & Day, 2005). The self-regulatory framework provides us with a powerful tool to understand how individuals pursue their goals, and personal and environmental factors that influence goal attainment. Through this framework we can understand how and when some individuals adapt their behavior in pursuit of their respective goals. However, much work remains to be done to clarify how the self-regulatory system, broadly conceived, operates.

Debates on the exact nature of self-regulation are on-going, based largely around the competing views of Social Cognitive Theory (Bandura, 1991) and Control Theory (e.g., Carver & Sheier, 1998). For example, Vancouver and his colleagues (Vancouver, Moore & Yoder, 2008; Vancouver, Gulleckson, Morse, & Warren, 2014; Vancouver, Thompson & Williams, 2001; Sun, Vancouver & Weinhardt, 2014) have argued that the standard view of efficacy as being positively related to outcomes such as performance (e.g. Stajkovic & Luthans, 1998) is not nuanced enough. This research has resulted in a discontinuous model of efficacy which describes how individuals engage in tasks the most at a moderate level of efficacy, and may not perform as well as expected when efficacy is high (Vancouver et al, 2008). Attempts to integrate these theories with other motivational constructs, such as expectancy, are also on-going. One key to better understanding the nature of self-regulation is to better understand how and where various personality traits fit into the hierarchical system of self-regulation.

Goal Orientations are one personality trait that has received some attention in the self-regulation literature. DeShon and Gillespie (2005) created a Motivated Action Theory of goal orientation where goal orientations exist in the hierarchical regulatory framework as a midlevel construct. As such, goal orientations affect lower, task-level regulatory systems and are affected by higher level systems more closely related to the core self-concept. However, little research examines how goal orientations impact those lower level systems and their behavioral outputs. Also, the research that does exist on goal-orientations in self-regulation generally focuses on between person differences (e.g. Kozlowski & Bell, 2006) rather than within person effects.

Of course, the regulatory process is much too large for one study to cover more than a small part of it. This study focuses on the regulatory role of self-efficacy, and the moderating effects of goal orientations on that role. One of the key disagreements between the Control and

Social Cognitive approaches to regulation lies in the nature of efficacy. While both views agree efficacy is important (Vancouver et al., 2008) there remains disagreement on its precise effects. The standard view in Social Cognitive Theory that efficacy has a monotonously increasing effect on performance, and this is generally the case when studied at the between person level (Stajkovic & Luthans, 1998). However, control theorists have found that efficacy can have a negative effect on performance at the within-person level (Vancouver et al., 2001). The reason for this finding appears to be that the amount of resources devoted to task performance varies by self-efficacy, such that individuals with higher self-efficacy are less likely to devote resources to a task they are confident they will succeed on relative to those who have less efficacy. Although individuals with very low efficacy may not devote any resources to the task, resulting in a discontinuous model of resource allocation by level of self-efficacy (Vancouver et al., 2008). This study looks to tease apart this relationship by examining how between person differences in goal orientations may affect the way efficacy leads to resource allocation within-individuals, partially answering a recent call from Sun et al. (2014) to study individual differences that may moderate this effect on resource allocation. Doing so allows us to better understand the operation of self-regulation as a whole system and how individuals adapt their self-regulatory behavior in an attempt to reach their respective goals.

This paper seeks to make several contributions to the literature on motivation. First and foremost, this study will further parse the within-person nature of self-efficacy (Vancouver et al., 2008) by examining a potential moderator of that relationship. Second, it further expands the research on the within-person nature of self-efficacy to look at how that relationship develops over time and in relation to other important self-regulatory constructs. This answers a call for more within-person studies with more time points to better understand the dynamic development of regulatory systems (Vancouver & Day, 2005). Third, by showing how goal orientations may affect the way self-efficacy leads to how individuals engage in their tasks, it builds on current goal orientation views of task engagement and further elucidates the mechanisms by which those orientations work. Relatedly, it further integrates goal orientations into the self-regulation framework, answering calls from several researchers to bring the two theories closer together, and works towards a more parsimonious theory of goal orientations and motivation (DeShon & Gillespie, 2005; Yeo, Loft, Xiao & Kiewitz, 2009; Kaplan & Maehr, 2007; Kozlowski & Bell, 2006). Fifth, this study adds to the relatively small literature that looks specifically at the development of motivational systems over time in relation to goal orientations. The need for more multi-time point studies to understand the consequences of goal orientations over time was highlighted by Payne, Youngcourt, and Beaubein (2007). Finally, this study looks to provide some guidance on parameters for use in future computational modeling of self-regulatory systems. This endeavor is highly important as self-regulation systems are complex and their dynamic nature is hard to study in a natural setting. The rise of computational modeling promises to advance our understanding of these dynamic systems, but lab studies are important for providing guidance to their development (Vancouver, Weinhardt, & Schmidt, 2010).

To accomplish these goals this paper will introduce the frameworks of self-regulation and goal orientations. Then, it will briefly introduce a control system model which will help guide the theorizing for the rest of the paper. Following this, an extensive development of the models and hypotheses being tested here. Once the models are established, the proposed research design will be covered in detail, along with the analytic frameworks to be used.

Literature Review

The Self-Regulatory Framework

Self-regulation represents the dominant view of motivation in Organizational Psychology today (Vancouver & Day, 2005). Through the process of self-regulation, individuals guide their actions towards goals over time and across changing circumstances (Karoly, 1993). The self-regulatory framework has provided a powerful tool from which to understand the nature of human behavior and has led to a vast body of research. However, Vancouver and Day (2005) point out that much research is confirmatory in nature and researchers do not show enough skepticism regarding the nature of self-regulatory constructs. To better parse our constructs and understand their nature we need to continue drawing on more powerful tools to study the dynamic and longitudinal behavior of regulatory systems. This paper seeks to do just that.

Hierarchical goal pursuit. Goals are internally represented desired states of being possessed by individuals (Lord, Diefendorff, Schmidt, & Hall, 2010). Research on goals has occurred since at least the mid-20^{th} century, and by 1968 Locke was able to state the foundation of what we now call Goal Theory. The tenants he described have held remarkably consistent over time. Individuals possess an internal set of goals towards which they strive through engaging in goal-oriented behaviors. Goals are an important source of motivation that help lead to positive behaviors (Locke, 1968, 1975). These goals exist in a hierarchy, such that individuals possess both short- and long-term goals. Short-term goals are nested under longer term goals, often acting as intermediate goals towards achievement of long-term goals. Lord et al. (2010) described a simple structure of four levels of goal pursuit labeled as micro (including working memory and muscle actions), low (very short-term and very immediate goals; seen as small tasks on the way to larger goals), intermediate (short-term, where most research occurs), and high (long-term, closely associated with the sense of self). As lower level goals are completed, individuals move closer to accomplishing their higher-level goals. The hierarchical goal system is pervasive in our literature, including in self-regulation (ex. Carver & Sheier, 1998). For each goal, at each level in the hierarchy, a self-regulatory system seeks to attain and maintain our desired goal states (Vancouver & Day, 2005).

Negative feedback systems and goal monitoring. Carver and Sheier (1998) wrote that "behavior is a continual process of moving toward, and away from, various kinds of mental goal representations, and…this movement occurs by a process of feedback control" (pp. 2). The basic unit of self-regulatory control is the negative feedback loop, which seeks to minimize any discrepancies between a person's goal and their perceived reality (Vancouver & Day, 2005). Occasionally, positive feedback loops occur to control behavior when an individual is seeking to avoid some state of being, but they are less prevalent (Carver & Sheier, 1998). Two major theories have been put forth that seek to describe these regulatory systems, Control Theory (Powers, 1973; Carver & Sheier, 1998), and Social Cognitive Theory (Bandura, 1991; Schunk & Usher, 2012).

Social Cognitive Theory. Albert Bandura's theory of self-regulation followed from his work on human learning, which resulted in his Social Learning Theory (Bandura, 1977b). Over the course of the 1980s, Bandura developed his Social Cognitive Theory (SCT) to explain a broader swath of human behavior. This was a descriptive theory where motivation is based on goals and monitoring one's progress towards them. Goals in SCT can be personal standards, social referents, or levels of past performance. These goals can be either upwards, trying to be like something or someone, or downwards, trying to avoid being like something or someone. Goal attainment and the behavior associated with it is regulated by an ongoing exercise of self-influence where individuals monitor their progress towards their goal and adjust their behavior accordingly. This monitoring occurs through the functions of self-diagnosis (which notices recurrent patterns of behavior and thoughts and information about when they occur in an attempt to modify them), self-motivation (the setting of personal goals which lead to improvement), and judgement (the analysis of activity compared to one's personal standards). Goals in SCT are hierarchical, with the attainment of lower level goals leading to the completion of higher ones. One key to SCT lies in the power of human agency. Humans in SCT are not only acted upon by their environments, but can act upon those environments. They can also engage in forethought to continuously raise the levels of their goals before they ever obtain the original goal. Through this process they stay motivated and maintain effort to reach the now higher-set goal (Bandura, 1977b, 1989, 1991; Bandura & Cervone, 1983). The importance of forethought and human agency in SCT stands in stark contrast to a literal interpretation of SCT's main competitor.

Control Theory. Control Theory (CT) has roots which predate SCT, with the first full model being articulated as early as 1973 by Powers. Powers' (1973) model built on cybernetics, which was developed for use in regulating machines and computers, the basis of such systems being a negative feedback loop. His model consists of nine levels of regulation where individuals hold goals at each level, monitor the discrepancy between goals and the perceived state of the system, and enact some change in order to bring their perception back in line with their goals. These systems are hierarchically nested as in Goal Theory, with the higher-level systems dictating the goals of the lower level systems and systems ranging from minute muscle movements all the way to societal level goals. Since that original work, several control theorists have expanded on our understanding of control systems, some building explicitly from Goal Theory (Campion & Lord, 1982).

Lord and Hanges (1987) articulated a model which they say is universal to all control systems, regardless of their sophistication. To them, all control systems have 1) some standard (goal) which the system seeks to maintain, 2) a sensor which monitors the state of the environment, 3) a comparator which compares the standard to the sensed environment, 4) a decision mechanism to decide whether something should be done to reduce any perceived discrepancy, and 5) an effector mechanism which produces some behavior meant to reduce the perceived discrepancy. As described by Campion and Lord (1982), these systems can lower discrepancies in multiple ways. Specifically, the control system can either change an output behavior meant to affect the perceived environment, or change the set-point of the goal. Some theorists contend that the goal is more easily adjusted, and that behavior is generally only changed when the environment or other factors do not allow the goal to be changed (Lord & Hanges, 1987).

Control Theory has been advanced in more recent years to cover a wider range of topics. Carver and Sheier (1998) presented a theory based in the same discrepancy reducing systems as other theorists, but expanded their thinking to include feelings, personality, and growth over time. Like Bandura, standards in Carver and Sheier's work can be social comparisons, group norms, instructions, or even attitudes. While not emphasizing human agency and forethought, goals can increase over time given continued success of the system, maintaining motivation for the individual. This is a point overlooked by Bandura in his arguments against CT (Bandura, 2012; Vancouver, 2012).[1]

As you can see, Social Cognitive Theory and Control Theory have much in common. They operate similarly, and Control Theorists have seen the similarities since at least the 1980s when Lord and Hanges (1987) pointed out their theory's similarities to Social Learning Theory.

In fact, SCT and CT make different predictions only under very specific circumstances (Vancouver et al., 2014). Both forms of self-regulation are useful, however, in this paper, CT will act as a guiding framework. This is not an indictment of SCT, but CT provides for a stronger framework within which to test regulatory mechanisms. The strength of this approach lies in the greater reliance of CT on more formal forms of logic than the SCT approach, which is based in a more informal, linguistic approach. The linguistic approach relies on description and is good for explanation of regulation, but suffers when attempting to make formal predictions of behavior which may be better described by laws that are more easily defined in a more computational, formal approach to research (Vancouver, 2012; see also Adner, Polos, Ryall & Sorenson, 2009).

Self-Efficacy. Self-efficacy, the belief of an individual in their ability to execute desired behaviors in the pursuit of some outcome (Bandura, 1977a), represents one of the key constructs in self-regulation. Bandura developed the concept of self-efficacy and considers it to be the primary mechanism of human agency (Bandura, 1977a, 1989, 1991; Bandura & Cervone, 1987). Agency here occurs when people choose tasks in which they will engage (Bandura & Cervone, 1987), and which environments they will enter (Bandura, 1989). Control theorists do not, generally, dispute the importance of efficacy (Vancouver, 2012), but they have begun to contest its nature. This dispute is of central importance for the present work.

Disagreement over the nature of self-efficacy. Most of the research on self-efficacy in the last forty years has followed the same narrative described by Bandura. In his earlier writings, Bandura (1977, 1989, 1991) describes efficacy as having a nearly uniformly positive effect on performance, except under some specific circumstances. Efficacy, through its influence on the tasks we engage in and environments we choose, has a generally positive effect on performance at the between-person level of analysis. Stajkovic and Luthens (1998) demonstrate this in their meta-analysis, showing a .38 relationship between efficacy and performance. Some within-person theorizing also considers the relationship between efficacy and performance to be positive. Lindsley, Brass and Thomas (1995) described a theory of efficacy-performance spirals where individuals could fall into deviation-amplifying loops such that good performance would lead to increased feelings of efficacy, which leads to increases in performance, which lead to further increases in efficacy, and so on. The same could occur in a negative direction. These loops could continue until the individual reached a point where they could not possibly succeed in the case of an upward spiral, or they withdraw as a defense mechanism in the case of a downward spiral. However, support for this within-person effect is limited, with support for negative spirals coming from Bandura's (1977) work on pathologies where anxiety and low efficacy created a negative framework from which individuals interpreted new efficacy information, leading individuals to perpetuate appraisals of inefficacy; or other studies which were only able to replicate some aspects of the spiral relationship (e.g., Shea & Howell, 2000).

However, following his own advice, Vancouver has been skeptical about the standard view of self-efficacy. Vancouver and his colleagues have called the standard view of efficacy into question, arguing that the relationship is not so simple as to be uniformly positive. Rather, the relationship between efficacy and performance is not positive under some conditions (Vancouver et al., 2014), or at the within-person level of analysis. This line of work began with a study where Vancouver, Thompson, and Williams (2001) drew on both CT and SCT to make specific predictions about task performance under varying conditions, and found that complacency by the participant could lead to negative effects on performance.

This initial finding grew into a discontinuous model for self-efficacy. Vancouver, Moore, and Yoder (2008) proposed this model using a task in which efficacy was manipulated at the within-person level by changing the size of a box that participants needed to click on as it jumped randomly around a computer screen. Following some practice, participants were given three minutes of time in which to click on as many boxes as they could. The participants chose how many seconds they would like to attempt each box size for (up to 10 seconds). The researchers found that the probability of participants allocating any time to a box was a function of the box size, such that they were more likely to allocate time for larger boxes than smaller boxes. This finding fit with the standard view of efficacy because larger boxes, being easier to click on, represent higher levels of efficacy, and the participants were choosing to engage in those easier tasks. However, the researchers also found that the number of seconds allocated to the task were negatively related to the size of the box, meaning the individuals were trying for fewer seconds on easier tasks. This finding supports a model of efficacy where individuals tend not to engage in tasks until they are relatively sure of success, at which point they put all their resources into succeeding. Above this point of efficacy, individuals begin to withdraw their resources instead of continuing to commit them. More recently, Sun, Vancouver, and Weinhardt (2014) have demonstrated that this model is moderated by the value attached to the task, such that the discontinuity at which individuals begin to engage in tasks shifts to lower levels of efficacy for higher value tasks.

This research has sparked a heated academic debate between Bandura and Vancouver. In response to Vancouver's findings, Bandura has come to the defense of SCT and has taken a harder line on the stance that efficacy has uniformly positive effects on performance (Bandura, 2012). This despite the new model of efficacy aligning with Bandura's previous discussions of complacency playing a role in that relationship. Vancouver (2012) has pointed these inconsistencies out, and asserts that it is not his goal to dismantle SCT, but rather lend more detailed support for the actual mechanisms which underlie the operation of self-regulatory systems. This paper takes the same stance in trying to further understand the nature of our important self-regulatory constructs. In doing so, it looks to build on the discontinuous model of efficacy described above by studying a possible new moderation of the model, and expanding our understanding of how regulatory systems develop over time.

Goal Orientations

To extend previous research, this study draws on the concept of goal orientations, which have the advantage of already being discussed in some regulation literature (DeShon & Gillespie, 2005; Kozlowski & Bell, 2006). Goal orientations represent a major, if not the major, perspective on the study of achievement motivation (Kaplan & Maehr, 2007). Work on goal orientations largely comes from educational psychology and dates back to at least Dweck's (1986) studies of adaptive and maladaptive learning patterns in students. In her attempt to build a model of motivation for educational settings, she found that the goals children pursued impacted their reactions to failure and influenced the quality of their performance. She broke the children's goals into two categories, learning goals and performance goals, which provide the purpose for engaging in a task, as well as provide the framework for how an individual interprets and experiences the environment. In learning goals, individuals seek to increase competence, gain understanding, or learn something new. In performance goals, individuals seek to gain favorable judgement, or to avoid negative judgement of their competence. Learning goals tend to be associated with more adaptive patterns of behavior, which "promote the establishment, maintenance, and attainment of personally challenging and personally valued achievement goals" (Dweck, 1986, pp. 1040). Performance goals are more associated with maladaptive patterns of behavior, which "are associated with a failure to establish reasonable, valued goals, to maintain effective striving toward those goals, or, ultimately, to attain valued goals that are potentially within one's reach" (Dweck, 1986, pp. 1040; see also, Eison, Pollio & Milton, 1986).

Then, in the 1990s, researchers argued for splitting performance goals into two separate constructs of approach and avoidance, creating a trichotomous view of goal orientations. Elliot and his colleagues (Elliot & Church, 1997; Elliot & Harackiewicz, 1996; Elliot, 1999) viewed achievement motivations as having oppositely valanced sides, a view that arose partially from a historical distinction between a desire for success and a desire to avoid failure, the study of which dates to at least the 1930s and hedonistic thought, and is relevant to other motivational theories such as Vroom's (1964) Valence, Instrumentality, Expectancy (VIE) Theory. Elliot (1999) provided an overview of the arguments for including the approach-avoidance dichotomy in the performance-learning framework, for example that only avoidance goals undermine intrinsic motivation, while approach goals do not (Elliot & Harackiewicz, 1996). Relatedly, other research has shown learning orientation to mediate the relationship between intrinsic motivation and performance (Cerasoli & Ford, 2014). Within performance orientation the inconsistent findings regarding the relationship between performance orientation and performance criteria suggested that something more was occurring within the construct. Upon reviewing the evidence, Elliot proposed a trichotomous framework composed of mastery (similar to learning goals and the terms are interchangeable, learning will be used most often in this paper) goals (where individuals are focused on gaining task or self-referential competence), performance approach (focus on gaining normative competence), and performance avoidance (focus on avoiding normative incompetence).

VandeWalle (1997) proposed a similar framework and developed a measure of goal orientation for the work place. His dimensions included learning ("a desire to develop the self by acquiring new skills, mastering new situations, and improving one's competence"), performance prove (approach; "the desire to prove one's competence and to gain favorable judgements about it"), and performance avoid ("the desire to avoid the disproving of one's competence and to avoid negative judgements about it"), orientations. One can easily see how the approach and avoid orientations match well with the self-regulatory framework in that individuals are either attempting to obtain some desired state, or avoid some undesired one (Carver & Sheier, 1998). SCT has a similar trichotomy where emotions can have approach (get more of something), avoid (get away from something), or attack (lower the value of something) orientations. Goal orientation researchers have also grounded orientations in self-regulation (Elliot & Harackiewicz, 1996). Thus, the trichotomous view of goal orientations will be adopted here.

In a review of the goal orientation literature, Kaplan and Maehr (2007) described much of the work on orientations as fitting of view of orientations as schemas for achievement situations. Schemas are patterns of thought or behavior that organize categories of information and the relationships among them (DiMaggio, 1997), which are then used to make sense of the world. Kaplan and Maehr (2007) discuss how situations can activate goal orientations as schemas that are associated with them, which in turn activate related scripts of behavior. Thus, it is expected that individuals will act in a way concordant with a schema intentionally activated through manipulation of a task environment they engage in and in turn influence their behaviors.

But can we view goal orientations as part of the regulatory system? Existing theory and research contends that we can. Going back to Powers (1973), and further articulated by more recent control theorists (Carver & Sheier, 1998), personality traits can be included in the regulatory system. In Powers' (1973) theory, personality can be analogous to the top-level systems of principles which guide all the lower order programs. Similarly, Carver and Sheier

(1998) include personality, but it exists across multiple levels, with more concrete and important types of personality existing further up in the hierarchy and closer to the concept of self. Other regulation theory has conceptualized goal orientations as a mid-level personality construct. DeShon and Gillespie (2005) placed goal orientations on a regulatory level immediately above task level, where each of the three types of orientations affect each of a set of possible task level goals, creating an interconnected goal network. Additionally, Dweck's (1986) work itself implies a hierarchy. Children in her studies would attempt to show competence in a new way if they were thwarted in their original attempts. This behavior is similar to what would be expected by hierarchical goal systems where an intermediate goal is to show competence and some lower level tasks are aimed at completing that goal. If one of these tasks fails, another task can be enacted instead to allow the intermediate goal of competence to be completed (Carver & Sheier, 1998). More recently, Elliot (2006) discussed goal orientations as being hierarchical, with goals from self-regulation as its conceptual centerpiece which individuals either try to attain (approach) or avoid. This position is also supported by research showing that goal orientations impact performance through their effect on goals (Elliot & Church, 1997), suggesting that goal orientations exist at a higher level in the regulatory hierarchy than the task level.

One important point to note here is the ability to view goal orientations as either states or traits. DeShon and Gillespie (2005) discussed how the literature on goal orientations variously views goal orientations as traits, quasi-traits, or states. Trait goal orientation describes an individual's preference for "consistent pattern of responses in achievement situations based on the individual's standing on goal orientation dimensions" (p. 468, Cellar et al, 2011). In this view, goal orientations are stable individual difference characteristics. On the other hand, state goal orientation is more specific to the task and context (Payne, Youngcourt & Beaubein, 2007), and is domain specific (VandeWalle, Cron & Slocum, 2001). In this view, goal orientations are more transient and heavily dependent on the context the individual finds themselves in. This view also fits with the schema-script paradigm discussed above (Kaplan & Maehr, 2007). This paper takes an integrative view of the state-trait dichotomy like that of Button, Mathieu and Zajac (1996) where individuals do have a personal preference for which goal orientation they will follow when able, or will default to when contextual cues for how to approach a situation are unavailable. However, they are still heavily influenced by situational characteristics and will tend to adopt the relevant orientation for a given situation. That approach also fits with DeShon and Gillespie's (2005) view of goal orientations where all individuals hold all three orientations, and while they may prefer one, any of them may be activated in connection with a task-level goal.

Goal orientations have received much attention in recent years. The work in educational psychology continues to look at the relationships between goal orientations and learning strategies (e.g. Diseth, 2011). However, most of the work on the subject is accomplished at the between person level of analysis. Those studies have shed light on some of the underlying mechanisms that show how orientations operate and how they impact performance, such as reactions to failure (ex. Dweck, 1986), behavior (Eison, Pollio, & Milton, 1986), and levels of efficacy (Wolters, Yu & Pintrich, 1996). Following Deshon and Gillespie's (2005) call for more research on systems over time, some studies have looked at multiple time points and focus on system development appears to be growing. However, even the longitudinal examples tend to be over short time periods such as three (Yeo, Loft, Xiao, & Kiewitz, 2009) time points, although some longer studies exist (e.g. Kozlowski & Bell, 2006). The research on goal orientations will be discussed more in depth below, but one goal of this paper is to build upon this research and further integrate goal orientations into the self-regulatory framework and expand our knowledge of how they affect the development of regulatory systems over time.

Model Development and Hypotheses

Having provided the broad framework in which this study seeks to be located, we now turn to an explication of the theoretical model and hypotheses to be tested here. These seek to advance our science in several ways. First, it seeks to further parse the nature of self-efficacy and its functioning in the regulatory system through testing a possible moderator of efficacy's within-person nature. Second, answering the call for more within-person studies with more time points (Vancouver & Day, 2005), this study extends our knowledge of within-person efficacy by studying its development over time. Third, expanding on the goal orientation literature it hopes to show another potential mechanism for how goal orientations affect behavior. Fourth, answer a similar call for more longitudinal studies in goal orientations (Payne, Youngcourt & Beaubein, 2007), this study examines the effects of goal orientations on the development of the regulatory system over time. Fifth, we look to further integrate two of our well-established motivational theories, represented by goal orientations and self-regulation.

Replication of Within-Person Model of Self-Efficacy

Prior to testing any new theories about the nature of self-efficacy and regulation, we must first replicate the basic effect found by Vancouver et al (2008), and moderated by Sun et al (2014). Their findings can be explained with a few well-established theoretical positions. First, it has long been established that people who are higher in efficacy for a task are more likely to engage in that task (Bandura & Cervone, 1983). Reciprocally, people who do not think they can succeed are unlikely to engage in that task (Bandura, 1989). Neglecting to engage in tasks where success appears unlikely is also discussed by Vroom (1964) in his VIE theory, where people decide what actions to take based on a combination of its likelihood for success and how well that action will advance them towards their end-goals. If individuals do not see the action as being likely to result in successful completion of their goals, they are unlikely to waste their energy in trying to succeed. Thus, it is predicted that:

Prerequisite 1: There will be a positive relationship between within-person efficacy and task engagement.

The tendency described by Vroom (1964) of individuals to make decisions based on instrumentality extends to their decisions on how much effort to put forth on a task once they have decided to engage. Vroom theorized that individuals would also not waste their resources by allocating them to situations in which they were sure of success. This tendency also aligns with Bandura's discussions of efficacy that describe complacent actions taken by participants. For example, in his book on self-efficacy, Bandura describes high-efficacy athletes as failing to see the benefit in engaging in tedious preparation when they are already sure of their success (Bandura, 1997). Vancouver and colleagues (Vancouver, 2012; Vancouver et al, 2008) assert that this is an adaptive behavioral pattern that leads to a conservation of resources that can then be applied to other tasks. In line with this, it is predicted that:

Prerequisite 2: There will be a negative relationship between the amount of resources allocated to a task and within-person self-efficacy.

The combination of these findings would align with other theorists who predicted a disjunction in effort applied to tasks as a function of expectancy, such that effort will not be applied when ability on a task is high because it is not needed, nor when success would require more effort than one is able to give (Kukla, 1972; Carver & Sheier, 1998). Assuming that efficacy is a form of expectancy, we should be able to replicate the model proposed by Vancouver et al (2008).

Moderation of the Discontinuous Model of Self-Efficacy

The main point of this paper is to test how the basic discontinuous model of self-efficacy may be moderated by goal orientations. It has already been established above that goal orientations can be placed in the hierarchical framework of self-regulation. The existence of goal orientations in the regulatory system suggests that orientations will affect the way individuals respond to goals and the environment around them. Thirty years of research on goal orientations have established behaviors that each orientation tend to display. When combining these tendencies with the operation of self-regulatory systems we can make some specific predictions about how the discontinuous model of self-efficacy will be moderated.

Many of the basic behavioral patterns attached with each goal orientation can be traced to the original work of Dweck. Dweck (1986) found that behavioral patterns varied between learning and performance oriented students such that learning oriented students were more likely to engage in adaptive behavioral patterns, and performance oriented students were more likely to engage in maladaptive behavior patterns. Key here is that learning oriented individuals are more likely to seek out challenges while performance individuals are more likely to avoid challenge. Part of the reason learning oriented individuals choose harder tasks lies in their tendency to choose tasks which will foster growth. Choosing to engage in slightly harder tasks than one can complete aligns with the well-established scaffolding technique used in education where learning is enhanced by placing students in situations that are slightly more challenging than they could handle on their own (van de Pole, Volman, & Beishuizen, 2010). In addition, Dweck (1986) wrote that individuals who perceive themselves to be lower on ability tend to only engage in very easy tasks. Payne, Youngcourt and Beaubein’s (2007) meta-analysis showed that mastery orientation is associated with higher levels of efficacy, and performance avoid with lower. We would expect individuals with lower efficacy to be less willing to engage in a task (Bandura & Cervone, 1987), and that is exactly what Dweck (1986) found in that performance oriented students needed to be surer of success before they would engage.

Other researchers have expanded on Dweck's work showing how performance and learning individuals engage in tasks. The reason individuals engage in a task depends on their achievement goals, which in turn depend on their goal orientation (Elliot, 1999). Learning oriented individuals are attempting to achieve competence in terms of the task itself, or for themselves, while performance oriented individuals are focused on achieving competence in reference to other individuals or standards. As such, learning individuals tend to be more absorbed in the task in question. One recent example of research that fits this view is that by Barry and Finney (2016) which showed that learning individuals put forth more effort on tasks, at least in low-stakes settings. In the trichotomous view of goal orientations, both learning and performance approach orientations are positively associated with task engagement, while performance avoid is negatively associated with engagement (Elliot & Harackiewicz, 1996). This tendency shows that performance avoidance orientation undermines intrinsic motivation, while learning enhances it (Elliot & Church, 1997). Learning oriented individual's greater intrinsic motivation also manifests in their greater desire to work hard (VandeWalle, 1997). These tendencies can be seen in results such as learning individuals showing greater engagement on college campuses (Ferrari, McCarthy, & Milner, 2009), and being more intense in their job-seeking behaviors than their performance oriented counterparts, even when those behaviors do not necessarily lead to greater personal outcomes (Creed, King, Hood, & McKenzie, 2009).

The demonstrated task focus for each goal orientation has other implications as well. The focus of learning individuals on gaining task or self-referential competence leads them to more often engage in a way such that they expend effort aimed at gaining future mastery on that task (VandeWalle, 1997). As such, these individuals exhibit more exploratory behaviors (Davis, Mero & Goodman, 2007), like engaging in harder tasks than they are completely confident they can succeed in. In addition, the differences between learning and performance individuals can be seen as a difference between individuals who are more task focused and ego focused, respectively. Task focused individuals are more likely to keep their resources focused on the task, while ego focused individuals are more likely to devote more resources to self-attention than to performing well (Kluger & DeNisi, 1996). This aligns with Dweck's (1986) discussion of how some individuals only engage in tasks they are completely sure of success, or where the blame for their failure can be displaced to another source in an act of self-preservation. These individuals are more likely to be performance oriented. These relationships are generally more pronounced for performance avoid individuals in that they tend to withdraw the most from tasks and allow themselves room for enacting cognitive defense mechanisms (Yamawaki, Tschanz, & Feick, 2004), which are driven by their fear of failure (Elliot, 1999).

From a self-regulation perspective, we can see how individuals with different goal orientations should differentially engage in tasks. In CT (Powers, 1973; Lord & Hanges, 1987; Carver & Sheier, 1998; Vancouver, 2006) individuals decide what actions to take based on the perceived difference between their goals and their current states. When an individual is further away from their goal they will tend to put forth more effort to close the perceived gap than if they were succeeding in their goal, or were relatively close to it. The exception to this occurs when individuals are so far from their goal they see the goal as being unattainable, in which case the individual is more likely to disengage from the goal entirely. We know that learning oriented individuals have the longest view of their goals as they are focused on gaining skills over time, while performance oriented individuals are more focused on immediate demonstration of their abilities. Within performance orientation, performance avoid individuals are utilizing a weak form of motivation, and are most likely to withdraw from any task (Elliot, 1999). When engaging in self-regulation, the learning oriented individuals should perceive a comparatively large difference between their current states and long-term goals because those goals are far away, while maintaining the confidence that they can eventually reach those goals. On the other hand, performance approach individuals may see a gap between their goal and their current state, but that goal should appear closer because it is more immediate. This should result in learning individuals expending more effort to close the perceived gap. Additionally, performance avoid individuals are exposed to two forces which could keep them from engaging in the task. First, their relatively weak motivation and short-term focus should lead to only a small perceived gap between their state and their goal and are likely to not expend needless effort to cover that short distance. Second, they are more likely to see a hard task as creating a gap so large in their regulatory system that it is pointless to engage at all, and will therefore withdraw from those tasks specifically. The combination of these should result in individuals who are unlikely to engage very much in easy tasks because they do not think they need to, or in hard tasks because doing so would be pointless.

Carver and Sheier (1998) also discuss how individuals engage in tasks based on their perceived ability. They show a discontinuous model of their own where individuals tend to engage in tasks up to a point and then suddenly disengage when they are no longer sure of success. Their view is based in system dynamics where a system tends to hold its current form until that form is no longer tenable, then a sudden shift can occur to a new form. Graphed in two dimensions, this results in a model that resembles an overhanging cliff such that being on top of the cliff and moving towards that cliff you pass over an open space below before finally falling off the cliff. Similarly, being below the cliff and moving towards it, you pass under the overhang, then would have to jump up to the higher level to continue forward. Here the cliff represents the discontinuity, and the overhang is the tendency of a system to hold its current form. Carver and Sheier use this model to describe how individuals hold onto goals over time, and we will return to that point later when we discuss how the system studied here should develop, but the same thinking may be applicable to efficacy. Bandura and Cervone (1983) wrote that self-efficacy impacts the commitment individuals show towards their goals. Those with higher efficacy should hold onto their goals for longer than those who are low in self-efficacy. In the analogy of the cliff, individuals high in efficacy should have a greater overhang and stay committed to their goal for longer before reaching the discontinuity where they abandon their goal. Obviously, the stated goal of a single task is to complete the task. If you vary the difficulty of that task within individuals, those who are more likely to stay committed to the goal should attempt the task at harder levels of difficulty before giving up. In combination with the discussed differences in efficacy between the goal orientations (Payne et al., 2007), we should see a difference in how the goal orientations engage in the task across levels of difficulty.

From the accumulated research, we see that in a task where difficulty will be varied at the individual level learning individuals should push themselves to attempt harder tasks than their performance oriented counterparts. Then, within the performance orientation, the undermining of intrinsic motivation within performance avoid individuals should lead to their greater withdrawal from the task than their performance approach brethren. In addition, the efficacy differences between the orientations, such that learning is greater than performance approach which is greater than performance avoid, should result in further differences in the willingness of individuals to engage across levels of difficulty. Further, the level of effort applied at each level of difficulty should differ in a way consistent with the various orientation's task focus. Mastery individuals should apply effort at a high level whenever they attempt the task, while performance avoid individuals should be reluctant to apply effort even when they attempt the task. Hence, it is predicted that:

> *Hypothesis 1: Goal orientations should moderate the relationship between within-person efficacy and task engagement such that learning/mastery oriented participants show the most engagement and performance avoid participants the least.*
>
> *Hypothesis 2: Goal orientations should moderate the negative slope between within-person efficacy and resource allocation such that mastery and performance approach are similar but performance avoid is more negative.*

Positive findings for these hypotheses should support a moderated discontinuous model of self-efficacy that looks like that depicted in Figure B1. All figures and tables can be found in the appendices.

Dynamic Model of Goal Orientation and Self-Efficacy

Self-regulation systems are complex and develop dynamically over time. Despite this inherent complexity, much of the research on self-regulatory constructs has been accomplished cross-sectionally. Of course, this problem cuts across most of our field despite repeated calls for more complex and dynamic research (e.g. Kozlowski & Klein, 2000). Thankfully, some researchers are beginning to heed these calls and more and more work, especially in top journals, take multi-level or longitudinal approaches to data collection and analysis. Some great examples of this exist in the self-regulation literature, such as Deshon, Kozlowski, Schmidt, Milner and Wiechmann's (2004) study of multiple goal pursuit where individuals needed to balance their own goals against those of their team over several task attempts. The complexity of regulatory systems makes them hard to study in their entirety in a lab setting, and doubly so in any field setting. The difficulty with this can be partially mediated by moving towards computational modeling approaches (Vancouver, 2006), but successful development of these models relies on continued lab and field research to provide parameters for computational modeling. This study examines the development of the within-person efficacy model and associated regulatory constructs over several iterations of a task to both extend the current research on the efficacy model and provide guidance for later computational models.

Goal orientation effect on self-efficacy. As has been discussed above, evidence points to a strong link between a person's goal orientation and their feelings of efficacy. For example, Kozlowski and Bell (2006) found that avoidance orientations were associated with lower levels of efficacy, and learning orientation was associated with higher. This finding has been confirmed by Payne et al.'s (2007) meta-analysis which found a positive (.37) relationship between learning, null (.03) between performance approach, and negative (-.26) between performance avoid, and efficacy. Fitting with our guiding control model, the effect of goal orientations on efficacy can be mediated by the effect those orientations have on goals. For example, the effect of performance avoidance on efficacy being mediated by a tendency to contrast one's-self with others (Carmona, Buunk, Dijkstra, & Peiro, 2008), which is the type of goal those individuals tend to adopt. With this strong evidence, we would expect to replicate these findings in the current study. We also have no reason to believe that the relative standing on efficacy between orientations will change over time when controlling for other factors such as goal success and failure, which will be discussed below. Therefore, it is predicted that:

Hypothesis 3: Across all time points, mastery orientation will be associated with the greatest efficacy, avoid the least, and approach in between.

Goal orientation effect on goals. If goal orientations indeed lie at an intermediate level just above the task in the regulatory system (DeShon & Gillespie, 2005), that orientation should have a direct effect on goal levels in the lower level regulatory system. In self-regulation (Carver & Sheier, 1998) lower level systems have standards (goals) which are determined by the outputs of higher level systems. Thus, it is obvious that a higher-level system that represents a goal orientation would affect the goal of the task level system connected to it. Therefore, we would expect to see differences in those goals based on which goal orientation is activated for the task in question. This process is seen in work showing the effects of goal orientations on regulatory constructs, such as efficacy, are mediated by the effect of those orientations on goals (VandeWalle, Cron, & Slocum, 2001). Work on the individualization of goals by personality also supports this connection (Langston & Cantor, 1989).

We have already seen that goal orientations lead to different types of goals (Elliot & Church, 1997). Going back to Dweck (1986), learning individuals are more task oriented and concerned with the long-term development of skills than their performance counterparts, who are more concerned with showing normative competence. Elliot and Harackeiwicz (1996) also show that motivation is undermined by performance avoid orientation due to that orientation’s detrimental effects on goals. The differences in the goal orientations manifest themselves in different goals at the task level, as shown in Payne et al.'s (2007) meta-analysis where learning orientation was positively (.19) associated with self-set goals, performance avoid orientation negatively (-.17), and performance approach orientation not (-.04). Thus, we expect:

Hypothesis 4: Initially, goals for mastery should be higher than performance approach or avoid, with avoid being the lowest.[2]

Due to the nature of the goal orientations, we also expect to see changes in the relative standing of their related goals over time. This boils down to how long the individual should remain fully engaged in the task. Learning individuals take a longer-term view of their participation as they try to develop competence in the task than performance individuals (Dweck, 1986; Elliot, 1999). Proving an ability to learn and develop skills in a task should naturally take longer than proving you can complete the task at a minimal level. Simultaneously, performance oriented individuals are more likely to view their skill as fixed and not as something that can be developed (VandeWalle, 1997). These together should lead to a difference in the behavior of the regulatory system for performance and learning individuals as they perform a task over time. According to Bandura (1991), individuals use forethought to raise their goals over time to maintain motivation. If this were the case, we should expect to see increases in goals over time for all orientations on average. However, in Control Theory (Carver & Sheier, 1998), goals do not have to necessarily rise over time, even if goals are being completed, although they may do so. Here, we propose that the path taken depends on one's goal orientation. Mastery/learning individuals should be more likely to raise their goals over time because they are more likely to see room for improvement and believe they can develop further skills. Whereas performance individuals would be less likely to make the decision to raise their goals because their ability is seen as fixed, and there is little to be gained personally from performing above the level required to show competence on the task. Additionally, the tendency of performance avoid individuals to raise their goals should be further undermined by the lack of intrinsic motivation they display (Elliot & Harackeiwicz, 1996). This should result in:

> *Hypothesis 5: Over time, the difference in goal level will increase such that mastery goal oriented individuals will increase their goals more than performance approach, and performance avoid will show the lowest increases.*

The self-efficacy-performance relationship. The general relationship between efficacy and performance has been well established. The standard view is that higher levels of efficacy lead to higher levels of performance on a task (Bandura, 1977a, 1989, 1991), a relationship which has been confirmed via meta-analysis (Stajkovic & Luthans, 1998). We have no reason to doubt that on any individual trial of a task the general relationship between efficacy and performance will show individuals with higher levels of efficacy will perform better than individuals with lower levels of efficacy. Therefore, this standard hypothesis is proposed:

> *Hypothesis 6: Stated self-efficacy prior to a trial will be positively related to performance on that trial.*

More controversial is the reciprocal relationship between efficacy and performance such that they feed into one another across repeated trials and create deviation amplifying loops known as efficacy-performance spirals. Proposed by Lindsley et al. (1995) these spirals represent the tendency for high performance to lead to increases in efficacy, which lead to further increases in performance. Similarly, low performance would lead to decreases in efficacy, and subsequently lower performance. Unfortunately, while intriguing and intuitive, support for this relationship is sparse. The design of the present study allows us a glimpse at any such spirals occurring over the course of many iterations of a task. This relationship also fits with the CT version of self-regulation. Specifically, Carver and Sheier (1998) discuss how expectancy feelings are a product of prior experience and memory more than a concern about the immediate task. The feelings of expectancy are associated with the individual's affective state associated with the task such that those feeling good about their performance tend to raise their feelings of expectancy. As already mentioned, Carver and Sheier view efficacy as a form of expectancy. If this is the case, we would expect individuals who are performing well to raise their levels of efficacy. To test the occurrence of spiral-type relationship here, two hypotheses are proposed:

Hypothesis 7: The relationship between prior attempt performance and subsequent attempt efficacy will be positive across all time points.

Hypothesis 8: Changes in performance across time points will be positively related to changes in efficacy across the same time points.

Self-efficacy effect on goals. Despite the controversy over the way self-efficacy operates, another well accepted relationship exists in the effect of efficacy on goal setting. Both Social Cognitive and Control Theorists can agree that people with higher beliefs in their ability tend to set higher goals, and this relationship is well supported in the self-regulation literature (Bandura, 1991, 1997; Vancouver & day, 2005; Kozlowski & Bell, 2006). Even in the literature questioning the nature of self-efficacy, the accepted relationship remains positive between efficacy and goal choice (Vancouver et al., 2014). In a Control system where we conceive of efficacy as feeding into the decision mechanism for the regulatory system you can see why this relationship is true. The decision made by the system would partially rely on how one views their own ability. When that view is high, individuals are likely to make a positive change in the operation of the system, by either increasing their effort to achieve a current goal, or by raising a goal they have already accomplished or believe is inevitable. This raising of goals also aligns with Bandura's (1991) belief that people use forethought to maintain their motivation. The newly raised goal would then create a new discrepancy in the system which would lead to maintained effort on the part of the self-regulator. In this study, individuals will get to set their own goals and it is expected that the accepted relationship between efficacy and goals will be replicated. Thus, this hypothesis:

> *Hypothesis 9: Stated efficacy on a task attempt will be positively related to self-set goals on that task attempt.*

Effect of goals on performance and effort. The effect of goals on performance is one of the most well-established relationships in organizational psychology. Research on goals and their subsequent effect on performance dates to at least the 1960s. Those early findings led to the establishment of goal theory as early as 1968. Originally developed for use in employment settings, Locke and his colleagues (Locke, 1968, 1975; Locke & Latham, 1990) have shown that challenging, yet attainable goals have strong positive effects on employee performance. This occurs through the enhancement of performance motivation (Locke, Shaw, Saari, & Latham, 1981). Even especially difficult goals can enhance performance if feedback regarding that performance is provided (Campion & Lord, 1982).

The effect of goals on performance is easy to see from a self-regulation perspective. A goal's set point determines decisions made by the rest of the regulatory system. A higher set goal by necessity creates a larger discrepancy between that goal and perceived reality (unless of course you have already succeeded in reaching that goal which is a special case to be discussed below). When individuals sense this discrepancy, they should act to reduce it, such as by increasing effort, and a greater action be taken for larger discrepancies (Carver & Sheier, 1998).

Thus, higher goals should lead to higher performance through their effect on effort. This is the effect we see in the literature: that once people accept a goal they tend to put forth the effort to reach those goals, increasing performance (Vancouver & Day, 2005).

Of special importance here is how individuals react to self-set goals. Since those goals are self-set, we should be able to assume that the goal has been accepted since you are unlikely to set a goal for yourself that you do not agree with.[3] Self-set goals have also been shown to relate to performance, both on the job (Latham & Marshall, 1982), and in experiments when both the goal level and performance are known to the experimenter (Harkins & Lowe, 2000). This, again, occurs because individuals who set higher goals for themselves tend to work harder to reach them (Bandura, 1991). Therefore, it is predicted that:

> *Hypothesis 10: Self-set goal level on each task attempt should be positively related to performance on that task attempt.*
>
> *Hypothesis 11: The effect of self-set goal level on performance should be partially mediated by the effect of goal level on effort (as measured by resource allocation).*

Goal orientations on performance. The relationship between goal orientations and performance can be tricky. We have already established that goal orientation affects feelings of efficacy (Payne et al., 2007), and it is well established that efficacy is positively related to performance at the between-person level (Stajkovic & Luthans, 1998). We also know that task involvement leads to task performance (Pintrich, 2000), and that learning oriented individuals tend to engage in tasks to a greater degree (Dweck, 1986). Naturally, then, we would expect that goal orientations would be directly related to performance. Some research finds such a relationship, such as learning orientation being positively related, and avoid orientation negatively related, to academic standing (Hsieh, Sullivan, & Guerra, 2007), or learning orientation being related to employee performance on challenging tasks (Preenan, van Vianen, & de Pater, 2014). Other research shows that goal orientations predict school performance above and beyond other traits like intelligence, openness to experience, conscientiousness (Steinmayr, Bipp, & Spinath, 2011). However, life is not so simple. Some research shows that performance approach orientation may enhance performance more than learning orientation, such as on grade performance in a class, while performance avoidance proves a detriment to performance as expected (Elliot & Church, 1997). One reason for this may be that learning individuals engage in greater exploration behaviors of tasks than either performance approach or avoid, and that exploration can detract from performance (Davis, Mero & Goodman, 2007). The greater exploratory behaviors of learning oriented individuals have roots in their greater willingness to make mistakes and to choose tasks which foster growth (Dweck, 1986). In initial stages of performing on a task, exploration may lead to a perceived waste of resources on tasks which are too difficult for the individual at that time, and initially lead to decreased performance, while individuals who are not exploring would more efficiently apply their resources to perform at a high level during initial task attempts. Some research shows this relationship in that individuals who explore more during training perform worse during training, but they then show better post-training adaptation than those who explored less (Bell & Kozlowski, 2008). However, even though they are engaging in more exploration and possibly wasting resources, learning individuals should still benefit from the positive effects of other regulatory constructs, such as their increased efficacy (Payne et al., 2007). A recent meta-analysis also shows that the relationship between goal orientations and performance is mediated by their effect on self-regulatory variables such as efficacy, self-monitoring, self-evaluation and self-reactions (Cellar et al., 2011). Thus, it is predicted:

> *Hypothesis 12: Initial performance for mastery and performance approach should be about equal or performance approach and higher than mastery, but both higher than performance avoid.*

Over time, we would expect that the initial exploration by mastery individuals to create a positive effect on their performance as they challenge themselves and gain competency on the harder aspects of the task over time. Seeking greater challenges is likely to cause more errors among participants, but a positive orientation towards those errors and use of them for growth, such as learning individuals tend to do, leads to greater performance over time (Arenas, Tabernera, & Briones, 2006). That exploration and the long-term view of skill development adopted by learning oriented individuals tends to result in their more smoothly developing skills and related performance than performance oriented individuals, though some performance individuals may reach the same level of ability (Pintrich, 2000). Research has also shown that learning orientation is positively related with performance over time, a relationship mediated by goal orientation effects on goal setting (Taing, Smith, Singla, Johnson, & Chang, 2013). Here, it is expected that even though mastery individuals may be initially hampered in their performance by their attempting too hard of tasks before they are ready, that experience will benefit them over time and will, on average, result in higher performance. Meanwhile, performance avoid individuals will not be able to recover from the negative effects of their lack of intrinsic motivation (Elliot & Harackeiwicz, 1996) and will remain unengaged from all levels of the task. Hence, the prediction that:

Hypothesis 13: Mastery orientation will result in higher levels of performance over time than performance approach, and performance approach higher levels of performance than avoid.

Performance on goals. The expected relationship between performance and goals should now be intuitive, and is supported by both Social Cognitive Theory and Control Theory. First, Bandura (1991) emphasizes the ability of individuals to use forethought to raise their goals before they ever meet them to maintain their motivation. Bandura (1983) also wrote that performance on a task should affect subsequent goals such that extremely bad performance would lead to goal abandonment, moderate performance short of the goal would lead to increased effort, and performance above the goal would lead to an increase in that goal. Thus, Bandura and SCT would support a positive relationship between performance on a task and subsequent goals. Control Theory would agree with this assessment. The premise of CT relies on negative feedback loops which reduce discrepancy between the goal of the system and perceived reality (Powers, 1973). As these systems function, individuals can either change their goals or increase their effort to reduce that discrepancy (Carver & Sheier, 1998). When individuals perform poorly, they are likely to lower their goals when they can, because doing so is easier than putting forth more effort (Lord & Hanges, 1987). Poor performers can scale back their goals, or disengage from a task completely (Carver & Sheier, 1998). Additionally, individuals performing well and succeeding are likely to raise their goals over time (Campion & Lord, 1982). Raising goals can also reduce discrepancies when performance exceeds the goal (Carver & Sheier, 1998). The combination of these findings again supports the prediction that:

Hypothesis 14: Performance (as task score) on one task attempt will be positively related to performance on subsequent attempts.

Performance on resource allocation and the effects of feedback (goal success or failure). As individuals perform a task over many iterations they receive feedback about their performance. In this study, they will receive direct feedback about whether they accomplished their stated goal or not for that task attempt. Their performance in relation to their goals should affect the behavior of the regulatory system.

Carver and Sheier (1998) wrote that "life, in [self-regulation], is a continual process of establishing goals and adjusting patterns of behavior to match those goals more closely, using informational feedback as a guide" (p. 63). As we succeed or fail at obtaining our goals, we must either change our goals or increase our effort to bring our self-regulation system back in balance (also Powers, 1973). When we fail, we tend to change our goals or abandon them if our task environment allows (Lord and Hanges, 1987). This goal abandonment can actually be a defense mechanism such that individuals will disengage from a task they are consistently failing at to protect their feelings of efficacy (Lindsley et al., 1995). These tendencies have implications when we look at the effects of success and failure on the within-person nature of self-efficacy. When self-efficacy is low on a task, failure on that task should lead more often to goal abandonment, whereas when self-efficacy is high effort may be increased. When we vary the difficulty of a task at the within-person level, we should see individuals change their strategy following failure such that they disengage from the harder levels of the task and increase their effort on the easier levels. This should be seen in the following prediction:

> *Hypothesis 15: Failure to meet one's goals on previous attempts will be associated with a lower level of task engagement across all difficulty levels on subsequent attempts, but with higher levels of resource*

allocation (indicating less willingness to attempt hard tasks but greater effort at completing the ones they are engaged in).

Goal orientations should moderate this relationship. As Dweck (1986) wrote, the type of goal people pursue affects the way they respond to feedback. Specifically, learning individuals engage in more feedback seeking behavior and tend to use that feedback to better themselves, while performance individuals are more likely to see negative feedback as an attack on themselves and subsequently to withdraw from the situation (Dweck, 1986; Bobko & Collela, 1994; VandeWalle et al., 2001). An recent example of the positive use of feedback by learning individuals showed that learning individuals are more creative following negative feedback than other orientations (He, Yao, Wang, & Caughron, 2016). The more positive use of feedback by learning individuals also leads to them showing greater persistence in the face of failure or obstacles (Dweck, 1986; Elliot, 1999), and continued engagement in tasks following negative feedback (VandeWalle, 1997). We also know that more resilient individuals tend to bounce back from setbacks faster than those who are less resilient (Tugade & Frederickson, 2004). Additionally, this manifests in learning individuals showing greater goal commitment (Johnson & Perlow, 1992), and organizational commitment (Lee, Tan, & Javalgi, 2010; Joo & Park, 2010), than performance individuals. Whereas performance avoidance is related to occupational withdrawal intentions and behaviors (Sims & Boytell, 2015). These findings also align with research on efficacy and goal commitment – where efficacy is positively related to goal commitment and resiliency in the face of obstacles (Bandura, 1989) – since learning oriented individuals also tend to have higher feelings of efficacy (Payne et al., 2007). The same reasoning can be applied to why we may see a difference between how performance approach and avoid respond to failure. Performance avoid individuals tend to have the lowest efficacy (Payne et al.,

2007) and should therefore show the least resilience in the face of failure because those who are least sure of themselves are more easily discouraged by failure (Bandura & Cervone, 1983). Additionally, failure in downward comparisons can have extremely negative effects on motivation (Bandura, 1991). Therefore, it is expected that:

> *Hypothesis 16: The effect of failure on the nature of self-efficacy and its related resource allocation will be moderated such that mastery oriented individuals will show the smallest decreases in task engagement, and avoid will show the greatest.*

Not everyone fails in reaching their goals. So, how do they respond to their success? Here, SCT and CT differ slightly. According to Bandura (1991), individuals should subsequently raise their goals, creating a discrepancy in their regulatory system, whereby it is necessary for them to keep their effort and task engagement elevated to reach the new goal. On the other hand, CT would suggest that while individuals may raise their goals following success (Carver & Sheier, 1998), complacency plays a key role. Individuals who are close to their goals may decide to begin reducing effort instead of changing their goal, thereby not wasting energy on a task that no longer requires it (Vancouver et al., 2001). When individuals succeed in this way, a monitoring system connected to the control loop in question may sense the rapid approach of goal accomplishment and create feelings of positive affect, this positive feeling may lead to disengagement from goals depending on how the individual views the task (Carver & Sheier, 1998). How an individual views the task is directly relatable to their goal orientation. Avoid orientation is mainly concerned with not showing incompetence, and performance approach with showing competence, while learning is concerned with skill development (Elliot, 1999). First, we know that positive feedback can lead to goal-level complacency among individuals who are primarily concerned with self-presentation (Higgs & Wood, 1999, as cited in VandeWalle et al, 2001) as both performance orientations are. Second, the time scope associated with the task by each outlook is likely to affect the way they view positive feedback. Learning oriented individuals are more concerned with their long-term development (Elliot, 1999), leading to relatively distal goals. While performance individuals are more concerned with proving their competence in the immediate task (Elliot, 1999), leading to relatively proximal goals. For learning individuals, a single success only moves them incrementally towards their overall goal, whereas success for performance individuals may move them very close to their proximal goals very quickly. This would create the positive affect discussed by Carver and Sheier (1998) which may lead to complacency. This effect should be especially strong for performance avoid individuals who could conceivably achieve their goal of proving they are not incompetent with a single success, at least more easily so than performance approach individuals who should still like to show they are at least better than most people. Therefore, it is expected that:

> *Hypothesis 17: Goal success will have an effect on task engagement moderated by goal orientations such that mastery individuals will maintain or increase their engagement, while performance avoid will lower theirs.*

The effect of goal success on subsequent goals should be moderated by the individual's feelings of efficacy. Bandura (1989) states that individuals change their goals over time, specifically upwards, as part of their exercise of agency. That agency is primarily exercised through a person's feelings of efficacy. Efficacy should affect the way individuals respond to goal success or failure through the way efficacy leads to goal commitment and abandonment. People who are high on efficacy tend to remain committed to their goals longer than individuals low on efficacy (Bandura & Cervone, 1983). This fits with the discussion above of goal commitment and abandonment in Carver and Sheier (1998). Individuals high in efficacy are more likely to stay on the higher-level goal despite failure because the location of the discontinuity where they abandon their goal shifts. Additionally, individuals low on efficacy would be expected to keep low goals despite success due to that same shift. The tendency for individuals to hold on to their goals as a function of their efficacy leads to the prediction that:

> *Hypothesis 18: Efficacy should moderate the effect of performance on goals such that individuals with higher efficacy will show smaller negative changes in goals following failures, and larger positive changes in goals following successes.*

In a control system, there should be a direct effect of an individual's success or failure of reaching their goals on their self-efficacy. This is supported by SCT and the efficacy-performance spiral relationship. This relationship is also seen in recent research, which suggests that the negative effects of performance on efficacy may be buffered by having a learning goal orientation (Dahling & Ruppel, 2016). Along these lines, it is expected that:

> *Hypothesis 19: Individuals will gain efficacy following goal success, and lose efficacy following failure. The amount lost following failure will be moderated by goal orientation such that mastery individuals will show smaller losses.*

Effect of time. Self-regulation is inherently a dynamic process that unfolds over time, and their study over time is one of the cutting-edge areas of our field. First, and most basically, the regulatory system should become more stable over repetitions of the task. This should easily be seen in a general increase in the strength of the relationships between measurement points for each variable. An easy example of increasing stability can be seen in quadratic growth patterns in job performance (e.g. Ployhart & Hakel, 1998). In a quadratic pattern for job performance we expect to see rapid rises in performance during early performance episodes, then a leveling off after several iterations. The relationship between points early in this growth may be weak as job performance varies wildly from one time point to the next. Later, the relationship should get stronger as performance stabilizes and people tend to perform at whatever level they have been. Within self-regulation some constructs are highly dependent on previous experience. Expectancy – and relatedly self-efficacy – is a product of one's prior experiences with a task (Carver & Sheier, 1998), as an individual repeats a task many times their history with that task will shape their expectancies towards it. The longer the history, the less effect any one attempt should have on the level of efficacy displayed for that task; for example, it is much more likely that a single failure early in task attempts will have a strongly detrimental effect on efficacy than a single failure following a long line of successes. Therefore, we would expect efficacy to stabilize as history with the task grows. In general, it is predicted that:

> *Hypothesis 20: The self-regulation system will show greater stability over time.*

Despite the increasing stability of the system, we should also see general trends emerge for several of the variables measured here. For example, we would expect to see a positive trend in performance over time. This positive trend would naturally be expected due to practice effects due to exposure (e.g. Hausknecht, Halpert, DiPaolo, & Morriarti Gerrard, 2007). The rate of performance change may also be moderated by goal orientation. While Pintrich (2000) found a positive increase in performance over time regardless of goal orientation, the effect of goal orientation may depend on context; as Davis, Meero, and Goodman (2007) found that performance avoid individuals do not exhibit the same improvement over time when they are being held accountable, and learning oriented individuals do not improve when they are not being held accountable. Other research has also shown that the relationship between goal orientations and performance growth trajectories can be complicated. Yeo, Sorbello, Koy, and Smillie (2008) found that performance trajectories increased the fastest for trait performance approach individuals when goal orientations were accounted for as single traits. But when high and low levels of each trait were crossed with each other, individuals with high mastery orientation and low performance avoidance increased their performance at the fastest rate. For this task, individuals should see at least some accountability due to the way the task will be framed for each orientation. Additionally, we would expect learning individuals to gain greater skill over time since that is their overarching goal (Elliot, 1999), and that gain in skill should translate into increases in performance. This activation of state learning orientation differs from the findings of Yeo et al. (2008) which focused on trait goal orientations, and the activation of learning orientation should allow us to assume that these individuals will, on average, have less of a state performance avoid orientation than those individuals for which avoid orientation is activated. Therefore, we may see an effect of performance such that:

> *Hypothesis 21: Performance will increase over time, but the rate will be moderated such that mastery oriented individuals increase the most and performance avoid the least.*

Other constructs may exhibit negative changes over time. For example, efficacy may decrease over time regardless of goal orientation, as previously found by Pintrich (2000). A similar trend may occur here where an initially easy seeming task (just click on the boxes) becomes frustrating as it is difficult to get good at clicking objects which are also jumping around at random. Thus, even if performance is increasing, and efficacy is related to performance, over time frustration may build and cause overall decreases in efficacy.

Hypothesis 22: Efficacy will decrease over time for all goal orientations.

Still others may exhibit a curvilinear trend over time. For example, Vancouver et al. (2014) discuss how once strong positive relationships between constructs such as performance and efficacy can become null or even negative over time as individuals get complacent. We would expect complacency to set in over the course of this task as individuals reach their goals and become disinterested. Returning to the discussion of the proximity of goals based on goal orientation from above, we should expect differences in these curvilinear relationships as well. Learning individuals, taking the longest view of the task (Elliot, 1999), should take the longest to become complacent. Whereas avoid individuals should become complacent the fastest with their much shorter views of the relevant task. Thus,

Hypothesis 23: The relationship between efficacy and performance will be curvilinear over time such that it is initially positive, then turns null or negative. The amount of time it takes for that change will be moderated by goal orientation such that mastery orientation takes the longest, and performance avoid the shortest.

Methods

Participants

Participants in this study were recruited from Michigan State University's human research subject pool (SONA). This system is primarily populated with individuals taking undergraduate psychology courses at the university. Initially, 44 individuals participated in a pilot study where major identifiable technical and procedural problems were solved. 392 individuals participated in the main study. The number of participants was based on a combination of guidance drawn from previous studies on this topic and known properties of power in HLM. Specifically, Vancouver et al. (2008) used 112 participants to support their initial discontinuous model. Second, Sun et al (2014) utilized 36 and 30 participants respectively in their two studies examining a moderation of the discontinuous model. Third, completing an a priori power analysis for HLM is difficult because power for HLM is based in part on the covariance structure of the data, which is not known until after the data has been collected (Fang, 2006). Fourth, attempts at multi-level power analyses often return impractically large sample sizes due to the lack of knowledge of the data structure. For example, Preacher has made power analysis calculators available (http://www.quantpsy.org/rmsea/rmsea.htm), which given standard rules of thumb in our field return required samples of over 1500 individuals. These impractically large samples run counter to at least one simulation that shows power for HLM can begin to approach .80 when sample sizes are around 200 participants per cell (Fang, 2006). Additionally, other simulations have shown that HLM models can be relatively unbiased once obtaining as few as five observations per cell at level two, given adequate power at level one (Clarke, 2008). Given the results of those studies and our desire to understand a possible interaction, we felt a sample of individuals slightly larger per condition than the overall pool utilized for the initial model, and four to five times as large as the entire pool of the moderation studies would provide adequate power while keeping the study to a reasonable size.

Participants read and signed multiple informed consents prior to participating in the study (one when they completed an initial on-line pre-survey, one upon their arrival at the laboratory, and on the computer which used for the task). Participants were compensated in the form of class credit for their participation. In addition, participants had the opportunity to earn a $100, $50, or $25 gift card for being one of the top three participants in each condition. This incentive was designed to help keep participants engaged in the task, and tied the task to something that is more personally meaningful to non-researchers. In all, the experiment took about two hours, with 30 minutes for a survey prior to participant arrival, and 1.5 hours in the lab.

Materials

Pre-experimental surveys. When participants initially signed-up for this study they were sent a link to an online pre-survey hosted by Qualtrics which they were to complete prior to their arrival at the laboratory. This survey collected both demographic and control variables. Demographic variables included age, race, sex, year in school and work experience. Most importantly, this survey included a measure of trait goal orientation adapted from Vandewalle (1997; 2001). This scale was focused on work contexts, but can be adapted by removing references to work settings. The scale consisted of four items for each of the three goal orientation dimensions, which were answered on a five-point Likert scale from “Strongly Disagree” to “Strongly Agree”.

Several other measures related to self-regulation and goal orientations were collected. First, given the way orientations were manipulated and the interests in this study connected to how individuals treat making errors, we collected a measure of error orientation adopted from the Error Orientation Questionnaire (EOQ; Rybowiak, Garst, Frese, & Batinic, 1999). The EOQ in its entirety covers eight dimensions of error orientation, and some of them seem pertinent to the research here. Specifically, this study included the dimensions of: error competence (the knowledge for immediate recovery from errors and mitigation of their consequences), learning (ability to prevent errors in the long run by learning from errors, planning, and changing processes), risk taking (the results of achievement-oriented attitudes requiring flexibility and taking of responsibility), and strain (a generalized fear of committing errors). Each of these scales was measured with four items on a five-point Likert scale from “Not at all” to “Totally.” Other goal orientation researchers have studied the relationship between dimensions of error orientation and goal orientations and found that learning goal orientation is positively associated with risk taking (Arenas, Tabernero, & Briones, 2006). Performance approach and especially avoid were expected to be negatively related to risk taking.

Second, measures of regulatory focus have previously stood in for measures of goal orientation is some papers (e.g. Carmona, Buunk, Dijkstra, & Peiro, 2008), using a measure based on the Regulatory Focus Questionnaire of Lockwood, Jordan, and Kunda (2002) which has promotion and prevention dimensions. Each subscale consists of nine items (18 total), which are measured on a nine-point Likert scale from “Not at all True of Me” to “Very True of Me.”

Next, personality is commonly collected in psychological research, and has been a topic of interest in the goal orientation domain. For example, Steinmayr, Bipp and Spinath (2011) examined the predictive ability of goal orientations in combination with personality and intelligence, finding that learning goals, openness to experience, conscientiousness, and intelligence predicted performance in a school setting. To limit the number of questions in the preliminary survey, a short 20-item measure of personality was chosen. Donnellan, Oswald, Baird and Lucas (2006) created a short measure of the Big Five personality traits with four items as indicators for each personality dimension measured on five-point Likert scales from “Strongly Disagree” to “Strongly Agree” that was used here.

Finally, two other dimensions of self-regulation that have received some attention lie in the dimensions of assessment and locomotion. Assessment refers to individuals evaluating possible alternative goals or means to achieve them. Locomotion is more concerned with the individual moving from one state to another and the commitment of psychological resources to initiating and maintaining their behavior (Kruglanski et al, 2000). These regulatory dimensions were likely to have consequences for how individuals engage with, explore, and maintain their behavior through the many iterations of the task used in this study. To measure where individuals stand on these dimensions we adopted a twelve-item measure for each created by Kruglanski and colleagues (Kruglanski et al, 2000). These measures can be found in Appendix A.

Task. The main method for this study was adapted from the work of Vancouver et al (2008) and Sun et al (2014). In those studies, and now here, participants completed a task called the “Hurricane Game.” The primary objective of the task was to click on a square (referred to as “boards”) as it randomly jumped around the computer screen every three-tenths of a second. Every attempt to click on (or “nail”) a board was considered one round, and a series of rounds existed in every trial of the game. Trials lasted for three minutes. Board size was chosen randomly from a set of six possibilities ranging from fairly large to very small. The smaller boards were, in theory, more difficult to click on as they moved around and therefore participants should have expected to be less successful in nailing them. Expectancy, defined as “a momentary belief concerning the likelihood that a particular act will be followed by a particular outcome” (p. 17, Vroom, 1964), is seen by several researchers to be closely related to efficacy. Carver and

Sheier (1998) view expectancy as a more all-encompassing version of efficacy, and Vancouver et al (2008) with Olson, Roese, and Zanna (1996) see efficacy as one form of expectancy. This seems clear when compared to the view of efficacy as the belief of an individual in their ability to execute desired behaviors in the pursuit of some outcome (Bandura, 1977a). By manipulating the expectation of an individual for their success by changing the difficulty of the task, we should have also been able to manipulate their efficacy. For every round within the trial participants decided for how many seconds they would have liked to attempt to nail the board, from zero seconds (passing an attempt entirely) to ten seconds. The game then ran for that amount of time with the participant attempting to click on the board, with the time in the trial ticking away to reflect that usage of time. However, even if they successfully nailed the board in less time than they allotted, the participant had to wait for the remainder of their allocated time to pass before proceeding. Through this, the participants got to allocate their three minutes of allotted time as they saw fit in order to maximize the number of boards they could successfully nail. The participants earned one point for every board they successfully nail, and their running point total for the trial was displayed on the screen. The game was run on standard desktop computers equipped with a mouse and a keyboard.

Goal Orientation Manipulations. To manipulate goal orientations between individuals, participants were given a different set of instructions based on their condition to prime them with the required goal orientation. All participants were exposed to the instructions for the task in two modes to increase the strength of the manipulation. The first mode was a short presentation by the researcher which walks participants through how to perform the task, and emphasizes the goals which they are pursuing. This first presentation was pre-recorded in PowerPoint to ensure identical administration to all participants. The second mode was written instructions on the first page of the game when it opens on their computer. To keep the manipulation salient throughout the experiment, an overview of the goal instructions remained on the projector at the front of the lab, and short directions within the game between each trial reminded participants of those goals. Changing the instructions for the task can help us manipulate goal orientations because it helps change the way individuals see the task environment, and changes in the environment affect the goal orientation individuals adopt (Elliot, 1999). The manipulation used here is like others in goal orientation research such as that of Elliot and Harackeiwicz (1996), and was consistent with the common way to manipulate orientations in experimental research in that the manipulation was accomplished using language to frame the task in different ways (Kaplan & Maehr, 2007).

For the learning condition, directions emphasized learning strategies that would allow participants to score highly on the task. A second part of the instructions encouraged them to master the task over time. For the learning condition, the presentation read the following script prior to giving directions on how to actually complete the task:

> "Welcome to the lab where our research group studies game playing strategies. The task you are about to complete will give you an opportunity to learn game playing strategies which will allow you to improve your abilities over the course of several trials. The computer you are using will track all of your actions and allow us to study your learning process. You will complete 10 trials of this task, and your primary goal should be to improve your strategy for the task over that time period. Following all data collection, we will be rewarding the three participants who show the greatest strategy improvement with the top learner getting a $100 Amazon gift card, plus $50 for second and $25 for third."

Additionally, the on-screen learning condition initial instructions read:

> “Welcome to the lab where our research group studies game playing strategies. The purpose of this study is to learn about college student's abilities to improve their game playing strategies. Your goal over the 10 trials in this study is to master this task to the best of your ability. For each trial we urge you to not focus on how well you are doing, but rather take each trial and feedback given as an opportunity to improve your strategies for the task.”

Following the introduction to the task, the researcher left up a screen that shows the prizes available, as well as a statement of the participants’ goal saying “Goal: To improve your game playing strategies as much as possible.”

Performance approach and avoid conditions did not receive directions that discussed learning, instead the directions emphasized aspects of performing. These were more strongly tied to social comparisons to other participants in terms of gaining more points or avoiding having as many errors as other participants respectively. For performance approach, participants received the initial verbal instructions:

> “Welcome to the lab where our research group studies game performance and winning. The task you are about to complete will test your game playing ability to and asks you to maximize your score for each trial. The computer you are using will track all of your actions and allow us to compare your performance to other participants. You will complete 10 trials of this task, and your primary goal should be to perform this task better than other participants, including scoring more points than them. Following all data collection, we will be rewarding the three participants

> who perform the best, with the top performer winning a $100 Amazon gift card, plus $50 for second and $25 for third."

The on-screen performance approach condition initial instructions read:

> "Welcome to the lab where our research group studies game performance and winning. The purpose of this study is to compare college student's abilities to play certain types of games. Your goal over the 10 trials in this study is to perform this task better than your peers. You should attempt to obtain as many points as you can over the course of the experiment."

The screen left on the lab projector during the task reminded performance approach individuals "Goal: to perform the task better than their peers."

Performance avoid individuals were primed to avoid committing errors, instead of directly looking to gain points. They received the following instructions:

> "Welcome to the lab where our research group studies game performance and failure. The task you are about to complete will test your game playing ability to and asks you to minimize your errors for each trial. The computer you are using will track all of your actions and allow us to study your performance in comparison to other participants. You will complete 10 trials of this task, and your primary goal should be to avoid committing as many errors as other participants. Following all data collection, we will be rewarding the three participants who commit the fewest errors, with whoever avoids the most errors getting a $100 Amazon gift card, plus $50 for second and $25 for third."

The on-screen performance avoid condition initial instructions read:

> "Welcome to the lab where our research group studies game performance and failure. The purpose of this study is to compare college student's abilities to play certain types of games. Your goal over the 10 trials in this study is to avoid committing as many errors as your peers. You should attempt to avoid errors while earning points over the course of the experiment."

The screen left on the lab projector during the task reminded performance approach individuals "Goal: to avoid committing as many errors as your peers."

The rest of the initial instructions provided to participants all read the same, and are covered in more detail below. However, in addition to the manipulation being placed at the beginning of the task, participants received feedback following each trial that reminded them of their goal. This is reminiscent of other studies which have utilized feedback to induce goal orientations (e.g. Kozlowski & Bell, 2006). As they prepared for the start of a new trial, learning participants saw a message saying:

> "Remember, you should try to improve on your strategies from last round."

Performance approach saw:

> "Remember, you should try to perform better on this task than your peers."

And performance avoid:

> "Remember, you should try to avoid committing as many errors as your peers."

Goal and Efficacy Measures. Between each trial, two questions were asked to ascertain the participant's current efficacy for the task, and to have them self-set a goal for the following trial. Asking these questions can be tricky as they may be confounded with each other. Vancouver and Day (2005) discuss this in pointing out that expectations and outcome expectancies are not efficacy. They suggest that this problem may be avoided by asking participants efficacy questions in the form of what they *can* do, instead of what they *will* do. Therefore, the first question between each trial is meant to be a state measure of efficacy for the task, and read:

> "What percentage of other participants do you think you can do better than?"

Immediately following this efficacy question, participants were asked to set a goal for the upcoming trial. Having participants self-set goals does not usually pose an issue in research designs, but may lead to a case where participants are merely predicting their performance, not setting a goal for what they will try to accomplish (Vancouver & Day, 2005; Vancouver et al., 2001). Thus, we will again avoid language of what they believe they *will* do to attempt to avoid mere prediction of performance. Instead, the question was asked in terms of what they will *try* to do. Therefore, it read:

> "What is your goal for the next trial?"

Finally, upon completion of the last trial, participants completed the same measure of goal orientations they filled out prior to the task (VandeWalle, 1997, 2001). This acted as a manipulation check to test if the participant's state goal orientation was activated differentially than their trait goal orientation by the experimental situation.

Through these measures we collected data on several variables. First, the difficulty of the task was manipulated by board size. Second, goal orientations as manipulated between individuals by the instructions and feedback they receive. Third, task efficacy as measured between each trial. Fourth, a self-set goal as measured prior to each trial. Fifth, goal acceptance, defined as the probability of a participant allocating even a single second to their attempt of a difficulty level. This was scored dichotomously as either a “yes” they allocated time, or “no,” they did not. Sixth, resource allocation, or degree of effort, through the number of seconds allocated to each attempt. Seventh, performance on each trial was recorded as the number of points accrued on that trial. And, finally, goal completion on each trial, dichotomously scored as to whether the participant scored as many points on the trail as they stated in their goal.

Procedure

Prior to arrival at the lab, participants were randomly assigned to an experimental condition by experimental block. Meaning, each scheduled period for data collection was randomly assigned a condition and everyone in the lab at the time was placed in that condition. This allowed for efficient data collection while maintaining randomness of individuals within each condition. All time periods were completely random until the final three time periods, where one was directly assigned to the learning, and two to the avoid conditions, to help balance the number of participants in each condition. Prior to their arrival at the lab, participants were also randomly assigned to computers and had their identification information entered into the proper work station by research assistants. Once in the lab, participants were directed to the proper work station to await start of the task. Stations were separated by partitions to block participants from reading their neighbor’s screens, or being distracted by others playing the game. Participants read and signed an informed consent prior to beginning the study.

Based on their assigned condition, participants then began to receive directions to manipulate their orientation as described above both orally and through text. A five-minute PowerPoint presentation walked participants through the basics of how to play the game both. At the end of this presentation, participants could begin playing the game on their computers, where they also received written instructions, as follows:

> "The object of this game is to 'nail' as many squares as possible in 3 minutes. Within a 3-minute game you will play several rounds. For every round, you have a possibility of gaining 1 point by clicking on (or 'nailing') a rapidly moving board. During a round, the board will 'fly' around the white space in which this text is printed. At the beginning of each round, the board size will be presented to you. The more rounds you play, the more points you earn. IMPORTANT: The number of rounds you play depends on the amount of time you allocate to each round. You can allocate from no time for the round (that is, pass on that round) or allocate as much as 10 seconds, depending on whether or how much time you think you need to nail the selected board. You select the amount of time you wish to designate to the round by clicking one of the radio buttons below (the small circles at the bottom of the screen). Once you have selected a time, press the GO button (above) and the square will begin to jump around within the game board area for the time you designate for the round. If you click on the square, you 'nail' it in place for the duration of the time you designated for the round and win the amount assigned to that board. It is not as easy as it sounds. To give you an idea of the difficulty

> of each board size, the computer will give you several practice rounds for each board size. However, before beginning, we need to reaffirm your informed consent. Please make sure you have read and signed the consent form if you agree to participate."

Once participants clicked the "go" button on this first screen, they were asked to confirm that they have signed the informed consent. Once affirmed, they were taken to an introduction period for the game. In this section, they were taken through each of the board sizes from largest to smallest and given three attempts of ten seconds each in which to try nailing the boards. This order is in line with the concept of enacted mastery (Bandura, 1997) where participants are introduced to a concept through a series of increasingly difficult levels. In this portion of the task participants were given constant feedback about their performance by having the board instantly change colors when it was successfully nailed and a message box informing them of their success. If the entire time passed for the attempt they were also informed of their failure. After three attempts on each board size the participant was informed of how many boards they successfully nailed for that size and what percentage of success that number represented. In addition, after the largest board size a message appeared informing the participant that the task would get harder as they proceeded. This process is repeated for all board sizes.

After this introductory period, participants were given one three-minute practice trial where they had the opportunity to assign lengths of time to their attempts. During this practice period, participants were given feedback on how many seconds they would have wasted on attempt if they successfully nail the board faster than the amount of time they allocated to the attempt. Upon completing practice, participants were asked "On average, how many seconds do you think it will take you to nail this board?" They could choose options from zero seconds to more than ten seconds. This question was asked in turn for every size of board. Reasoning that it would take longer on average to hit harder boards than easy ones, this process acts as a manipulation check to ensure that participants are indeed seeing the smaller boards as being harder to nail than the large.

After the manipulation check, and prior to the beginning of every subsequent trial, participants were given the message “Okay, ready for the next 3-minute trial?” This message was accompanied by a short reminder of their goal orientation (“remember, try to improve on your performance from last round,” “remember, we can only use data from participants who score well,” or “remember, we can only use data from participants who do not score poorly” for learning, performance approach and performance avoid respectively). These reminders were followed by the two efficacy and goal questions discussed above. These questions were given open-ended responses but were limited to real numbers from zero to 100.

Following each trial participants received feedback on their performance for that trial. They were both informed of their score for that trial (“On that trial you earned x points”), and of their success or failure in meeting their goal for that round (“Congratulations, you met your goal for that trial!” or “Sorry, you failed to meet your goal for that trial”). This process was repeated for a total of 10 trials (1 practice trial and 9 full trials). Upon completion of the final trial, participants filled out the final survey, were thanked for their participation, given a written debrief in the form of a short paragraph covering the topic of the study, and dismissed.

Results

Participants and Final Data Set

As stated above, 392 individuals participated in the primary data collection for this study. Following data collection, the data was compiled, checked for accuracy, and cleaned. While attempting to retain as many participants in the final data set as possible, some participants had to be eliminated. 33 individuals were eliminated automatically for failing a series of attention check questions built into the post-task survey which simply asked the participant to choose "strongly agree" for their response. In addition, 47 other individuals had to be dropped from the data set for a combination of voluntary quits, technical errors which forced early task termination, or skipping the between-trial questions multiple times.[4] This process resulted in 312 individuals eligible for the final overall data set. Then all possible were matched with their pre-surveys. Unfortunately, only 30 of the 76 participants who were eliminated in the cleaning process, and 263 of 312 in the final data set were successfully matched.[5] To retain all possible data for hypothesis testing the 53 individuals who qualified for the data set but did not complete a pre-survey were retained because the information in the pre-surveys is secondary to the interests of the main study. The pre-surveys approximate the final participant pool as being 19.50 (SD = 1.73) years old, 55.5% female, and 66.9% white or Caucasian.

Method Checks

Pre-survey scales. Prior to their use, all pre-survey measures were tested for adequate psychometrics. The series of factor analyses and reliability tests can be found Appendix B. The goal here was to check for adequate psychometric performance, defined in this case using standard guidelines in our field. Specifically, desirable reliabilities were defined as Cronbach's Alpha as being .70 or higher. In addition, for factor analyses, desirable fit statistics were defined as when CFI is greater than .95, RMSEA less than .07, and SRMR less than .08 (a review of cutoffs for these and other fit indices can be found in Hooper, Coughlan & Mullen, 2008). These tests resulted in the elimination of 5 items total from the locomotion and assessment regulation scales (Kruglanski et al, 2000), and the full elimination of using the Regulatory Focus scale (Lockwood et al, 2002) for poor psychometrics. Multiple scales in the Big 5 Personality inventory also displayed questionable psychometrics, but could not be improved post-hoc; these were retained with the knowledge of their sub-optimal performance. Scale scores were calculated for all participants as the means of their responses to the scale items. Table A1 displays descriptive information for each of these scales for both the overall data set, and relevant sub-groupings of the data set. Intercorrelations and reliabilities (Cronbach's alpha) can be found in Table A2.

Random assignment. Utilizing all available participants with valid pre-surveys, a MANOVA was completed to test for significant differences between conditions, using a Bonferonni correction for multiple comparisons. As the subject of the primary study, of primary importance were the tests for learning goal orientation [$F(2, 290) = 1.52$, $p = .221$, $\eta^2 = .01$], performance prove orientation [$F(2, 290) = 2.57$, $p = .079$, $\eta^2 = .02$], and performance avoid [$F(2, 290) = 2.81$, $p = .062$, $\eta^2 = .02$], which showed no significant differences. In addition, the scales which were proposed as potential factors to control for, error competency [$F(2, 290) = .58$, $p = .563$, $\eta^2 = .00$], learning from errors [$F(2, 290) = .23$, $p = .799$, $\eta^2 = .00$], error risk taking [$F(2, 290) = .65$, $p = .521$, $\eta^2 = .00$], error strain [$F(2, 290) = 1.53$, $p = .218$, $\eta^2 = .01$], extraversion [$F(2, 290) = 1.18$, $p = .308$, $\eta^2 = .01$], agreeableness [$F(2, 290) = .18$, $p = .834$, $\eta^2 = .00$], conscientiousness [$F(2, 290) = 1.62$, $p = .199$, $\eta^2 = .01$], neuroticism [$F(2, 290) = 2.35$, $p = .098$, $\eta^2 = .02$], openness [$F(2, 290) = 2.44$, $p = .089$, $\eta2 = .02$], locomotion regulation [$F(2, 290)$

= .14, p = .868, η2 = .00], and assessment regulation [F(2, 290) = .77, p = .466, η2 = .01] also showed no significant differences, therefore random assignment appears to have been successful. With the success of random assignment, we have stronger evidence that any observed differences between the conditions is due to the experimental manipulations, and not to any other observed variables (Shadish, Cook, & Campbell, 2002). As such, no trait survey measures were used in primary hypothesis testing as direct controls to refrain from arbitrarily removing variance from the data set.

Attention check. To test for differences between the conditions on rate of failing the attention check imbedded in the post-survey, a one-way ANOVA comparing success rates was completed. No significant difference was found ($F(2, 340) = .39$, $p = .678$).

Personality differences in attrition. To check for potential bias in attrition rates from the initial participant pool to the final data set, a MANOVA was completed assessing the differences between individuals in the final data set and those eliminated, using a Bonferroni correction for multiple comparisons. No significant differences were found for any variables collected in this study (learning goal orientation [$F(1, 291) = .08$, p = .773, $\eta^2 = .00$], performance prove orientation [$F(1, 291) = .06$, p = .808, $\eta^2 = .00$], performance avoid [$F(1, 291) = 3.76$, p = .054, $\eta^2 = .01$], error competency [$F(1, 291) = .28$, p = .599, $\eta^2 = .00$], learning from errors [$F(1, 291) = .01$, p = .913, $\eta^2 = .00$], error risk taking [$F(1, 291) = 1.04$, p = .309, $\eta^2 = .00$], error strain [$F(1, 291) = 1.09$, p = .296, $\eta^2 = .00$], extraversion [$F(1, 291) = 1.10$, p = .296, $\eta^2 = .00$], agreeableness [$F(1, 291) = .36$, p = .551, $\eta^2 = .00$], conscientiousness [$F(1, 291) = 3.37$, p = .067, $\eta^2 = .01$], neuroticism [$F(1, 291) = .15$, p = .698, $\eta^2 = .00$], openness [$F(1, 291) = 2.87$, p = .091, $\eta^2 = .02$], locomotion regulation [$F(1, 291) = .50$, p = .480, $\eta^2 = .00$], assessment regulation [$F(1, 291) = .21$, p = .644, $\eta^2 = .00$]). This provides some evidence that attrition was essentially random.

Efficacy manipulation. The experimental manipulation of self-efficacy was tested using a simple regression predicting the number of seconds participants said it should take them to "nail" (click on, or hit) a board from the board size. If the efficacy manipulation worked, they should feel it takes shorter time to hit the larger boards, represented by a negative slope. To test this, responses of seconds from 1-10 coded were coded as such, while responses of 10+ seconds were coded as 11 (this gives higher number than 10 without severely skewing slope with a higher number). Boards were coded 0 as smallest, through 5 as largest here and in all such analyses below, making the intercept represent the smallest board and lowest level of efficacy. All available responses were utilized. A significant negative slope was found ($b = -.79$, $t(1900) = 138.71$, $p < .001$), and board size accounted for a significant amount of variance in time estimated ($R^2 = .32$, $F(1, 1900) = 911.52$, $p < .001$). This supports the conclusion that the within-person manipulation of efficacy was effective.

Goal orientation manipulation. To test for the effectiveness of the goal orientation manipulation, a series of analyses were conducted to test for significant effects on the goal orientation questionnaires collected in the post-task phase. Initially, a MANOVA was completed testing for significant differences between the conditions on participant's stated orientations, and no significant differences between the orientations were found for any of the three orientation scales (learning [$F(2, 308) = 1.76$, $p = .175$, $\eta^2 = .01$], approach [$F(2, 308) = 2.03$, $p = .133$, $\eta^2 = .01$], avoid [$F(2, 308) = 1.01$, $p = .366$, $\eta^2 = .01$]). To further test for an effect of the manipulation on reported goal orientation, a MANCOVA was completed utilizing all participants who could be matched with a pre-survey and differences on the post-survey between the conditions were tested for while controlling for pre-survey responses. Descriptive statistics for the matched pre- and post-survey measures of goal orientation can be found in Table A3. This also found no significant effect of condition (learning [$F(2, 258) = 1.26$, $p = .285$, $\eta^2 = .01$], approach [$F(2, 258) = .25$, $p = .776$, $\eta^2 = .00$], avoid [$F(2, 258) = .41$, $p = .665$, $\eta^2 = .00$]). Thus, the manipulations did not have an apparent effect on self-reports of goal orientations.

Behavioral manipulation checks. Despite the lack of evidence for clear effects of the manipulations on self-reports of goal orientation, the manipulations may have impacted how individuals behaved in the task environment. To explore this possibility, a series of basic comparisons were made between the conditions to check for statistical differences. The tests are further detailed in Appendix B, but at least two differences of interest between the conditions were found. First, there were statistical differences in how frequently individuals engaged with some of the board sizes depending on their condition. Second, learning individuals tended to play more rounds per trial than the other two conditions, and avoid the least. Both findings point to potentially interesting differences between the conditions in the task world because differences in engagement rates are of primary interest in this study. In addition, the willingness to play more rounds by learning individuals is arguably a better measure of true task engagement than any other measures in this study because doing so indicates a greater sacrifice of personal time to play the task so deeply. Given the potential important behavioral differences between the conditions, it was decided to continue with hypothesis testing.

In-task Descriptive Statistics

To provide information on how participants interacted with the task overall, and by condition over time, a series of descriptive statistics have been reported in Tables 3-9. These report stated self-efficacy prior to each trial, stated goals prior to each trial, rounds attempted in each trial, points earned on each trial, engagement rates for each board size, and resources allocated for each board size, respectively. Each are broken down by condition and trial, or by board size, as is fitting.

Hypothesis Testing

Prerequisite 1. Prerequisite 1 stated "There will be a positive relationship between within-person efficacy and task engagement."

Following the method used to test the original discontinuous model of self-efficacy (Vancouver et al, 2008), Hierarchical Linear Modeling (Bryk & Raudenbush, 1992) was utilized to account for the nesting of data in this study of repeated observations within individuals. This modeling approach is utilized for all regression analyses reported here unless otherwise noted. To test for differences in engagement rates by level of within-person efficacy, a logistic regression with a Bernoulli distributed outcome (engage or not engage) was specified, with board size (representing manipulated efficacy, coded 0-5) entered as a fixed predictor, creating an equation predicting the log likelihood of engaging in a presented board size. This can be expressed mathematically as:

$$\text{Level 1: Prob(direction} = 1|\pi) = \varphi$$

$$\text{Log}\left[\frac{\varphi}{1-\varphi}\right] = \beta_0 + \beta_1(\text{board size})$$

$$\text{Level 2: } \beta_0 = \gamma_{00} + R_0$$

$$\beta_1 = \gamma_{10} + R_1$$

To estimate the model, all available observations (199,609) within individuals (312) were utilized. All models here were estimated in the open-source statistical program R. Logistic regressions were estimated using the glmer function in the lem4 package (Bates, Maechler, Bolker, & Walker, 2015). This returns an intercept indicating the average likelihood of engagement at the lowest level of efficacy (smallest board size), and a slope indicating the rate of change in likelihood of engagement for every one-unit increase in efficacy (every one-size increase in board).

Initially, a random intercepts only model was estimated. A negative intercept was found (b_0 = -2.57, SE = .16, z = -15.78, p < .001), and a positive slope of efficacy on likelihood of engagement (b_1 = 1.40, SE = .01, z = 209.33, p < .001). Nagelkerke's pseudo R^2 was calculated using the rcompanion package to obtain an estimate of variance accounted for by the model, R^2 = .56. Next, a model allowing for both random intercepts and slopes for board-size was estimated. This model also found a negative intercept (b_0 = -3.16, SE = .28, z = -11.45, p < .001) and a positive slope (b_1 = 1.30, SE = .06, z = 22.64, p < .001), R^2 = .62, ΔR^2 = .06 (change in R^2 represent the extra variance accounted for by the new model over the baseline model on which the new model was built). This random intercepts and slopes model fit significantly better than the random intercepts only model (χ^2 = 13370, DF = 2, p < .001) and is therefore retained. Pre-requisite 1 was therefore supported.

All future modeling in the paper follows a similar trajectory, but all models are not necessarily reported. All hypotheses were initially tested using a random intercepts only model, then a random intercepts and slopes model, with the better fitting model being the final retained and reported model. Whenever possible, models were nested within each other to allow for direct comparison of fit, only models which fit significantly better than their baseline models were taken as evidence of an existing effect. In this case, the random intercepts and slopes model for engagement over efficacy becomes the baseline model upon which all moderations are built.

Prerequisite 2. Prerequisite 2 stated "There will be a negative relationship between the amount of resources allocated to a task and within-person self-efficacy."

To test the resource allocation side of the model, standard hierarchical linear modeling approaches were utilized. Here, only the observations where participants allocated *any* time (instead of passing) were included in the models. The number of seconds allocated (resource allocation) was again predicted from within-person efficacy (board size, coded 0-5). This model can be expressed mathematically as:

$$\text{Level 1: Seconds Allocated} = b_0 + b_1(\text{board size})$$

$$\text{Level 2: } b_0 = \gamma_{00} + R_0$$

$$b_1 = \gamma_{10} + R_1$$

All observations that met the inclusion criteria were utilized (80,042) within individuals (312). Here, a random intercepts and slopes model found a significant negative relationship between within-person efficacy and seconds allocated (resource allocation) (b_0 = 7.76, SE = .15, DF = 79898, t = 50.09, p < .001; b_1 = -.28, SE = .04, DF = 79898, t = -8.05, p < .001, R^2 = .09). Pseudo R^2 for resource allocation models were computed using the r2beta function, which computes the generalized R^2 from Jaeger, Edwards, Das & Sen (2017). Pre-requisite 2 was also supported. This model becomes the baseline model from which to test all moderators of resource allocation below.

Hypothesis 1. Hypothesis 1 stated "Goal orientations should moderate the relationship between within-person efficacy and task engagement such that learning/learning oriented participants show the most engagement and performance avoid participants the least."

To test for a moderation of the likelihood of engagement over self-efficacy by goal orientation, goal orientation condition was entered into the model supported in pre-requisite 1 as a conditional predictor. The estimated parameters for this model can be found in Table A10. This model fits significantly better than the baseline model (df = 2, χ^2 = 8.53, p = .014, ΔR^2 = .00). To understand the possible moderation, the effect was broken down by dummy coding for each condition to estimate the parameters for each condition compared to the others. The resultant models can be found in Table A11. A graphic representation of the baseline model and models for each of the goal orientations can be found in Figure B2. An examination of the results displayed here show that there are no significant differences in parameters between the conditions, despite the model accounting for goal orientation fitting significantly better than baseline. Therefore, Hypothesis 1 is not supported.

Ad hoc test for changes in engagement model over time. A primary interest of this study was to understand the development of the within-person model of efficacy over time, though no hypotheses regarding time trends were put forward. To test for model changes in the likelihood of engagement over time, as in the testing of Hypothesis 1, time, represented by trial number coded 0-8, was entered as a conditional predictor of engagement in the baseline model supported in Pre-requisite 1. Details of this test can be found in Appendix B, but a significant effect of time was found and the model accounting for time fit better than the baseline model. This effect was also broken down using dummy coding for each trial. This showed that over time the likelihood of engagement changed such that in the first four to five trials the likelihood of engaging at low levels of efficacy steadily declined, while it remained high at high levels of efficacy. Then, in later rounds, the likelihood of engagement at low levels of efficacy began to increase, while still maintaining engagement at high levels of efficacy as before. In addition, goal orientation condition was added as a second conditional predictor to create a three-way interaction between condition, time, and within-person efficacy predicting likelihood of engagement. While the model fit significantly better than the model only accounting for time, the differences between conditions did not appear substantively meaningful as all conditions follow the same general pattern.

Hypothesis 2. Hypothesis 2 stated "Goal orientations should moderate the negative slope between within-person efficacy and Resource Allocation (seconds allocated) such that learning and performance approach are similar but performance avoid is more negative."

The model supported from pre-requisite 2 was used as a baseline and goal orientation condition was entered as a conditional predictor of resource allocation. This model fits significantly better than the baseline model (df = 2, *L* ratio = 14.60, $p < .001$, $R^2 = .13$, $\Delta R^2 = .04$), and overall parameters for this model can be found in Table A12. This significant effect was broken down further using dummy coding for each condition, the resulting models for each condition are in Table A13. In addition, the models have been displayed graphically in Figure B3. This shows that while there is not an overall intercept difference between the conditions, the significant interaction shows that learning individuals tend to invest the most resources at low levels of efficacy and then reduce their resource allocation (seconds allocated) at the fastest rate as efficacy increases, while performance avoid tends to invest about the same level of resources at all levels of efficacy, and performance approach invests about the same number of resources as avoid at low levels of efficacy reduces resource allocation (seconds allocated) instead of maintaining it as efficacy increases. With this finding, Hypothesis 2 is not supported, however, the significant interaction is retained.

Ad hoc test for changes in Resource Allocation (seconds allocated) over time. As with the engagement side of the model, the resource allocation half of the model was tested for possible changes over time, and for a three-way interaction with goal orientation. These models are explicated further in Appendix B. These models found a significant effect of time on resource allocation, as well as a significant interaction with condition and were broken down using dummy coding. The general results suggest that resource allocation (seconds allocated) changes over time such that the negative slope with efficacy disappears and the intercept lowers in the early trials, and the negative slope gradually returns in the later rounds. Between conditions, the primary difference appears to be that even though all three conditions even out their resource allocation (seconds allocated) instead of conserving resources at high levels of efficacy in the early trials, learning and approach both get their negative slopes of resource allocation (seconds allocated) back by the mid trials, but avoid stays flat and does not return to the negative slope until the final trials.

Hypothesis 3. Hypothesis 3 stated "Across all time points, learning orientation will be associated with the greatest efficacy, avoid the least, and approach in between."

To test this hypothesis, a repeated measures ANOVA was completed for all available individuals across all nine measurement episodes of stated self-efficacy for the task. This analysis found no significant differences between the conditions ($F(2, 280) = .23$, $p = .796$, $\eta^2 = .00$). However, power was lost due to the default listwise deletion procedure used for this test in SPSS, where all individuals who missed even a single measurement episode were eliminated from the analysis. An exploration of the data shows that only 2.3% of data points were missing from these measures, but this resulted in a 9% loss of the final sample. To combat this, a multiple imputation procedure was applied to estimate the missing data points. Multiple imputation is generally considered the most unbiased estimate of missing data, and is better able to account for the uncertainty of the missing data when calculating standard errors (Rubin, 1987; Furlow & Beretvas, 2005). To do this, five data sets were estimated using SPSS's multiple imputation procedure, which uses a Markov Chain Monte-Carlo (MCMC) estimation procedure where missing values are estimated using all available information related to the data point in an iterative process where values are estimated once, then those values become the starting point for repeated re-estimations of the missing values. This process is repeated 1000 times, and every 200th estimation is saved, resulting in five data sets being utilized for analysis. This procedure follows established guidelines which show that possible bias is nearly eliminated once five imputed data sets are analyzed (Pigott, 2001). Once the data sets are analyzed, resulting statistics are pooled to obtain the final result. However, this process also failed to find a significant difference ($F(2, 309) = .11$, $p = .896$, $\eta^2 = .001$). Thus, Hypothesis 3 is not supported.

Hypothesis 4. Hypothesis 4 stated "Initially, goals for learning should be higher than performance approach or avoid, with avoid being the lowest."

Here, a one-way ANOVA was completed comparing the means of self-set goals on the first trial only between the three conditions. A significant difference was found ($F(2, 309) = 3.44$, $p = .033$). This significant finding was broken down using a post-hoc Tukey test, which found that the primary difference among the conditions was between learning and avoid orientations (dif = 11.40, SE = 4.38, $p = .026$, $d = .36$). Means for first trial goals by condition can be found in Table A5, and a graphic representation of goal means on the first trial can be found in Figure B4. Hypothesis 4 was not supported because the rank order of the conditions was reverse of what was expected and the avoid condition instead set the highest initial goals.

Hypothesis 5. Hypothesis 5 stated "Over time, the difference in goal level will increase such that learning goal oriented individuals will increase their goals more than performance approach, and performance avoid will show the lowest increases."

To test this hypothesis, a Hierarchical Linear Growth Model, observations within individuals, was utilized. Trial, coded 0-8 so that the intercept would represent the first trial, was entered as a fixed factor predictor of self-set goal level. A random intercepts and slopes model found a significant negative effect of time (trial) on self-set goal level (b_0 = 25.73, SE = .96, t = 26.93, DF = 2471, p < .001; b_1 = -1.84, SE = .18, t = -10.35, DF = 2471, p < .001, R^2 = .09). To test for a possible moderating effect of goal orientation, experimental condition was then entered as a conditional predictor of self-set goals. The model parameters showed a potential significant interaction between goal orientation and time (trial) (b_3 = -.50, SE = .22, t = -2.28, DF = 2469, p = .023, R^2 = .09), but this model did not fit significantly better than the unmoderated version (DF dif = 2, L ratio = 5.22, p = .074, ΔR^2 = .00) so was not retained. Therefore, Hypothesis 5 was not supported because there was not a significant difference in the way goals changed over time between goal orientation conditions. Moreover, goal levels decreased over time instead of increasing.

Hypothesis 6. Hypothesis 6 "Stated self-efficacy prior to a trial will be positively related to performance on that trial."

Prior to testing this hypothesis, both stated self-efficacy and performance on each trial were standardized to create a fully standardized model whose coefficients could be interpreted as an effect size. Both stated-efficacy and performance were then tested for stationarity using the tseries package in R. This package tests for both mean and trend stationary using a Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski, Phillis, Schmidt, & Shin, 1992). This test found that stated-efficacy (KPSS Level = 0.03, p > .100) and performance (KPSS Level = 0.18, p > .100) were both mean stationary, but that they both may be stationary about some trend (efficacy KPSS Trend = 0.03, p > .100; performance KPSS Trend = 0.04, p > .100). Thus, to remove any possible spurious relationship due to mutual change over time (Yule, 1926), both time series were detrended by fitting a regression equation with time as a predictor and the residuals were saved for analysis. Hierarchical Linear Modeling was then utilized, observations within individuals, with stated-efficacy entered as a fixed factor predictor of performance. This analysis found a significant positive relationship ($\beta_1 = .26$, SE = .02, $t = 11.11$, DF = 2446, $p < .001$). This positive relationship supports Hypothesis 6.

Hypothesis 7. Hypothesis 7 stated "The relationship between prior attempt performance and subsequent attempt efficacy will be positive across all time points."

Building from the variables created while testing Hypothesis 6, a lagged variable of stated-efficacy was created. This allowed for the alignment of performance on every trial x with every stated-efficacy on trial x + 1. As before, both performance and efficacy were in standardized form. In Hierarchical Linear Modeling, observations within individuals, performance on trial x was entered as a fixed factor predictor of stated-efficacy on trial x + 1. A positive relationship was observed ($\beta_1 = .25$, SE = .01, $t = 19.19$, DF = 2108, $p < .001$). Thus, Hypothesis 7 was supported.

Hypothesis 8. Hypothesis 8 stated "Changes in performance across time points will be positively related to changes in efficacy across the same time points."

To test this hypothesis, change scores for both performance and stated-self efficacy from all trial x to trial x + 1 were created. These variables were also standardized as above, and analyzed using Hierarchical Linear Modeling, observations within individuals, with changes in performance entered as a fixed factor predictor of changes in stated-efficacy. A random intercepts only model found no significant relationship ($\beta_1 = -.004$, SE = .02, $t = -.18$, DF = 2109, $p = .856$). Thus, Hypothesis 8 was not supported.

Hypothesis 9. Hypothesis 9 stated "Stated efficacy on a task attempt will be positively related to self-set goals on that task attempt."

Taking the same approach as for testing Hypothesis 6, self-set goals were standardized and tested for stationarity. Self-set goals were also found to be mean stationary (KPSS Level = 0.19, $p > .100$) but potentially not trend stationary (KPSS Trend = .00, $p > .100$). A regression with time as predictor was fit to goal level and residuals were saved for analysis. Using Hierarchical Linear Modeling, observations within individuals, self-stated efficacy was entered as a fixed factor predictor of self-set goals, and a positive relationship was found ($\beta_1 = .33$, SE = .02, $t = 14.49$, DF = 2452, $p < .001$). This supports Hypothesis 9.

Hypothesis 10. Hypothesis 10 stated "Self-set goal level on each task attempt should be positively related to performance on that task attempt."

To test this hypothesis, the same procedure was followed as in Hypotheses 6 and 9. Here, self-set goal level was entered as a fixed factor predictor of performance on the same trial. A random intercepts and slopes model found a small positive relationship ($\beta_1 = .05$, SE = .02, $t = 2.85$, DF = 2446, $p = .004$). Despite the small effect size, Hypothesis 10 is supported.

Hypothesis 11. Hypothesis 11 stated "The effect of self-set goal level on performance should be partially mediated by the effect of goal level on effort (as measured by Resource Allocation (seconds allocated))."

To test this hypothesis, the average number of seconds allocated on all decisions to engage were calculated at the trial level for all individuals, these were also standardized. The logic here being that the more time devoted to attempts, the harder the participant is working and the higher their motivation. These were then matched with the trial level self-set goals and performance data. The supported model from Hypothesis 10 was modified to test for a mediating role of effort. To that model, effort (as average resource allocation) was added as a second predictor, but initially held to 0. This model confirmed the relationship between goals and performance to be positive (β_1 = .05, SE = .02, t = 2.87, DF = 2407, p = .004). Effort was then allowed to be freely estimated in the model. In the newly estimated model, the relationship between goals and performance dropped to non-significance (β_1 = .02, SE = .01, t = 2.78, DF = 2405, p = .100), while the newly estimated relationship between effort and performance was substantially negative (β_2 = -1.83, SE = .05, t = -37.49, DF = 2405, p < .001). This model also fit significantly better than the model where effort was held to 0 (df = 1, L ratio = 1097.86, p < .001). An additional model shows a small negative relationship exists between goals and effort (β_1 = -.01, SE = .01, t = -2.18, DF = 2408, p = .030). This set of models is displayed visually in Figure B7. Hypothesis 11 is not supported because the effect of effort, as defined here, was negative on performance instead of positive.

Hypothesis 12. Hypothesis 12 stated "Initial performance for learning and performance approach should be about equal or performance approach higher than learning, but both higher than performance avoid."

As with Hypothesis 4, a one-way ANOVA comparing points earned on only the first trial between the three goal orientation conditions was completed. A significant difference was indicated (F(2, 309) = 4.82, p = .009). A set of post-hoc Tukey tests were used to follow up this finding. They found there was no significant difference between learning and avoid (dif = .27, SE = .73, p = .932, d = .05), but that approach was significantly higher than both learning (dif = 1.76, SE = .72, p = .040, d = .33), and avoid (dif = 2.03, SE = .71, p = .013, d = .39). Hypothesis 12 was therefore partially supported in that approach orientation was indeed the highest initial scoring condition, but the expected difference between learning and avoid orientations was not found.

Hypotheses 13 and 21. Hypotheses 13 and 21 stated "Learning orientation will result in higher levels of performance over time than performance approach, and performance approach higher levels of performance than avoid."[1]

To test for differences in the development of performance over time between the goal orientation conditions, a moderated Hierarchical Linear Growth Model (observations within individuals) was estimated. First, trial, coded 0-8, was entered as a fixed factor predictor of performance. This showed there was no significant relationship between time (trial) and performance level (b_0 = 14.96, SE = .37, t = 40.23, DF = 2471, p < .001, b_1 = .07, SE = .08, t = .90, DF = 2471, p = .369, R^2 = .00). Goal orientation condition was then entered into this model as a conditional predictor of performance. No significant effects were found for condition (b_1 = -.45, SE = .46, t = -.98, DF = 2469, p = .326), or trial (b_2 = .13, SE = .20, t = .65, DF = 2469, p = .513); and no significant interaction between condition and trial was found either (b_3 = -.03, SE = .09, t = -.35, DF = 2469, p = .729, R^2 = .01). This moderated model also did not fit significantly better than the model predicting performance from time alone (df = 2, L ratio = 1.71, p = .424). Additionally, a repeated measures ANOVA showed no significant differences on the number of points earned across the 9 trials between the three orientation conditions (F(2, 279) = 3.00, p = .052). Therefore, there was no significant difference in performance between the conditions across the study, and there was not an interaction such that any condition improved more over time than another. Thus, Hypotheses 13 and 21 were not supported.

Hypothesis 14. Hypothesis 14 stated "Performance (as task score) on one task attempt will be positively related to performance on subsequent attempts."

[1] Hypotheses 13 and 21, though worded slightly differently, were intended to ask the same question and make the same prediction. This was not noticed until after the fact, but are now collapsed together for simplicity.

As with other lagged hypotheses above, a lagged variable representing performance at trial x + 1 was created for every trial x. Performance was completed standardized prior to analysis using Hierarchical Linear Modeling, observations within individuals. A significant positive relationship was found (β_1 = .55, SE = .02, t = 32.32, DF = 2108, p < .001). Thus, Hypothesis 14 was supported.

Hypothesis 15. Hypothesis 15 stated "Failure to meet one's goals on previous attempts will be associated with a lower level of task engagement across all difficulty levels on subsequent attempts, but with higher levels of Resource Allocation (seconds allocated) (indicating less willingness to attempt hard tasks but greater effort at completing the ones they are engaged in)."

Due to the nature of this hypothesis and the data matrix resulting from this study, this hypothesis was not able to be directly tested in the way originally planned that would create purely statistical results. However, it was still possible to explore using a combination of the predominant modeling approach used for other hypotheses in this study and visual/logical comparison. First, goal success or failure was defined as meeting your self-set goal on that trial or not, and was coded 1 for yes, and 0 for no. Then, two series of models were calculated. The first model showed the engagement rates for trial x (equivalent to the model in pre-requisite 1), with goal success entered into the equation as a conditional predictor. This conditional model fit significantly better than the baseline model (df = 3, χ^2 = 2046.7, p<.001, ΔR^2 = .04).

Next, a model for success on the previous trial (trial x – 1) was fit. This creates a model that is not nested under the same trial success model, so is not directly comparable statistically. Due to the loss of the first trial with this approach (because there is no previous trial to have succeeded or failed on), this model is based on 183,207 observations. A model allowing for the effect of previous trial success or failure fit significantly better than a model where that effect was held to 0 (df = 3, χ^2 =674.86, p<.001, ΔR^2 = .01). Model parameters for both same and previous trial success can be found in Table A14. These do not need to be broken down by dummy coding because the single moderation coded 0 and 1 automatically creates an equation where both models may be calculated. Graphic depictions can be found in Figure B6. These models show that individuals who succeed tend to be engaging less than those who are failing at low levels of efficacy. And we can observe that, regardless of whether one succeeded or failed on the previous trial, engagement at low levels of efficacy decreases, but remains comparable at high levels of efficacy. This lends some support to the first part of this hypothesis.

The resource allocation (seconds allocated) side of our discontinuous model was then analyzed in a similar way to assess differences in models for goal success and failure. A model for same trial success fit significantly better than the baseline model from prerequisite 2 (df = 3, L ratio = 793.99, p<.001, R^2 = .09, ΔR^2 = .00). In addition, the model for previous trial success also fit better than its respective baseline (df = 3, L ratio = 1227.05, p<.001, R^2 = .09, ΔR^2 = .00), however, losing the first trial, this model is based on 70,719 observations. Parameters for these models can be found in Table A15. Figures comparing each can be found in Figure B7.

Differences in the overall models for the resource allocation models are minor and difficult to interpret. Essentially, all models show same Resource Allocation (seconds allocated) at high levels of efficacy. Those who are successful on a trial tend to invest more at low levels of efficacy on the next trial, but generally fewer than people who are failing. Those who fail, instead of investing more resources at low levels of efficacy, they invest fewer on the next trial, but this difference is small. This does not support the second half of the hypothesis.

Hypothesis 16. Hypothesis 16 stated "The effect of failure on the nature of self-efficacy and its related Resource Allocation (seconds allocated) will be moderated such that learning oriented individuals will show the smallest decreases in task engagement, and avoid will show the greatest."

Hypothesis 17. Hypothesis 17 stated "Goal success will have an effect on task engagement moderated by goal orientations such that learning individuals will maintain or increase their engagement, while performance avoid will lower theirs."

Building from the models retaining in testing Hypothesis 15, goal orientation was added as a conditional predictor to the prediction equation dummy coded for goal success. This resulted in a model testing for a significant three-way interaction between goal orientation, goal success and failure, and within-person efficacy (board size) predicting likelihood of engagement. Both the model for current trial success (df = 5, χ^2 =2218.8, p < .001, ΔR^2 = .00), and the model for previous trial success (df = 5, χ^2 =53.09, p<.001, ΔR^2 = .00) fit significantly better accounting for goal orientation than goal success alone, although neither increase the amount of variance explained by a substantial amount. Both the current and previous trial models were broken down using dummy coding for each goal orientation. Parameters for the overall and orientation models can be found in Table A16, and a graphic representation of these models can be found in Figure B8. All orientations from one trial to the next appear to shift from engagement at low levels of efficacy to high, whether they succeed or fail, and do so more when they previously failed. The exact amount and nature varies slightly by orientation, but these appear largely meaningless. The biggest difference between the orientations appears to be that avoid individuals who fail at their own goals engage to an especially high degree at low levels of efficacy. Hypothesis 17 is not supported because learning individuals do not increase their engagement. Hypothesis 16 is not supported because learning individuals do not appear to decrease their engagement following failure any more than the other conditions.

Ad hoc test of effect of success and failure on Resource Allocation (seconds allocated).

As with the discussion above under Hypotheses 16 and 17, the supported models from Hypothesis 15 for resource allocation (seconds allocated) by goal success were further moderated by adding a goal orientation as a conditional predictor. The models for both same trial success (df = 5, *L* ratio = 447.27, $p < .001$, $\Delta R^2 = .04$) and previous trial success (df = 5, *L* ratio = 447.27, $p < .001$, $\Delta R^2 = .04$) fit significantly better when accounting for goal orientation condition. These also account for noticeably more variance, whereas they did not for the likelihood of engagement models. These models were then broken down using dummy coding for orientation condition, the parameters for these models can be found in Table A17, and a graphic representation in Figure B9. These models show that, when failing, all orientations appear to decrease their resource allocation (seconds allocated) at low levels of efficacy, and increase it when they succeed. Resource allocation (seconds allocated) at high levels of efficacy does not appear to be much affected. The most interesting finding is the near lack of a negative slope for avoid individuals when they are succeeding at their goals, compared to a slight negative one when they are failing.

Hypothesis 18. Hypothesis 18 stated "Efficacy should moderate the effect of performance on goals such that individuals with higher efficacy will show smaller negative changes in goals following failures, and larger positive changes in goals following successes."

To test this hypothesis, change scores for goals from every trial x to trial x + 1 were calculated. Hierarchical Linear Modeling was utilized, observations (the trial level) within individuals. Goal success, coded 1 for yes, 0 for no, was initially entered as the only predictor of goal level change as a fixed factor. This model indicated a general negative change in goal level from one trial to the next (b_0 = -11.06, SE = .47, t = -23.53, DF = 2136, p < .001), but a significant positive effect of meeting one's goal (b_1 = 13.28, SE = .60, t = 22.02, DF = 2136, p < .001, R^2 = .17). This indicates that on average goals decrease from one trial to the next, but they actually increase a small amount following goal success. To test for an effect of efficacy, self-stated efficacy was added to the model as a conditional predictor. Self-stated efficacy at trial x + 1 was utilized as it was measured more proximally to the goal judgement which determines the amount of goal change. This model did fit significantly better (DF = 3, L ratio = 346.43, p < .001, ΔR^2 = .00) though did not substantially increase variance explained. This model again showed a general negative change in goal level from one trial to the next (b_0 = -10.54, SE = .86, t = -12.29, DF = 2114, p < .001), and a positive effect of goal success (b_2 = 12.02, SE = 1.03, t = 11.67, DF = 2114, p < .001), but no main effect of efficacy (b_1 = .02, SE = .02, t = .96, DF = 2114, p = .338), or interaction between efficacy and goal success (b_3 = .01, SE = .02, t = .40, DF = 2114, p = .689). Thus, even though goals do significantly change following success or failure in the expected directions, and although the moderated model fits significantly better than the non-moderated model, there are no significant effects in that model based on their reported level of efficacy, so the hypothesis not supported.

Hypothesis 19. Hypothesis 19 stated "Individuals will gain efficacy following goal success, and lose efficacy following failure. The amount lost following failure will be moderated by goal orientation such that learning individuals will show smaller losses."

Much as with hypothesis 18, a change score in self-stated efficacy from every trial x to trial x + 1 was calculated. An initial model predicting change in efficacy from goal success on previous trial was estimated. A random intercepts only model found a negative general change in stated-efficacy (b_0 = -5.57, SE = .70, t = -7.92, DF = 2111, p < .001) with a significant positive effect on efficacy by goal success (b_1 = 8.00, SE = .90, t = 8.87, DF = 2111, p < .001, R^2 = .03) indicating a negative change in efficacy following failures, and positive changes following success. Goal orientation condition was then added as a conditional predictor to this model. However, this model did not fit significantly better than the non-moderated model (DF = 2, *L* ratio = 4.32, p = .115) so was not retained. Thus, efficacy does increase following goal success, and decreases following goal failure. However, there is not a significant moderating effect of goal orientation, so the hypothesis is only partially supported.

Hypothesis 20. Hypothesis 20 stated "The self-regulation system will show greater stability over time."

To test this hypothesis correlation coefficients were computed from one trial to the next (trial 1 predicting 2, 2 predicting 3, etc.) for each of the primary self-regulatory variables collected at the trial level (goals, efficacy, performance). If the system became more stable a regression of time on these should show a positive slope. The model was completely standardized prior to estimation. Efficacy indeed showed a significant positive slope (β_1 = .77, t = 2.95, p = .026), but self-set goals (β_1 = .60, t = 1.85, p = .114) and performance (β_1 = -.37, t = -.99, p = .361) did not. This hypothesis is partially supported, efficacy does get more stable over time from trial to trial but neither goals or performance do.

Hypothesis 22. Hypothesis 22 stated "Efficacy will decrease over time for all goal orientations."

To test this hypothesis, the same general procedure was used as to test Hypothesis 13/21. The first Hierarchical Linear Growth Model (observations within individuals) found no significant relationship between time and efficacy (b_0 = 42.23, SE = 1.33, t = 31.70, DF = 2448, p < .001, b_1 = -.34, SE = .23, t = -1.48, DF = 2448, p = .140, R^2 = .00). Adding goal orientation to this model as a conditional predictor of efficacy also did not significantly improve the model (DF dif = 2, L ratio = .91, p = .635, ΔR^2 = .00) so was not retained. Therefore, Hypothesis 22 was not supported.

Hypothesis 23. Hypothesis 23 stated "The relationship between efficacy and performance will be curvilinear over time such that it is initially positive, then turns null or negative. The amount of time it takes for that change will be moderated by goal orientation such that learning orientation takes the longest, and performance avoid the shortest."

Building from the model supported in Hypothesis 6, trial (coded 0 to 8) was entered as a conditional predictor of performance. This model fit significantly better than the baseline model (df = 2, L ratio = 10.05, p = .007), but found a positive interaction between time and stated self-efficacy (β_3 = .02, SE = .01, t = 2.98, DF = 2444, p = .003). This positive interaction between trial and efficacy indicates that the relationship between efficacy and performance becomes more positive over time on average, therefore never turns null or negative. Thus, Hypothesis 23 is not supported.

Discussion

As individuals engage in tasks, they do so strategically to meet a set of goals, which may be set by themselves or imposed upon them in some way. Psychology has long studied this goal directed behavior and has developed several theories for understanding it. Two of the most popular have been Self-Regulation Theory (consisting of Social Cognitive Theory and Control Theory; Vancouver & Day, 2005), and Goal Orientations (Elliot, 1999). These two theories have explained much about how individuals engage in tasks to meet their goals. However, work on them is not complete. First, within self-regulation, there is disagreement as to the nature of the central construct of self-efficacy. Self-efficacy is generally viewed as a universally positive construct, but recent work has shown that it can have negative effects in some instances (e.g., Vancouver et al, 2001). Further work is needed to understand the nature of self-efficacy, especially at the within-person level, and the boundary conditions of previous findings. Second, Goal Orientations and Self-Regulation theories need further conceptual and empirical integration. Deshon and Gillespie (2005) theoretically integrated the two theories when they conceptualized goal orientations as mid-level self-regulatory systems, just above the task level. While this implies that goal orientations then effect the operation of the lower, task-level regulatory system, very little is known about how they do so. Third, little is known about the regulatory mechanisms through which goal orientations may operate to produce the behavioral patterns we see arising from them. Fourth, none of the research on the within-person nature of self-efficacy (Vancouver et al, 2008; Sun et al, 2014) examines the development of the effects of efficacy over time. This study sought to address these gaps by examining how goal orientations moderate the nature of within-person efficacy and related regulatory constructs, and how the within-person model of efficacy develops over time. Unfortunately, some problems with the study ultimately limit the ability to fully address all the original research questions. However, there are a handful of interesting findings which deserve further discussion and research.

Findings and Interpretation

Pre-Requisites 1 and 2. Prior to testing any of the hypotheses of interest, it was imperative that we could replicate the original model of Vancouver and colleagues (2008). The two pre-requisite findings were that of a positive slope between manipulated, within-person self-efficacy and the likelihood of engaging in the task, as well as a negative slope between manipulated self-efficacy and resource allocation (seconds allocated to tasks). Both were supported, replicating the original findings. It is notable that variance accounted for by efficacy was substantially lower than in the original study, especially for the resource allocation side of the model. There are at least three potential reasons for this. First, the much larger sample size utilized in the present study than in the original should provide a closer point estimate of the true effect, and the original finding may have been inflated. Second, the extension of this data collection over many more time points appears to dilute the stronger negative slope in resource allocation that occurs during the first trials, a finding shown in Appendix B. With fewer trials in the original studies, the originally strong relationship in the first trial has less data collected afterwards diluting the effect. These first two points together may call into question the robustness of the entire within-person model of efficacy, at least in it being a substantial effect. Instead, the negative slope of resource allocation over efficacy may be highly susceptible to effects of time and task environment. Third, the general greater complexity of this study compared to the original with verbal and incentive-based manipulations, and the greater time frame, may serve to dilute the effect of efficacy on resource allocation by taking variance away from the direct manipulation of efficacy.

Hypothesis 1. The first hypothesis represented one of the primary interests of this study, and predicted that the effect of within-person efficacy on the likelihood of task engagement would be moderated by goal orientation with learning individuals most likely to engage in the task, and avoid individuals the least. This prediction was not supported. The lack of a finding here does not fit with established research showing learning orientation is positively related to task engagement, and avoid orientation negatively (e.g., Elliot & Harackiewicz, 1996). However, the failure to find a significant difference between conditions is more likely due to ineffectiveness of the goal orientation manipulations to produce strong between-person differences. This was seen in the failure of the direct manipulation check on their stated orientations in the post-task survey.

Hypothesis 2. The second primary hypothesis predicted that resource allocation would be moderated by goal orientation, such that avoid individuals would show the most negative slope while approach and learning individuals would not differ. This hypothesis was not supported. However, a significant finding arose such that avoid individuals had the least negative slope and learning individuals the most. While this finding does not fit with the original predictions and model proposed, it does fit with a deeper interpretation of the Vancouver et al (2008) model as being adaptive. The new logic proposed is that if resource conservation at high levels of efficacy is an adaptive response, the goal orientations seen as more adaptive should show a greater tendency to conserve those resources. In this study, this occurs as learning oriented participants engage in a greater amount of resource conservation as efficacy increases than their counterparts, seen in their greater negative slope of efficacy on resource allocation. In addition, the orientation generally seen as least adaptive, avoid orientation, should then be the least adaptive in this model. This can be seen in the near absence of a slope between efficacy and resource allocation for avoid oriented individuals, indicating they are not drastically conserving their resources as efficacy increases. One potential explanation for why avoid individuals do not conserve resources to as great an extent as other orientations as efficacy increases is that they are mitigating their chance of failure to the greatest extent possible at all levels of efficacy, this tendency could lie in their greater general fear of failure than other orientations (Elliot, 1999). Whatever the explanation, the greater resource conservation among learning individuals, and lower conservation among avoid individuals at high levels of efficacy helps to explicate the underlying mechanisms that allow goal orientations to operate and lead to the general differences in success commonly seen between goal orientations. In this vein, learning individuals tend to be more successful because they waste fewer of their resources when they are sure of their own success while avoid individuals waste theirs. This allows learning individuals to channel available resources to tasks which need them for success, while avoid individuals do not.

Hypothesis 3. This hypothesis predicted that learning individuals would have the highest feelings of efficacy during the task, and avoid the lowest. This was predicted based on previous meta-analytic findings regarding the efficacy espoused by each orientation (Payne et al, 2007). However, this hypothesis was not supported as there were no significant differences between the conditions. The lack of a finding here is more likely due to the type and weakness of the goal orientation manipulation rather than evidence against the generalizability of previous findings.

Hypothesis 4. Our fourth hypothesis predicted that learning individuals would have the highest initial self-set goals, and avoid individuals the lowest. This hypothesis was not supported, and avoid individuals instead had the highest initial goals. This finding is opposite of what was expected from previous meta-analyses (Payne et al, 2007). It is unclear as to why avoid individuals would set high goals which would make goal accomplishment difficult for them, exposing them to failure (Elliot, 1999). It may be possible that learning individuals would set lower initial goals in a focus on learning over time instead of performing highly right away, but this was again unexpected.

Hypothesis 5. Here, it was predicted that goals would increase over time, and that they would increase the fastest for learning, and slowest for avoid oriented individuals. This prediction was not supported as there was no difference in goal level over time between orientations. Moreover, goals decreased over time instead of increasing. This does not fit with expectations based on SCT and the general expectation that individuals would raise their goals as they met previous ones to maintain their motivation (Bandura, 1991). Not raising goals automatically over time could be support in this instance for CT (Carver & Sheier, 1998) over SCT. However, the lack of a finding seems likely a result of an ongoing calibration by participants to the high difficulty level of the task, especially the difficulty of improving drastically.

Self-Regulatory Hypotheses. A set of proposed hypotheses were designed to place the within-person model of efficacy and this paradigm more firmly into the wider self-regulation theory. These hypotheses will be discussed as a set here and are out of strict numerical order.

Hypothesis 6. Here, it was predicted that stated self-efficacy prior to a trial would be positively related to performance on that trial. This hypothesis was supported.

Hypothesis 7. This hypothesis predicted a positive relationship between prior trial performance and stated self-efficacy on the following trial. This relationship was also supported.

Hypothesis 9. Hypothesis 9 predicted that stated efficacy on a trial would be positively related to self-set goals on that same trial. This was supported.

Hypothesis 10. This hypothesis stated that self-set goals on a trial would be positively related to performance on that trial. This relationship was also supported.

Hypothesis 14. This hypothesis predicted that performance on one trial would be positively related to performance on the following trial. This hypothesis was also supported.

Overall set of self-regulatory hypotheses. Taken together, these hypotheses show that the task used in this study operates as we would expect based on self-regulation theory (Bandura, 1991; Carver & Sheier, 1998), and as expected based on the Control Theories used to guide this research.

Hypothesis 8. This hypothesis was aimed at testing the existence of a performance-efficacy spiral (Lindsley et al, 1995). It stated that changes in performance across time would be positively related to changes in efficacy across the same time points. This prediction was not supported. The lack of a significant finding is not particularly surprising given the lack of strong evidence for the existence of spirals in the literature.

Hypothesis 11. This hypothesis predicted that the effect of self-set goal level on performance would be partially mediated by the effect of self-set goals on level of effort. With effort operationalized in this task strictly as amount of time devoted to task attempts, this hypothesis was not supported. Instead, there was a negative relationship between effort and performance. At first glance, this finding would contradict the well-established notion that performance is a function of ability and motivation or effort (Campbell, 2012). However, this contradictory finding is likely not a problem with the underlying theory. Instead, it is more likely a function of the way effort has been defined. Motivation, or effort, as defined in this task is problematic when thinking about how participants should really be going about trying to reach a performance goal. Playing many rounds with small amounts of seconds allocated is likely indicative of working very hard at the task and showing higher motivation, not lower as is assumed by the overall model. This points to a problem of the task when extrapolating the findings to the wider self-regulation world. However, if we rethink what effort means in this task, fewer seconds allocated per task attempt across the task likely indicates higher total effort because it then requires the participant to attempt more rounds and spend more of their own time in the study. If we think about effort in this way, a negative relationship between effort as defined in the task and performance would be expected and the present findings fit.

Hypothesis 12. This hypothesis predicted that performance for approach oriented individuals would initially be the highest, and avoid oriented individuals the lowest. This hypothesis was partially supported as approach orientation did perform significantly better than avoid orientation on the first trial. However, learning orientation was not significantly different from avoid. This finding points to the potential short-term advantage of an approach orientation. Avoid orientation is not usually expected to be beneficial, but in early attempts learning individuals may waste resources exploring the task and developing their skills. Instead, approach individuals start out attempting to perform highly, and initially better utilize their resources which gives them a performance advantage (e.g., Davis et al, 2007).

Hypotheses 13 and 21. Both hypotheses predicted that learning orientation would result in the highest performance over time, and avoid the lowest. This builds from the logic in hypothesis 12 that learning individuals would sacrifice early performance to learn the task over time, and that learning would result in higher performance. This prediction was not supported. Though this finding does not fit with the well-established benefits of learning orientation for performance over time (e.g., Pintrich, 2000), this is likely at least partially due to the difficulty in general task improvement in the paradigm used in this study. Learning individuals do not have much in the task to learn other than a better strategy, and it is not clear how much that better strategy impacts performance as defined by point accrual in this task.

Hypothesis 15. Here, it was predicted that failure on one trial would lead to lower rates of engagement, but higher levels of resource allocation on the following trial. This prediction was partially supported as those who fail on one trial engaged less often at lower levels of efficacy on the following trial. However, engagement was also reduced following success. In addition, following goal failure, participants reduced resource allocation, especially at low levels of efficacy. Given a rethinking of the strategy it takes to be successful in this task world, likely engaging only at high levels of efficacy and for short attempts, these changes make sense. Self-Regulation Theory (Bandura, 1991; Carver & Sheier, 1998) tells us individuals take their experience as feedback to adjust their strategy following a failure, which was the logic behind the original prediction. However, the strategy to be successful required participants to make changes different from those expected. So, it is likely that participants were using their experience as feedback and adjusting their strategies. It is interesting to note that even when succeeding individuals appear to engage slightly less at lower levels of efficacy on the next attempt, and those that failed still engage more on lower levels of efficacy than those who succeed. This difference may show that individuals who are failing at their own goals are especially miss-calibrated to the task and may be in effect over-extending themselves by engaging in attempts for which they have little hope of success.

Hypotheses 16 and 17. These hypotheses built on hypothesis 15 and predicted that the effects of goal failure and success on engagement and resource allocation would be moderated by goal orientation, such that learning individuals would show the smallest decrease in engagement, and avoid the greatest. On the other hand, success would lead learning individuals to increase engagement and avoid still lower theirs. These hypotheses were partially supported as all orientations lower their engagement following failure, and avoid individuals appear to have the largest change in engagement. However, they do not increase their engagements following success. While partially supported, the larger decrease in engagement for avoid individuals may be a function of them being very miss-calibrated to this task by engaging to a large extent at very low levels of efficacy. Following failure, their engagement simply comes to more closely resemble that of the other orientations, and is not substantially lower at that point as was implicitly expected. The possible over extension of avoid individuals to engage in low levels of efficacy when failing their self-set goals is particularly interesting. Their engagement in these levels of efficacy at all is contrary to expectations. However, considering a broader view of what it means to be adaptive in this task, it begins to make sense. This over extension appears to be especially maladaptive for success in the task given that the best strategy for success is likely to be complete non-engagement in low levels of efficacy, and we would expect avoid individuals to be the most maladaptive. In addition, even avoid individuals who are better calibrated to meeting their own goals are better adapted to the task in terms of their own engagement.

Ad hoc moderation of resource allocation by goal orientation and success and failure. Though no specific hypotheses were proposed regarding the resource allocation side of the model, these analyses were related to the propositions from hypothesis 16 and 17. These analyses found that all individuals tend to outlay more resources at low levels of efficacy when they have just succeeded on their personal goals, and fewer when they just failed. Within these analyses can be found the most interesting findings of this study. Specifically, we see that avoid individuals follow different patterns of resource allocation when they are succeeding or failing at meeting their personal goals. If conservation of resources at high levels of efficacy should be considered adaptive, we would expect that individuals would follow a highly adaptive form of the within-person model of efficacy when they are meeting their goals. This is the case for learning and performance approach individuals. However, for avoid individuals their pattern of resource allocation gets more *maladaptive* (in the logic of Vancouver et al, 2008), when they are succeeding *at their own* goals. That is, they do not strategically conserve their resources when they meet their own goals, even though they do when they are failing. This behavioral pattern will still likely result in lower general performance for avoid individuals because they may "waste" their resources from a standpoint of maximizing their performance. But, this distinction emphasizes the need to understand the difference between being adaptive in terms of externally imposed meanings of success, and adaptation in terms of what success means to that individual. When thought of in these terms, avoid oriented individuals may be mislabeled as being maladaptive. Instead, they may be better thought of as adaptive as well, but in a way different from what others may want them to be.

Hypothesis 18. Hypothesis 18 predicted that goal orientations would moderate the effects of goal success or failure on subsequent changes on self-set goal levels. This hypothesis was not supported as goal orientations did not account for more of an effect on changes in self-efficacy than goal success or failure alone, although goal success and failure did have the expected positive and negative effects on goals respectively. This finding fits with the expectations from self-regulation that performance on one task attempt should be positively related to goals on the next attempt (Locke & Latham, 1990), and is an extension of the direct linear relationship tested elsewhere in this study between performance as a count of points and self-set goals.

Hypothesis 19. This hypothesis predicted that goal orientations would moderate the effects of goal success and failure on changes in goal level. It was found that efficacy increases following goal success, and decreases following failures. However, there is not a significant moderating effect of goal orientation, so the hypothesis was only partially supported. It was expected that learning orientation would have a buffering effect such that they would experience smaller negative effects of goal failure (Dahling & Ruppel, 2016). The lack of a significant finding here is likely due to the weakness of the goal orientation manipulation in the study. In addition, manipulating an individual's orientation as done here may not adequately create a mindset where they would be buffered from failure, and any buffering effect may instead rely more closely on their personal trait orientations.

Hypothesis 20. Here, it was predicted that the self-regulation system would show greater stability over time. Some support for this was found in that feelings of efficacy show greater stability over time. However, with the approach taken to test this hypothesis, power was limited given only eight data points from measuring effects of variables on one trial to those on the next. In addition, there was a severe decrease in the lagged correlation for both performance and goals in the final two trials. This decreased relationship could be indicative of some level of disengagement near the end of the task where instead of behaving and performing as would be expected based purely on prior experiences they drastically change their behavior, creating a break in measurements which are captured in substantially lowered correlations. The fact that stated self-efficacy did not show such a change may be especially telling. In those final trials, participants may have established how they felt about their ability to succeed or not on the task, but had decided the task was no longer worth engaging with in the same way, even though their feelings about their ability on task ceased to change drastically.

Hypothesis 22. This hypothesis predicted that self-stated efficacy would decrease over time for all goal orientations. However, this was not supported. This does not replicate previous findings that efficacy decreases over time for all goal orientations (e.g., Pintrich, 2000).

Hypothesis 23. Finally, hypothesis 23 predicted that the relationship between efficacy and performance would be curvilinear over time, starting out positively then becoming null or negative. This was not found, and the relationship between performance and efficacy became more positive over time. The hypothesis was proposed due to an expectation of increasing performance and decreasing efficacy over time (Pintrich, 2000), but neither occurred. However, the increasingly positive relationship between these two variables could be expected from an increasingly stable self-regulatory system as the two variables become calibrated to each other within the system over time.

Overall findings. Taking these findings together, the original model for this study, presented in Figure B1, is rejected. Following the scientific process, a new possible model is suggested and is depicted in Figure B10. This model shows that the discontinuity in the within-person model of efficacy is not moderated by goal orientation. However, the rate at which they conserve resources at levels of self-efficacy above the discontinuity is moderated by goal orientations such that learning individuals conserve their resources at the greatest rate, and avoid individuals the least. In addition, a further model is proposed accounting for success or failure on personal goals, which is depicted in Figure B11. This model suggests that individuals who are poorly calibrated to meeting their personal goals tend to engage in tasks more often at lower levels of efficacy than which they are likely to succeed. This difference in engagement also makes some sense from a self-regulatory perspective. Individuals who are failing at their goals are obviously further away from their goals than those who are succeeding. According to regulation (Carver & Sheier, 1998), they should increase their effort to meet those goals. This increased effort may take the form of engaging in tasks for which they have lower levels of efficacy in their push to complete their goal. Individuals may also differentially employ their time resources than those who are succeeding in meeting their personal goals based on their goal orientation. This difference is especially prominent for avoid oriented individuals, who may not conserve their resources at high levels of efficacy when they are succeeding at meeting their own goals. This model suggests that what should be considered adaptive use of resources over levels of efficacy for individuals is dependent upon their goal orientation.

While the results presented in this paper suggest these new models, much more work needs to be completed to confirm their existence and the strength of these findings should be tempered for a few reasons. First, the effect sizes of goal orientations, as well as goal success and failure, are relatively small. With the high amount of power for some of the analyses here, these findings may be an aberration and need to be replicated. Further, the small effect sizes may mean the findings are not practically meaningful. In addition, while evidence was presented here that fits the primary model of self-efficacy and the present task within the broader regulation framework, several hypotheses based on well-established findings regarding goal orientations were not supported. Although this is likely due to weaknesses in the goal orientation manipulation, to be discussed further below, this raises the possibility that the proposed models are a result of chance instead of true differences between the orientations. As such, the new model's impact cannot be truly stated until more work is completed to ensure their robustness.

Limitations

Unfortunately, several aspects of this study limited the utility of the findings and would need to be addressed in future tests of the proposed theory.

Weakness of manipulations. The manipulations in this study closely followed the types of manipulations commonly used in the goal orientation literature. However, verbal manipulations are not always very strong or effective. To increase the strength of the manipulation, the verbal instructions were paired with a monetary incentive to tie participant behavior to a higher level personal goal. Unfortunately, this combination did not have as strong of an effect as desired. The weakness of the manipulation could easily mask any true differences between the goal orientations on the within-person model of efficacy, even given our large amount of data. In addition, the manipulation may have been too ambiguous for the task, especially for learning oriented individuals. Telling learning individuals to learn the task could be interpreted in at least two ways: get better at nailing the hard boards, or find a better strategy to play the game. The related hypotheses assumed they would attempt to get better at nailing smaller boards. However, the better strategy for the game itself is likely to not attempt them at all. This could mask any effect of them being willing to engage in harder tasks. For future research on this moderating effect, the manipulation needs to be stronger and clearer. One potential way to do this would be to include error framing for the learning orientation. Error framing attempts to induce individuals to be willing to make errors when engaging with a new task and to treat those errors as an opportunity to learn from their mistakes. This has been shown to increase learning/mastery orientation in other research, and increases individual's willingness to engage in tasks on which they may fail (e.g., Kieth & Frese, 2008).

A related point is the difficulty of the task and the extent to which the task was learnable. In addition to learning possibly meaning two things in this task, learning in terms of getting better at nailing smaller boards proved even more limited than anticipated. This is a product of two things. First, the task is largely a motor task which gives little room for personal improvement due to the limiting speed of human reflexes and motor skills. You may learn a better strategy for nailing boards (likely being not to “chase” the boards with your mouse and instead keep clicking the same place and let the board randomly come to you), but this only offers limited improvement. Second, the task in general is extremely difficult, but especially so at low levels of efficacy, where it becomes nearly impossible. This potentially limits the range of engagement decisions at low levels of efficacy, because it simply is not worth attempting. This also seemingly forces true learning to be more about a good strategy, which again likely means not engaging at all on low levels of efficacy, and is counter to the expectations in this study. The ambiguity and lack of ability to learn the task may have proved frustrating to the learning oriented individuals and led to disengagement from the task. There is some evidence for this in the data as well, particularly in the number of rounds played each trial. You can see in Table A6, learning individuals play many more rounds than their counterparts in the middle trials of the experiment, and then drop off drastically in the number of rounds played in the final trials. This may be an indication that they are learning the strategy of passing many more hard boards and making short attempts when they do engage, but eventually learn that the task is not learnable, so then disengage. This changing behavior may also work to mask larger conditional differences by providing conflicting information regarding these individuals over time.

In-task Survey Questionnaires. Another limitation was the choice of how goal orientations were tracked during the task itself. The task included a single measure following the end of the final trial, well separated in time from the main manipulation, and after fatigue was likely to have set in. In addition, this measure was not reworded to be a state measure of goal orientation. The combination of time between the manipulation and measurement, and the measure still being trait-like could have served to mask the condition effects on stated goal orientations. It would be better in subsequent research to 1) place the manipulation check closer in time to the manipulation itself, 2) utilize a state measure for the manipulation check that would be more susceptible to in-task changes in orientation, and 3) measure orientation state multiple times throughout experiment, doing so would also allow for analyzing the data with respect to how changing orientations may affect the model of interest.

Variable Operationalization. In retrospect, the way some of the variables were operationalized in the task environment were not conducive to the way they were thought about in hypothesizing. A primary example of this here is the operationalization of effort. Here, effort was defined as the amount of resources one was willing to allocate attempting a board size. This assumes that spending more time on a task indicates that you are trying harder to succeed on it. However, when looking at the task as a whole, and the strategy required to succeed on the task, spending more time on a task attempt on average is likely not indicative of trying hard to succeed. Instead, spending large amounts of time on a task attempt could be indicative of merely trying to move the task along as fast as possible, regardless of your performance. Effort, then, would need to be redefined. One possibility would be a count of the number of clicks per unit time in task attempts, or some other objective measure showing how hard the participant was working at an individual task attempt. More broadly, this itself leads to questions about the initial within-person model of efficacy. Motivation being defined as amount of time chosen to attempt a task conflates motivation for the task with the underlying reason for *why* they are behaving in that way. A highly motivated individual in this task environment could easily be allocating very little time to any individual attempt because they realize this is a better strategy for overall task success, but the original model would classify them as unmotivated due to lower resource allocation. This conflation is a problem which would need to be addressed in a task redesign.

Technology. Some issues with technology were expected prior to undertaking this study due to the nature of adapting someone else's task. However, more issues arose than originally anticipated. The nature of the code underlying the task made it difficult to work with and constrained how many changes could be made to the platform, and how any changes may have been implemented. The constraints in the technology led to some attrition from the study on its own through computing failures, though thankfully these appear to be random so results discussed here should not be biased. Further study of this topic should involve a rebuild, with associated redesigns, of the task.

Data Structure. Associated with the limitation of using another researcher's technology is the limitations imposed by the existing data structure. The existing operationalization's and storage of variables in the task were more limiting for analysis than anticipated. Hypotheses for this study were written prior to fully understanding these limitations and made testing difficult in some instances. Future work on this topic needs to take the hypotheses of interest into account when designing the task platform to provide the correct data in the proper structure to test them.

Survey Matching. The design of using a pre-survey and later matching with in-lab data also proved more difficult to implement than anticipated. The system relied on participants providing the research team with an identifier that we could match with the university's research pool system, where we took their id's from to set up the computers utilized for the primary task. The first problem is that participants often did not provide the proper identification, so could not be reliably matched with their laboratory data. The second issue with this system was that even though participants were assigned computers upon their arrival to the lab, at least some participants did not use the proper computer (there are just a few known instances of this occurring). Meaning that while we can be certain the individual was in the proper condition and match their pre-survey to that condition, we cannot necessarily reliably match their pre-surveys directly to their task data. The combination of these two problems essentially rendered the pre-surveys as possible direct controls in analyses useless. Future efforts need to revamp this system to either eliminate the use of pre-surveys, or ensure the task platform can allow for participants to enter their own identification in both systems.

Future Research Directions

Study redesign. Of primary interest for future research is to create and build a new task which addresses many of the limitations discussed above. Simply rebuilding a task from scratch on a modern platform under full control of the present researchers would solve many of the problems related to technology. This change will also allow all relevant data for the study to be collected within the primary task environment, instead of in a piece-meal fashion. More importantly, however, would be to redesign the task to include components not achievable in the present paradigm. The greatest need is to find a task that has some demonstrable learning component, but that could still be used to manipulate efficacy within-individuals, and do so easily for short durations. Assuming we accept the argument from Vancouver et al (2008) and others (Olson, Roese, & Zanna, 1996) that efficacy is a form of expectancy and therefore can be manipulated through changing task difficulty, short tasks with multiple levels of difficulty would be ideal. One possible candidate for such a task is mirror drawing, which has been used in training research for decades (see Goldstein & Ford, 2002, for a discussion of this research). Other cognitively based tasks could be useful as well, such as mental rotation or anagram tasks. In any case, it would also be beneficial to pre-test these tasks to determine exactly how participants view the tasks in terms of their feelings of efficacy for them, and not rely on a secondary measure such as how long they feel it would take them to solve the problem as was done in the original study of within-person efficacy (Vancouver et al, 2008).

A second step for future research on this topic would be to run a study where we merely account for individual trait goal orientation and not attempt to manipulate it. As seen in this study, manipulating goal orientations is not always straight forward, but individuals theoretically carry around all three orientations at all times. Accounting for their personal tendencies may be strong enough to tease apart how those traits moderate how their personal feelings of efficacy result in task behaviors. If a study is run to directly manipulate goal orientations, state measures of orientations, measured at multiple time points in the task should be implemented, as well as an improvement in the framing of learning orientation, as previously mentioned.

A third major change in a redesign is a more dedicated focus on the primary variables of interest to this study. That is, thinking deeply about the meaning of the two halves of the within-person efficacy model, and how they are operationalized in a redesign. It seems reasonable that we could still conceive of the first half of the model as a likelihood of engaging a task, and therefore measure the willingness of participants to even attempt the task at some level of efficacy or not. However, the resource allocation side of the model is more complicated and the current operationalization has severe limitations as mentioned previously. In a redesign, it is proposed that resource allocation could become a better measure of effort and motivation in such a task if looked at in multiple ways simultaneously. First, resource allocation should be viewed as time allocated a priori to participants attempting a task, which would allow for a direct replication of the original model. From there, to get closer to the actual motivation participants show within the task, they should be allowed to continue engaging in the task even after their stated time has elapsed, either until they succeed, or they give up. Then we would have a measure of how they a priori think about the task in its relation to their feelings of efficacy, and how they behave regarding their resources once the task begins. Highly motivated individuals on a task are likely to continue to engage in a task even beyond their original predictions regarding time to reach their goal. Of course, this measurement would be contaminated by a sunk cost fallacy where participants may refuse to give up on a task once begun, not because they are highly motivated to finish the task per se, but because they already wasted resources in attempting it in the first place and do not want those resources to go to waste. This contamination may be mitigated through some form of training and reminders throughout the task.

Other potential moderators of within-person efficacy model. As called for previously by Sun et al (2014), other potential moderators of the within-person model of self-efficacy should be studied. Here, we successfully replicated the original model and showed some potential for differences between goal orientations in how that model operates, though this itself needs further study. In addition, other individual differences likely exist which may moderate the operation of this model. In fact, any which could be conceived as part of the regulatory hierarchy has the potential to moderate the effects. One possibility here is individual competitiveness, which seems likely to moderate the model such that competitive individuals would be more likely to engage at low levels of efficacy to prove themselves. Extraverted individuals may be more willing extend themselves and engage in levels of efficacy others are uncomfortable with, and open individuals may be more curious as to the harder tasks than others, at least initially. Environmental variables should also be investigated, along the lines of how Sun et al (2014) studied the impact of task value. Other possibilities could be stress; do individuals under stress retreat to familiar or easy tasks where they have higher levels of efficacy? Or do they make less-sound decisions and overextend themselves to engage in tasks for which they have low levels of efficacy? Another likely moderator is resource availability. Individuals with abundant resources seem likely to be more willing to take a less adaptive approach, in the Vancouver sense, to the task because they would have resources to burn. Whereas individuals with fewer resources should better conserve their resources. Finally, the resource allocation side of the model may be effected by the ability to choose to engage at all or not. If you must engage in a task, a very real possibility in the real world, you may choose to put forth little effort (seen in resource allocation in this task) even though you have low efficacy. These and other questions deserve future research.

Practical Implications

With the lack of clear findings in many instances, and the shortcomings of the study, it is not appropriate to draw sweeping conclusions regarding how this study should inform practice. If future work replicates the finding that learning individuals best conserve their resources at high levels of efficacy, and avoid individuals the worst, but that avoid individuals can still meet their personal goals following a maladaptive behavioral pattern, possible guidelines may be created which could allow managers to best assign tasks for resource use, or provide coaching to individuals on how best to allocate their personal resources for personal and organizational success.

Conclusion

This study sought to fill multiple research gaps by replicating and extending the within-person model of self-efficacy developed by Vancouver and colleagues (Vancouver et al, 2008 Sun et al, 2014). Specifically, it looked to further integrate two of our most important and well-supported motivational theories in self-regulation and goal orientations, by showing how goal orientations may moderate the nature of the within-person model of efficacy. Further, it looked to study the development of the within-person model of efficacy over time. Unfortunately, due to a confluence of foreseen and unforeseen limitations, the ability of this study to fill those gaps is limited. However, there are a few important contributions of note, and findings worth further study. First, this study provides an independent replication of the original within-person model of efficacy, with a much larger sample size. Second, it shows that other important regulatory variables, such as goals, operate in this task environment generally as we would expect, helping to confirm the general model's place in the self-regulatory system. Third, for that model replication, it shows there may be important changes in that model over time in this task environment which are not explored in the original studies and may negatively affect the robustness of the model. However, fourth and most intriguingly, goal orientation may impact the adaptive conservation of resources at high levels of efficacy such that learning individuals engage in greater resource conservation and avoid individuals the least. Based on Vancouver's (2008) logic about the adaptive nature of this model, this finding would again show a way that learning individuals are better adapted to their environments, and avoid individuals less well adapted. However, proper adaptation may mean different things depending on individual goals. Here, individuals with avoid goals follow a different adaptation pattern than other orientation conditions that allow them to meet their own goals rather than the goals imposed upon them.

Further research is needed to confirm this finding and to overcome the limitations of the present study.

NOTES

NOTES

1. Another major advance, of tangential importance here, has been a move towards using computational modeling to study the interdependence of these complex control systems. Vancouver has been a primary driver of this development and has successfully articulated a dynamic process model of control-based regulation in which many interconnected regulation systems can be studied for their effects on human behavior (Vancouver, 2006). While this paper does not take a computational modeling approach, a greater understanding the longitudinal development of regulatory systems represents a next major step for the field. The need to study the development of these systems also fits with the broader call in Organizational Psychology to complete more longitudinal work (ex. Ployhart & Hakel, 1998).

2. It is possible that our data will show mediating effects between other self-regulatory constructs and goal setting, which would seem to imply that goal orientations do not in fact feed directly into goals in a hierarchical manner. For example, Fan, Meng, Billings, Litchfield, and Kaplan (2008) found that state self-efficacy mediated the effect of goal orientations on goals, implying a causal model where orientations feed into efficacy, which then effect goals. However, the operation of the control loops would explain findings along the same lines. In this loop, goal orientations do directly affect the goal level of the task-level system in question, but the way we collect data on goals and efficacy in our research is likely not sensitive enough to pick up the initial effect on the goal. Instead, once that goal is changed, the control system automatically compares the new goal to the present state of the system and makes a decision on whether that goal is tenable or should be abandoned/adjusted. That decision is based partly on the individual's state self-efficacy. The system should operate iteratively such that it continually adjusts the new goal until it reaches a level which is seen as tenable, a level determined in part by the person's feeling of efficacy. This process has likely happened faster than we are collecting data on the system under normal conditions, and would result in data which show efficacy as functioning between goal orientations and goal levels instead of merely in tandem with them in a larger system. This study also will not likely be sensitive enough to directly test this operation, but will also not directly test these types of mediations as they can be explained by multiple models.

3. Obviously, you may state a goal you do actually accept for other reasons, but we will not be able to tell the difference and must assume participants are not being deliberately misleading.

4. Skipping one of these questions multiple times unexpectedly changed the data-storage matrix in a way that made their data unrecoverable and uninterpretable. Participants who only missed one of these questions were usually recovered.

5. Individuals who had been eliminated from the data set in cleaning also returned surveys at a much lower rate. This may be indicative of their much lower overall level of compliance.

APPENDICES

APPENDIX A

Tables for Main Paper

Table A1. *Means and (Standard Deviations) for pre-survey scales for all participants and broken down by conditions and completion of task.*

Scale	All	Learning Condition	Prove/Approach Condition	Avoid Condition	In Final Data	Dropped from Data
Learning Orientation	4.13 (.57)	4.14 (.59)	4.06 (.57)	4.19 (.55)	4.13 (.58)	4.10 (.55)
Prove Orientation	3.89 (.75)	4.05 (.67)	3.82 (.74)	3.84 (.82)	3.89 (.75)	3.93 (.74)
Avoid Orientation	2.97 (.85)	2.86 (.84)	3.12 (.88)	2.89 (.82)	2.93 (.85)	3.25 (.80)
Error Competence	3.52 (.58)	3.47 (.60)	3.53 (.57)	3.55 (.58)	3.53 (.58)	3.47 (.65)
Learn from Errors	4.06 (.74)	4.01 (.86)	4.07 (.68)	4.08 (.70)	4.06 (.74)	4.04 (.77)
Error Risk	3.76 (.65)	3.76 (.70)	3.71 (.55)	3.82 (.69)	3.78 (.65)	3.65 (.58)
Error Strain	3.22 (.81)	3.15 (.84)	3.33 (.79)	3.16 (.82)	3.20 (.81)	3.37 (.85)
Extraversion	3.25 (.93)	3.37 (.87)	3.24 (1.01)	3.16 (.88)	3.27 (.95)	3.10 (.71)
Agreeableness	4.00 (.68)	4.03 (.68)	3.97 (.68)	4.01 (.70)	4.01 (.69)	3.93 (.66)
Conscientiousness	3.61 (.76)	3.56 (.74)	3.54 (.75)	3.71 (.77)	3.63 (.76)	3.37 (.71)
Neuroticism	2.76 (.80)	2.70 (.81)	2.90 (.76)	2.68 (.83)	2.77 (.82)	2.71 (.62)
Openness	3.64 (.79)	3.78 (.76)	3.52 (.83)	3.66 (.76)	3.67 (.77)	3.42 (.92)
Locomotion Regulation	3.78 (.56)	3.77 (.59)	3.76 (.57)	3.80 (.54)	3.79 (.56)	3.71 (.56)
Assessment Regulation	3.53 (.64)	3.58 (.63)	3.55 (.61)	3.47 (.68)	3.52 (.64)	3.58 (.69)

Note: Overall means based on 293 responses. Means of conditions based on number able to match with pre-surveys, 86 for learning, 103 for prove, 104 for avoid. Those in final data set are based on 269 participants, those who are not are based on 278 responses. Lab completion versus non-completion is only among those who came to the lab session, therefore complete is based on 263 individuals, and non-complete on 30.

Table A2. *Correlations between pre-survey measures and reliabilities.*

Scale	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Learning Orientation	(.80)													
2. Prove Orientation	.23**	(.80)												
3. Avoid Orientation	-.23**	.17**	(.81)											
4. Error Competence	.17**	.19**	-.02	(.71)										
5. Learn from Errors	.31**	.08	-.23**	.19**	(.92)									
6. Error Risk	.38**	.15**	-.32**	.24**	.45**	(.75)								
7. Error Strain	-.24**	.11	.50**	.03	-.10	-.12*	(.79)							
8. Extraversion	.11	.19**	-.12**	.02	11	.17**	-.21**	(.80)						
9. Agreeableness	.10	.08	-.14**	.01	.10	.17**	.12*	.23**	(.71)					
10. Conscientiousness	.13**	.04	-.08	.26**	.26**	.21**	-.08	.06	.07	(.69)				
11. Neuroticism	-.17**	.04	.15*	-.13**	-.15**	-.12*	.37**	-.10	.06	-.12*	(.60)			
12. Openness	.28**	.07	-.24**	.05	.22**	.19**	-.18**	.16**	.29**	.04	-.12*	(.69)		
13. Locomotion Regulation	.54**	.25**	-.36**	.36**	.42**	.49**	-.21**	.28**	.13*	.36**	-.22**	.29**	(.82)	
14. Assessment Regulation	.03	.32**	.22**	.14*	-.02	-.06	.35**	.00	.01	-.12*	.22**	-.06	.05	(.71)

Note: N = 293. Cronbach's Alpha in diagonal.

Table A3. *Means and (standard deviations) for pre-survey and post-survey measures of goal orientations.*

Condition	Pre-Learn	Post-Learn	Pre-Prove	Post-Prove	Pre-Avoid	Post-Avoid
Learning/Learning	4.13 (.60)	4.16 (.57)	4.05 (.70)	3.91 (.72)	2.84 (.89)	2.95 (.93)
Prove	4.10 (.57)	4.02 (.63)	3.74 (.76)	3.68 (.86)	3.11 (.88)	2.94 (.96)
Avoid	4.17 (.53)	4.03 (.52)	3.88 (.77)	3.68 (.83)	2.82 (.81)	2.84 (.93)

Note: Learning condition N = 69, Prove condition N = 71, Avoid condition N = 70. Lower than 312 due to listwise deletion in MANOVA.

Table A4. *Means and (standard deviations) for in-task self-efficacy.*

	Condition			
Trial	All	Learning	Prove	Avoid
All Trials	40.19 (26.96)	40.38 (26.86)	39.70 (25.99)	40.55 (28.08)
1	43.73 (24.50)	42.12 (24.17)	43.73 (24.17)	45.28 (25.31)
2	39.04 (25.25)	40.03 (23.60)	38.32 (25.01)	38.86 (27.26)
3	42.04 (25.57)	43.90 (24.60)	41.46 (25.74)	40.84 (26.21)
4	41.72 (26.00)	44.58 (26.36)	39.79 (25.84)	41.01 (25.84)
5	41.96 (27.17)	43.17 (27.19)	40.26 (25.61)	42.62 (28.92)
6	40.04 (28.00)	41.28 (28.80)	39.91 (26.44)	38.95 (29.08)
7	38.59 (28.00)	37.13 (27.03)	38.78 (27.00)	39.73 (30.05)
8	37.55 (28.79)	35.11 (29.50)	37.67 (27.26)	39.67 (29.87)
9	36.51 (28.79)	34.53 (29.30)	37.18 (27.09)	37.56 (30.34)

Note: N = 100 for learning, 109 for prove, 103 for avoid, 312 total.

Table A5. *Means and (standard deviations) for in-task goals.*

	Condition			
Trial	All	Learning	Prove	Avoid
All Trials	18.46 (18.09)	18.13 (17.80)	19.12 (18.30)	18.06 (18.13)
1	36.99 (31.65)	31.38 (30.51)	35.92 (31.20)	42.78 (32.56)
2	18.17 (15.89)	16.44 (12.85)	19.06 (16.00)	18.89 (18.34)
3	17.58 (12.65)	17.89 (10.32)	19.26 (16.50)	15.45 (9.27)
4	17.35 (13.35)	17.84 (12.65)	18.80 (16.16)	15.32 (10.18)
5	16.26 (11.68)	18.00 (11.58)	16.41 (12.63)	14.44 (10.50)
6	15.93 (11.55)	16.43 (10.09)	17.10 (13.34)	14.12 (10.62)
7	14.44 (11.16)	14.39 (9.81)	15.57 (13.02)	13.29 (10.12)
8	14.87 (16.94)	15.80 (23.46)	14.77 (13.43)	14.12 (12.84)
9	13.73 (15.99)	12.95 (20.10)	14.70 (15.11)	13.36 (12.51)

Note: N = 100 for learning, 109 for prove, 103 for avoid, 312 total.

Table A6. *Means and (standard deviations) for number of rounds attempted.*

	Condition			
Trial	All	Learning	Prove	Avoid
Per Trial	72.24 (84.61)	84.57 (114.98)	74.98 (75.93)	57.43 (50.11)
1	43.34 (33.42)	43.61 (35.04)	45.77 (36.03)	40.47 (28.65)
2	69.17 (66.88)	71.69 (66.91)	74.80 (75.63)	60.48 (55.40)
3	83.83 (80.85)	94.63 (87.79)	89.99 (90.03)	66.53 (57.89)
4	90.35 (106.79)	115.30 (151.45)	86.05 (78.81)	70.74 (70.47)
5	88.62 (94.35)	112.54 (130.91)	90.47 (82.96)	63.63 (46.39)
6	85.84 (118.58)	114.51 (181.52)	85.06 (84.47)	58.33 (41.87)
7	75.14 (89.94)	95.87 (127.25)	76.33 (78.53)	54.77 (44.66)
8	59.40 (63.78)	60.87 (76.05)	64.68 (67.06)	52.22 (44.76)
9	52.06 (56.62)	44.92 (56.44)	60.70 (65.78)	48.86 (43.56)

Note: N = 100 for learning, 109 for prove, 103 for avoid, 312 total.

Table A7. *Means and (standard deviations) for number of points earned.*

	Condition			
Trial	All	Learning	Prove	Avoid
All Trials	15.08 (8.65)	15.28 (10.43)	15.91 (8.03)	13.97 (7.17)
1	11.87 (5.38)	11.34 (5.09)	13.10 (5.55)	11.07 (4.95)
2	15.43 (7.09)	15.73 (7.36)	15.92 (7.39)	14.58 (6.45)
3	16.52 (7.63)	16.81 (7.88)	17.29 (7.85)	15.39 (7.08)
4	16.63 (8.30)	17.84 (8.73)	16.85 (8.10)	15.22 (7.95)
5	16.61 (8.49)	17.07 (9.52)	17.56 (8.01)	15.16 (7.79)
6	15.70 (8.39)	15.79 (9.09)	16.82 (8.56)	14.36 (7.28)
7	15.50 (9.78)	16.17 (12.74)	16.38 (8.54)	13.97 (7.51)
8	14.22 (12.43)	14.89 (19.11)	14.76 (8.43)	13.00 (7.21)
9	12.99 (7.61)	11.32 (6.68)	14.47 (8.57)	12.84 (6.99)

Note: N = 100 for learning, 109 for prove, 103 for avoid, 312 total.

Table A8. *Engagement rates for board sizes across all trials.*

	Board Size					
Condition	1	2	3	4	5	6
All	.14 (.35)	.17 (.38)	.21 (.41)	.32 (.47)	.62 (.49)	.96 (.19)
Learning	.13 (.33)	.14 (.35)	.18 (.39)	.27 (.44)	.47 (.50)	.96 (.20)
Approach	.13 (.34)	.16 (.37)	.19 (.39)	.31 (.46)	.65 (.48)	.96 (.18)
Avoid	.19 (.39)	.22 (.41)	.27 (.45)	.41 (.49)	.78 (.42)	.97 (.17)

Table A9. *Seconds allocated following engagement decision for board sizes across all trials.*

	Board Size					
Condition	1	2	3	4	5	6
All	7.23 (3.74)	6.84 (3.57)	6.83 (3.17)	6.74 (2.70)	6.00 (2.40)	5.09 (2.36)
Learning	7.46 (3.68)	7.13 (3.59)	6.90 (3.22)	6.76 (2.77)	5.95 (2.50)	4.55 (2.41)
Approach	7.24 (3.74)	6.78 (3.61)	6.84 (3.18)	6.50 (2.61)	5.68 (2.38)	4.99 (2.17)
Avoid	6.99 (3.78)	6.64 (3.51)	6.75 (3.11)	6.97 (2.72)	6.43 (2.26)	6.01 (2.28)

Note: Overall N for board sizes are (1) 4841, (2) 5727, (3) 7056, (4) 10786, (5) 20646, (6) 31746

Table A10. *Model parameters for moderations of likelihood of engagement.*

Goal Orientation (GO)				
Parameter	Coeff.	SE	*z*	*p*
Intercept	-3.60	1.37	-2.63	.009
Main effect of goal orientation	.22	.64	.34	.731
Board-Size	1.25	.27	4.60	< .001
GO x Board-Size interaction	.03	.13	.21	.834

Number of observations is 199,609 in 312 individuals

Table A11. *Models for engagement moderated by goal orientation.*

	Learning				Approach				Avoid			
Parameter	Coeff.	SE	*z*	*p*	Coeff.	SE	*z*	*p*	Coeff.	SE	*z*	*p*
Intercept	-3.11	.31	-10.04	< .001	-3.04	.20	-10.08	< .001	-3.33	.37	-8.91	< .001
Main effect of GO	-.15	.52	-.29	.773	-.35	.56	-.62	.536	.50	.69	.72	.470
Board-Size	1.34	.07	20.54	< .001	1.25	.06	19.74	<.001	1.31	.08	17.09	< .001
GO x Board-Size interaction	-.11	.11	-1.02	.309	.14	.12	1.20	.230	-.03	.14	-.22	.824

Number of observations is 199,609 in 312 individuals

Table A12. *Model parameters for moderation of Resource Allocation (seconds allocated).*

Goal Orientation (GO)					
Parameter	Coefficient	SE	*t*	DF	*p*
Intercept	8.23	.42	19.84	79897	< .001
Main effect of GO	-.24	.19	-1.22	310	.22
Board-Size	-.57	.09	-6.17	79897	< .001
GO x Board-Size interaction	.14	.04	3.36	79897	< .001

Table A13. *Model parameters for moderation of Resource Allocation (seconds allocated) by goal orientation.*

	Learning				Approach				Avoid			
Parameter	Coeff.	SE	*t*	*p*	Coeff.	SE	*t*	*p*	Coeff.	SE	*t*	*p*
Intercept	7.61	.19	40.58	< .001	7.85	.19	40.81	< .001	7.83	.19	41.50	< .001
Main effect of GO	.48	.33	1.45	.147	-.25	.32	-.77	.439	-.22	.33	-.66	.513
Board-Size	-.22	.04	-5.14	< .001	-.28	.04	-6.35	< .001	-.35	.04	-8.40	< .001
GO x Board-Size interaction	-.21	.07	-2.76	.006	-.02	.07	-.21	.830	.22	.07	2.98	.003

DFs for all parameters are 79897, except the main effect of goal orientation is 310.

Table A14. *Engagement parameters for same and previous trial goal success.*

	Same Trial Success				Previous Trial Success			
Parameter	Coeff.	SE	*z*	*p*	Coeff.	SE	*z*	*p*
Intercept	-2.30	.29	-8.02	< .001	-4.35	.42	-10.27	< .001
Main effect of goal success	-1.72	.04	-41.07	< .001	-1.00	.05	-21.49	< .001
Board-Size	1.12	.06	18.76	< .001	1.66	.09	18.00	< .001
Success x Board-Size interaction	.38	.01	30.74	< .001	.20	.01	14.31	< .001

Table A15. *Parameters for Resource Allocation (seconds allocated) when successful on that trial, and the previous trial.*

	Same Trial Success				Previous Trial Success			
Parameter	Coeff.	SE	*t*	*p*	Coeff.	SE	*t*	*p*
Intercept	7.92	.16	50.70	< .001	7.38	.18	40.15	< .001
Main effect of goal success	-.37	.04	-9.60	< .001	.82	.04	21.93	< .001
Board-Size	-.31	.04	-8.73	< .001	-.19	.04	-4.68	< .001
Success x Board-Size interaction	.07	.01	7.09	< .001	-.15	.01	-15.48	< .001

Table A16. *Parameters for goal success and failure for engagement by condition.*

		Same Trial Success				Previous Trial Success			
Model	Parameter	Coeff.	SE	*z*	*p*	Coeff.	SE	*z*	*p*
Overall	Intercept	-3.35	.72	-4.67	< .001	-5.25	.85	-6.17	< .001
	Condition	.54	.34	1.61	.107	.46	.41	1.12	.264
	Goal Met	-.35	.11	-3.29	< .001	-.27	.12	-2.23	.026
	Board-Size	1.17	.15	7.88	< .001	1.67	.19	8.65	< .001
	Condition x Goal Met	-.71	.05	-13.35	< .001	-.38	.06	-6.62	< .001
	Condition x Board-Size	-.03	.07	-.41	.680	-.01	.09	-.06	.955
	Goal Met x Board-Size	.11	.03	3.55	< .001	.00	.04	-.11	.914
	Condition x Goal Met x Board-Size	.14	.02	8.65	< .001	.11	.02	6.14	< .001
Learn	Intercept	-2.06	.31	-6.62	< .001	-4.19	.48	-8.67	< .001
	Condition	-.67	.51	-1.32	.187	-.44	.78	-.57	.569
	Goal Met	-2.06	.05	-38.45	< .001	-1.09	.06	-18.71	< .001
	Board-Size	1.12	.07	17.12	< .001	1.68	.11	15.79	< .001
	Condition x Goal Met	.96	.09	11.33	< .001	.24	.10	2.43	.02
	Condition x Board-Size	-.02	.11	-.20	.842	-.07	.17	-.42	.68
	Goal Met x Board-Size	.44	.02	26.58	< .001	.23	.02	12.79	< .001
	Condition x Goal Met x Board-Size	-.18	.03	-7.26	< .001	-.08	.03	-2.85	.004

Table A16 (cont'd)

		Same Trial Success				Previous Trial Success			
Model	Parameter	Coeff.	SE	*z*	*p*	Coeff.	SE	*z*	*p*
Approach	Intercept	-2.23	.34	-6.62	< .001	-4.19	.64	-6.52	< .001
	Condition	-.20	.61	-.32	.747	-.47	1.08	-.44	.66
	Goal Met	-1.71	.05	-32.70	< .001	-1.21	.06	-20.79	< .001
	Board-Size	1.08	.07	15.28	< .001	1.61	.14	11.63	< .001
	Condition x Goal Met	.00	.09	-.02	.980	.61	.10	6.11	< .001
	Condition x Board-Size	.12	.13	.98	.329	.16	.23	.67	.504
	Goal Met x Board-Size	.39	.02	25.31	< .001	.25	.02	14.19	< .001
	Condition x Goal Met x Board-Size	-.03	.03	-.98	.329	-.14	.03	-4.49	< .001
Avoid	Intercept	-2.58	.31	-8.33	< .001	-4.64	.58	-7.98	< .001
	Condition	.95	.66	1.44	.150	.94	1.12	.84	.401
	Goal Met	-1.41	.05	-29.31	< .001	-.73	.06	-13.00	< .001
	Board-Size	1.15	.07	17.55	< .001	1.69	.13	13.43	< .001
	Condition x Goal Met	-1.14	.10	-11.44	< .001	-.93	.10	-8.87	< .001
	Condition x Board-Size	-.11	.14	-.82	.413	-.09	.24	-.39	.696
	Goal Met x Board-Size	.32	.01	22.56	< .001	.13	.02	7.95	< .001
	Condition x Goal Met x Board-Size	.23	.03	7.55	< .001	.25	.03	7.46	< .001

Table A17. *Parameters for goal success and failure for Resource Allocation (seconds allocated) by condition.*

		Same Trial Success				Previous Trial Success			
Model	Parameter	Coeff.	SE	*t*	*p*	Coeff.	SE	*t*	*p*
Overall	Intercept	8.17	.42	19.53	< .001	7.78	.49	15.79	< .001
	Condition	-.13	.19	-.67	.505	-.20	.23	-.89	.372
	Goal Met	.23	.10	2.18	.029	1.70	.10	16.94	< .001
	Board-Size	-.58	.09	-6.23	< .001	-.50	.11	-4.59	< .001
	Condition x Goal Met	-.29	.05	-6.06	< .001	-.44	.05	9.39	< .001
	Condition x Board-Size	.14	.04	3.19	.001	.15	.05	3.05	.002
	Goal Met x Board-Size	-.01	.03	-.32	.745	-.30	.02	-12.10	< .001
	Condition x Goal Met x Board-Size	.04	.01	2.95	.003	.08	.01	6.55	< .001
Learn	Intercept	7.78	.19	41.25	< .001	7.22	.22	32.55	< .001
	Condition	.41	.33	1.23	.220	.50	.39	1.27	.204
	Goal Met	-.42	.05	-8.96	< .001	.68	.05	15.18	< .001
	Board-Size	-.23	.04	-5.49	< .001	-.12	.05	-2.43	.015
	Condition x Goal Met	.20	.08	2.37	.018	.43	.08	5.37	< .001
	Condition x Board-Size	-.22	.07	-2.99	.003	-.22	.09	-2.59	.010
	Goal Met x Board-Size	.06	.01	4.73	< .001	-.13	.01	-10.88	< .001
	Condition x Goal Met x Board-Size	.02	.02	.82	.415	-.07	.02	-3.42	< .001

Table A17 (cont'd)

Model	Parameter	Same Trial Success Coeff.	SE	*t*	*p*	Previous Trial Success Coeff.	SE	*t*	*p*
Approach	Intercept	8.07	.19	41.51	< .001	7.52	.23	32.83	< .001
	Condition	-.45	.33	-1.36	.173	-.40	.39	-1.04	.299
	Goal Met	-.54	.05	-11.12	< .001	.66	.05	14.29	< .001
	Board-Size	-.33	.05	-7.40	< .001	-.19	.05	-3.78	< .001
	Condition x Goal Met	.46	.08	5.82	< .001	.42	.08	5.46	< .001
	Condition x Board-Size	.05	.07	.69	.487	.01	.09	.06	.953
	Goal Met x Board-Size	.12	.01	10.04	< .001	-.11	.01	-9.52	< .001
	Condition x Goal Met x Board-Size	-.15	.02	-7.31	< .001	-.09	.02	-4.76	< .001
Avoid	Intercept	7.90	.19	41.57	< .001	7.40	.22	32.98	< .001
	Condition	.03	.33	.10	.919	-.10	.39	-.25	.801
	Goal Met	-.16	.05	-3.38	< .001	1.10	.05	24.31	< .001
	Board-Size	-.37	.04	-8.61	< .001	-.26	.05	-5.33	< .001
	Condition x Goal Met	-.68	.08	-8.13	< .001	-.85	.08	-10.72	< .001
	Condition x Board-Size	.18	.07	2.40	.016	.22	.09	2.61	.009
	Goal Met x Board-Size	.03	.01	2.36	.018	-.20	.01	-17.69	< .001
	Condition x Goal Met x Board-Size	.13	.02	6.10	< .001	.16	.02	7.80	< .001

APPENDIX B

Figures for Main Paper

Figure B1. A moderated discontinuous model of self-efficacy by goal orientation.

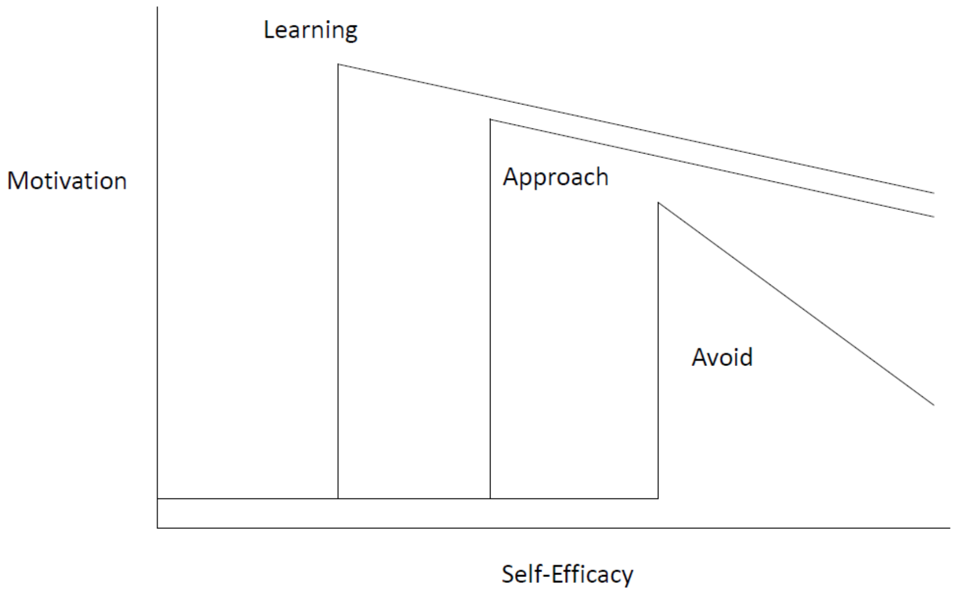


Figure B2. Engagement model for within-person efficacy by goal orientation.

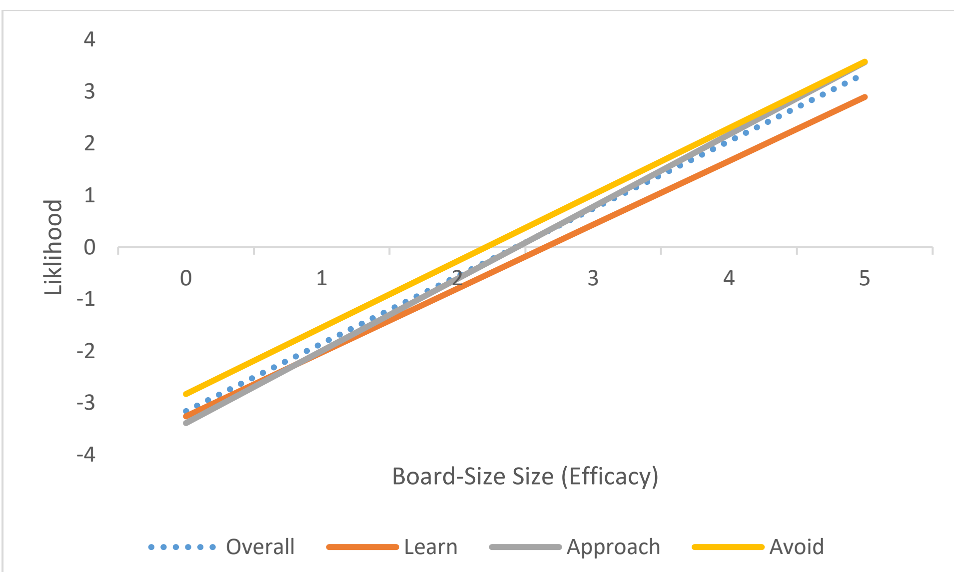


Figure B3. Resource Allocation (seconds allocated) by goal orientation models.

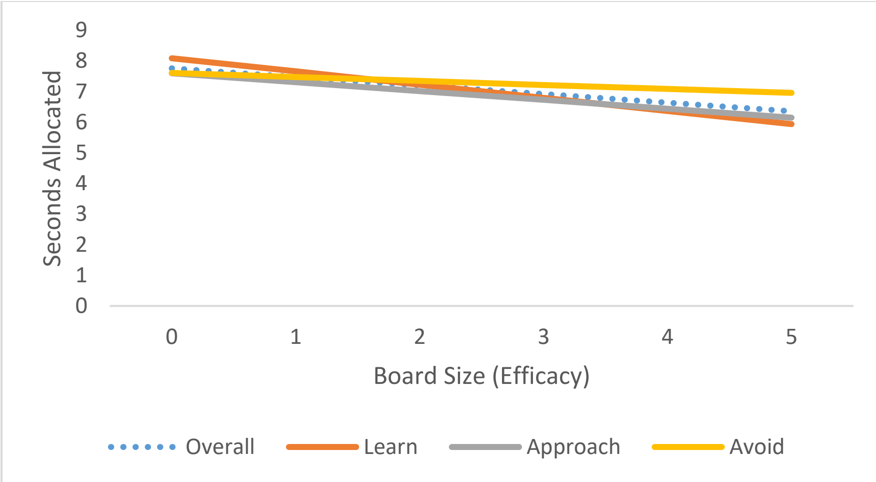


Figure B4. Goals on first trial by condition.

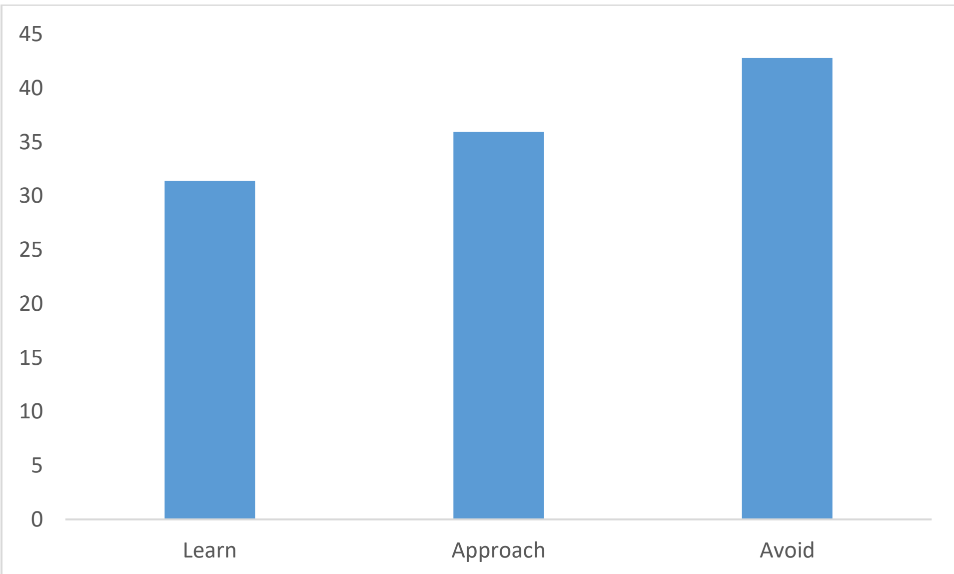


Figure B5. Non-mediated and mediated models of goals on performance.

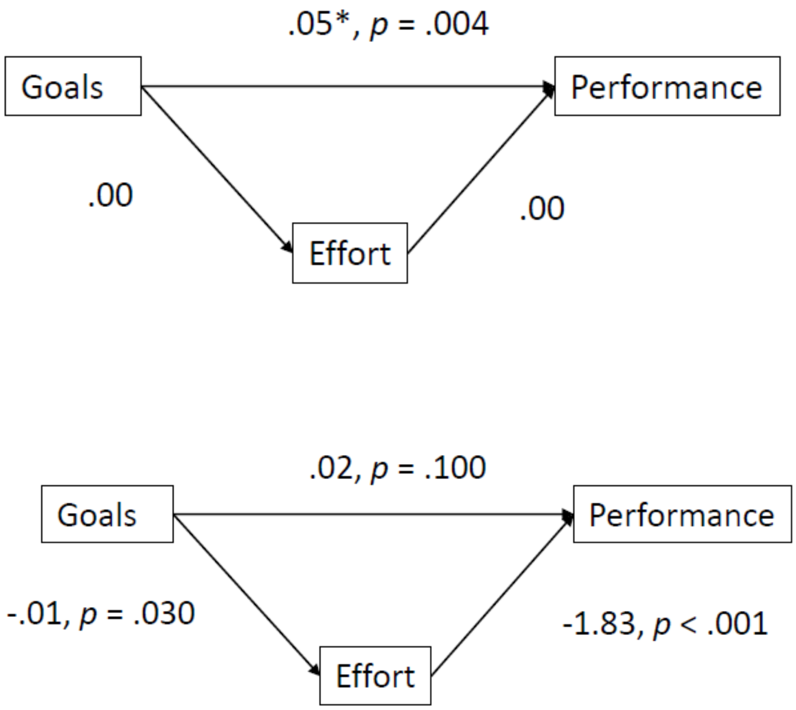


Figure B6. Overall models of same and previous trial success and failure.

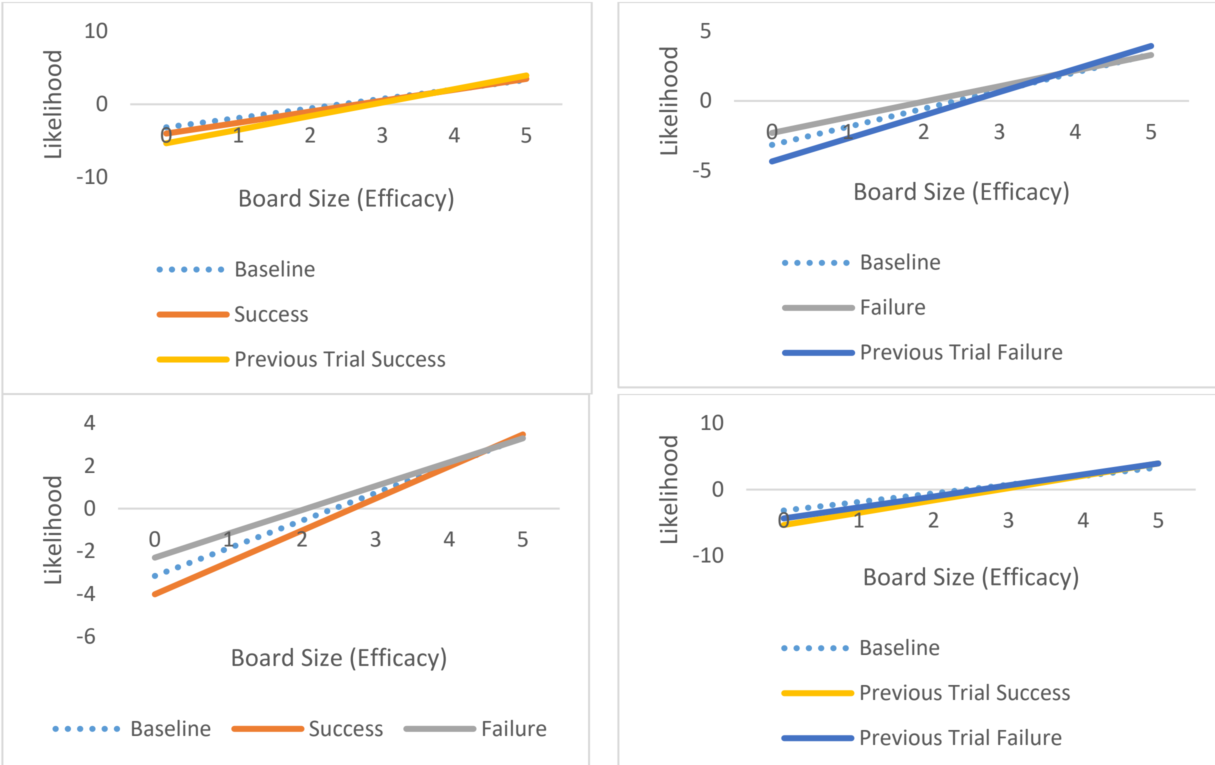


Figure B7. Models of success and failure for same and previous trial.

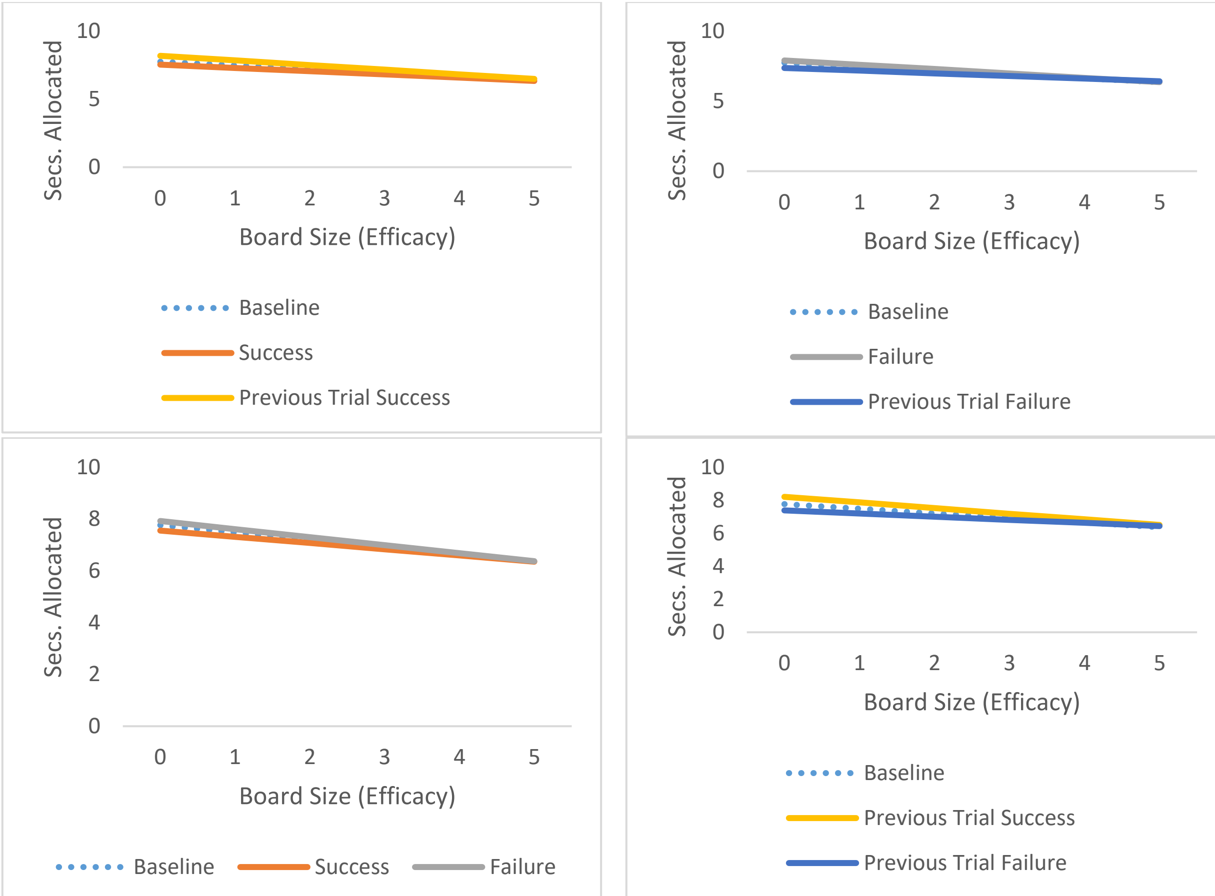


Figure B8. Engagement for successful and failure trials by goal orientation.

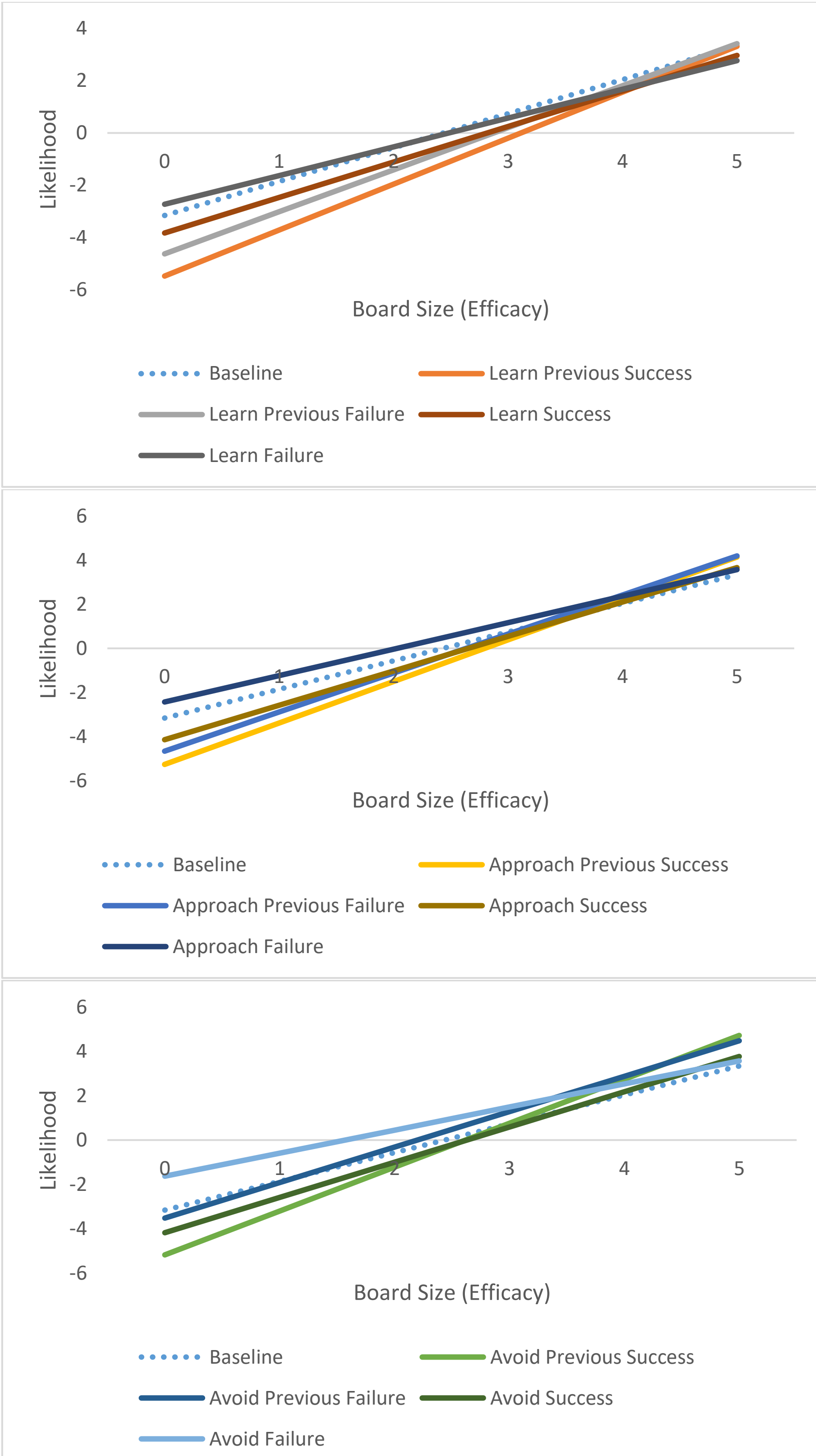


Figure B9. Resource Allocation (seconds allocated) success and failure on same and previous trial by goal orientation.

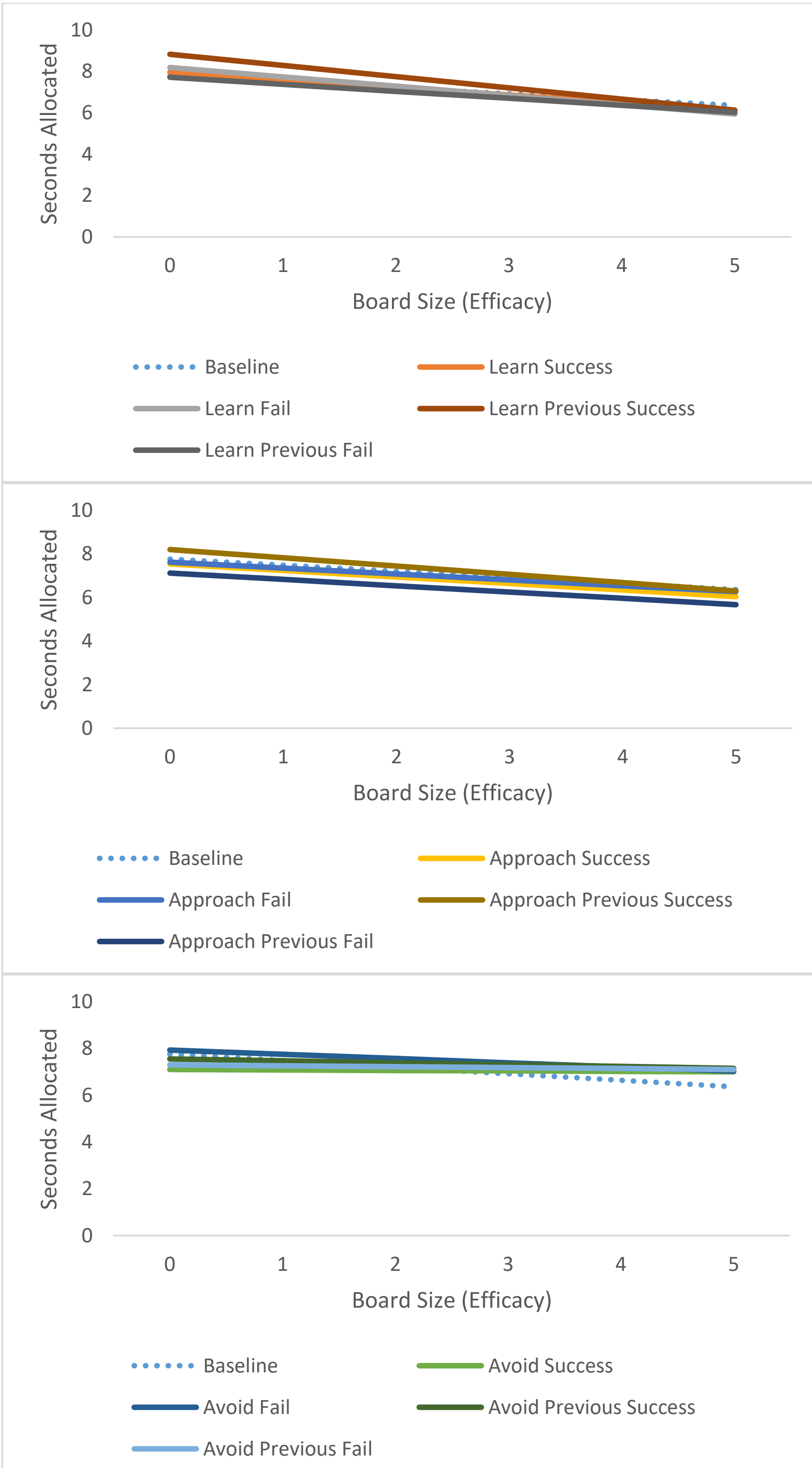


Figure B10. Supported and newly proposed overall model of goal orientation effect on within-person efficacy.

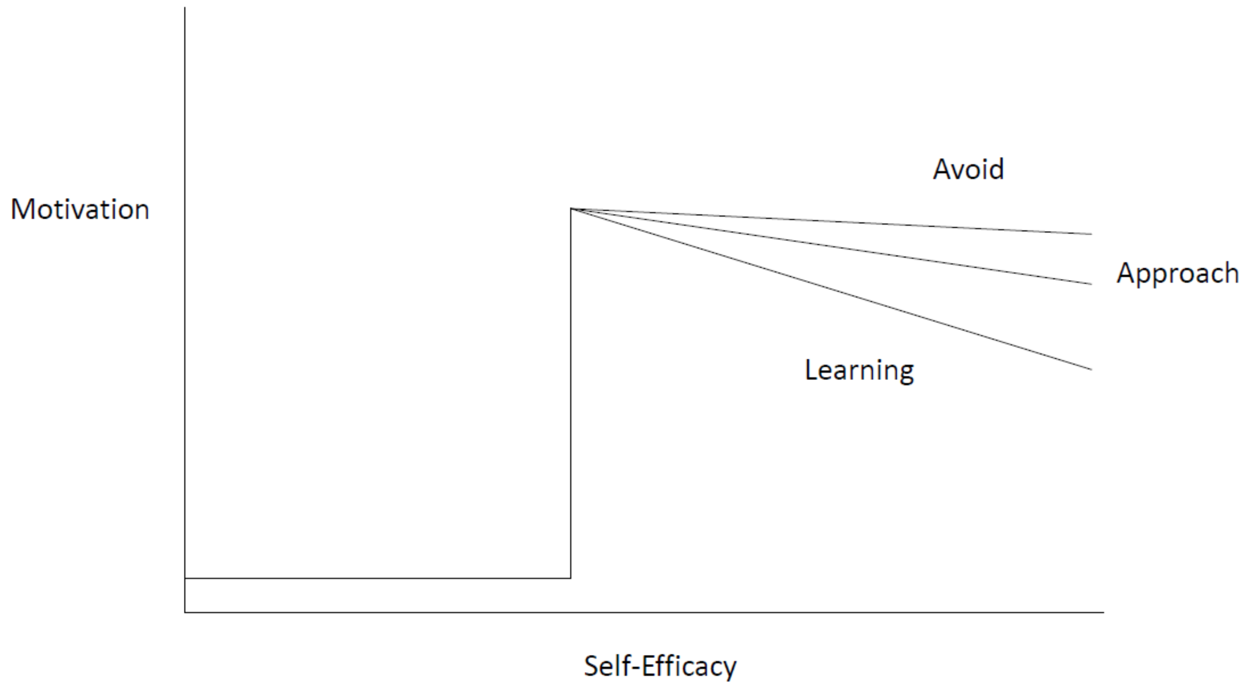
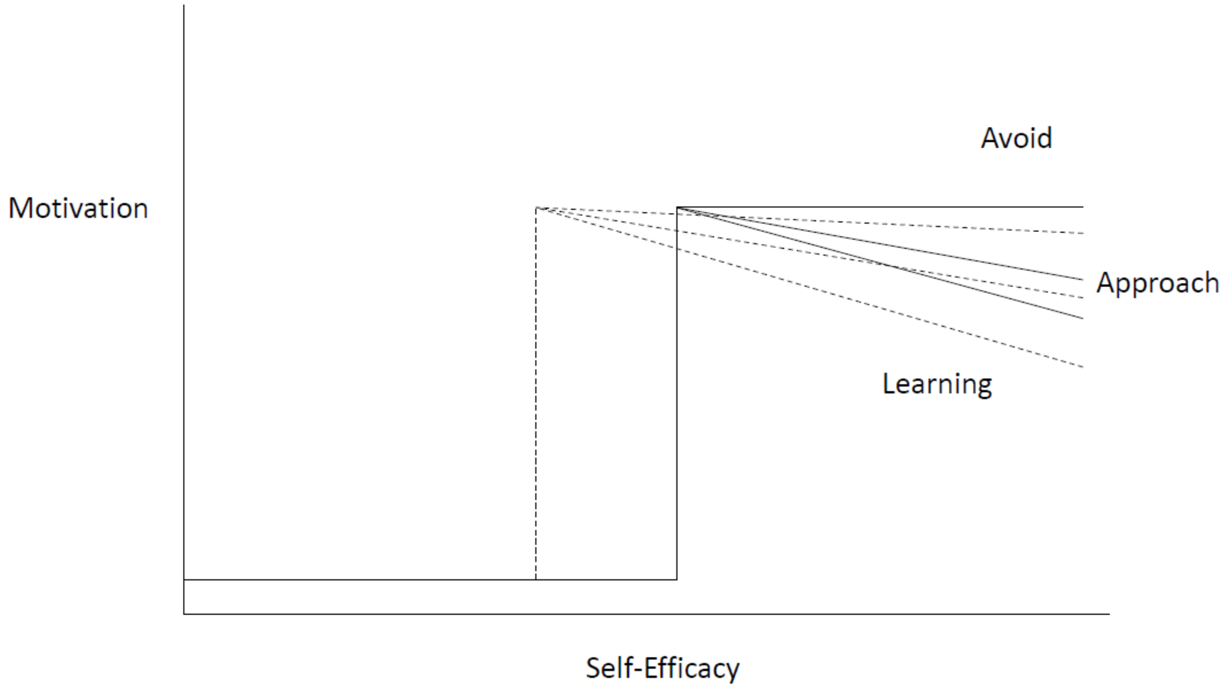


Figure B11. Overall model of goal orientations on self-efficacy moderated by goal success (solid lines) and failure (dashed lines).



APPENDIX C

Survey Measures

Goal orientations, adopted from VandeWalle (1997, 2001)

1. Learning Goal Orientation
    a. I am willing to select a challenging assignment that I can learn a lot from.
    b. I often look for opportunities to develop new skills and knowledge.
    c. I enjoy challenging and difficult tasks where I'll learn new skills.
    d. For me, further development of my ability is important enough to take risks.
2. Performance Prove Orientation
    a. I like to show that I can perform better than my peers.
    b. I try to figure out what it takes to prove my ability to others.
    c. I enjoy it when others are aware of how well I am doing.
    d. I prefer projects where I can prove my ability to others
3. Performance Avoid Orientation
    a. I would avoid taking on a new task if there was a chance that I would appear incompetent to others.
    b. Avoiding a show of low ability is more important to me than learning a new skill.
    c. I'm concerned about taking on a task at work if my performance would reveal that I had low ability.
    d. I prefer to avoid situations where I might perform poorly.

Error Orientation Questionnaire (Rybowiak et al, 1999)

1. Error competence
    a. When I have made a mistake, I immediately know how to correct it
    b. When I do something wrong, I correct it immediately
    c. If it is at all possible to correct a mistake, then I usually know how to go about it

    d. I don’t let go of the goal, although I may make mistakes

2. Learning from errors
    a. Mistakes assist me to improve my work
    b. Mistakes provide useful information for me to carry out my work
    c. My mistakes help me to improve my work
    d. My mistakes have helped me t improve my work
3. Error risk taking
    a. If one wants to achieve at work, one has to risk making mistakes
    b. It is better to take the risk of making mistakes than to ‘sit on one’s behind’
    c. To get on with my work, I gladly put up with things that can go wrong
    d. I’d prefer to err, than to do nothing at all
4. Error strain
    a. I find it stressful when I err
    b. I am often afraid of making mistakes
    c. I feel embarrassed when I make an error
    d. If I make a mistake at work, I ‘lose my cool’ and become angry
    e. While working I am concerned that I could do something wrong

Regulatory Focus (Lockwood et al, 2002)

1. In general, I am focused on preventing negative events in my life.
2. I am anxious that I will fall short of my responsibilities and obligations.
3. I frequently imagine how I will achieve my hopes and aspirations.
4. I often think about the person I am afraid I might become in the future.
5. I often think about the person I would ideally like to be in the future.

6. I typically focus on the success I hope to achieve in the future.
7. I often worry that I will fail to accomplish my academic goals.
8. I often think about how I will achieve academic success.
9. I often imagine myself experiencing bad things that I fear might happen to me.
10. I frequently think about how I can prevent failures in my life.
11. I am more oriented toward preventing losses than I am toward achieving gains.
12. My major goal in school right now is to achieve my academic ambitions.
13. My major goal in school right now is to avoid becoming an academic failure.
14. I see myself as someone who is primarily striving to reach my "ideal self"—to fulfill my hopes, wishes, and aspirations.
15. I see myself as someone who is primarily striving to become the self I "ought" to be—to fulfill my duties, responsibilities, and obligations.
16. In general, I am focused on achieving positive outcomes in my life.
17. I often imagine myself experiencing good things that I hope will happen to me.
18. Overall, I am more oriented toward achieving success than preventing failure.

Big Five Personality (Donnellan et al, 2006)

1. Am the life of the party
2. Sympathize with others' feelings
3. Get chores done right away
4. Have frequent mood swings
5. Have a vivid imagination
6. Don't talk a lot
7. Am not interested in other people's problems

8. Often forget to put things back in their proper place

9. Am relaxed most of the time

10. Am not interested in abstract ideas

11. Talk to a lot of different people at parties

12. Feel others' emotions

13. Like order

14. Get upset easily

15. Have difficulty understanding abstract ideas

16. Keep in the background

17. Am not really interested in others

18. Make a mess of things

19. Seldom feel blue

20. Do not have a good imagination

Locomotion and Assessment Regulation (Kruglanski et al, 2000)

1. Locomotion

    a. I don't mind doing things even if they involve extra effort.

    b. I am a "workaholic."

    c. I feel excited just before I am about to reach a goal.

    d. I enjoy actively doing things, more than just watching and observing.

    e. I am a "doer."

    f. When I finish one project, I often wait awhile before getting started on a new one. (reverse-scored)

    g. When I decide to do something, I can't wait to get started.

h. By the time I accomplish a task, I already have the next one in mind.

i. I am a "low energy" person. (reverse-scored)

j. Most of the time my thoughts are occupied with the task I wish to accomplish.

k. When I get started on something, I usually persevere until I finish it.

l. I am a "go-getter."

2. Assessment

a. I never evaluate my social interactions with others after they occur. (reverse-scored)

b. I spend a great deal of time taking inventory of my positive and negative characteristics.

c. I like evaluating other people's plans.

d. I often compare myself with other people.

e. I don't spend much time thinking about ways others could improve themselves. (reverse-scored)

f. I often critique work done by myself or others.

g. I often feel that I am being evaluated by others.

h. I am a critical person.

i. I am very self-critical and self-conscious about what I am saying.

j. I often think that other people's choices and decisions are wrong.

k. I rarely analyze the conversations I have had with others after they occur. (reverse-scored)

l. When I meet a new person I usually evaluate how well he or she is doing on various dimensions (e.g., looks, achievements, social status, clothes).

Demographics

1. How many years old are you?
2. What is your race?
3. What is you gender?
4. What year are you in school?
5. How many years of experience do you have working?

APPENDIX D

Supplementary Analyses

Measurement Checks

Prior to utilizing the individual difference variables collected in the pre-survey, an attempt was first made to verify the structure of the various scales collected. This was initially accomplished utilizing a series of Exploratory and Confirmatory Factor Analyses (EFA and CFA; Millsap, 2005) to examine the factor structure of the latent variables being assessed. Ensuring that the measures used in our models are operating sufficiently well is an important prerequisite for their use.[2]

The first set of scales to be examined were the goal orientation scales (VandeWalle, 1997, 2001), as they were of primary interest for this study. An initial EFA was completed in SPSS 23 using a Maximum Likelihood estimator and an oblique (direct oblimin) rotation, extracting all factors with eigenvalues greater than one, loadings of less than .5 were suppressed to retain only substantial loadings, the same estimation technique is used in all EFAs discussed below. When all goal orientation items were included, a three-factor solution was extracted, with eigenvalues of 3.14 (26.16% of variance explained), 3.07 (25.58%), and 1.42 (11.84%). The pattern loading matrix for this solution can be found in Table E1. There, the rotated solution cleanly separates the expected factors representing learning, avoid, and approach/prove orientations respectively. The hypothesized three-factor solution was then tested using a CFA conducted in LISREL 9.3 and the covariance matrix was analyzed for all measurement checks. The standardized solution can also be found in Table E1. Fit for this model was compared to standard guidelines on the Comparative Fit Index (CFI; Bentler, 1990), Root Mean Square Error of Approximation (RMSEA; Steiger, 1990), and Standardized Root Mean Square Residual

[2] Taking this dual approach and using both EFA and CFA on the same data to explore the structures of the measures used here is based on a talk by Larry Williams (Intermediate SEM, CARMA Short Courses, Wayne State University, June 2017).

(SRMR; Bentler, 1995, as cited in Hu & Bentler, 1999). Adequate fit is usually indicated when CFI is greater than .95, RMSEA less than .07, and SRMR less than .08 (a review of cutoffs for these and other fit indices can be found in Hooper, Coughlan & Mullen, 2008). The three-factor CFA displayed adequate fit on all three standard fit indices (CFI = .97, RMSEA = .04, SRMR = .04). The three-factor model was also compared to a single factor model (chi-square = 1364.87, df = 54, $p < .001$), and the three-factor model fits significantly better (chi-square difference = 1258.45, df = 3, $p < .001$). It should also be noted that an EFA on the post-task version of this questionnaire also results in the same clear three-factor structure. These results indicate that the goal orientation questionnaire used in this study has sound psychometrics.

Next, the Error Orientation Questionnaire (Rybowiak et al, 1999) was examined. Here, a four-factor solution was identified, with eigenvalues of 4.97 (29.26% of variance explained), 2.68 (15.77%), 1.80 (10.60%), and 1.25 (7.37%). The pattern loading matrix for this solution can be found in Table E2. This pattern shows that much of the structure hypothesized by the original measure was recovered, with the factors corresponding to learning from errors, error strain, error competence, and error risk respectively; but that two items did not load substantially onto any of the four factors. The first of these items should load onto the error competency subscale, the second onto error strain. To further examine these subscales, Cronbach's alpha was computed for versions both with and without the questionable items. For error competence, alphas were .68 and .71. For strain, .78 and .79. This indicates that internal reliabilities are slightly higher when removing the problem items from these scales, despite having one fewer item, which would not be expected if those items were functioning similarly to the other items in the scale (Crocker & Algina, 1986). When analyzing error competence alone, a one-factor solution is returned, eigenvalue 2.08 (51.99%), loadings of .713, .630, .675, and .369 (chi-square = 10.80, df = 2, p =

.005). For strain, a one-factor solution as also returned, eigenvalue 2.69 (53.73%), loadings of .526, .862, .832, .389, and .591. Even when treated alone, both scales have an item that may not fit the operation of the rest of the scale. To analyze further, a four-factor CFA with all original items was completed. The standardized solution can also be found in Table E2. Fit for this model (CFI = .90, RMSEA = .08, SRMR = .09) was inadequate. A second CFA was completed removing item four from the error strain, and item four from the error competence scales by dropping them from the scale (as opposed to setting the factor loadings to zero, however, this results in a non-nested model and direct comparison is not possible). The standardized solution for this model can also be found in Table E2. Fit for this model (CFI = .95, RMSEA = .06, SRMR = .06) is adequate. A one-factor model (chi-square = 1487.84, df = 90, p = < .001) fits significantly worse than the four-factor model (chi-square difference = 1231.07, df = 6, p < .001). Given these results, future use of the error orientation scales will use the four subscales, but will not include item four from both the strain and competence scales.

When the Five Factor Model measure (Donnellan et al, 2006) was subjected to the same procedure, a six-factor solution was extracted from the EFA. These factors had eigenvalues of 3.49 (17.44% of variance explained), 2.27 (11.35%), 2.07 (10.34%), 1.98 (9.88%), 1.53 (7.64%), and 1.38 (6.90%). The pattern matrix for this solution can be found in Table E3. The pattern matrix shows that much of the corresponding factor solution for The Big 5 is recovered, with the factors corresponding to extraversion, conscientiousness, agreeableness, openness, neuroticism, and an undefined factor, respectively. However, several items (six of them) did not load directly onto their theoretical factors in a substantial matter. The sixth factor is not shown in the table because no items loaded onto this factor substantially, either. Alphas for these subscales with and without these questionable items are: .71 and .75 for agreeableness, .69 and .65 for openness, and

.60 and .70 for neuroticism. For agreeableness and neuroticism, this shows that internal reliability of the scales may be higher if the questionable items are removed from the scales. Exploring these scales further using EFAs only on the subscale, openness results in a single factor solution, eigenvalue 2.06 (51.54%), with loadings of .519, .635, .583, and .644 (chi-square = 66.98, df = 2, $p < .001$). Agreeableness alone also shows a single factor solution, eigenvalue 2.20 (54.96%), with loadings of .803, .464, .718, and .509 (chi-square = 63.23, df = 2, $p < .001$). As does neuroticism, with an eigenvalue of 1.86 (46.53%), factor loadings of .878, .391, .616, and .230 (chi-square = 22.73, df = 2, $p < .001$). Thus, when treated separately, items for the openness subscale appear to work better than when combined with the other personality traits, but there are still issues with items in the agreeableness and neuroticism scales. CFAs were then completed. The standardized solution for the basic five-factor model can also be found in Table E3. It is interesting that for the openness factor, the two items that loaded poorly in the EFA are the strongest indicators in the CFA. The fit for this model (CFI = .73, RMSEA = .09, SRMR = .08) is sub-par. In combination with the earlier EFAs, the worst performing items appear to be the second and fourth items in the neuroticism scale, and a second CFA was completed dropping these two items, the standardized loadings for which are also reported in Table E3. Fit for this model was not adequate either (CFI = .74, RMSEA = .10, SRMR = .08). Individual CFAs for each factor were then completed. Extraversion (chi-square = 57.35, df = 2, $p < .001$, CFI = .92, RMSEA = .23, SRMR = .05), agreeableness (chi-square = 63.54, df = 2, $p < .001$, CFI = .87, RMSEA = .24, SRMR = .08), conscientiousness (chi-square = 42.82, df = 2, $p < .001$, CFI = .89, RMSEA = .20, SRMR = .06), openness (chi-square = 68.02, df = 2, $p < .001$, CFI = .83, RMSEA = .25, SRMR = .08), and neuroticism (chi-square = 23.15, df = 2, $p < .001$, CFI = .93, RMSEA = .14, SRMR = .06) all display borderline or questionable fit when analyzed on their own. Based on this series of analyses, it does not appear that there is an easy adjustment to improve this set of measures substantially. Therefore, the original scales as published will be utilized, but with the acknowledgement that they display sub-optimal psychometrics.

Problems were encountered when examining the regulatory focus scale that was adopted from Lockwood et al (2002). This scale was designed with two dimensions, promotion and prevention. Unfortunately, the original paper does not appear to specify which dimension each item is supposed to load on. To attempt to recreate the correct scales, an initial EFA was completed to extract two factors. The two factors extracted had eigenvalues of 5.84 (32.42% of variance explained), and 3.28 (18.24%) respectively.[3] These factors have a correlation of .17, which is identical to the interfactor-correlation reported by Lockwood et al (2002). The pattern loading matrix for this EFA is presented in Table E4. Even though nine items are supposed to load on each of two underlying factors, three items do not load significantly on either extracted factor. From the strong loadings that did emerge, it appears that the first factor is the promotion scale, and the second is the prevention scale. Cronbach's alpha for the promotion factor as a scale would be .89. For the prevention scale, only including the six items which load on the second factor, alpha is .81. Adding the three remaining items to this scale to create two nine-item scales as in the original measure, alpha remains .81. This suggests these three items may not substantially add to the prevention scale as they do not load onto the prevention factor in the EFA, and, given a constant average inter-item correlation, adding items to a scale should increase alpha (Crocker & Algina, 1986). Following this pattern of items, two CFAs were completed. The first included all items, with the nine identified as most strongly related to promotion used to identify the first factor, and the remaining nine items on the second factor. Fit

[3] An EFA was also run which extracted all factors with eigenvalues greater than 1. 3 factors were found with the 3rd having an eigenvalue of 1.06 (5.91% of variance explained), but no items load on this factor substantially.

for this model (CFI = .80, RMSEA = .10, SRMR = .13) is poor in all regards. A second CFA dropping the three worst performing items identified previously fits (CFI = .89, RMSEA = .09, SRMR = .09) still fits poorly. Due to the lack of clarity in this measure, its poor psychometrics, and status as merely a possible control variable in this study, it was not utilized.

Locomotion and Assessment Regulation (Kruglanski et al, 2000) were also examined in a similar way. The results for which were not promising. The initial EFA returned a six-factor solution, with eigenvalues of 4.60 (19.16%), 3.38 (14.09%), 1.79 (7.47%), 1.24 (5.18%), 1.15 (4.80%), and 1.11 (4.63%), instead of the expected two-factor solution. The pattern loading matrix for this analysis can be seen in Table E5. As you can see, only a few items load substantially (above .5) on the first two factors. Not depicted here is that the last three factors each have no more than one item loading on them at a high level either, and only 13 of the 24 items load on *any* factor at a level above .5. As such, the requirements for loadings were relaxed to .4. The scree plot for the measure was also examined, and can be seen in Figure F1. Here, we see a clear elbow between the third and fourth factor, this three-factor solution is the one depicted in the table. One item, assessment regulation item 7, loads in the opposite direction of expected onto the assessment factor. This does not appear to be accounted for by wording, this item is being dropped from all subsequent analyses. Cronbach's alpha for the full locomotion scale is .82, with the two questionable items removed it is also .82. For assessment, the full scale (minus the negatively loading item) alpha is .71, and .71 with questionable items removed. Further CFAs were run to examine these scales further. The initial CFA examined the baseline two-factor solution with all items from the original measures included. The standardized solution for this model can be found in Table E5 as well. This model's fit (CFI = .77, RMSEA = .07, SRMR = .07) shows mixed results. A second CFA was run without the items identified in the earlier EFA as potentially problematic (items six and 10 for locomotion, and one, two, three, five, seven and 11 for assessment) removed. This model's fit (CFI = .87, RMSEA = .07, SRMR = .07) also shows mixed results, but appears to fit better than the original model. Based on these results, further use of these scales will only utilize the items included in this second CFA as they are more clearly measuring the latent constructs of interest.

Behavioral Manipulation Checks

Engagement rates. The first set of tests completed to check for possible differences in conditions were completed for engagement rates on each board size. To test this, engagement rates for each board for each trial for each individual were calculated as a percentage of times choosing to attempt a board size for any amount of time. Then, multiple imputation was completed to regain lost power due to the listwise deletion procedure in repeated measures MANOVA in SPSS. Power was lost purely by chance due to dropping any participants who for even a single round never saw a particular board size, which by definition occurred by chance because boards were chosen completely at random, so their engagement rates were incalculable. This resulted in a very conservative test of group differences as the imputed numbers are heavily influenced by the overall mean for each size. In a repeated measures MANOVA, engagement rate for each board size was entered as a dependent variable, with condition as a between subjects factor. Most board sizes show no significant differences in engagement by condition [smallest ($F(2, 310) = .17$, $p = .840$), second ($F(2, 310) = .40$, $p = .674$), third ($F(2, 310) = .42$, $p = .657$), fourth ($F(2, 310) = .95$, $p = .388$), largest ($F(2, 310) = .67$, $p = .512$)]. However, the second largest board does show significant difference ($F(2, 310) = 4.06$, $p = .018$). A Tukey follow up shows avoid individuals engaged at a significantly higher rate than learning individuals (dif = .09, SE = .03, $p = .014$, $d = .19$).

In addition, the number of rounds played was examined across conditions. This is a potentially stronger indication of self-regulation behavioral differences because playing more rounds indicates a greater use of personal time instead of merely task-allotted time, so shows greater personal sacrifice. A repeated measures ANOVA using multiple imputation for missing data shows significant difference in rounds played between conditions ($F(2, 311) = 5.66$, $p = .004$, $\eta^2 = .035$). A follow-up Tukey tests showed that the primary difference was learning being higher than avoid orientation (dif = 27.00, SE = 8.17, $p = .003$, $d = .30$), while the difference between approach and avoid approached significance (dif = 17.44, SE = 7.94, $p = .073$, $d = .27$) with approach being higher, and the difference between learning and approach was (dif = 9.56, SE = 6.43, $p = .460$, $d = .10$). In conclusion, there appears to be some difference between conditions in how participants are behaving in the task but that behavior is more complex than can be readily captured in these general tests.

Ad Hoc Test for Changes in Engagement Model Over Time

One main point of study was to look at changes in model over time, though no specific hypotheses were proposed. To the baseline model supported in Pre-Requisite 1, time (trial coded 0-8) was added as a conditional predictor of likelihood of engagement. This model fit significantly better than the model just accounting for within-person efficacy (board-size) (df = 2, $\chi^2 = 611.2$, $p < .001$, $\Delta R^2 = .01$). This was broken down by dummy coding for each trial, the parameters for the overall model and for each trial can be found in Table E6. Depictions of models can be found in Figures F2 and F3. To this model, goal orientation condition was entered as a second conditional predictor. This model also fit significantly better (df = 4, $\chi^2 = 24.78$, $p < .001$, $\Delta R^2 = .00$). This model was also broken down using dummy coding. The parameters for these can be found in Tables E7-E9. Figures comparing each condition over time can be found in

Figures F4-F7. All orientations tend to follow the same trend over time, starting with higher engagement across all levels of efficacy, then the engagement for low levels of efficacy gets depressed in the middle trials, and begins to raise again in the later trials. The major difference between orientation conditions appears to be that in the early-mid trials the level of engagement depression for avoid individuals is less than that of learning individuals.

Ad Hoc Test for Changes in Resource Allocation (seconds allocated) Over Time

As with the engagement side of the model, resource allocation was explored as it changed over time, and how goal orientation condition may have moderated that change. First, trial (coded 0-8) was entered into the supported model for Resource Allocation (seconds allocated) from Pre-requisite 2. This model fit significantly better (df = 2, *L* ratio = 1902.52, $p < .001$, $R^2 = .14$, $\Delta R^2 = .01$). This was then broken down using dummy coding for each trial. Overall model and trial parameters can be found in Table E9. Condition was then added to the model accounting for time. This model also fit significantly better (df = 4, *L* ratio = 210.43, $p < .001$, $R^2 = .18$, $\Delta R^2 = .04$). As with engagement, this was broken down for each condition and trial. The parameters can be found in Tables E10-E12. Figures can be found in Figures F8-F12. In general, Resource Allocation (seconds allocated) changes over time such that the negative slope with efficacy flattens out and the intercept lowers in the early trials, and gradually returns in the later rounds. Between conditions, the primary difference appears to be that even though all three conditions flatten out their Resource Allocation (seconds allocated) in the early trials, learning and approach both get their negative slopes of Resource Allocation (seconds allocated) back by the mid trials, but avoid stays flat and doesn’t return to the negative slope until the final couple of trials.

APPENDIX E

Tables for Supplementary Analyses

Table E1. *EFA and CFA for Goal Orientation* (*Vandewalle, 1997, 2001) scales.*

	EFA			CFA		
Item	Learning	Avoid	Prove	Learning	Avoid	Prove
LGO1	.742			.72		
LGO2	.685			.72		
LGO3	.830			.81		
LGO4	.584			.60		
PAGO1		.747			.72	
PAGO2		.629			.70	
PAGO3		.736			.76	
PAGO4		.711			.71	
PPGO1			-.735			.72
PPGO2			-.786			.78
PPGO3			-.646			.66
PPGO4			-.664			.68
Chi-Square		69.51			106.42	
DF		33			51	
P		<.001			<.001	
Factor Correlation						
Avoid	-.25			-.25		
Prove	-.29	-.28		.30	.25	

Note: LGO = learning goal orientation, PAGO = performance avoid orientation, PPGO = performance prove orientation.

Table E2. *EFA and CFAs for Error Orientation Questionnaire* (*Rybowiak et al, 1999) scales.*

	EFA				CFA 1				CFA 2			
Item	Learn	Strain	Comp	Risk	Learn	Strain	Comp	Risk	Learn	Strain	Comp	Risk
Learn 1	.821				.81				.81			
Learn 2	.824				.83				.83			
Learn 3	.937				.92				.92			
Learn 4	.843				.87				.87			
Strain 1		.577				.52				.53		
Strain 2		.866				.86				.89		
Strain 3		.824				.84				.81		
Strain 4		*				.40						
Strain 5		.592				.59				.56		
Comp 1			.786				.66				.72	
Comp 2			.589				.63				.62	
Comp 3			.601				.67				.68	
Comp 4				**			.46					
Risk 1				.760				.73				.74
Risk 2				.754				.74				.74
Risk 3				.520				.59				.59
Risk 4				.503				.54				.54
Chi-square	241.40				496.93				256.77			
DF	74				113				84			
P	<.001				<.001				<.001			
Factor Correlations												
Strain	-.16				-.17				-.16			
Comp	.15	.12			.30	.01			.20	.04		
Risk	.58	-.16	.30		.61	-.18	.44		.61	-.17	.34	

*Actual loading is .326

**Actual loading is .368, note that this is not on the expected factor

Table E3. *EFA and CFAs for Big Five personality scales* (*Donnellan et al, 2006).*

	EFA					CFA 1					CFA 2				
Items	Extra	Cons	Agree	Open	Neuro	Extra	Cons	Agree	Open	Neuro	Extra	Cons	Agree	Open	Neuro
Extra1	.737					.63					.63				
Extra2	.636					.68					.68				
Extra3	.750					.75					.75				
Extra4	.748					.76					.76				
Cons1		-.576					.48					.47			
Cons2		-.681					.78					.78			
Cons3		-.538					.43					.43			
Cons4		-.656					.67					.67			
Agree1			.787					.74					.74		
Agree2			*					.51					.51		
Agree3			.737					.70					.70		
Agree4			**					.59					.59		
Open1				-.714					.45					.45	
Open2				***					.68					.68	
Open3				****					.64					.64	
Open4				-.729					.59					.59	
Neuro1					.768					.87					.80
Neuro2					*****					.39					
Neuro3					.677					.63					.68
Neuro4					******					.22					
Chi-Square			226.51					931.32					821.59		
DF			85					160					125		
P			<.001					<.001					<.001		
Factor Correlations															
Cons	-.03					.02					.03				
Agree	.19	-.14				.33	.18				.33	.18			
Open	-.11	.02	-.18			.17	.13	.33			.17	.14	.33		
Neuro	-.10	.10	.00	.20		-.16	-.26	-.03	-.23		-.16	-.28	-.05	-.26	

*Loading is .369 on agreeableness factor, .417 on 6th, undefined factor

Table E3 (cont'd)

**Loading is .338 on agreeableness factor, .389 on 6th, undefined factor

***Loading is -.479 on agreeableness factor

****Loading is -.451 on agreeableness factor, -.304 on neuroticism

*****Loading is .453 on 6th, undefined factor

******Loading is .380 on 6th, undefined factor

Table E4. *EFA and CFAs for Lockwood et al* (*2002) Regulatory Focus Scales.*

	EFA		CFA 1		CFA 2	
Item	Promotion	Prevention	Promotion	Prevention	Promotion	Prevention
1	*			.37		
2		.562		.63		.61
3	.732		.74		.74	
4		.659		.62		.65
5	.700		.73		.73	
6	.814		.81		.81	
7		.688		.72		.75
8	.662		.68		.67	
9		.767		.74		.76
10		**		.57		
11		.675		.55		.57
12	.607		.62		.62	
13		.529		.56		.53
14	.706		.69		.69	
15				.35		
16	.785		.76		.76	
17	.669		.66		.66	
18	.597		.54		.55	
Chi-Square	461.43		899.05		458.68	
Df	118		134		89	
P	<.001		<.001		<.001	
Factor Correlation	.17		.29		.15	

*Loading is .432

**Loading is .462, cross-loads on promotion at .404

Note: Loadings less than .5 are suppressed for EFA. For CFA, the loadings for items 1, 10 and 15 are fixed to 0, for CFA 2 they are allowed to be estimated.

Table E5. *EFA and CFAs for Locomotion and Assessment Regulation* (*Kruglanski et al, 2000).*

	EFA			CFA 1			CFA 2		
Item	Locomotion	Assessment	Undefined	Locomotion	Assessment	Undefined	Locomotion	Assessment	Undefined
Loco 1	.559			.54			.54		
Loco 2	.507			.50			.50		
Loco 3	.542			.55			.55		
Loco 4	.708			.71			.71		
Loco 5	.772			.77			.78		
Loco 6				.18					
Loco 7	.503			.50			.49		
Loco 8	.480			.48			.46		
Loco 9	.473			.45			.46		
Loco 10				.40					
Loco 11	.478			.48			.46		
Loco 12	.761			.75			.75		
Assess 1			.636		.29				
Assess 2					.46				
Assess 3					.41				
Assess 4		.499			.54			.47	
Assess 5					.25				
Assess 6		.619			.65			.71	
Assess 7		-.709			-.74				
Assess 8		.669			.61			.72	
Assess 9		.508			.58			.53	
Assess 10		.499			.35			.40	
Assess 11			.755		.26				
Assess 12		.498			.41			.40	
Chi-square		551.48			967.58			376.69	
DF		207			251			103	
P		<.001			<.001			<.001	
Factor Correlations									
Assess	.06			.16			.21		
Undefined	.11	.16							

*Based on extracted 3-factor solution instead of larger 6 factor solution

Table E6. *Parameters for engagement by trial.*

Trial	Parameter	Coeff.	SE	*z*	*p*
Overall	Intercept	-2.72	.30	-9.05	< .001
	Trial	-.12	.01	-15.18	< .001
	Board-Size	1.27	.06	20.21	< .001
	Trial x Board-Size Interaction	.01	.002	4.79	< .001
Trial 1	Intercept	-3.55	.29	-12.16	< .001
	Trial	3.27	.06	53.07	< .001
	Board-Size	1.39	.06	22.77	< .001
	Trial x Board-Size Interaction	-.51	.02	-23.82	< .001
Trial 2	Intercept	-3.19	.28	-11.26	< .001
	Trial	.16	.05	2.94	.003
	Board-Size	1.30	.06	22.09	< .001
	Trial x Board-Size Interaction	.06	.02	3.75	< .001
Trial 3	Intercept	-3.04	.25	-11.99	< .001
	Trial	-.98	.06	-17.77	< .001
	Board-Size	1.28	.05	23.87	< .001
	Trial x Board-Size Interaction	.23	.02	14.02	< .001
Trial 4	Intercept	-3.00	.27	-10.95	< .001
	Trial	-1.32	.06	-23.02	< .001
	Board-Size	1.27	.06	22.21	< .001
	Trial x Board-Size Interaction	.28	.02	16.75	< .001
Trial 5	Intercept	-3.02	.29	-10.49	< .001
	Trial	-1.17	.06	-20.01	< .001
	Board-Size	1.28	.06	21.40	< .001
	Trial x Board-Size Interaction	.22	.02	12.94	< .001
Trial 6	Intercept	-3.08	.30	-10.36	< .001
	Trial	-.69	.06	-11.83	< .001
	Board-Size	1.29	.06	20.91	< .011
	Trial x Board-Size Interaction	.13	.02	7.74	< .001

Table E6 (cont'd)

Trial	Parameter	Coeff.	SE	*z*	*p*
Trial 7	Intercept	-3.14	.28	-11.35	< .001
	Trial	-.24	.06	-4.04	< .001
	Board-Size	1.30	.06	22.61	< .001
	Trial x Board-Size Interaction	.02	.02	1.32	.187
Trial 8	Intercept	-3.22	.27	-11.97	< .001
	Trial	.61	.06	10.23	< .001
	Board-Size	1.32	.06	23.39	< .001
	Trial x Board-Size Interaction	-.15	.02	-8.06	< .001
Trial 9	Intercept	-3.23	.29	-11.13	< .001
	Trial	.81	.06	13.04	< .001
	Board-Size	1.32	.06	21.90	< .001
	Trial x Board-Size Interaction	-.18	.02	-9.18	< .001

Table E7. *Engagement by trial for learning condition, and overall model.*

Trial	Parameter	Coeff.	SE	*z*	*p*
Overall	Intercept	-3.28	1.10	-2.98	.003
	Condition	.28	.50	.56	.575
	Trial	-.09	.02	-4.57	< .001
	Board-Size	1.28	.22	5.74	< .001
	Condition x Trial	-.01	.01	-1.34	.179
	Condition x Board-Size	-.01	.10	-.10	.924
	Trial x Board-Size	.00	.01	-.79	.429
	Condition x Trial x Board-Size	.01	.003	2.97	.003
Trial 1	Intercept	-3.48	.40	-8.67	< .001
	Condition	-.23	.70	-.33	.740
	Trial	3.06	.08	39.60	< .001
	Board-Size	1.42	.08	17.18	< .001
	Condition x Trial	.61	.13	4.63	< .001
	Condition x Board-Size	-.09	.14	-.63	.526
	Trial x Board-Size	-.47	.03	-17.34	< .001
	Condition x Trial x Board-Size	-.10	.04	-2.32	.020
Trial 2	Intercept	-3.11	.43	-7.21	< .001
	Condition	-.21	.88	-.25	.805
	Trial	-.02	.07	-.32	.750
	Board-Size	1.33	.09	15.10	< .001
	Condition x Trial	.52	.11	4.72	< .001
	Condition x Board-Size	-.10	.18	-.55	.581
	Trial x Board-Size	.10	.02	4.48	< .001
	Condition x Trial x Board-Size	-.10	.04	-2.90	.004
Trial 3	Intercept	-3.00	.34	-8.87	< .001
	Condition	-.13	.54	-.26	.799
	Trial	-.94	.07	-13.85	< .001
	Board-Size	1.31	.07	18.68	< .001

Table E7 (cont'd)

Trial	Parameter	Coeff.	SE	*z*	*p*
Trial 3	Condition x Trial	-.11	.11	-.96	.339
	Condition x Board-Size	-.12	.11	-1.02	.310
	Trial x Board-Size	.21	.02	10.29	< .001
	Condition x Trial x Board-Size	.04	.03	1.21	.227
Trial 4	Intercept	-3.01	.29	-10.32	< .001
	Condition	.03	.48	.07	.942
	Trial	-.89	.07	-12.92	< .001
	Board-Size	1.32	.06	21.40	< .001
	Condition x Trial	-1.30	.13	-10.38	< .001
	Condition x Board-Size	.16	.10	-1.53	.127
	Trial x Board-Size	.16	.02	7.53	< .001
	Condition x Trial x Board-Size	.34	.04	9.77	< .001
Trial 5	Intercept	-2.99	.30	-9.83	< .001
	Condition	-.09	.51	-.17	.864
	Trial	-1.01	.07	-14.17	< .001
	Board-Size	1.32	.06	20.46	< .001
	Condition x Trial	-.55	.13	-4.36	< .001
	Condition x Board-Size	-.12	.11	-1.11	.269
	Trial x Board-Size	.19	.02	8.98	< .001
	Condition x Trial x Board-Size	.10	.04	2.76	.006
Trial 6	Intercept	-3.04	.33	-9.21	< .001
	Condition	-.13	.51	-.26	.795
	Trial	-.64	.07	-8.87	< .001
	Board-Size	1.33	.07	19.25	< .001
	Condition x Trial	-.14	.12	-1.14	.254
	Condition x Board-Size	-.11	.11	-1.05	.295

Table E7 (cont'd)

Trial	Parameter	Coeff.	SE	*z*	*p*
Trial 6	Trial x Board-Size	.12	.02	5.63	< .001
	Condition x Trial x Board-Size	.02	.03	.s66	.508
Trial 7	Intercept	-3.10	.33	-9.52	< .001
	Condition	-.11	.55	-.20	.839
	Trial	-.12	.07	-1.67	.096
	Board-Size	1.34	.07	19.68	< .001
	Condition x Trial	-.37	.12	-3.09	.002
	Condition x Board-Size	-.12	.12	-1.01	.31
	Trial x Board-Size	.01	.02	.53	.594
	Condition x Trial x Board-Size	.05	.03	1.47	.141
Trial 8	Intercept	-3.16	.38	-8.24	< .001
	Condition	-.19	.74	-.26	.798
	Trial	.47	.07	6.34	< .001
	Board-Size	1.35	.08	17.23	< .001
	Condition x Trial	.46	.13	3.66	< .001
	Condition x Board-Size	-.10	.15	-.69	.491
	Trial x Board-Size	-.12	.02	-5.16	< .001
	Condition x Trial x Board-Size	-.09	.04	-2.42	.015
Trial 9	Intercept	-3.16	.35	-9.14	< .001
	Condition	-.22	.81	-.27	.788
	Trial	.53	.08	6.97	< .001
	Board-Size	1.35	.07	18.81	< .001
	Condition x Trial	.91	.13	6.76	< .001
	Condition x Board-Size	-.10	.16	-.58	.561
	Trial x Board-Size	-.12	.02	-5.16	< .001
	Condition x Trial x Board-Size	-.17	.04	-4.19	< .001

Table E8. *Engagement by trial for approach condition.*

Trial	Parameter	Coeff.	SE	*z*	*p*
Trial 1	Intercept	-3.40	.35	-9.72	< .001
	Condition	-.45	.68	-.67	.506
	Trial	3.02	.08	39.64	< .001
	Board-Size	1.33	.07	18.21	< .001
	Condition x Trial	.71	.13	5.41	< .001
	Condition x Board-Size	.18	.14	1.26	.207
	Trial x Board-Size	-.46	.03	-17.41	< .001
	Condition x Trial x Board-Size	-.15	.05	-3.26	.001
Trial 2	Intercept	-3.09	.33	-9.26	< .001
	Condition	-.27	.52	-.53	.599
	Trial	.38	.07	5.88	< .001
	Board-Size	1.26	.07	18.08	< .001
	Condition x Trial	-.67	.11	-5.86	< .001
	Condition x Board-Size	.12	.11	1.10	.269
	Trial x Board-Size	.00	.02	.23	.820
	Condition x Trial x Board-Size	.18	.04	4.86	< .001
Trial 3	Intercept	-2.96	.44	-6.74	< .001
	Condition	-.23	.70	-.34	.737
	Trial	-.69	.07	-10.32	< .001
	Board-Size	1.24	.09	13.87	< .001
	Condition x Trial	-.86	.12	-7.28	< .001
	Condition x Board-Size	.12	.14	.81	.417
	Trial x Board-Size	.16	.02	7.96	< .001
	Condition x Trial x Board-Size	.22	.04	6.13	< .001
Trial 4	Intercept	-2.86	.36	-8.07	< .001
	Condition	-.39	.56	-.70	.484
	Trial	-1.41	.07	-19.93	< .001
	Board-Size	1.22	.07	16.57	< .001

Table E8 (cont'd)

Trial	Parameter	Coeff.	SE	*z*	*p*
Trial 4	Condition x Trial	.26	.12	2.15	.032
	Condition x Board-Size	.15	.12	1.29	.197
	Trial x Board-Size	.30	.02	14.77	< .001
	Condition x Trial x Board-Size	-.06	.04	-1.76	.078
Trial 5	Intercept	-2.91	.47	-6.16	< .001
	Condition	-.31	.90	-.34	.731
	Trial	-1.08	.07	-15.13	< .001
	Board-Size	1.23	.10	12.89	< .001
	Condition x Trial	-.30	.13	-2.40	.017
	Condition x Board-Size	.12	.18	.72	.470
	Trial x Board-Size	.19	.02	9.32	< .001
	Condition x Trial x Board-Size	.09	.04	2.49	.013
Trial 6	Intercept	-2.95	.35	-8.49	< .001
	Condition	-.37	.60	-.62	.536
	Trial	-.75	.08	-10.57	< .001
	Board-Size	1.24	.07	17.16	< .001
	Condition x Trial	.20	.12	1.61	.107
	Condition x Board-Size	.15	.12	1.20	.231
	Trial x Board-Size	.15	.02	7.50	< .001
	Condition x Trial x Board-Size	-.07	.04	-2.05	.041
Trial 7	Intercept	-3.00	.36	-8.39	< .001
	Condition	-.40	.62	-.65	.515
	Trial	-.41	.07	-5.71	< .001
	Board-Size	1.25	.07	16.88	< .001
	Condition x Trial	.52	.12	4.27	< .001
	Condition x Board-Size	.15	.13	1.21	.228

Table E8 (cont'd)

Trial	Parameter	Coeff.	SE	*z*	*p*
Trial 7	Trial x Board-Size	.07	.02	3.16	.002
	Condition x Trial x Board-Size	-.13	.04	-3.67	< .001
Trial 8	Intercept	-3.09	.31	-10.11	< .001
	Condition	-.39	.50	-.79	.432
	Trial	.47	.07	6.51	< .001
	Board-Size	1.27	.06	19.69	< .001
	Condition x Trial	.43	.13	3.45	< .001
	Condition x Board-Size	.15	.11	1.42	.156
	Trial x Board-Size	-.12	.02	-5.56	< .001
	Condition x Trial x Board-Size	-.08	.04	-2.07	.038
Trial 9	Intercept	-3.11	.40	-7.84	< .001
	Condition	-.35	.78	-.45	.653
	Trial	.81	.08	10.70	< .001
	Board-Size	1.27	.08	15.61	< .001
	Condition x Trial	-.01	.13	-.10	.918
	Condition x Board-Size	.15	.16	.92	.357
	Trial x Board-Size	-.16	.02	-6.44	< .001
	Condition x Trial x Board-Size	-.05	.04	-1.31	.192

Table E9. *Engagement by trial for avoid condition.*

Trial	Parameter	Coeff.	SE	*z*	*p*
Trial 1	Intercept	-3.78	.33	-11.45	< .001
	Condition	.69	.63	1.10	.273
	Trial	3.69	.07	50.05	< .001
	Board-Size	1.42	.07	20.41	< .001
	Condition x Trial	-1.40	.13	-10.66	< .001
	Condition x Board-Size	-.09	.13	-.66	.506
	Trial x Board-Size	-.59	.03	-23.41	< .001
	Condition x Trial x Board-Size	.26	.05	5.59	< .001
Trial 2	Intercept	-3.35	.32	-10.54	< .001
	Condition	.49	.67	.73	.463
	Trial	.11	.06	1.75	.081
	Board-Size	1.31	.07	19.59	< .001
	Condition x Trial	.16	.12	1.40	.163
	Condition x Board-Size	-.02	.14	-.17	.864
	Trial x Board-Size	.09	.02	4.28	< .001
	Condition x Trial x Board-Size	-.09	.04	-2.35	.019
Trial 3	Intercept	-3.16	.36	-8.76	< .001
	Condition	.37	.56	.67	.506
	Trial	-1.30	.07	-19.18	< .001
	Board-Size	1.28	.07	17.06	< .001
	Condition x Trial	1.01	.12	8.87	< .001
	Condition x Board-Size	.00	.12	.01	.993
	Trial x Board-Size	.31	.02	15.93	< .001
	Condition x Trial x Board-Size	-.28	.04	-7.54	< .001
Trial 4	Intercept	-3.12	.31	-10.18	< .001
	Condition	.36	.64	.57	.572
	Trial	-1.66	.07	-23.23	< .001

Table E9 (cont'd)

Trial	Parameter	Coeff.	SE	*z*	*p*
Trial 4	Board-Size	1.27	.06	19.64	< .001
	Condition x Trial	1.05	.12	8.63	< .001
	Condition x Board-Size	.01	.13	.05	.960
	Trial x Board-Size	.37	.02	18.37	< .001
	Condition x Trial x Board-Size	-.30	.04	-8.26	< .001
Trial 5	Intercept	-3.16	.36	-8.71	< .001
	Condition	.41	.57	.73	.468
	Trial	-1.45	.07	-19.80	< .001
	Board-Size	1.29	.08	17.12	< .001
	Condition x Trial	.79	.12	6.39	< .001
	Condition x Board-Size	-.02	.12	-.14	.891
	Trial x Board-Size	.28	.02	13.71	< .001
	Condition x Trial x Board-Size	-.16	.04	-4.31	< .001
Trial 6	Intercept	-3.25	.32	-10.08	< .001
	Condition	.51	.57	.90	.369
	Trial	-.67	.07	-9.63	< .001
	Board-Size	1.30	.07	19.29	< .001
	Condition x Trial	-.10	.13	-.82	.414
	Condition x Board-Size	-.04	.12	-.35	.730
	Trial x Board-Size	.12	.02	5.96	< .001
	Condition x Trial x Board-Size	.08	.04	2.04	.042
Trial 7	Intercept	-3.31	.41	-8.08	< .001
	Condition	.52	.88	.59	.554
	Trial	-.19	.07	-2.77	.006
	Board-Size	1.31	.08	15.69	< .001
	Condition x Trial	-.23	.13	-1.74	.082

Table E9 (cont'd)

Trial	Parameter	Coeff.	SE	*z*	*p*
Trial 7	Condition x Board-Size	-.04	.18	-.25	.802
	Trial x Board-Size	.00	.02	-.05	.962
	Condition x Trial x Board-Size	.13	.04	3.06	.002
Trial 8	Intercept	-3.41	.34	-10.00	< .001
	Condition	.58	.64	.92	.360
	Trial	.92	.07	12.65	< .001
	Board-Size	1.33	.07	18.75	< .001
	Condition x Trial	-.85	.13	-6.70	< .001
	Condition x Board-Size	-.05	.13	.35	.728
	Trial x Board-Size	-.21	.02	-9.55	< .001
	Condition x Trial x Board-Size	.15	.04	3.69	< .001
Trial 9	Intercept	-3.42	.30	-11.41	< .001
	Condition	.57	.65	.88	.378
	Trial	1.09	.08	14.52	< .001
	Board-Size	1.34	.06	21.04	< .001
	Condition x Trial	-.84	.13	-6.32	< .001
	Condition x Board-Size	-.05	.13	-.39	.697
	Trial x Board-Size	-.25	.02	-10.99	< .001
	Condition x Trial x Board-Size	.23	.04	5.18	< .001

Table E10. *Resource Allocation (seconds allocated) by trial for learning condition, and overall model.*

Trial	Parameter	Coeff.	SE	*t*	*p*
Overall	Intercept	6.98	.41	16.93	< .001
	Condition	.12	.19	.62	.534
	Trial	.39	.02	22.98	< .001
	Board-Size	-.32	.09	-3.47	< .001
	Condition x Trial	-.11	.01	-13.49	< .001
	Condition x Board-Size	.04	.04	1.00	.318
	Trial x Board-Size	-.08	.004	-17.24	< .001
	Condition x Trial x Board-Size	.03	.002	13.84	< .001
Trial 1	Intercept	7.55	.19	40.16	< .001
	Condition	.48	.33	1.46	.146
	Trial	.37	.06	6.58	< .001
	Board-Size	-.20	.04	-4.64	< .001
	Condition x Trial	-.14	.10	-1.42	.157
	Condition x Board-Size	-.21	.07	-2.87	.004
	Trial x Board-Size	-.16	.02	-10.47	< .001
	Condition x Trial x Board-Size	.10	.03	3.76	< .001
Trial 2	Intercept	7.70	.19	41.40	< .001
	Condition	.60	.33	1.83	.068
	Trial	-.69	.06	-11.36	< .001
	Board-Size	-.23	.04	-5.49	< .001
	Condition x Trial	-.92	.11	-8.57	< .001
	Condition x Board-Size	-.24	.07	-3.29	.001
	Trial x Board-Size	.10	.02	6.01	< .001
	Condition x Trial x Board-Size	.30	.03	10.92	< .001
Trial 3	Intercept	7.69	.19	41.19	< .001
	Condition	.51	.33	1.54	.123
	Trial	-.88	.06	-13.84	< .001

Table E10 (cont'd)

Trial	Parameter	Coeff.	SE	*t*	*p*
Trial 3	Board-Size	-.23	.04	-5.45	< .001
	Condition x Trial	-.41	.12	-3.56	< .001
	Condition x Board-Size	-.21	.07	-2.91	.004
	Trial x Board-Size	.14	.02	8.50	< .001
	Condition x Trial x Board-Size	.11	.03	3.98	< .001
Trial 4	Intercept	7.67	.19	40.94	< .001
	Condition	.47	.33	1.41	.159
	Trial	-.73	.06	-11.21	< .001
	Board-Size	-.23	.04	-5.42	< .001
	Condition x Trial	-.01	.12	-.08	.935
	Condition x Board-Size	-.20	.07	-2.67	.008
	Trial x Board-Size	.14	.02	8.59	< .001
	Condition x Trial x Board-Size	-.03	.03	-1.05	.294
Trial 5	Intercept	7.63	.19	40.67	< .001
	Condition	.47	.33	1.41	.159
	Trial	-.30	.07	-4.59	< .001
	Board-Size	-.22	.04	-5.23	< .001
	Condition x Trial	.15	.12	1.28	.199
	Condition x Board-Size	-.20	.07	-2.72	.007
	Trial x Board-Size	.06	.02	3.38	< .001
	Condition x Trial x Board-Size	-.04	.03	-1.39	.164
Trial 6	Intercept	7.62	.19	40.63	< .001
	Condition	.43	.33	1.30	.196
	Trial	-.07	.07	-1.05	.292
	Board-Size	-.22	.04	-5.25	< .001
	Condition x Trial	.47	.12	4.07	< .001

Table E10 (cont'd)

Trial	Parameter	Coeff.	SE	*t*	*p*
Trial 6	Condition x Board-Size	-.18	.07	-2.46	.014
	Trial x Board-Size	.04	.02	2.39	.017
	Condition x Trial x Board-Size	-.20	.03	-7.03	< .001
Trial 7	Intercept	7.56	.19	40.35	< .001
	Condition	.45	.33	1.36	.175
	Trial	.56	.07	8.45	< .001
	Board-Size	-.21	.04	-5.00	< .001
	Condition x Trial	.36	.12	3.08	.002
	Condition x Board-Size	-.19	.07	-2.58	.010
	Trial x Board-Size	-.08	.02	-5.10	< .001
	Condition x Trial x Board-Size	-.14	.03	-4.92	< .001
Trial 8	Intercept	7.53	.19	40.30	< .001
	Condition	.52	.33	1.56	.119
	Trial	.78	.06	12.02	< .001
	Board-Size	-.21	.04	-4.95	< .001
	Condition x Trial	-.34	.11	-2.97	.003
	Condition x Board-Size	-.21	.07	-2.86	.004
	Trial x Board-Size	-.09	.02	-5.45	< .001
	Condition x Trial x Board-Size	.07	.03	2.22	.026
Trial 9	Intercept	7.51	.19	40.41	< .001
	Condition	.43	.33	1.30	.194
	Trial	1.12	.07	16.72	< .001
	Board-Size	-.20	.04	-4.89	< .001
	Condition x Trial	.40	.12	3.40	< .001
	Condition x Board-Size	-.20	.07	-2.77	.006

Table E10 (cont'd)

Trial	Parameter	Coeff.	SE	*t*	*p*
Trial 9	Trial x Board-Size	-.14	.02	-8.08	< .001
	Condition x Trial x Board-Size	.07	.03	2.39	.017

DF for individual effects = 310, all others = 79891

Table E11. *Resource Allocation (seconds allocated) by trial for approach condition.*

Trial	Parameter	Coeff.	SE	*t*	*p*
Trial 1	Intercept	7.74	.19	40.08	< .001
	Condition	-.10	.33	-.29	.770
	Trial	.56	.06	9.71	< .001
	Board-Size	-.25	.04	-5.63	< .001
	Condition x Trial	-.66	.10	-6.83	< .001
	Condition x Board-Size	-.05	.07	-.71	.475
	Trial x Board-Size	-.19	.02	-11.97	< .001
	Condition x Trial x Board-Size	.17	.03	6.51	< .001
Trial 2	Intercept	7.97	.19	41.72	< .001
	Condition	-.22	.32	-.70	.487
	Trial	-.92	.06	-14.80	< .001
	Board-Size	-.30	.04	-6.97	< .001
	Condition x Trial	-.22	.11	-2.11	.035
	Condition x Board-Size	-.02	.07	-.23	.815
	Trial x Board-Size	.19	.02	11.85	< .001
	Condition x Trial x Board-Size	.01	.03	.50	.615
Trial 3	Intercept	7.93	.19	41.41	< .001
	Condition	-.23	.32	-.71	.475
	Trial	-.92	.07	-13.97	< .001
	Board-Size	-.29	.04	-6.72	< .001
	Condition x Trial	-.26	.11	-2.35	.019
	Condition x Board-Size	-.02	.07	-.24	.812
	Trial x Board-Size	.16	.02	9.79	< .001
	Condition x Trial x Board-Size	.04	.03	1.27	.204
Trial 4	Intercept	7.90	.19	41.14	< .001
	Condition	-.25	.32	-.77	.442
	Trial	-.73	.07	-10.75	< .001

Table E11 (cont'd)

Trial	Parameter	Coeff.	SE	*t*	*p*
Trial 4	Board-Size	-.28	.04	-6.53	< .001
	Condition x Trial	.02	.11	.19	.846
	Condition x Board-Size	-.02	.07	-.25	.799
	Trial x Board-Size	.12	.02	7.29	< .001
	Condition x Trial x Board-Size	.01	.03	.47	.641
Trial 5	Intercept	7.88	.19	40.90	< .001
	Condition	-.27	.32	-.83	.406
	Trial	-.32	.07	-4.73	< .001
	Board-Size	-.28	.04	-6.44	< .001
	Condition x Trial	.19	.12	1.63	.103
	Condition x Board-Size	-.01	.07	-.16	.876
	Trial x Board-Size	.06	.02	3.42	< .001
	Condition x Trial x Board-Size	-.04	.03	-1.49	.136
Trial 6	Intercept	7.85	.19	40.77	< .001
	Condition	-.27	.32	-.83	.408
	Trial	.02	.07	.33	.742
	Board-Size	-.27	.04	-6.27	< .001
	Condition x Trial	.23	.11	2.06	.039
	Condition x Board-Size	-.01	.07	-.20	.844
	Trial x Board-Size	-.02	.02	-1.49	.135
	Condition x Trial x Board-Size	-.03	.03	-1.02	.308
Trial 7	Intercept	7.79	.19	40.53	< .001
	Condition	-.25	.32	-.76	.447
	Trial	.71	.07	10.57	< .001
	Board-Size	-.26	.04	-6.07	< .001
	Condition x Trial	-.07	.11	-.66	.511

Table E11 (cont'd)

Trial	Parameter	Coeff.	SE	*t*	*p*
Trial 7	Condition x Board-Size	-.02	.07	-.26	.794
	Trial x Board-Size	-.15	.02	-8.92	< .001
	Condition x Trial x Board-Size	.04	.03	1.42	.156
Trial 8	Intercept	7.81	.19	40.72	< .001
	Condition	-.33	.32	-1.02	.310
	Trial	.43	.07	6.55	< .001
	Board-Size	-.28	.04	-6.35	< .001
	Condition x Trial	.71	.11	6.32	< .001
	Condition x Board-Size	.00	.07	.02	.987
	Trial x Board-Size	-.02	.02	-1.01	.315
	Condition x Trial x Board-Size	-.16	.03	-5.40	< .001
Trial 9	Intercept	7.75	.19	40.65	< .001
	Condition	-.30	.32	-.95	.344
	Trial	1.07	.07	15.70	< .001
	Board-Size	-.27	.04	-6.23	< .001
	Condition x Trial	.53	.12	4.56	< .001
	Condition x Board-Size	.00	.07	.00	.998
	Trial x Board-Size	-.06	.02	-3.41	.001
	Condition x Trial x Board-Size	-.17	.03	5.77	< .001

Table E12. *Resource Allocation (seconds allocated) by trial for avoid condition.*

Trial	Parameter	Coeff.	SE	*t*	*p*
Trial 1	Intercept	7.83	.19	41.39	< .001
	Condition	-.38	.33	-1.15	.252
	Trial	.06	.06	1.06	.290
	Board-Size	-.35	.04	-8.31	< .001
	Condition x Trial	.85	.10	8.57	< .001
	Condition x Board-Size	.27	.07	3.62	< .001
	Trial x Board-Size	-.04	.02	-2.66	.008
	Condition x Trial x Board-Size	-.30	.03	-10.58	< .001
Trial 2	Intercept	8.01	.19	42.73	< .001
	Condition	-.36	.33	-1.11	.267
	Trial	-1.37	.06	-22.30	< .001
	Board-Size	-.39	.04	-9.36	< .001
	Condition x Trial	1.14	.11	10.73	< .001
	Condition x Board-Size	.26	.07	3.54	< .001
	Trial x Board-Size	.30	.02	18.83	< .001
	Condition x Trial x Board-Size	-.32	.03	-11.45	< .001
Trial 3	Intercept	7.94	.19	42.23	< .001
	Condition	-.27	.33	-.81	.418
	Trial	-1.23	.07	-18.74	< .001
	Board-Size	-.37	.04	-8.89	< .001
	Condition x Trial	.64	.11	5.78	< .001
	Condition x Board-Size	.23	.07	3.15	.002
	Trial x Board-Size	.22	.02	13.75	< .001
	Condition x Trial x Board-Size	-.14	.03	-5.02	< .001
Trial 4	Intercept	7.88	.19	41.81	< .001
	Condition	-.20	.33	-.62	.539
	Trial	-.71	.07	-10.48	< .001

Table E12 (cont'd)

Trial	Parameter	Coeff.	SE	*t*	*p*
Trial 4	Board-Size	-.36	.04	-8.59	< .001
	Condition x Trial	-.04	.11	-.31	.759
	Condition x Board-Size	.21	.07	2.92	.004
	Trial x Board-Size	.12	.02	7.26	< .001
	Condition x Trial x Board-Size	.03	.03	.90	.366
Trial 5	Intercept	7.84	.19	41.51	< .001
	Condition	-.18	.33	-.55	.580
	Trial	-.14	.07	-2.00	.046
	Board-Size	-.35	.04	-8.40	< .001
	Condition x Trial	-.33	.11	-2.87	.004
	Condition x Board-Size	.21	.07	2.87	.004
	Trial x Board-Size	.01	.02	.88	.377
	Condition x Trial x Board-Size	.08	.03	2.84	.005
Trial 6	Intercept	8.00	.19	41.32	< .001
	Condition	-.14	.33	-.43	.664
	Trial	.34	.07	5.08	< .001
	Board-Size	-.34	.04	-8.13	< .001
	Condition x Trial	0.76	.11	-6.63	< .001
	Condition x Board-Size	.19	.07	2.62	.009
	Trial x Board-Size	-.11	.02	-6.71	< .001
	Condition x Trial x Board-Size	.25	.03	8.83	< .001
Trial 7	Intercept	7.77	.19	41.17	< .001
	Condition	-.19	.33	-.57	.570
	Trial	.78	.07	11.67	< .001
	Board-Size	-.34	.04	-8.06	< .001
	Condition x Trial	-.31	.12	-2.72	.007

Table E12 (cont'd)

Trial	Parameter	Coeff.	SE	*t*	*p*
Trial 7	Condition x Board-Size	.21	.07	2.82	.005
	Trial x Board-Size	-.17	.02	-10.31	< .001
	Condition x Trial x Board-Size	.11	.03	3.89	< .001
Trial 8	Intercept	7.76	.19	41.19	< .001
	Condition	-.17	.33	-.53	.596
	Trial	.80	.07	12.16	< .001
	Board-Size	-.34	.04	-8.19	< .001
	Condition x Trial	-.38	.11	-3.37	< .001
	Condition x Board-Size	.21	.07	2.85	.004
	Trial x Board-Size	-.10	.02	-5.98	< .001
	Condition x Trial x Board-Size	.09	.03	3.12	.002
Trial 9	Intercept	7.68	.19	41.03	< .001
	Condition	-.12	.33	-.36	.722
	Trial	1.57	.07	23.30	< .001
	Board-Size	-.33	.04	-8.00	< .001
	Condition x Trial	-.93	.12	-8.00	< .001
	Condition x Board-Size	.20	.07	2.78	.005
	Trial x Board-Size	-.17	.02	-9.64	< .001
	Condition x Trial x Board-Size	.12	.03	3.98	< .001

APPENDIX F

Figures for Supplementary Analyses

Figure F1. Scree plot for Locomotion and Assessment Regulation scales (Kruglanski et al, 2000).

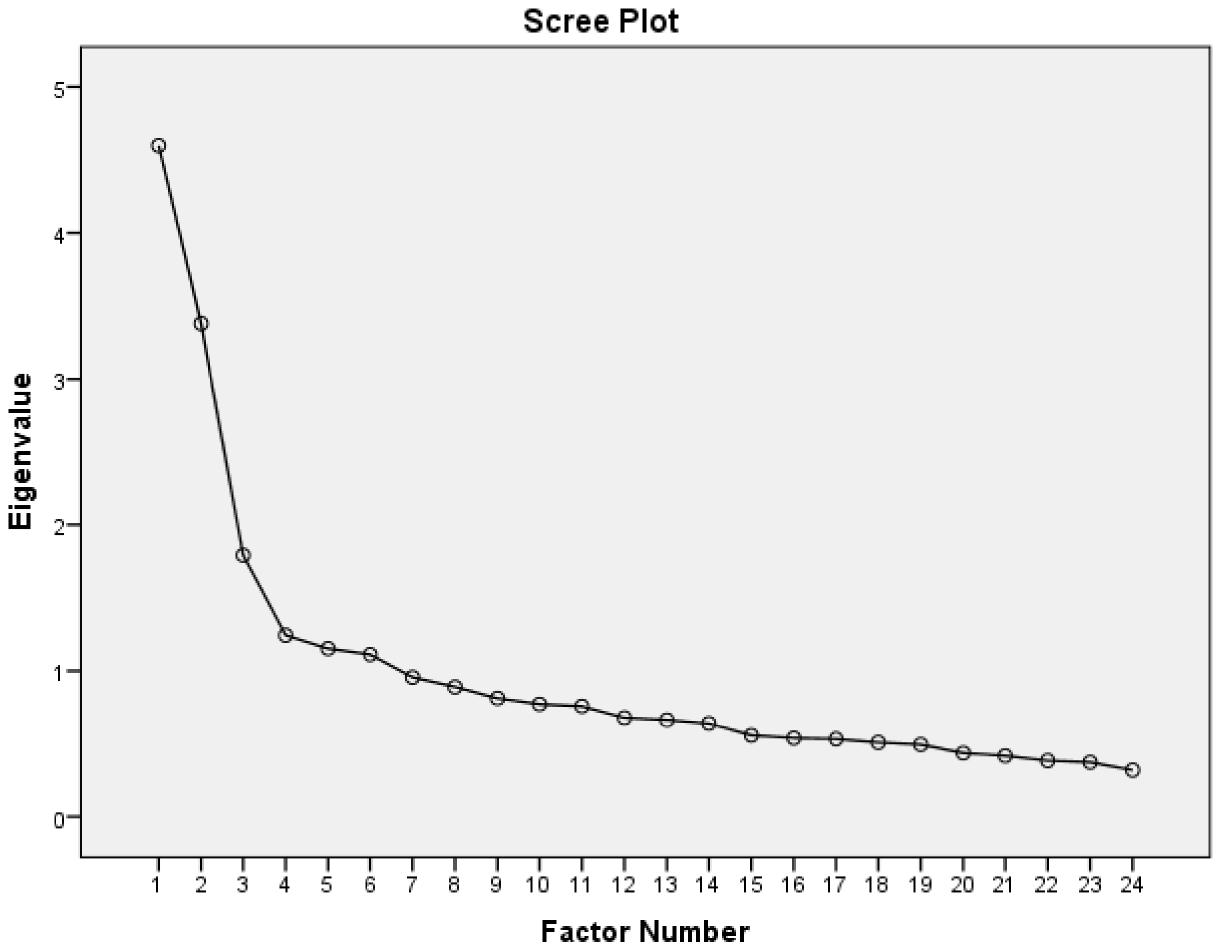


Figure F2. Engagement by trial, trials 1-4.

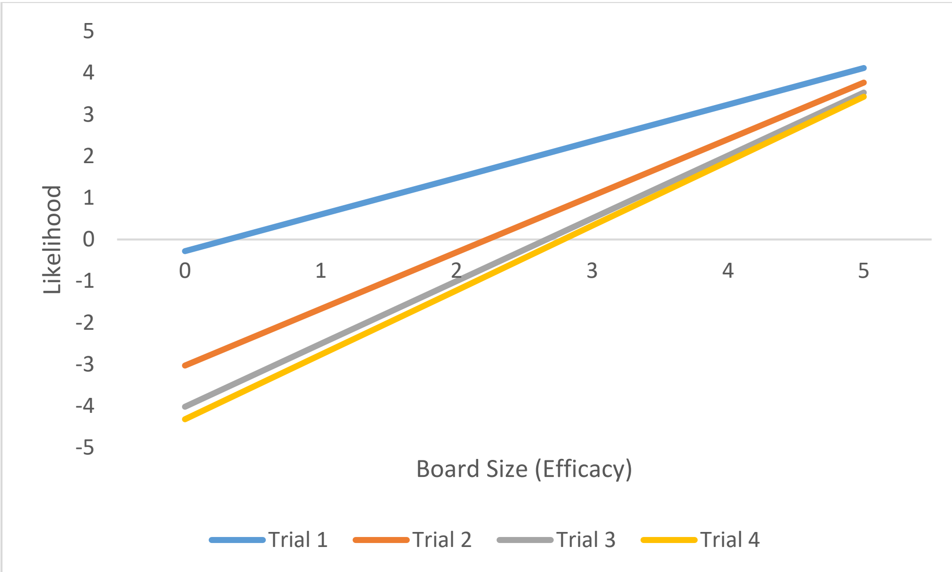


Figure F3. Engagement by trial, trials 5-9.

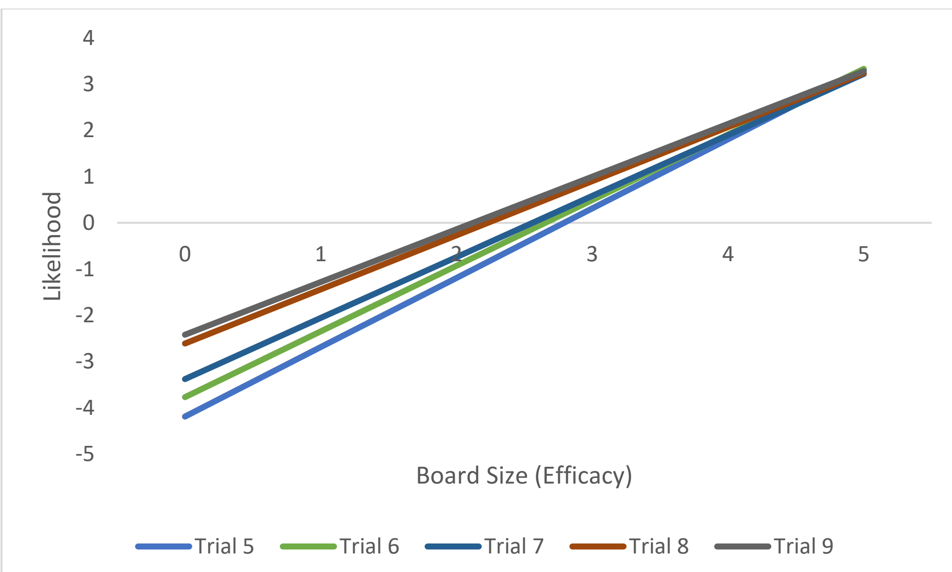


Figure F4. Engagement for learning orientation over time.

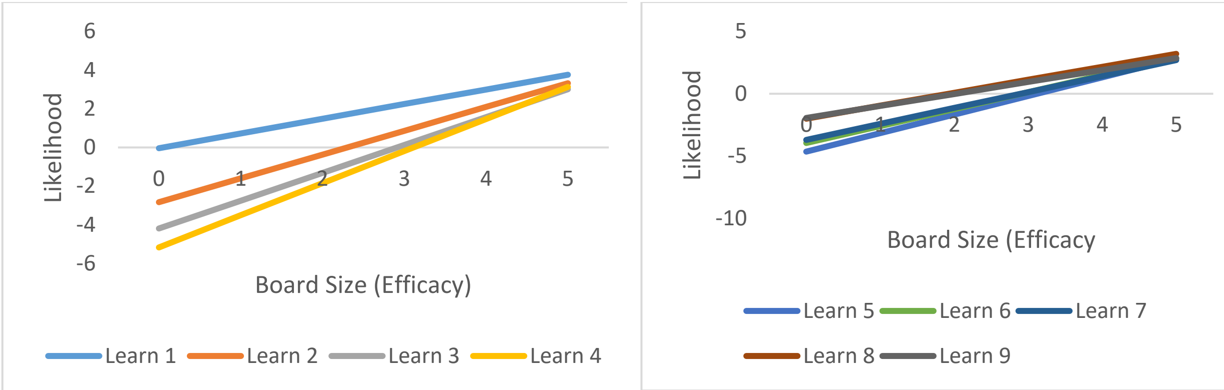


Figure F5. Engagement for approach orientation over time.

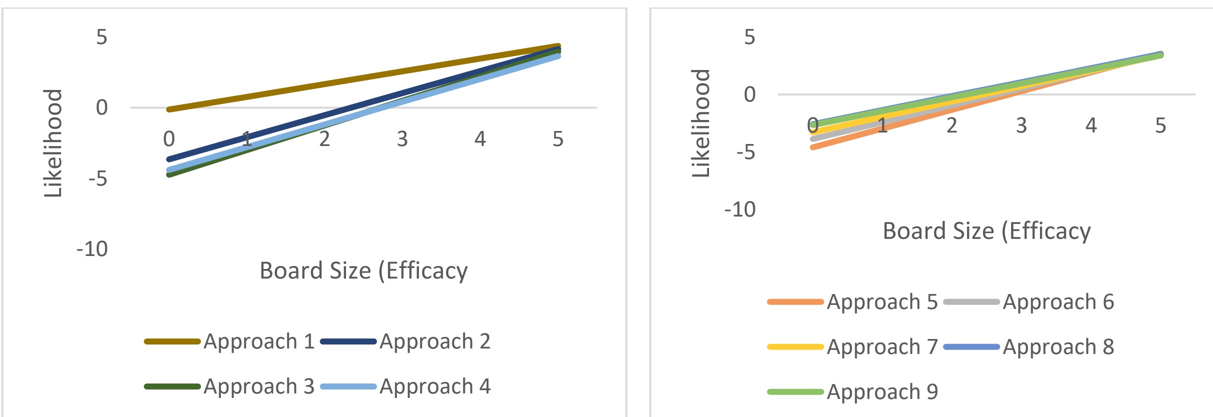


Figure F6. Engagement for avoid orientation over time.

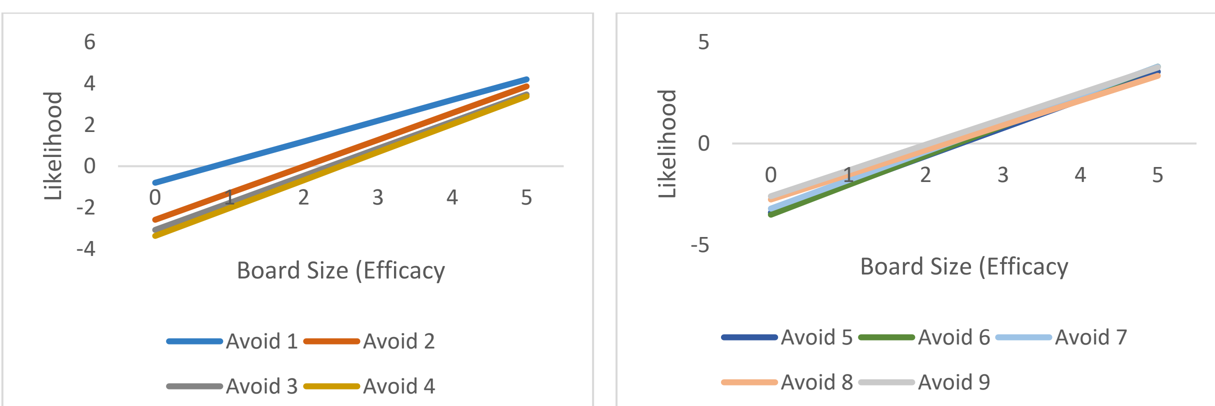


Figure F7. Comparisons of orientations by trial. (Trial number in legends.)

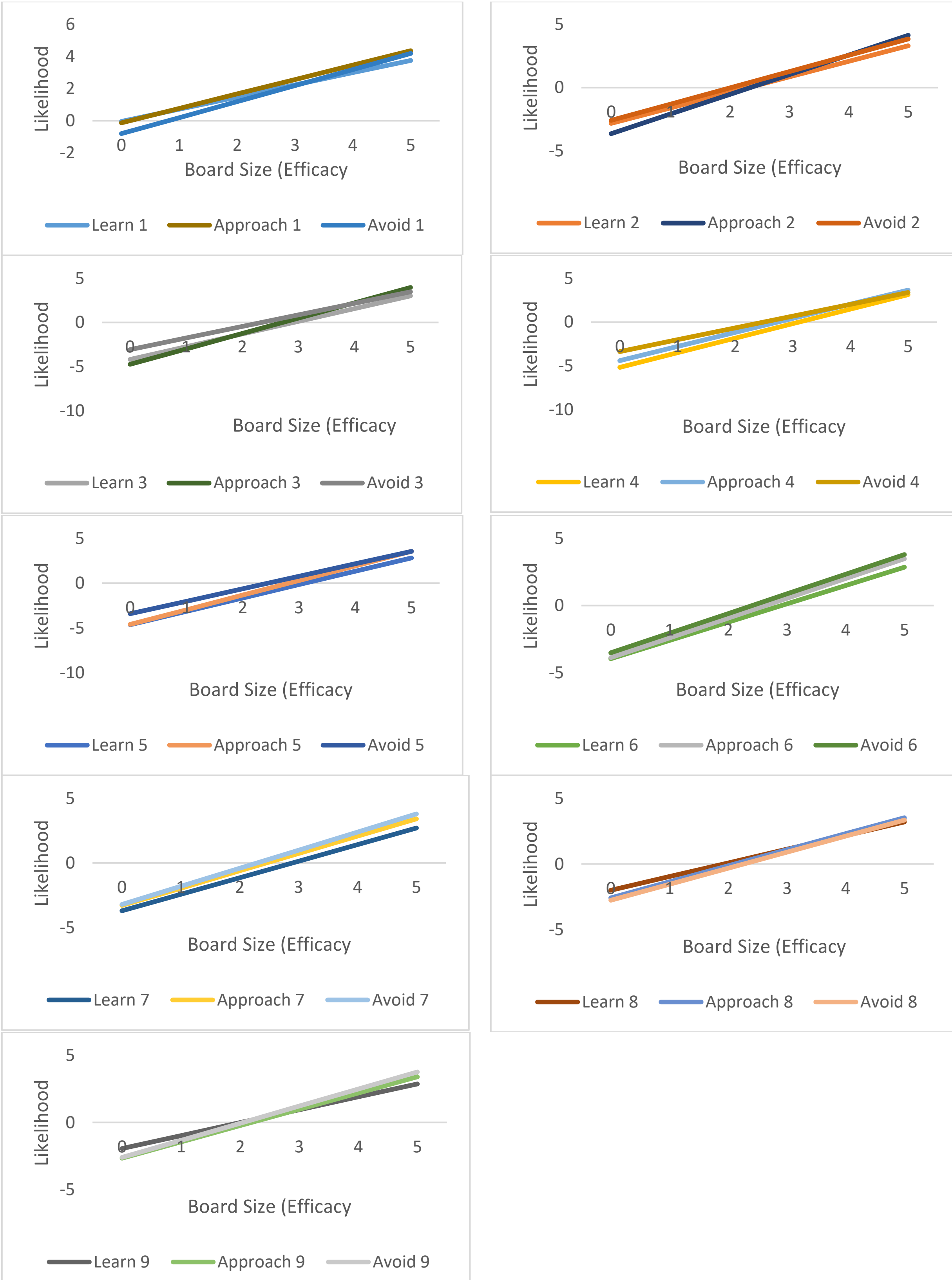


Figure F8. Resource Allocation (seconds allocated) by trial.

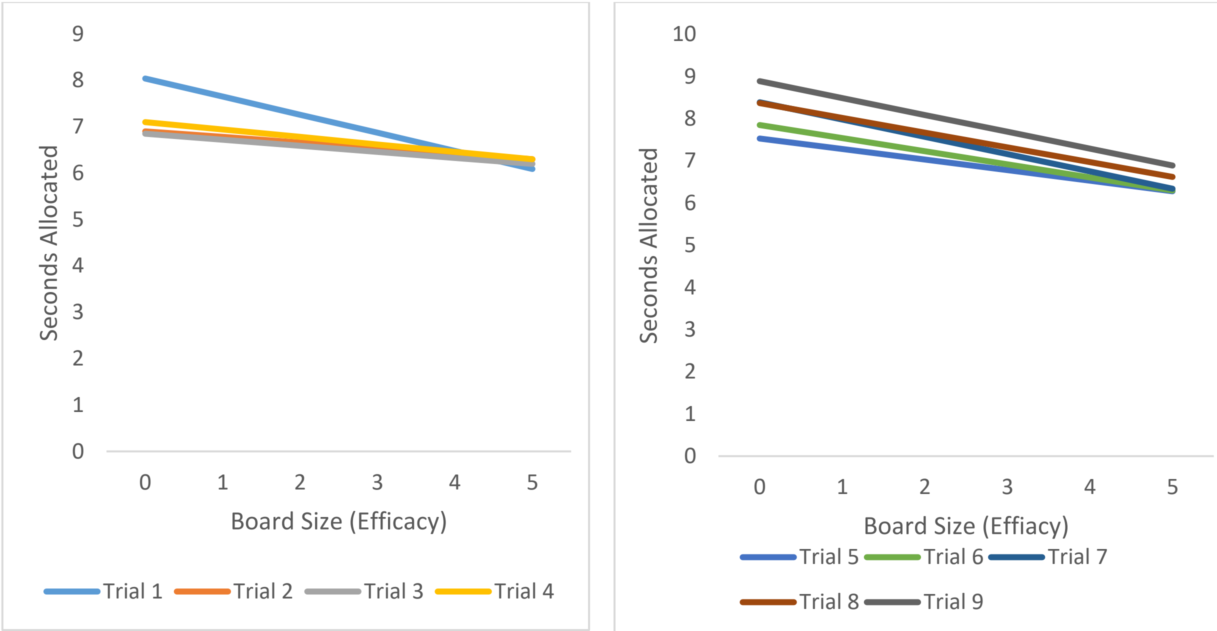


Figure F9. Resource Allocation (seconds allocated) by trial, learning orientation.

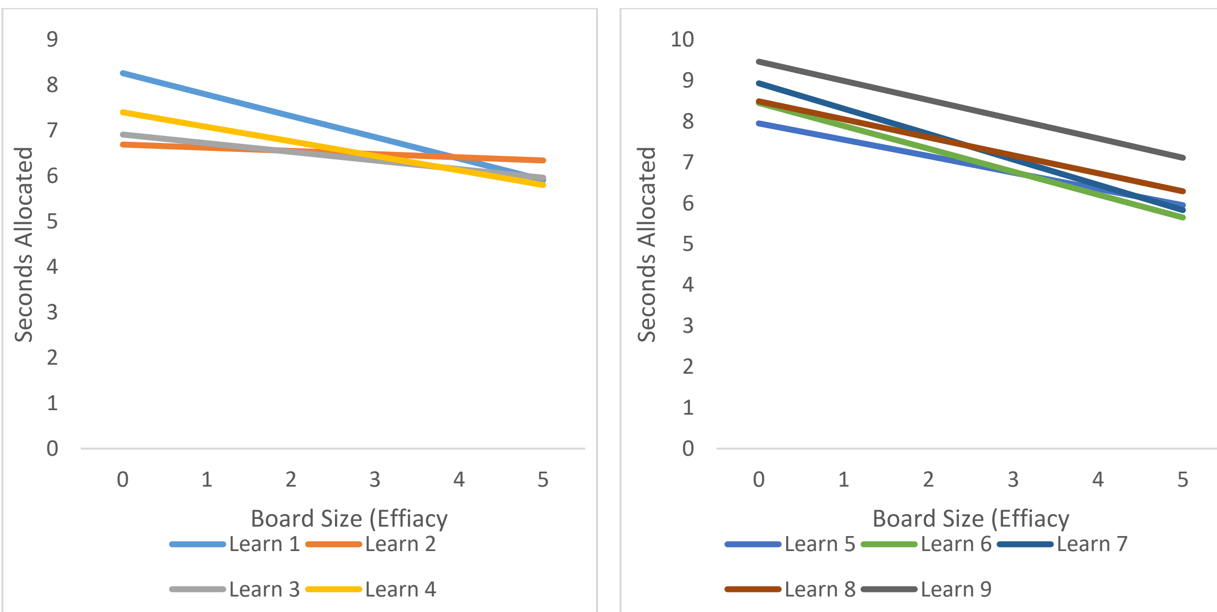


Figure F10. Resource Allocation (seconds allocated) by trial, approach orientation.

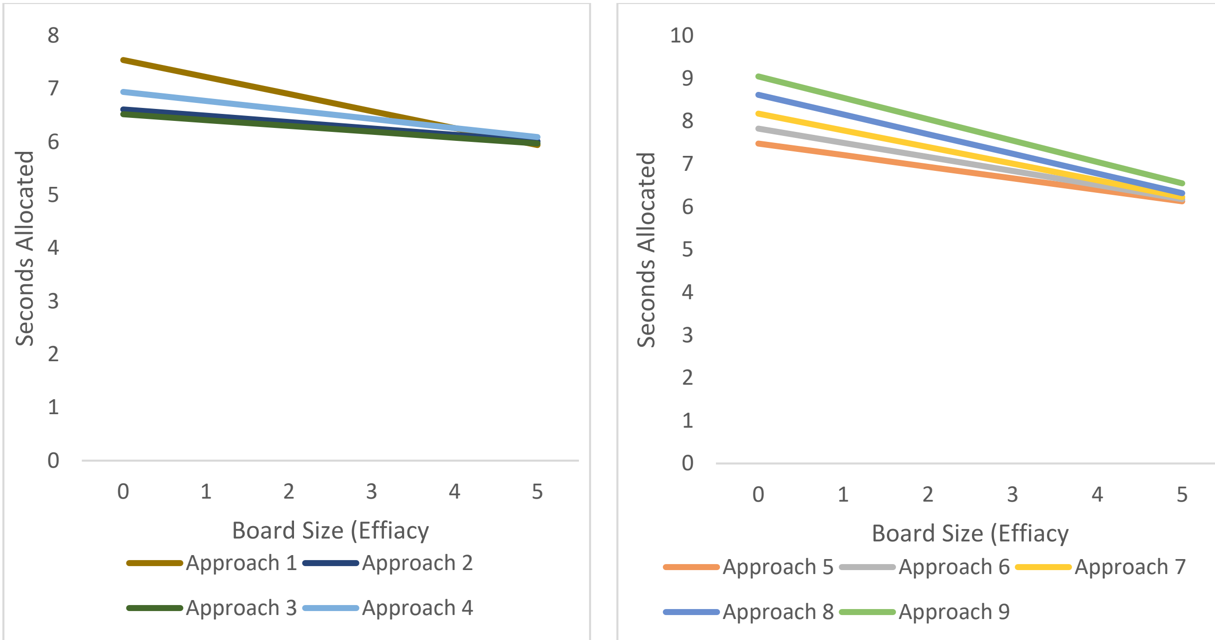


Figure F11. Resource Allocation (seconds allocated) by trial, avoid orientation.

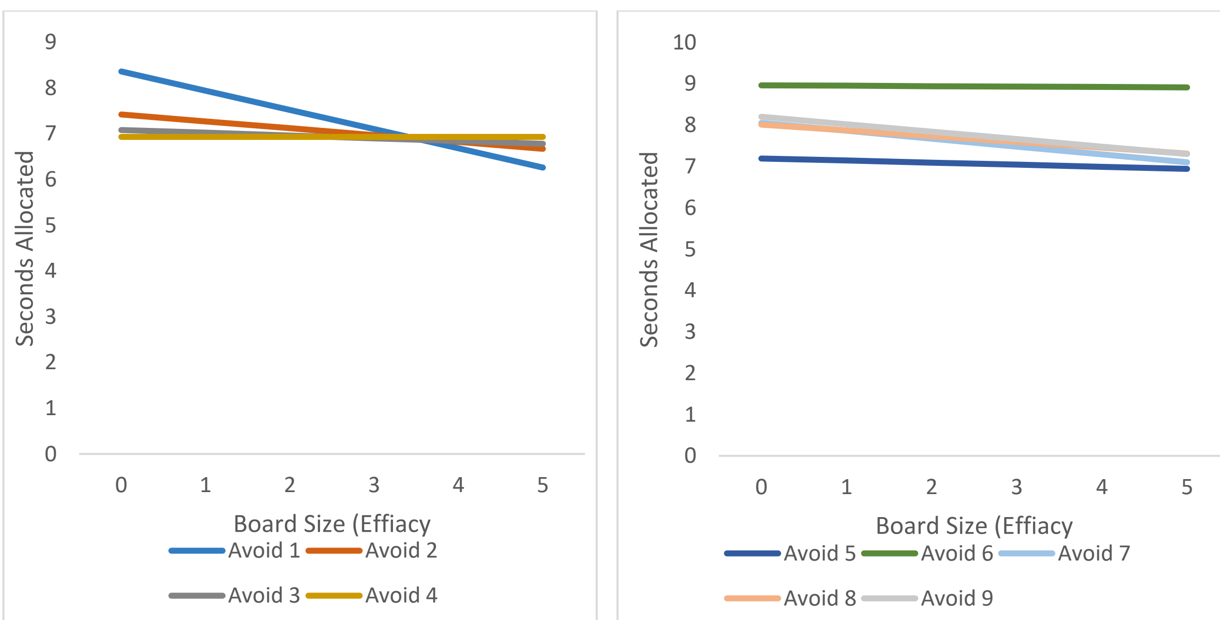


Figure F12. Resource Allocation (seconds allocated) compared by condition for each trial.

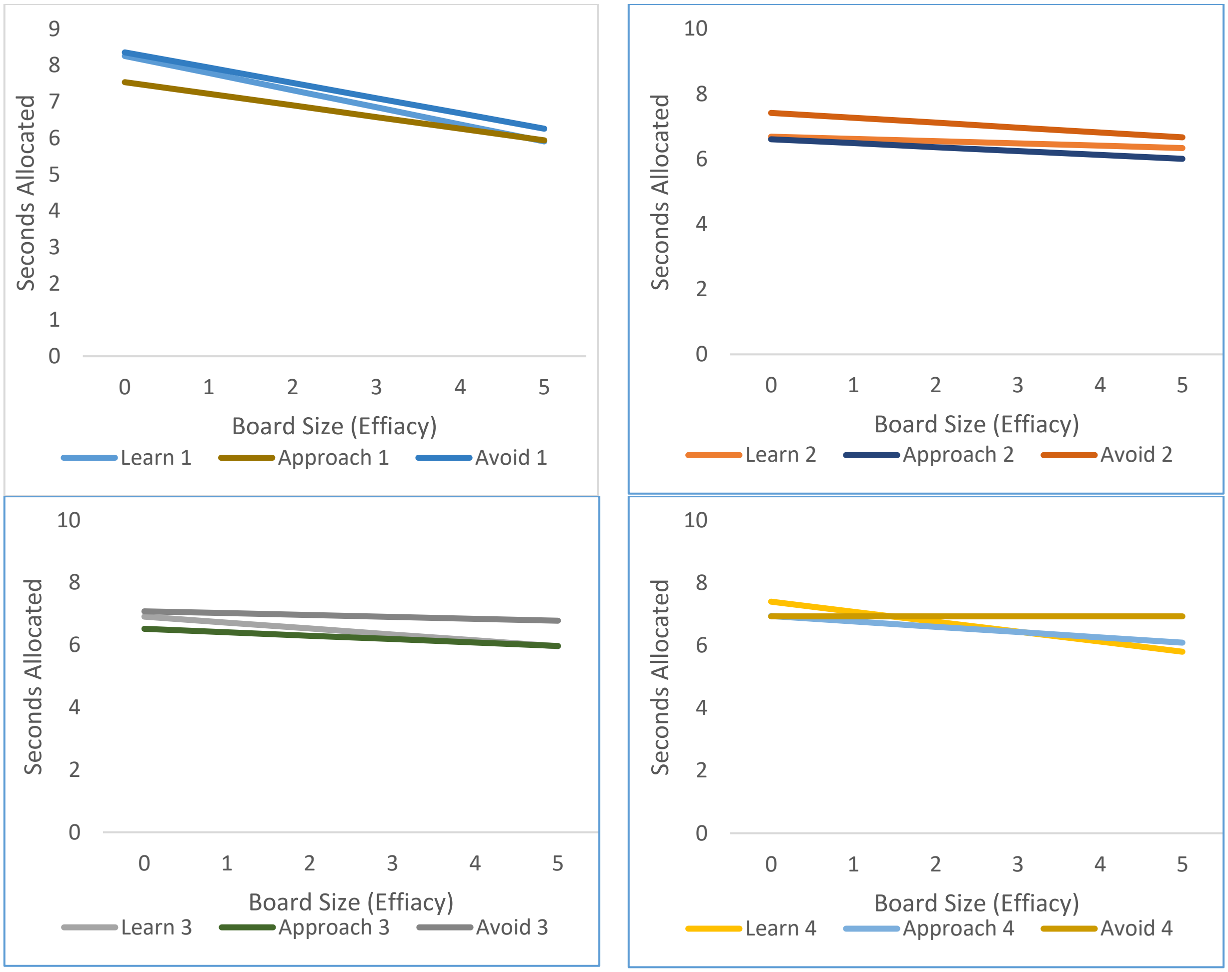
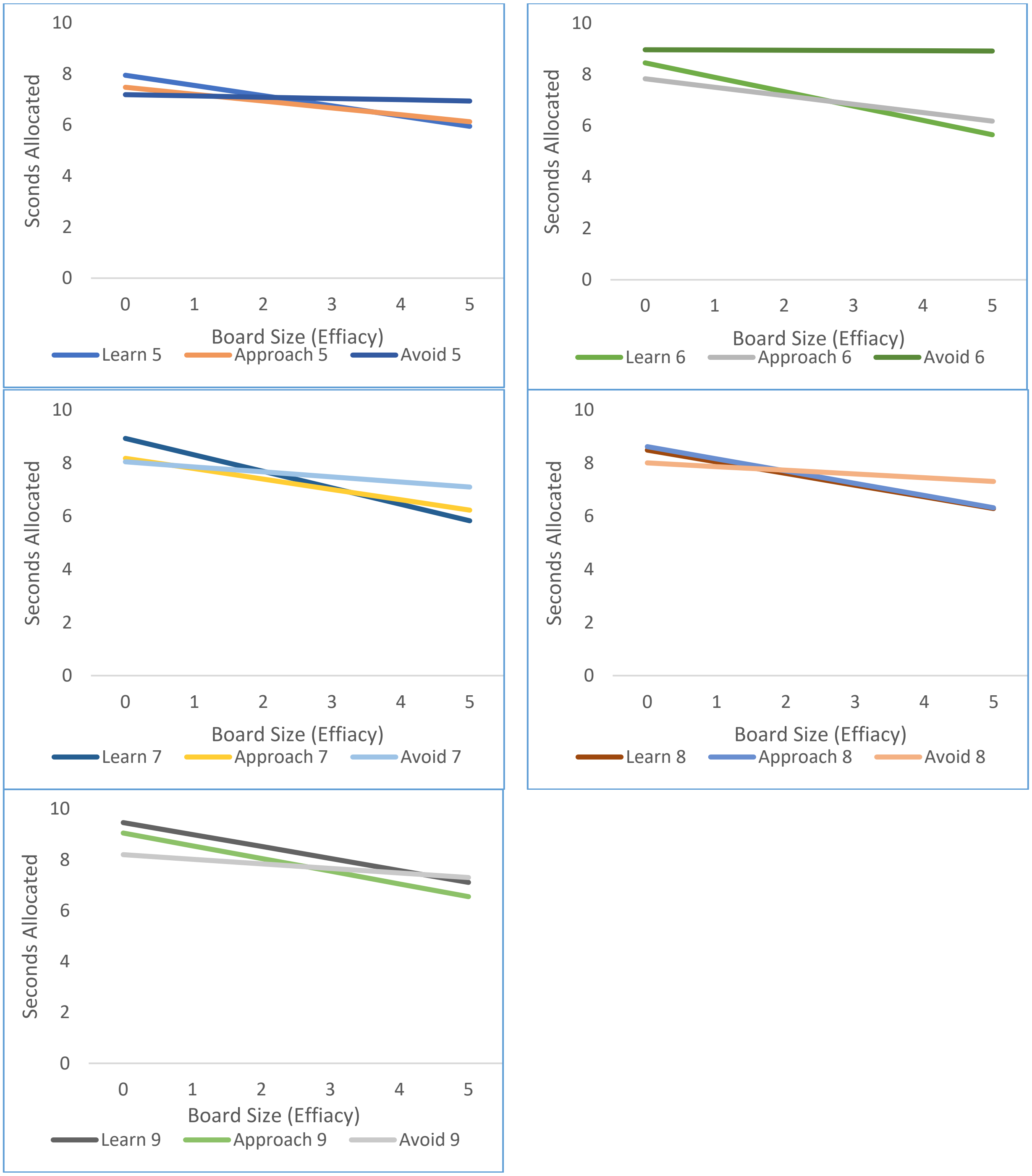


Figure F12 (cont'd)



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