A Formal, Computational Theory of Multiple-Goal Pursuit:
Integrating Goal-Choice and Goal-Striving Processes

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Understanding the processes involved when pursuing multiple goals over time is a central question for motivational theorists. A dynamic, computational model integrating theories of goal striving and goal choice is presented to account for data emerging from Schmidt and DeShon’s (2007) multiple-goal-pursuit protocol. The simulated results match the results reported in their study, including the finding that relative discrepancy from the goals positively predicted resource allocation early on but negatively predicted it toward the end of the session. Variance in parameters in the model also accounted for individual differences found in the data. Discussion focuses on the theoretical contribution of formally integrating elements of self-regulation theories, further empirical work needed to test the model, and further theoretical work needed to continue the integration process exemplified here.

Keywords: multiple goals, dynamic self-regulation, computational modeling, expectancy, decision making

As you read this, you may be vaguely or even acutely aware of other things you could or should be doing. At any one time, most of us have many goals we could be pursuing, though we often find ourselves focusing on only one (Vallacher & Wegner, 1987). Likewise, research on motivation and goal processes has tended to focus on processes involved in pursuing a single goal, despite the recognition that multiple-goal pursuit is the norm, not the exception (Austin & Vancouver, 1996; Locke & Latham, 2002). Fortunately, scholars have begun to approach the question of how individuals handle the often-conflicting goals hanging unfinished over their heads (e.g., Ashford & Northcraft, 2003; Kernan & Lord, 1990; Louro, Pieters, & Zeelenberg, 2007; Mitchell, Harman, Lee, & Lee, 2008; Schmidt & DeShon, 2007; Shah, Friedman, & Kruglanski, 2002; Vancouver, Putka, & Scherbaum, 2005). However, this research has revealed gaps in the field’s understanding of the processes involved.

Two particularly noteworthy gaps concern (a) the integration of the goal-striving processes and decision-making or goal-choice processes (Diefendorff & Lord, 2008; Klein, Austin, & Cooper, 2008; Steel & König, 2006; Vancouver, 2008), and (b) incomplete descriptions of the dynamics of motivation (Dalal & Hulin, 2008; Fried & Slowik, 2004; Karniol & Ross, 1996; Mitchell & James, 2001). Theories of goal striving, often rooted in control theory (Carver & Scheier, 1998; Klein, 1989; Lord & Levy, 1994), depict a dynamic process whereby effort, strategies, and so forth are determined by the changing discrepancy between current and desired states (e.g., “Have I achieved the level of performance I am striving to achieve?”). These discrepancies may change over time due to changes in the desired states (i.e., goals), as well as changes in the current state. Changes in current states can result from one’s own actions as well as external sources. Although dynamic in conceptualization, applications of control theory to motivational processes have mostly been limited to understanding the pursuit of a goal in isolation or have considered multiple goals arranged hierarchically in a means–ends framework (e.g., a proximal goal leading towards a longer term distal goal), largely neglecting the issue of how individuals allocate resources back and forth across competing goals over time. Goals are in competition if the pursuit of one prevents or detracts from the pursuit of another at any one time, perhaps due to physical (i.e., only two hands) or psychological (i.e., attention) limitations.

In contrast, the dominant decision-making theories, such as expectancy theory, focus on the choice among competing options but traditionally have been relatively static and largely have emphasized one-time decisions (Luce, 1995). These models are most often rooted in the concept of expected utility, the view that decisions are determined in large part by the multiplicative combination of the subjective value placed on outcomes (i.e., valence) and the perceived likelihood of their occurrence (i.e., expectancy). These theories have been applied to a wide range of choice behavior, including the choice of which goal level to pursue (e.g., whether to accept an assigned goal). On the surface, these theories seem well suited to explaining resource allocation across time. However, their static nature creates substantial limitations in this regard. In particular, key components, such as expectancy and value, are typically construed as constant throughout the decision.
Recognizing the limitations of the more narrowly focused motivation theories, researchers have been developing new theories that integrate goal-striving and decision-making concepts. For example, Steel and König’s (2006) temporal motivation theory (TMT) integrates several theories of motivation—hyperbolic discounting, expectancy theory, cumulative prospect theory, and need theory—to predict subjective utility and the resulting task choices over time. This theory explicitly and formally (i.e., mathematically) incorporates time to deadlines as a central determinant of subjective utility. Although other key components of TMT such as expectancy and valence are described in dynamic terms, they have not yet been formally modeled as such. One of the objectives of our efforts is to expand upon TMT by explicitly considering and modeling the dynamics of expectancy and valence. We do so in part by incorporating another integrative theory—Vancouver’s (2008) dynamic process theory of self-regulation. Vancouver’s theory uses the idea of a network of simple, information-processing agents in which discrepancies between desired and observed (or estimated) states are weighted to understand action, thought, learning, and feeling. Yet, details are needed on how these simple agents might be organized to account for particular behavioral phenomenon.

To illustrate the type of integration among goal-striving and decision-making theories that we seek to accomplish and to provide some focus to those efforts, we seek to model and explain results observed by Schmidt and DeShon (2007) in their study on multiple-goal pursuit. Specifically, Schmidt and DeShon found that valence (manipulated via financial incentives) influenced the relative amount of time spent working on two competing tasks, moderating the relationship between discrepancies (i.e., distance to goal) and time allocation. They also found that goal discrepancies positively predicted resource allocation (i.e., more time toward the task furthest from attainment) during much of their participants’ work period. Both these observations were consistent with the dynamic self-regulation theory they presented. However, they also found that the effect of goal discrepancies reversed as the deadline approached. That is, several individuals began working on the task with the smaller goal discrepancy as the work period ended. It is interesting that Schmidt and DeShon predicted this dynamic effect but acknowledged the lack of theory to explain it. Indeed, they noted that “examining the role of time represents an important step toward developing more comprehensive and valuable theories (Mitchell & James, 2001)” (Schmidt & DeShon, 2007, p. 932).

In this article, we take on that specific challenge. We propose that a more complete integration of goal-striving and goal-choice models—in particular, incorporating dynamic valence and expectancy constructs—could explain intriguing dynamic phenomena of this sort, thus demonstrating the merits of such integrated models and pointing the way toward additional novel findings. Moreover, in so doing, we also wish to provide an example of model building and testing by developing a computational model in which cognition and behavior can be simulated over time. Hulin and Ilgen (2000) and others (e.g., Harrison, Lin, Carroll, & Carley, 2007; Vancouver, Tamanini, & Yoder, 2010) have argued that computational modeling, particularly the kind that can be simulated over time, can be very useful to the fields of applied psychology and organizational behavior. This is especially true given the aforementioned dynamics and complexity of the phenomenon studied in these disciplines. Without formal (i.e., computational) theory, it can be difficult to (a) understand what theorists are specifically trying to say (i.e., informal theories can be ambiguous) and (b) understand how behavior will play out over time (i.e., prediction without external supports such as simulation software is difficult when theory or phenomenon exhibit nonlinearities). In contrast, computational models explicitly describe the nature of relationships proposed and, if dynamic, allow researchers to observe the behavior that emerges as the theorized system interacts with its environment. If this behavior matches the behavior of the systems (e.g., individuals) theorized about, the model can be said to represent a viable explanation, at least until another contender matches better or more parsimoniously.

Thus, incorporating elements from multiple theoretical traditions, we seek to (a) explicitly address the issue of multiple-goal pursuit; (b) provide an account of the effects of deadlines; (c) explicitly consider the role of time in the conceptualization of expectancies and how the effects of expectancies and valence change over time; (d) specify key points where individual differences may influence multiple-goal processes, resulting in variability in resource allocation strategies across time; and (e) provide an example of computational model building and testing. The remainder of this article is organized as follows. First, we describe Vancouver’s (2008) formal, computational model of self-regulation, which provides the foundation for the model proposed and tested herein. Vancouver’s model is comprehensive, but missing details are needed to address the issue of multiple-goal pursuit under a deadline. We elaborate these missing details and use them to construct a computational model that might account for the resource allocation processes observed within Schmidt and DeShon’s (2007) study on multiple-goal self-regulation. Second, we assess the viability of the computational model by simulating it and determining whether it can produce results consistent with those reported by Schmidt and DeShon (2007). We also examine whether individual differences proposed within the model can account for between-person variability in within-person resource allocation patterns existing in the Schmidt and DeShon data. This examination is done both qualitatively and quantitatively. Finally, we describe places where our model can be expanded using elements found in Vancouver (2008) and the motivational literature more generally. We also discuss the broader implications of the model specifically and as an example of the benefits of computational modeling more generally.

A Dynamic Process Theory of Self-Regulation

Self-regulation theories have become the dominant perspective for understanding motivation, particularly in applied areas of psychology (e.g., Bandura, 1997; Carver & Scheier, 1998; Ciprozzano, James, & Citera, 1993; Ford, 1992; Frese & Zapf, 1994; Fried & Slowik, 2004; Karniol & Ross, 1996; Kruglanski et al., 2002; Lord & Levy, 1994; Steel & König, 2006; Vancouver, 2000). These theories include conceptualizations of the individual pursuing goals and making choices regarding the allocation of resources across these goals. In an attempt to give some structure, formality, and parsimony to the literature on self-regulation, Vancouver (2008) articulated a comprehensive, computational description of self-regulation using a subsystems approach based on
control theory models of human behavior (e.g., Grush, 2004; Jagacinski & Flach, 2003; Powers, 1973). This approach describes system-level behavior (i.e., human behavior) in terms of the sub-systems responsible for that behavior. By reducing behavior to this lower subsystem level, researchers may potentially achieve both conceptual parsimony and comprehensiveness. Vancouver (2008) suggested that psychologists could use combinations of the single, simple information-processing subsystem structure to account for acting, thinking, learning, and feeling.

Like most control theory models of self-regulation, a central concept in Vancouver’s (2008) dynamic process theory is the discrepancy-reducing negative feedback loop, illustrated in Figure 1. In essence, the negative feedback loop captures the idea that goals represent desired states (e.g., the level of performance one is seeking to achieve), which serve as the standard by which perceptions of the state (e.g., one’s perception of his or her current level of performance) are compared. Gaps or discrepancies between desired and perceived states determine the output, such as effort exerted toward task performance, which in turn influences the true state of the variable, often in combination with additional external influences (e.g., one’s performance may be determined by both his or her own effort and assistance or interference from coworkers). Although this conveys the basic structure of the negative feedback loop, details are provided later for each of the major components represented in Figure 1. It is important to note the distinction between the self-regulatory agent, which refers to the elements of the negative feedback loop that reside within the agent–environment border represented by the gray, round-cornered rectangle in Figure 1, and the subsystem’s environment, upon which the agent acts and from which the agent draws perceptions of the variable in question. The term agent is used to convey the purposive nature of the structure. That is, its operation works to obtain and maintain its desired state.

From Perception to Output: The Self-Regulatory Agent

Input function. The self-regulatory agent refers to a simple information-processing structure consisting of input, comparator, and output functions. The input function represents the process by which perceptions (p) of some variable (v) are formed, such as one’s perception of one’s current level of performance. The input functions are critical for defining a particular self-regulatory agent because they determine what is being regulated (Powers, 1973). For example, Vancouver and Scherbaum (2008) showed that it was the perception of the current level of performance, as opposed to information on actions taken (i.e., behavior), that determined persistence on a task. A primary contribution in the current article is to specify certain agents by describing the signals that their input functions are processing.

The input function is represented mathematically as the product of a vector of weights and a vector of signals (see Equation 1). Consistent with a hierarchical organization (e.g., Powers, 1973), the signals are often perceptions from the input functions of lower level agents (p̂j). For example, the perception of the contribution of an article that one is writing is likely some combination of the perception of the relevance of the research question, the design’s ability to address the question, the appropriateness of the data analysis, and the clarity of writing. To represent this combination process, we assumed that the perceptions are quantitative (i.e., represented as numbers). Thus, we can represent the input function using the following formula:

$$ p = w_v p_v $$ (1)

In this equation, the bold letters represent vectors, and thus Equation 1 is analogous to a regression equation. Fortunately, for many problems, a simple input function can be assumed, which translates the state of some variable (v) directly into a perception (p). This is called an identity function. For example, if we were interested in how the length of an article is regulated, we might assume that p refers to the last page number of the text, without concern for the visual and cognitive processes that translate the symbols on a page or computer screen into the perception of the page number. Thus, for our present purposes, we make the simplifying assumption that perceptions directly and accurately reflect the state of the variable as represented in Equation 2:

$$ p = v $$ (2)

Note that in the writing example, the state of the variable (v) and thus the perception (p) will change substantially over time. Indeed, this will become a central issue as we attempt to account for motivated behavior over time and across goals.

Comparator function. Perceptions (p) of the current state are compared with the desired state (p*) (often called the reference signal (Powers, 1973) or goal (Austin & Vancouver, 1996). For example, for an agent focused on the quality of the article, the desired state might refer to the level of quality one is seeking to attain. In essence, this function represents a comparison of what one perceives the case to be with what one desires it to be. It is represented in Figure 1 by the comparator function. Mathematically, this is represented as the difference between perceived (p) and desired (p*) states, and the resulting value is referred to as error or discrepancy (d). Following Powers (1973), we conceptualized the comparator as generally asymmetric, in that negative

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1 Conceptual parsimony is distinguished from model parsimony, the latter of which is a direct function of the number of free parameters in a model.
discrepancies (i.e., the desired state is less than the perceived state) are treated as zero discrepancy. For example, the page length control system likely only passes on the discrepancy when the page limit is exceeded and the quality control system only passes on discrepancies below the standard—that is, page lengths under the limit, and above-standard quality perceptions likely do not create any motivational tension. The equations for the comparator are as follows:

\[ \text{Output function. Responses to the discrepancy (d) between perceived and desired states (e.g., effort exerted towards task performance) are represented in Figure 1 by the output function. However, output (o) is not determined solely by the magnitude of the discrepancy. In particular, responses to discrepancies on highly valued goals may be exaggerated, such that small discrepancies create large responses, whereas responses to discrepancies on unimportant goals may be muted, such that discrepancies must be relatively large in magnitude to create a notable response. Within the motivation literature, this weighting term is often referred to as error sensitivity (Hyland, 1988; Schmidt & DeShon, 2007). Here, we refer to this weighting term as gain, consistent with the larger control theory literature (e.g., Jagacinski & Flach, 2003). We also use this literature’s symbol for gain, } k, \text{ rather than } o \text{ (e.g., Schmidt & DeShon, 2007) or } g \text{ (e.g., Vancouver, 2008). As with the other variables described, gains can be variable over time, emanating from other dynamic agents (Vancouver, 2008). Thus, the resulting equation for output is} \]

\[ o = kd \]

\[ \text{From Output Back to Perception: Closing the Loop} \]

The negative feedback loop is completed through the effects of output (combined with external influences) on the environment and an updated perception of the resulting state of the variable in question. For example, an author might revise a manuscript in response to a journal’s invitation to revise and resubmit. During this process, the author will compare his or her perception of the revision’s quality with his or her comprehension of the quality desired by the journal to determine whether any discrepancy from goal remains and thus whether subsequent revisions are needed. Whereas this fundamental idea is relatively intuitive and straightforward, there are complications discussed next that must be considered to adequately model these processes.

\[ \text{Goal hierarchies and agent output. Most self-regulation models based on control theory (e.g., Carver & Scheier, 1998; Lord & Levy, 1994; Powers, 1973; Vancouver, 2008) posit the existence of a hierarchy of goals arranged in a means–ends manner, such that higher level distal goals (e.g., contributing to the accumulation of knowledge on a particular topic) are attained via more proximal, lower level goals (e.g., asking interesting questions), which are themselves accomplished via lower level goals (e.g., reading the literature) and so on. Each of these hierarchical levels represents a feedback subsystem, whereby the results of output on true states are perceived and compared with the relevant standard. One of the most pertinent aspects of this hierarchical structure concerns the points of connection between superordinate and subordinate agents. In particular, the outputs from higher level agents can determine the desired perceptions } (p^*) \text{ for a lower level agent. For example, Lord and Hanges (1987) found that goals for examinations changed as discrepancies from course grades changed. As another example, one might expect goals for an article would be a function of the targeted journal, with top-tier journals dictating more stringent standards for quality. Moreover, the perceptions in these lower level agents are thought to be inputs into the higher level systems (e.g., the perceptions of the importance of the research question, the quality of the design, and the cleanliness of the results would combine into a perception of the overall quality of the manuscript). Scherbaum and Vancouver (in press) tested a computational model representing this type of connection between levels of agents and demonstrated how it could account for discrepancy creation in the lower level agents (i.e., the setting of more difficult goals).} \]

Another connection between agents was described and tested by Vancouver et al. (2005). In that study, they observed and modeled individuals who were working on a scheduling task. In the model, they assumed a cost agent devoted to revising schedules until they were below a budget limit, with the cost determined by the hours and pay of the workers. Additionally, the model contained a scheduling agent devoted to processing a certain number of schedules. In their model, the output of the cost agent influenced the gain } (k) \text{ parameter of the scheduling agent to prevent the scheduling agent from trying to work on new schedules before the current schedule was complete (i.e., zero discrepancy in the cost agent). That is, if discrepancy existed regarding the goal representing the budget for a schedule (i.e., discrepancy in such a subsystem would represent an overbudget schedule), the output function sent a signal to inhibit (i.e., attenuate by setting to 0) the gain for the scheduling agent. Conversely, no discrepancy in the cost agent allowed the gain in the schedule agent to take on a positive value. If discrepancy existed in the scheduling agent, its output resulted in a new, overbudget schedule that once again created discrepancy in the cost agent. Indeed, it is this type of potential interaction among agents and the environment that motivates our desire to represent the dynamics and complexities (e.g., nonlinearities) likely involved in determining behavior. That said, for many purposes we need not represent all levels of the hierarchy involved in creating complex cognition or behavior evoked in response to discrepancy in subordinate agents. For example, it may be sufficient for us to note that a researcher revises an article in response to a gap between perceived and desired quality without needing to specify all the various subordinate agents involved (e.g., moving fingers on a keyboard). Rather, as with perception, we can often simplify these relatively microlevel} \]

\[ 2 \text{ Our use of the term negative discrepancy to refer to discrepancies beyond the goal also departs somewhat from convention within the industrial and organizational psychology literature (e.g., Lord & Levy, 1994; Mitchell et al., 2008; Schmidt & DeShon, 2007), but the mathematics seems clear regarding the sign of the result. Also note that sometimes the asymmetry is reversed, as in the case of a cooling system in which discrepancy arises only if the perception is greater than the desired state. This was the case in a key agent in the Vancouver et al. (2005) model, operationalized mathematically as a simple reversal of the } p^* \text{ and } p \text{ terms (e.g., } p - p^*). \text{ However, as previously described, only positive discrepancies are passed on.} \]
aspects of our modeling problem by assuming that those agents can handle regulating the perceptions evoked by the higher level agents. We take such a simplifying approach when modeling how outputs are translated into actions on the environment (Vancouver, 2008). Indeed, a potential strength of this modular approach is that theorists can include the level of detail they believe necessary to adequately model a particular phenomenon. In the present case, we sought to extend existing theories by adding agents related to decision processes and subsystems potentially involved when pursuing multiple goals. We also more explicitly considered the dynamic elements of goal pursuit.

Modeling the dynamics involved in linking output to perception. In addition to the hierarchy issue, a second issue that arises when closing the loop relates to the dynamics of environmental variables. To model the dynamics properly, one needs to recognize that translating outputs into actions that affect an environmental variable takes time. For example, if an agent’s output is revising an article, we need not model all the microlevel processes involved in thinking, analyzing, and writing, but we must consider the time required to complete the cognitive and behavioral sequences involved in doing so. To represent the time for outputs to have an effect, we include a rate parameter that weights the output (\( o \)) from the individual (Vancouver & Scherbaum, 2008). Depending on the nature of the task, rates might be a function of environmental factors that might inhibit or facilitate action (e.g., a slow computer that takes hours to run a sophisticated analysis) or individual differences like ability, strategy, or strength (e.g., some individuals have greater knowledge of statistical software and procedures than others). We return to the role of individual differences later in this article.

Another important consideration regarding the dynamics is that the state of the variable (\( v \)) is seldom determined exclusively by the agent’s output but often is also influenced by external factors originating outside the agent. For example, a colleague may assist one in analyzing a complex data set, such that results that are presented are the combined effects of one’s own actions and those of the colleague. Likewise, as one analyzes data, additional analysis may become relevant, reducing one’s progress. Consistent with control theory terminology, we refer to such external influences as disturbances (\( D \)).

Finally, but perhaps most important, environmental variables tend to be what system dynamics researchers call level or stock variables (e.g., Forrester, 1968) but are more generally recognized as dynamic variables (Powers, 1978). Dynamic variables retain a value at some level (i.e., they have a “memory”) and move from that level at some rate only when forces are applied, just as the stock in an inventory rises and falls as product is added to or removed from the inventory or just as the length of an article only changes as text is written or deleted. Dynamic variables can be contrasted with auxiliary variables whose value at one instance is independent of its value at a previous instance. As previously described, the forces that move a dynamic variable according to a control-theory framework are the agent’s outputs (\( o \)) and disturbances (\( D \)) from outside the agent. For many contexts, change can be represented in discrete time. In those cases, a difference function (i.e., \( v_{t+1} - v_t \)) could be used. Alternatively, change can be represented in continuous time. In that case, an integral function like the following is used (Forrester, 1968; Powers, 1978):

\[
v_t = \int_{t_0}^{t} (ro + D)dt + v_0
\]

For example, one can represent the quality of an article, the variable (\( v \)), at a time (\( t \)) as a function of the action output (\( o \); revising) at some rate (\( r \); speed of revising), plus the effect of coauthor’s contributions (\( D \); a positive disturbance) and the initial quality of the manuscript (\( v_0 \)). Together (\( ro + D \)) determines the instantaneous rate of change in \( v_t \) at any one time. Note, \( f \) and \( dt \) indicate that we are differentiating the expression in the parenthesis with respect to time.

Extending the Model to Account for Multiple Goals With a Deadline

Having described the conceptual and mathematical underpinnings of Vancouver’s (2008) model of self-regulation, we now describe the additional explanatory components necessary to account for the dynamic allocation of attention across multiple goals with a single deadline. Specifically, our model seeks to explain the processes by which individuals shift their resources back and forth in pursuit of two goals bounded by a deadline. The presence of a deadline for goal attainment creates resource conflict among the multiple goals, as time spent pursuing one goal means less time available to pursue the other. The incorporation of a deadline is crucial, as most tasks involve deadlines, particularly at work (e.g., Austin and Vancouver, 1996; Locke & Latham, 1990). Yet, its formal incorporation into theories of motivation has been notoriously slow (Fried & Slowik, 2004).

To accomplish this goal, we integrate Steel and König’s (2006) TMT with a control-theory-based subsystems approach (e.g., Vancouver, 2005). TMT is itself an integration of several classic decision-making theories, most notably variations of the expectancy-value decision-making framework. Traditional expectancy-value models propose that the choice among alternative courses of action is made by determining which alternative possesses the highest expected utility. In most expectancy-value theories, expected utility is derived by multiplying expectancy by valence (i.e., subjective value), which captures the notion that an option with very low expectancy would not be particularly attractive even if the valence were very high and vice versa. Expectancy-value theories have been relatively useful for predicting choice behavior at the within-person level—that is, individuals are often inclined to select the option with the highest expected utility (Van Eerde & Thierry, 1996). However, in their traditional form, these theories are not well suited to account for dynamic choice behavior, where recurring decisions must be made over time as the situation evolves in response to, and perhaps independent of, one’s prior choices.

The dynamics of the disturbance are often complicated by its own dynamics. Indeed, it is often a function of environmental factors or the indirect effects of other agents. For instance, one might model the contributions of coauthors as a function of the current state of the manuscript. Thus, the disturbance occurs at some rate that might change over time. This potential for complexity is captured in the capitalization, which connotes a function (though the factors going into the function are not listed). For example, we can assume the rate of \( D \) is captured within \( D \), though in any model these dynamics will need to be explicit, which they are in our model.
We agree with TMT on the criticality of expectancy, valence, and time to deadline in determining choices. However, by integrating TMT and control-theory-based subsystems approaches, we seek to represent more fully and formally the dynamics involved. In particular, although Steel and König (2006) acknowledged the likely temporal variability in expectancy and valence, the formal representation of TMT only explicitly incorporates dynamics by dividing the expectancy-value product by the time to deadline. The dynamics of expectancy and valence are acknowledged but not directly addressed. However, prediction of many dynamic phenomena—such as allocation of time to two competing goals as they are pursued over time—may be greatly enhanced by more fully accounting for the dynamic nature of expectancy and valence. We explicitly address the temporal component of multiple-goal striving by (a) describing an agent devoted to monitoring deadlines; (b) incorporating perceptions of the time remaining for goal pursuit into the formation of expectancies; (c) describing how valence changes as a function of the progress that remains to be made to meet one’s goals as they are pursued over time; and (d) integrating these dynamic conceptualizations of expectancy, valence, and approaching deadlines into a decision mechanism that allocates resources between two goals over time.

**Monitoring Deadlines: The Time Agent**

When an individual is pursuing a goal with a deadline, the amount of time remaining may have important implications for cognition, affect, and behavior (Dalal & Hulin, 2008; Fried & Slowik, 2004; Karniol & Ross, 1996; Mitchell et al., 2008). Therefore, it is essential to incorporate the goal seeker’s perceptions of time remaining and model the effects of these perceptions on subsequent goal processes. We do so by specifying an agent that monitors the time and results in a subjective sense of the time left until the deadline, which is illustrated in Figure 2. It is important to note that the time perception may vary in accuracy and sampling rate depending on the quality of stimuli available to track time (i.e., the presence or absence of a clock), personal dispositions, other exigencies impinging on one’s attention, and so on (Fried & Slowik, 2004; Karniol & Ross, 1996; Mitchell & James, 2001). However, we make the simplifying assumption of an accurate perception of time (t), which is monitored continuously (i.e., *time input* always reflects the actual time at that precise moment). We also assume that the reference value (i.e., goal) for the time agent is the deadline (T) given for the task. Thus, we describe a comparator function that subtracts current time from the deadline (e.g., T − t) to arrive at the time remaining until the deadline.

Although we ignored individual differences in perceptions of the passage of time, an individual difference variable that might be relevant is impulsiveness (Monterosso & Ainslie, 1999). That is, individuals can differ widely in how they react to deadlines. As we shall be shown later, such individual differences in reactions to deadlines may be a key to understanding between-person variability in resource allocation patterns over time. Therefore, in our model, the objective time remaining until the deadline (T − t) is weighted by a time sensitivity parameter (i.e., a gain), which is often labeled gamma (Γ) in hyperbolic discounting models of decision-making behavior (Steel & König, 2006). This gain parameter captures sensitivity to deadlines. The weighted difference output from this agent is a *subjective* sense of the time remaining (ω).

**Dynamic Expectancy: The Expectancy Agent**

Expectancy beliefs have a long and storied history in theories of motivation (Bandura, 1977; Campbell & Pritchard, 1976; Carver & Scheier, 1981; Ford, 1992; Kanfer, 1990; Lewin, 1951; Olson, Roese, & Zanna, 1996; Tolman, 1932) and decision making (e.g., Beach & Connelly, 2005; Edwards, 1954; Kahneman & Tversky, 1979). Expectancies pertain to beliefs concerning the contingencies between events (e.g., actions and outcomes). Within the motivation literature, expectancy typically refers to the belief in the likelihood that a particular level of performance (often the goal level) can be achieved and is positively related to goal acceptance (e.g., Locke & Latham, 1990). From a decision-making perspective, expectancies are a key determinant of choices among alternative risky or uncertain options, with expectancies positively related to the likelihood of selecting a particular option (Beach & Connelly, 2005). Despite the prevalence of expectancy in classic and contemporary research, its explanatory power within dynamic models of behavior has been limited by its static conceptualization or operationalization (Luce, 1995). To present expectancy as a belief that is unchanging across time is to ignore the internal (e.g., learning) and external (e.g., changing conditions) dynamics that shape expectancies. Thus, a static expectancy concept is limited in its ability to explain decisions in dynamic contexts. Although, in their narrative descriptions of TMT, Steel and König (2006) indicated that expectancy may be dynamic across time, the dynamics of expectancy are not formally modeled or described within TMT.

To address this limitation regarding the static treatment of expectancy, we begin by suggesting that a critical determinant of expectancy is an individual’s belief in the time it takes to change a variable by some amount (i.e., lag) given some action or event (Karniol & Ross, 1996). We call this belief *expected lag* (α). For example, in our writing example, expected lag might correspond to the speed at which one believes he or she can write. We propose that expected lag beliefs are combined with information about (a) the discrepancy that remains to be eliminated (d) and (b) the time remaining to do so (t;), to determine individuals’ moment-to-moment beliefs in the possibility of eliminating the discrepancy before time runs out. Conveniently, the way this information is combined conforms to the functions described previously for con-
trol agents. These functions and the inputs into them are illustrated in Figure 3. Specifically, within the expectancy input function, the discrepancy from some task agent is multiplied by the expected lag (α) for the task. Expected lag is determined by “actual lag,” plus a “bias” parameter. This reflects the fact that individuals’ beliefs in their potential pace of work are likely to bear meaningful resemblance to the actual pace that could be accomplished but may often be positively or negatively biased. The result from the expectancy input function represents an estimate of the amount of time needed to eliminate the discrepancy and, thus, achieve the goal (e.g., number of pages left to write × amount can write per hour = estimated hours needed to complete a manuscript). This estimate will change over time as discrepancy and, possibly, expected lag beliefs change. Next, for tasks with a deadline, one is likely to consider whether there is sufficient time to eliminate the discrepancy and attain the goal. This is accomplished by the expectancy comparator, which compares the predicted time to reduce the discrepancy with the sense of the approaching deadline (i.e., the output from the time agent). This comparison provides an estimated possibility of eliminating the discrepancy by the deadline. Finally, the expectancy output function merely passes on this estimate, which is a dynamic expectancy, to be used by another agent. Together, the equation for the expectancy agent is the following:

\[ e = o - \alpha d \] (6)

In sum, in our model, the expectancy concept is dynamic because it takes on different values over time in response to changes in (a) the magnitude of the discrepancy, (b) beliefs in the time it takes to perform, perhaps changing via a learning process, and (c) available time. This is similar to a view of expectancy as contextually based, as found in Bandura’s (1977) concept of self-efficacy. It is also consistent with Campion and Lord’s (1982) control-theory model, in which discrepancy from a goal agent feeds into a decision mechanism. Indeed, as described next, this dynamic conceptualization of expectancy is a central component in the decision-making component of our model of multiple-goal self-regulation.

Dynamic Valence

Our concept of valence, like expectancy, is not fixed over time. Like traditional expectancy-value theories, our theory posits that valence is determined, in part, by factors such as the positive or negative value placed on the consequences associated with the outcome’s occurrence. For example, all else being equal, an individual would be predicted to perceive more value in gaining $100 than $10. However, an important aspect of our theory is our argument that the subjective immediate value of working on a particular task can vary across time. Specifically, we propose that subjective immediate value is determined not only by the consequences associated with an outcome (e.g., a monetary award for goal attainment) but also by the progress that remains to be made to achieve that outcome.

To elaborate, we argue that the magnitude of the discrepancy from the desired state provides information about the current need to act on the task. For example, there is a stronger need to focus relatively immediately on a task when there is a large discrepancy as opposed to when the discrepancy is small. Indeed, in the extreme case of no discrepancy (i.e., goal has been met; the individual is satisfied), there may be little value in working on a task even though it has been highly rewarding in the past, particularly if there is no risk of external factors creating a renewed discrepancy (e.g., a coauthor loses work that one has just completed) and no incremental incentive exists for exceeding the goal. This more complex and dynamic conceptualization of immediate subjective value is captured by Equation 4, which represents the task agent’s output. Specifically, the discrepancy between the current and desired states for some task is multiplied by the importance of the task for the individual. From a control-theory perspective, the importance that the individual places on the task is represented as the gain of the agent, with greater importance resulting in a stronger reaction to discrepancies of a given size. For example, individuals may show little response to small discrepancies on a task perceived as only minimally important but may respond more quickly or vigorously to even small discrepancies on highly important tasks.

It is via the subjective importance (i.e., gain) parameter that the traditional notion of value enters back into our valence concept. That is, a task agent’s gain is likely influenced by numerous factors, such as external rewards, perhaps weighted by individual differences. In particular, individuals might differ in their sensitivity to various incentives. For example, if monetary incentives are involved, then individual differences related to the importance of money are likely to determine the extent to which the incentives create a subjective sense of importance for the associated task (Tang & Chiu, 2003). If incentives are differentiated between tasks in terms of approach or avoidance, then individual differences such as goal orientations (e.g., DeShon & Gillespie, 2005) or regulatory focus (Higgins, 1997, 2000) might be highly relevant. Regardless

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4 Indeed, a version of the computational model not presented here includes a learning agent that develops the expected lag based on experience with the task. This model includes a bias parameter as well as parameters related to learning (see Vancouver, 2008). However, beyond the bias parameter, the dynamics and parameters involved in the learning processes made little difference regarding the multiple-goal pursuit examined here and thus was not included in the final model presented here.
of the source(s) of subjective importance, the task agent’s output representing the product of discrepancy and gain is presented as a dynamic valence term (i.e., subjective immediate value of task) because it includes information about the value of the goal or task as well as information about the current need to act on the task.

The Decision Mechanism: The Task Choice Agent

Having detailed the dynamics underlying perceptions concerning expectancy, valence, and time remaining, we now describe how these perceptions are combined to determine moment-to-moment goal selection via the task choice agent. As we have highlighted previously, much of the information-processing work needed to realize psychological concepts and phenomenon can be conceptualized as occurring within simple control agents. Here subjective expected utility (called simply expected utility from here on), which in classic decision-making theories is the product of expectancy and valence (e.g., Edwards, 1954; Vroom, 1964), arises from a task choice agent’s input function (see Figure 4). In modern decision-making theories, expectancy and valence are both conceptualized as curved functions of their objective counterparts, probability and value, on the basis of empirical research on decision making (e.g., TMT, Steel & König, 2006; prospect theory, Kahneman & Tversky, 1979). However, it is unclear whether combinations of simple weighted differences, like the type described in the present modeling approach, might account for these curves (see Vancouver, Gonzáles-Vallejo, Weinhardt, & More, 2008). For now, we want to keep the operations we suggest are occurring within the mind as simple as possible.

That is, recall that the input function (Equation 1) can be a simple multiplicative function. In this case, we argue that our dynamic expectancy and valence constructs are multiplied by each other to form an expected utility to be used by the task choice comparator function. Also consistent with classic decision-making models, a decision is assumed to arise from a comparison of expected utilities (Beach & Connelly, 2005). If only two alternatives exist, it is straightforward to assume a comparator function that subtracts one expected utility from the other (e.g., Schmidt & DeShon, 2007). At this point, we limit our theorizing to this type of context. We also assume, given the dual task context, that the comparator is symmetric. Thus, discrepancy in one direction is translated (by the task choice output function) into a choice for one task, discrepancy in the other direction is translated into a choice for the other task, and no discrepancy is translated into a default preference for one of the tasks. Alternatively, we could represent two asymmetric goal agents—one for each task—to conform to our assumption (operationalized in Equation 3) that the agents are asymmetric. However, the symmetric operationalization is more parsimonious and accomplishes the same objective (see Vancouver et al., 2005).

Model Summary

In sum, we described four types of agents related to multiple goal-striving when two goals with the same deadline are pending. In so doing, we integrated notions from Steel and König’s (2006) TMT with a control-theory model, unpacking the decision mechanism described by Campion and Lord (1982) when they introduced control theory to the applied motivation literature. In the next section, we combine the agents we have described with acting agents described by Vancouver (2008) and use them to construct a working computational model of an individual in context to see if such a model can actually work once all the pieces are put together and time is simulated, which provides an initial test of the theory’s viability.

Developing a Computational Model of Multiple-Goal Pursuit

The agents described earlier, along with the agents described in Vancouver (2008), integrate concepts from goal theories (e.g., Kruglanski et al, 2002), expectancy theories (e.g., Vroom, 1964), economic decision theories (e.g., Steel & König, 2006), and dynamics (e.g., Fried & Slowik, 2004; Powers, 1978), all from a self-regulation perspective (e.g., Carver & Scheier, 1998; Klein, 1989; Lord & Levy, 1994). This complexity can make theory testing difficult. Fortunately, the theory has been described formally (i.e., mathematically) and dynamically, providing the potential for simulations of computational models derived from the theory. Computational models are more narrowly focused instantiations of a theory, usually focused on one phenomenon or particular context (Vancouver et al., 2005). These models, and the simulations based on them, provide a means of examining the viability of the theory (i.e., does the model behave as described; does it match data?). In this case, we modeled an empirical protocol used by Schmidt and DeShon’s (2007) to examine multiple-goal pursuit. We then simulated the model to see if its behavior matched data found by Schmidt and DeShon. We first describe the protocol and the findings from Schmidt and DeShon and then describe the computational model based on the agents previously discussed as well as additional agents described by Vancouver (2008).

The Schmidt and DeShon Protocol and Findings

In Schmidt and DeShon’s (2007) study of multiple-goal pursuit, participants were asked to create schedules of classes for students

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5 The dynamics and translation functions related to how incentives, and particularly the framing manipulation used by Schmidt and DeShon (2007), are translated into gains are beyond the theorizing described in this article. We merely assumed Hyland’s (1988) assumption that gains are positively related to value or incentive.
in two schools. Goals were set for each school (i.e., “Process all the students seeking schedules in each school”), with experimental conditions manipulating the incentives available for each school’s goal. The protocol created circumstances one might find in real-life situations. For instance, it was difficult, but not impossible, to meet both goals in the time available; continuous information was provided regarding progress on both goals (i.e., the number of students in each line and the time remaining); and unpredictable external events (i.e., disturbances) affected the state of that progress. The primary dependent variable of interest was the time participants spent (i.e., resources allocated) on each task as the session progressed.

Many of Schmidt and DeShon’s (2007) findings were predicted on the basis of some of the concepts described previously. For example, they predicted and found that, in general, relative discrepancies positively predicted resource allocation (i.e., individuals worked on the school with the longer line of students, switching schools as the queues changed relative length). They also found that the influence of discrepancies on resource allocation was moderated by goal value, manipulated via the level and gain–loss framing of incentives. This finding is consistent with the notion of error sensitivity (i.e., gain) described earlier, in that discrepancies can be amplified by goal value. As a result, they also found that goal value positively predicted resource allocation—when incentives differed across the two tasks, individuals spent more time on the task with the higher incentive.

A particularly interesting finding in Schmidt and DeShon’s (2007) study was that resource allocation strategies appeared to depend on the amount of time remaining. Whereas participants generally allocated more time to the school with the longer line of students, switching schools as the queues changed relative length. They also found that the influence of discrepancies on resource allocation was moderated by goal value, manipulated via the level and gain–loss framing of incentives. This finding is consistent with the notion of error sensitivity (i.e., gain) described earlier, in that discrepancies can be amplified by goal value. As a result, they also found that goal value positively predicted resource allocation—when incentives differed across the two tasks, individuals spent more time on the task with the higher incentive.

Acting Agents for Regulating Queues and Creating Schedules

Regulating the queues: The task agents. Figure 5 shows two agents needed to represent the task of scheduling as described by Schmidt and DeShon (2007). The upper agent (i.e., the task agent) pertains to the number of students in a school who need a schedule of classes. For simplicity, we only present one task agent for a single school at this point, but two task agents (one for each school) are represented in the full computational model presented subsequently. The output from the task agent represents the dynamic valence of the task as described earlier. In addition, these types of agents are similar to the agents Vancouver (2008) described as involved in acting and that Vancouver et al. (2005) used to explain the goal difficulty effect (Locke & Latham, 1990), except that they are specific to the particular task. That is, two variables below the person/environment line represent the task. The circle labeled “Task A state” represents the number of students needing schedules at a school. It is a level variable (i.e., calculated with an integral function) with an initial value of five, which is the number of students initially in the queue, though it is a discrete variable in that it can only take on integer values (i.e., whole numbers). This initial value is noted in the figure, but due to Vensim convention, there is no arrow to indicate this relationship because it does not affect the state of the variable beyond the initial time (t0). Otherwise, the relationships among variables are depicted by arrows. Specifically, origins of arrows pointing to a variable name indicate the variables in the domain of the function located at the variable pointed to, and the variable name represents the result (generally used in the domain of other functions).

Consistent with Equation 5, Task A state is influenced by two processes: output by the individual (i.e., schedule done) and external disturbances (i.e., additional students joining the queue). The rate of the output’s effect on Task A state is instantaneous for the purposes of this model; hence, there is no rate parameter for this function. This is because change to Task A state is discrete as opposed to continuous. Discrete change is simply a special case of continuous change. Pure discrete models are usually represented with difference equations to simplify the modeling. In this case, because both continuous and discrete change is involved, a model with integral equations is needed. It is important to note, however, that even though the output’s effect on Task A state is instantaneous, the output is occurring only periodically. Indeed, the dynamics of Task A state change are completely a function of the dynamics in the output and the disturbance term. The process of creating schedules is described later. In the meantime, Task A disturbance is represented as a series of pulse functions that determines when additional students join the line and how many students join the line at that time. The timing and number of new students joining the lines conform to the additions to each school’s queue as experienced by the Schmidt and DeShon participants (see Table 1).

6 A free version of Vensim can be downloaded from www.vensim.com. The model described here can be performed with this software. The model is downloadable from the first author’s web site, http://www.psych.ohiou.edu/people/faculty/vancouver/vancouver.html. Alternatively, the model can be reproduced from Figure 6 and the equations from Appendix A.

7 The environment represented below the person/environment line refers to what is outside the larger system (i.e., person), not simply what is outside a particular agent’s subsystem. That is, system and environment are relative terms depending on the level of system being discussed. What distinguishes them here is the label we gave to the system. The larger system is labeled person whereas the subsystems nested within person is labeled agent.

8 The pulse function takes two arguments; the first determines the time since the beginning of the simulation that the pulse “fires,” and the second determines the length of time it fires. This function provides a means for operationalizing the disturbances to which participants were exposed.
The task agent monitors the number of students (e.g., the Task A state) via the “Task A input” function. Because Schmidt and DeShon (2007) provided continuous and accurate feedback concerning the number of students in line, Task A input simply reflects the true level of Task A state (i.e., $p = v$). Note that without frequent, specific, and accurate feedback, this relationship would be more complex. However, in the present context, Task A input simply passes on the level of Task A state to the “Task A comparator,” which subtracts the number of students in the queue from the desired number (i.e., zero), represented by “Task A goal.” The comparator\(^9\) passes on positive differences (i.e., discrepancy) to “Task A output” which, consistent with Equation 3, multiplies this discrepancy by “Task A gain.” Task A gain, in turn, is a function of “Task A incentive,” a form of an input function where the incentive value is a cue weighted by an \textit{incentive sensitivity} parameter. Recall from the earlier discussion that this gain parameter captured the importance of reaching the Task A goal, an element of valence. Finally, “Task A output” determines the gain for a subtask—creating the schedules—that processes students out of the school’s queue. In particular, as long as there is any discrepancy (and any nonzero gain) in the Task A agent, there will be a nonzero gain to the scheduling agent (i.e., representing the importance of completing any incomplete schedules, as described next).

\textbf{Creating schedules: The schedule agent.} The schedule agent is consistent with an acting agent as described by Vancouver (2008). That is, “schedule status” indicates whether a schedule in progress is complete. It is represented as an integral function and a continuous variable with a value between 0 and 1, with values

\begin{table}[h]
\centering
\caption{External Disturbances to the School’s Queue}
\begin{tabular}{c|c|c}
\hline
Time (seconds in) & Disturbance & School \\
\hline
60 & 2 & B \\
90 & 1 & B \\
170 & 1 & A \\
240 & 3 & A \\
330 & 1 & B \\
450 & 1 & B \\
510 & 1 & A \\
540 & 2 & A \\
630 & 1 & B \\
660 & 3 & B \\
810 & 2 & A \\
840 & 1 & B \\
900 & 2 & A \\
960 & 1 & B \\
1,080 & 2 & A \\
1,110 & 1 & A \\
1,260 & 1 & B \\
1,320 & 2 & A \\
1,350 & 2 & B \\
1,440 & 2 & B \\
1,500 & 2 & A \\
1,595 & 1 & A \\
1,623 & 1 & B \\
\hline
\end{tabular}
\end{table}

\textit{Footnote:} Recall that comparator functions subtract a perception ($p$) from a desired perception ($p'$) or reference signal and pass on positive differences. We typically used a maximum (MAX) function, which outputs the higher of two parameters. Specifically, the code $\text{MAX}(p' - p, 0)$ passes on positive discrepancies but truncates negative discrepancies to 0.
less than one indicating an incomplete schedule. The input function for this agent also simply passes the value in schedule status to the comparator, which takes as a reference the schedule goal, 1, the value representing a completed schedule. The output from the scheduling agent is 1 (i.e., the individual is working on a schedule) as long as a schedule is incomplete. That is, we assumed that the output from the scheduling agent was dichotomous (i.e., all or nothing) rather than a matter of degree. Powers (1992) argued that this was a reasonable assumption for cognitive agents (as opposed to motor control agents). However, the action is still expected to take time (i.e., have a rate), and it is essential to model the time required to complete a schedule.

The time required to complete a schedule may depend on one’s skill level with the scheduling task or the diligence with which one pursues the task (i.e., trying to create schedules that distribute types of classes in a term). Individuals are likely to differ in their initial proficiency at the task, with some able to create schedules more quickly than others from the outset. Moreover, our model specifies that the time it takes to schedule decreases over time as the participants become more accustomed to the task. To operationalize these dynamic elements, we modeled the individual participants’ scheduling rate as a linear function of time, with an intercept representing the initial scheduling rate and a slope term for the rate change as a function of time. In this way, we could model individual differences in both initial proficiency and speed of skill acquisition. Note that the scheduling rate variable is an integral function that takes as an argument the initial rate to determine its initial value. We also took the inverse of the scheduling rate to represent the rate as a lag (i.e., “scheduling lag” is the time required to complete a schedule). Finally, we set the “schedule done” flag to trigger when a schedule reached 1 and to reset the “schedule status” variable to 0 to represent a new, blank schedule. When the “schedule done” flag was triggered, the state of the chosen task (A or B) decremented by 1.

Putting It All Together

Figure 6 represents the entire dual-goal model applied to the Schmidt and DeShon (2007) protocol. As described earlier, most of the variables in the model are determined by other variables in the model (i.e., endogenous). However, 15 variables or constants are exogenous (i.e., not determined by other variables in the model). We set many of these variables to match the protocol used by Schmidt and DeShon (2007). Specifically, the task goals were each set to 0 to reflect the assigned goals for the participants (i.e., to empty the queues of students in both schools by the end of the study). The initial line length for both schools was set to five. The deadline (and length of the model run) was set to 1,800 to reflect the 30-min session in seconds, which was the time unit used in the simulation. The “Time” variable, initially set to 0, represented the seconds into the simulation/session as the simulation played out over time. The task disturbance terms reflected the additions to each school’s queue based on when and how many students were added during the protocol (described earlier). The “completed schedule” goal was set to 1. We also set the task incentives to either both 1 or to 1 and 2 to represent the varying task incentive conditions we later modeled separately.

The other exogenous variables were time-invariant constants that could be used to represent individual differences between participants (Vancouver, 2009). They are bolded and italicized in Figures 6. That is, time gain, incentive sensitivity, initial and change in rate, and bias are all potential sources of individual differences and might determine how the individual interacts with the task. One advantage of computational modeling is that one can explore the effect of these types of variables on the results or estimate them from data, providing clues regarding the source of individual differences in behavior. We describe the effect of these variables in the Model Results section.

Model Results

The evaluation of computational models includes multiple processes and multiple criteria, similar to theory testing more generally (Bacharach, 1989). Some of these processes and criteria are unrelated to data. For example, one concept of model evaluation is internal validity (Taber & Timpone, 1996). In the computational modeling community, internal validity refers to the degree that the model represents a successful translation of theory. Internal validity is generally assessed via expert opinion, but one element of it is that the model works (e.g., runs without error). Indeed, it can be difficult to translate theory into a working model, which represents a nonstarter for the model but might also say something about the theory (or the talent of the modelers). Suffice it to say, our model made it past this stage.

The next concept of model evaluation is outcome validity (Taber & Timpone, 1996), often called model fit (Forster, 2000). Model fit is usually assessed both qualitatively and quantitatively. Qualitative fit begins with a form of hypothesis testing, where the results of the model are compared with data from the units being modeled (Forster, 2000). That is, models are assessed on how well they predict behavior. Here, as is often the case with model testing (Taber & Timpone, 1996), the behavior has already been evaluated (see Schmidt & DeShon, 2007), so the assessment is more about postdiction than prediction. In particular, we wanted to confirm that the model could predict, after the fact, the reversal and incentive effects found by Schmidt and DeShon.

A third concept in model evaluation is process validity (Taber & Timpone, 1996). Process validity refers to the correspondence between the model’s mechanisms and the real-world processes presumably being modeled. Process validity often involves expert evaluation of the correspondence. In this case, you, the readers, serve that role. To facilitate this, we provide detailed descriptions of our model’s mechanism responsible for the reversal effect our model was designed to explain. We also revisit process validity in the Discussion section.

A concept of model evaluation that intersects process and outcome validity is sensitivity analysis, which involves the assessment of the effects of free parameters on the behavior of the model (Taber & Timpone, 1996). These parameters indicate various points at which individual differences might produce important...
behavioral variations in resource allocation patterns. Generally, variability in behavioral patterns exhibited by study participants within experimental conditions is considered error variance. However, our theoretical approach describes several potential sources of individual differences that may result in varying patterns of resource allocation across time. Here we describe the effects of variance in the parameters on the behavior of the model to show that they might account for individual differences found in the Schmidt and DeShon (2007) data.

In the final section of the Results section, we demonstrate a more quantitative method of model evaluation. Similar to other quantitative model-fitting procedures (e.g., regression, structure equation modeling), the computational modeling-fitting procedures involve parameter estimation on the way to the calculation of goodness-of-fit indices (Myung, 2003). Also similar to other fitting procedures, interpretations of the goodness-of-fit indices are difficult without alternative models for comparison. Here we assess our model against a chance model, a simplified version of our model, and a hypothetically saturated model (i.e., one that leads to perfect prediction). At that point and again in the Discussion section, we describe another major criterion of model evaluation: parsimony (Taber & Timpone, 1996).

**Figure 6.** The Vensim model of the Schmidt and DeShon (2007) paradigm. Dashed lines signify information passed to or from a self-regulatory agent. Solid lines within agent boxes indicate information passed among the components of the agents. Bold and italicized constructs represent potential individual differences.

**Qualitative Model Evaluation**

**The reversal effect.** In evaluating our model, the primary question is whether we find a period of time when the model “works” on the task with the larger discrepancy (i.e., longer queue) followed by a period of time when the model works on the task with the smaller discrepancy, no longer switching between tasks. To examine this, we ran a simulation with equal incentive values for both tasks and tracked resource allocation (i.e., time on task) over time. Although we subsequently explored the effects of individual differences in scheduling rates, for this initial model we used the median initial scheduling rate and change in rate values derived directly from the Schmidt and DeShon (2007) data. Median values were used for initial and change rate because the skewness of the distributions were 6.24 and 15.37, respectively. The median initial rate for scheduling was .0168, which translated to just under a minute to complete a schedule. The average correlation between time and rate was .21, indicating scheduling speed generally improved over time. The median rate change was 4.83E-06 for every second of the session. This resulted in a rate of 0.0255 or about 40 s to complete a schedule by the end of the session. These and the other individual difference parameters for
the simulations are listed in Table 2. Except for the rate parameters, we used values for the individual difference parameters that neutralized their effects on the simulation (i.e., 1s for multipliers and 0s for additive terms) during this part of model evaluation. This initial simulation is specified in Appendix A.

Figure 7a shows the results of the simulation in terms of the length of each school’s queue during the course of the 30-min session. Because the assigned goals were to have no students in line at the deadline, the length of the queues represents the discrepancy for each school. In general, both queues are flat over time. Step increases represent new students being added to the queue, as determined by the Schmidt and DeShon (2007) protocol and implemented in the disturbance terms. Downward steps represent a completed schedule for that school. Toward the bottom of the graph, the notched line indicates which of the two goals the “individual” is working on at the time. When the line is up (1), the model is working on the Task A goal. When the line is down (0), the model is working on the goal for Task B. As Figure 7a shows, for most of the simulated period, the model moves back and forth between the schools, switching to the school with the larger discrepancy (i.e., more students in the queue). However, at about four fifths through the procedure, the model processes Task A until time runs out. These results show that our theoretical model is capable of reproducing the reversal effect that Schmidt and DeShon (2007) described in their data. To further illustrate the correspondence between our model’s behavior and that reported by Schmidt and DeShon, Figure 7b displays the behavior of a participant from Schmidt and DeShon’s equal-incentive conditions. This figure not only confirms that one individual in the equal-incentive conditions behaved as Schmidt and DeShon described but also resembles the simulated data presented in Figure 7a.

Understanding the reversal process. Beyond mimicking the reversal effect described by Schmidt and DeShon (2007), our model describes the processes through which such reversals may occur. Recall that our model posits that resource allocation is determined by changing expected utilities, which are composed of dynamic expectancy and valence terms. Both these latter terms are determined by discrepancies, but the expectancy term is also a function of time to deadline. To get a sense of the relative influence of these terms as time passes, we examined the extent to which expectancies and valences differed across the two tasks as the simulation unfolded over time (see Figure 8). First, for each moment of the simulation, we computed the difference between the larger and the smaller expectancies, which was then divided by the larger expectancy. This resulted in a proportion indicating the degree to which the two tasks can be differentiated with regard to their expectancies. Smaller values indicate that the expectancies for the two tasks were similar in magnitude, and thus the tasks were not very differentiated on expectancies (i.e., a value of .00 indicates that tasks were indistinguishable with regard to expectancies), whereas larger values indicate that expectancies for the two tasks were divergent. For example, a value of .25 indicates that the expectancy for one task was 75% smaller than expectancy for the other (i.e. the smaller expectancy was three quarters the size of the larger expectancy), whereas .75 indicates that the expectancy for one task was 25% smaller than the other (i.e. the smaller expectancy was only one quarter the size of the larger). We then computed similar information for the dynamic valence terms, which indicates the extent to which the two tasks are differentiated with regard to valence. The graph visually presents this information for both expectancies and valence across the entire simulation.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Default value</th>
<th>Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time gain</td>
<td>1</td>
<td>Positively relates to timing of reversal (i.e., higher values translate into a later reversal)</td>
</tr>
<tr>
<td>Incentive sensitivity</td>
<td>1</td>
<td>No effect if incentives are equal; otherwise positively related to incentive effect</td>
</tr>
<tr>
<td>Initial rate</td>
<td>0.0168</td>
<td>Positively related to number of schedules completed</td>
</tr>
<tr>
<td>Change in rate</td>
<td>4.83E-06</td>
<td>Positively related to number of schedules completed</td>
</tr>
<tr>
<td>Bias</td>
<td>0</td>
<td>Negatively related to timing of reversal</td>
</tr>
</tbody>
</table>
Two features of the figure reveal the underlying dynamics. First, one can see that early on, there is much greater differentiation among the tasks with regard to valences than expectancies. For much of the simulation, there is only a 5%–15% difference in the magnitude of the expectancies for the two tasks, whereas the valences differ in magnitude by 20%–50%. Given the multiplicative nature of expected utility, this gives valence greater influence in determining which of the two tasks possesses greater utility, such that the task with greater valence is chosen at each moment, despite possessing lower expectancy. That is, the differences in expectancies were not substantial enough to differentiate between the tasks, whereas differences in valence were a relatively large differentiator. In this early period, changes in either component are almost exclusively a function of adding or subtracting schedules (i.e., changing discrepancies), creating steplike functions. However, as time passes, the expectancies for the two tasks begin to diverge, such that expectancies begin to rival valences in the extent to which they differentiate between the two tasks. This change is due to the effect of time on expectancies. This can be seen by the increasing slope in relative expectancies between steps (i.e., between changes in queues). That is, the slopes of the steps start out nearly flat for the relative expectancy line but increase to nearly vertical toward the end of the simulation (i.e., before reaching the ceiling, which indicates reaching one of the goals). With roughly 6 min remaining, the proportional difference in expectancies is great enough to outweigh the differences in valence, leading the participant to select the task with greater expectancy. The fast-approaching deadline causes expectancy for the neglected task to plummet, such that its low expectancy outweighs the rising need (i.e., valence) to act. Thus, whereas differences in valence outweighed the differences in expectancy through much of the time, task choice was more strongly determined by expectancies near the end. Said in more human terms, the simulation’s arising concern for not completing a goal overcomes its desire to meet both goals. Appendix B describes an example of how to calculate the time when the reversal would happen and the mathematics one could use to predict it.

**The incentive effect.** For our next set of simulations, we wanted to confirm that the simulation could account for the incentive effect. To do this, we doubled the incentive for one of the schools. This represents the additional reward attached to completing the schedules in one of the schools or the approach framing of the school’s incentive system (see Schmidt & DeShon, 2007). Figure 9a presents the queue’s status over time as well as the task worked on (i.e., Task A) when the extra incentive was given to Task A. The results clearly demonstrate a preference for Task A, though Task B was still processed when the relative discrepancy was high enough. When Task B was given the greater incentive, the results were similar except that preference was given to Task B. These results are consistent with Schmidt and DeShon’s results when they compared the differential incentive conditions. Again, a further illustration of the match of our model’s behavior with that described by Schmidt and DeShon is provided by Figure 9b, which displays the behavior of a participant from one of Schmidt and DeShon’s unequal incentives conditions. As in the equal incentive condition, this figure confirms the similarity, qualitatively, between the behavior of our simulation and that of an actual research participant in Schmidt and DeShon’s study. Thus, our model not only replicates and provides a process-oriented explanation for the reversal effect on the basis of changes in expectancy but also reproduces the key valence finding from the Schmidt and DeShon study.
study. An inability to produce either effect would raise substantial concerns regarding our model's validity. However, the replication of both of these effects provides evidence supporting our model's fertility, another criteria of computational models (Taber & Timpone, 1996).

Parameters that account for variance in the timing of the reversal. Schmidt and DeShon (2007) noted variance in the behavior of the participants on their experiment. This was confirmed by our own analysis of the data. In particular, to get a handle on the various patterns observed, we created the time series graphs shown in Figures 7b and 9b for every individual in the study. One obvious finding was that when individuals exhibited the reversal, or whether they did at all, was highly variable. That is, some individuals exhibited the reversal earlier than shown in Figure 7a, others showed the reversal later, and still others exhibited no reversal at all (i.e., they mostly allocated more time to the most discrepant task throughout). Several parameters in the model might account for these differences.

One possible influence on the timing of the reversal is individuals’ speed at creating schedules, reflected in the time required to complete a schedule (i.e., scheduling rate). With a slower scheduling rate, fewer schedules should be created, meaning larger discrepancies would exist as one approached the deadline, which in turn should exacerbate the effect of the deadline on expectancy. As a result, expectancy should more quickly overtake valence as the greater differentiator between the two tasks (i.e., larger proportional differences in expectancies than for valences), causing expectancy to be the dominant driver of task choice earlier in the process. Because expectancy is higher for the task with the smaller discrepancy, this would mean that the simulated participant would more quickly reverse from selecting the task with the largest discrepancy to selecting the task with the smallest discrepancy. Indeed, when slower initial rates or slower growth in rates was entered in simulations, this prediction held. The predictions were also consistent with the pattern of behavior observed for a few of the slower participants in the Schmidt and DeShon (2007) data.
Conversely, our computational model shows that a faster scheduling rate pushes the reversal later in the simulation. Indeed, if schedules can be completed quickly enough, then expectancies for both tasks remain sufficiently high throughout, and they never become a sufficient differentiator between the two tasks to overtake the influence of valence. In essence, expectancies for the two tasks cancel each other out, such that task choice is determined solely by valence. As a result, the reversal effect never occurs because the simulated individual is never placed in the position of needing to abandon one goal for the other, as both goals are perceived as being obtainable in the available time. Again, simulations with faster initial rates as well as faster growth rates confirmed this predicted pattern. Support for this proposition can be found within the Schmidt and DeShon data, as approximately 17% of the individuals in the equal incentives condition completed schedules quickly enough that the reversal would not occur if one had an accurate perception of his or her rate of discrepancy reduction—indeed, these individuals were categorized as using positive discrepancies throughout the session.11

This discussion concerns the effects of differences in actual rate of schedule creation. However, similar effects were obtained via the bias parameter. Recall that the bias reflects the possibility that individuals may not accurately perceive their true rate of schedule creation—some may believe they can create schedules more quickly than they actually can, whereas others’ beliefs may be biased in a pessimistic direction. Any nonzero bias term had a substantial effect on expectancies and thus on behavior. Specifically, negative bias terms resulted in underestimating the scheduling rate (i.e., belief in faster scheduling) and moved the point of reversal later in the timeline, whereas positive biases resulted in overestimating the rate and moved the reversal earlier in the timeline. Expectancies were not measured in the Schmidt and DeShon (2007) protocol, so we do not know if individuals miscalibrated expectancies in any way. However, research on completion time estimates indicate that individuals tend to underestimate how long it will take them to do something (i.e., the planning fallacy; Buehler, Griffin, & Ross, 1994). Thus, we might expect more to not engage in the reversal effect than their actual speed of completing schedules would warrant because of overestimated expectancies. Indeed, in the Schmidt and DeShon data, several individuals (33%) were found who did not exhibit the reversal effect even though their scheduling rate would have predicted the reversal.

Another individual difference that could impact the timing of the reversal is the time gain parameter, which reflects one’s sensitivity to time and deadlines. Time gain values of less than 1 translate into perceptions of less time left before the deadline (i.e., hypersensitive to deadline), whereas values greater than 1 result in perceptions of more time before the deadline (i.e., hyposensitive). Increases in the time gain parameter moved the reversal to a later point in the process—only when the deadline was very close at hand did it influence resource allocation patterns. Decreases in the value of the time gain parameter moved the reversal earlier in the timeline; these simulated individuals altered their resource allocation in response to the deadline even when it was relatively far off in the future. This type of an effect is unusual for a gain parameter (e.g., the larger it is, the less the effect time has on behavior). This is a function of how the output is used (i.e., as a reference for the expectancy agent). Again, however, we had no information from the Schmidt and DeShon (2007) paradigm to determine if individual differences related to the time agent might have influenced behavior or whether this parameter is the one responsible for the planning fallacy mentioned earlier.

**Variation in reactions to incentives.** Another point at which individual differences may come into play is with regard to reactions toward differential incentives—that is, the extent to which one task is favored over the other as a result of the larger incentive offered for that task. Within our computational model, one parameter—incidence sensitivity—affected the reaction to incentives. As briefly discussed in our initial presentation of dynamic valence, incentive sensitivity reflects differences in individuals’ concern for particular incentives, which may amplify or attenuate the effects of the incentives. As discussed previously, numerous factors may influence such variation in responses to incentives, including various individual differences such as goal orientation, regulatory focus, and so on. For our present purposes, we are less concerned with the sources of incentive sensitivity than we are with its effects on the resource allocation processes of interest. Consistent with our logic, small values for incentive sensitivity—reflecting little concern for the incentives provided—reduced the effect of differences in the task incentives, and a zero value removed the effect altogether. Likewise, large values—indicating great subjective value placed on the incentives—increased the behavioral focus on the single goal. Both patterns were observed in the Schmidt and DeShon (2007) data. Meanwhile, the incentive sensitivity parameter had no effect when the incentives were equal.

### Quantitative Model Evaluation

In the previous section, we presented the qualitative effects of the model and its parameters. In this section, we illustrate a more quantitative procedure for evaluating models. When models have free parameters, quantitative methods have the dual function of finding (i.e., estimating) parameter values and indexing the fit. Indeed, the procedures generally involve minimizing some type of error or cost function, which can be the inverse of a fit index. This is similar to the idea of estimating regression weights, which are the free parameters, and the total variance explained, which is an index of model fit. In addition, and like multilevel modeling (Bryk & Raudenbush, 1992), the parameters values can be unique for each individual, and thus must be estimated for each. However, because of the nonlinearities and dynamics involved in many computational models, the process is often more complex (Myung, 2000). Fortunately, software is available that can automate and optimize much of the process. In our case, Vensim Professional provides an optimization routine that both estimates parameters

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11 These results are based on rater-derived categorizations of the participants in Schmidt and DeShon’s (2007) study. Specifically, using Schmidt and DeShon’s data, we produced graphs like those presented in Figures 7b and 9b for each of the 241 individuals in their study. These graphs were then sorted independently into behavior pattern categories (i.e., reversers; positive discrepancy driven throughout; positive discrepancy driven throughout fast enough to reach or nearly reach both goals; myopically focused on one goal; and unclear) by three judges trained by the first author. Their level of agreement (kappa) was .64, .54, and .75 for the equal, single, and mixed incentive conditions, respectively. These fall in the fair to moderate agreement ranges (Landis & Koch, 1977).
and assesses fit, though for only one unit at a time. We describe this process and some results in the following paragraphs.

For the estimation of parameters and index fit, the software can compare the values of one or more endogenous variables estimated from the model with external values provided from an external source (e.g., a participant’s data). Here we input the task data from 10 participants, one at a time, to estimate parameters and index fit. The optimization routine within Vensim minimizes the squared difference between the input data and the modeled data with a gradient descent method, outputting the sum of these differences across the time period once new parameter values result in small changes in this sum (Oliva, 2003). Because we only used one matching variable and it was dichotomous (0, 1), errors between the input and modeled data could easily be interpreted as percentages of the time the variables matched by dividing the sum by 1,800 (i.e., total seconds of the time series). This index could then be interpreted as having a soft lower bound of 50%, representing chance, and a hard upper bound of 100%, representing a perfect match. These values also represent two alternative models for the behavior: a random model and a completely saturated model (Singer & Willett, 2003). Completely saturated models are ones in which any data set can be perfectly matched because there are enough free parameters to fit any data set. Such models are of little conceptual value because they lack generalizability (Forster, 2000); they merely represent the theoretical maximum fit possibility and serve as one anchor for model comparison.

In addition to considering random and saturated models, we also operationalized another model to serve as a comparison model for fit evaluation. Specifically, we operationalized Schmidt and DeShon’s (2007) theory into a computational model that could be simulated. The Schmidt and DeShon model is a simplified version of our model, in which choice is only dependent on relative valence, which is derived from task goal discrepancies and gains. Thus, it excluded the time and expectancy agents.12 This resulted in a more parsimonious model because it only required four instead of seven agents and three free parameters instead of five (i.e., the bias and time gain parameters were no longer meaningful). This valence model could produce the positive discrepancy effect (i.e., task with the larger discrepancy is worked on) and the incentive effect but not the reversal effect. Recall from the qualitative results described earlier that more participants exhibited this discrepancy without reversal pattern than with reversal pattern.13 Except when noted, the change in rate parameter used for each individual was based on the ordinary least squares (OLS) procedure, and the bias parameter was set to 0 and incentive sensitivity was set to 1.

Table 3 presents the results of the quantitative parameter estimation and fit values. Specifically, in Column 1 is a sequential code to represent the individual modeled. Column 2 lists the initial scheduling rate parameter estimated previously with standard OLS. Columns 3 and 4 list the initial rate estimated with Vensim’s optimization procedure. Generally, these estimates did not differ much from each other. Column 5 presents the time gains that were estimated along with initial rate for the full model. Time gain was not a parameter in the valence model. Finally, Columns 6 and 7 present the fits for the full and valence models, respectively. All the fits were significantly better than chance. In half the cases, the full and valence models were significantly different from each other.

Several issues need to be considered in the interpretation of the results from Table 3. First, we found a case in which the fit of the simpler nested model was better than the fit of the more complex model. Generally, nested models cannot fit better than the models in which they are nested (Forster, 2000). However, in this case, the nonlinearities in the models make this possible. Second, in one of the cases in which the full model fit better than the valence model, the observed pattern was one where a reversal could have occurred because the individual ran out of time before reaching either goal but clearly did not. Although the time gain parameter could account for this—indeed, its estimated value was high compared with those of others—it is probably not reasonable to suggest the full model fit the data better. Likewise, the fits for one of the individuals (i.e., Individual 6) were significant, but this individual only completed one schedule, which is why an OLS estimate could not be calculated. However, because of the number of observations (n = 1,800), significance was easily reached. Finally, poor fit arises somewhat from (a) the inability of the models to predict the working task when the discrepancies of the tasks are identical and (b) the false assumption that scheduling rate follows a smooth pattern. That is, sometimes an individual will take awhile to complete a schedule and then finish another one relatively quickly. The notion of smooth change in rate is merely a convenience. These problems are most dramatic for Individual 5 (individual in Figure 7b). An examination of the pattern of behavior reveals a perfect match with the logic of the full model (i.e., worked on the task with the larger discrepancy until about halfway through and then worked on the task with the small discrepancy, finishing it near the deadline). Yet, we only got a fit of 79% for this individual. We will further discuss the implications of the findings with respect to the Schmidt and DeShon (2007) data, as well as the implications of the model more generally.

Discussion

Theories of motivation attempt to explain “fluctuations in the choices made among the possible things an organism might do” (Beck, 2004, p. 3). Toward that end, many theories have emerged to account for aspects of the larger problem. For example, some theories have focused on the discrepancies between current and desired states to explain goal-striving behavior (Diefendorff & Lord, 2008), whereas other theories have focused on expectancies and valence beliefs to explain goal choice (Klein et al., 2008). Yet, putting these kinds of theories together to more fully account for

12 To operationalize this simpler model, we merely changed the task choice input and comparator functions in a way that rendered the expectancy terms inert. Specifically, for the input function, we changed the domain from “expectancy A output * task A output” to “expectancy A output * 0 + task A output.” Likewise for the comparator function, we changed the equation within the “if, then” statement from “task choice input — expectancy B output * task B output” to “task choice input — expectancy B output * 0 — task B output.”

13 Although this observation from the qualitative analysis seems inconsistent with the findings reported in Schmidt and DeShon (2007), we suspect that the divergence in the relative discrepancies for the minority who engaged in the reversal effect overwhelmed the relative lack of discrepancies among those consistently working on the task with the greater discrepancy.
behavior over time (i.e., the “fluctuations”), where multiple possible tasks or goals exist (i.e., “possible things an organism might do”), has proven to be a greater challenge (Mitchell, 1997). An illustration of that challenge was presented by Schmidt and DeShon (2007), who examined multiple-goal pursuit with deadlines. They used the difference between goal discrepancies weighted by differences in incentives to account for much of their data, but they recognized the need for an additional theory to account for how time affected the goal–discrepancy effect. In addition, they did not account for the individual differences observed. To address those theoretical gaps, we developed a model that incorporated dynamic valence and expectancies concepts. Using a computational rendition of that model, we were able to account for all the major findings and much of the individual differences observed in the Schmidt and DeShon data. We discuss the implications of our modeling in terms of (a) accounting for specific phenomena (e.g., the reversal effect and individual differences), (b) integrating motivational theories, and (c) inspiring future research.

### Accounting for Phenomena

Our immediate goal was to provide an explanation for the reversal effect that Schmidt and DeShon (2007) found in their unique protocol examining multiple-goal pursuit with deadlines. Citing a connection between concepts in goal-choice models (i.e., valence as represented in a weight) and goal-striving models (i.e., discrepancy driven negative feedback loops), they hypothesized that a comparison of discrepancies, sometimes differentially weighted by unequal incentives, could predict resource allocation (time on task) between two goals over time. They also hypothesized that the discrepancy effect would likely reverse as the deadline approached for individuals. This latter hypothesis was made in the hopes of inspiring theory development. Specifically, they recognized that dynamic phenomena are rarely examined, and thus theorists have not been pushed to explain such phenomena. With the goal of theory development in mind, we added the expectancy construct to the valence and goal constructs already mentioned in Schmidt and DeShon’s theorizing on the behavior. More important, we infused all these constructs with dynamic elements to account for the reversal effect as well as much of the individual differences observed within the Schmidt and DeShon data.

On a practical level, accounting for the kind of behavior exhibited in the Schmidt and DeShon study may be important because of the multiple demands commonly found in the workplace today (Mitchell et al., 2008). That is, if the explanation holds up, then managers might have levers for affecting the task-switching behaviors of their subordinates. For example, if the manager wants a subordinate to balance responsibilities throughout a period of time, increasing expectancies or hiding time limits might prove useful. If accomplishing one task at the expense of another is more important, making sure expectancies are realistic and highlighting approaching deadlines would be more appropriate.

Another practical implication of our theory relates to the individual differences observed in the behavior exhibited. Much of this variety was a function of individual differences in the speed with which they accomplished the task, which mattered because of the dynamics inherent in the task. However, rate differences did not completely account for observed differences. Fortunately, we could evoke free (i.e., exogenous) parameters to possibly explain much of the individual differences observed. By varying these parameters, which potentially represent individual difference constructs (Vancover, 2009), we could examine their possible role in affecting behavior (e.g., the timing of the reversal effect). As described in Tables 2 and 3, variance in the parameters could match with qualitative as well as quantitative differences in patterns of behavior. Of course, without independent measures of the levels of these constructs in the participants, we were not able to determine if or which constructs were responsible for any particular participant’s deviation from the default patterns. We return to this issue in the section on future research.

### Integrating Motivational Theories

A second major goal of our modeling efforts was to continue the process of integrating motivation theories. A strong set of motivation theories has emerged after decades of research on the topic, as noted by reviewers of the field (e.g., Ambrose & Kulik, 1999; Kanfer, 1990; Mitchell, 1997; Pinder, 2008). However, as these

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**Table 3**

<table>
<thead>
<tr>
<th>Individual modeled</th>
<th>Initial rate</th>
<th>Time gain in</th>
<th>Model fit* (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>full model</td>
<td>full model</td>
</tr>
<tr>
<td>1</td>
<td>0.024</td>
<td>0.023</td>
<td>0.022</td>
</tr>
<tr>
<td>2b</td>
<td>0.017</td>
<td>0.020</td>
<td>0.023</td>
</tr>
<tr>
<td>3b</td>
<td>0.018</td>
<td>0.022</td>
<td>0.023</td>
</tr>
<tr>
<td>4b</td>
<td>0.015</td>
<td>0.020</td>
<td>0.020</td>
</tr>
<tr>
<td>5bd</td>
<td>0.012</td>
<td>0.013</td>
<td>0.008</td>
</tr>
<tr>
<td>6b</td>
<td>—</td>
<td>0.022</td>
<td>0.022</td>
</tr>
<tr>
<td>7c</td>
<td>0.017</td>
<td>0.021</td>
<td>0.022</td>
</tr>
<tr>
<td>8</td>
<td>0.023</td>
<td>0.013</td>
<td>0.018</td>
</tr>
<tr>
<td>9</td>
<td>0.021</td>
<td>0.013</td>
<td>0.022</td>
</tr>
<tr>
<td>10</td>
<td>0.018</td>
<td>0.021</td>
<td>0.021</td>
</tr>
</tbody>
</table>

*Note.* OLS = ordinary least squares.

+ Differences of 2.4% are significant at 50%.
+ Fit was better using the median change in rate, rather than the OLS calculated rate.
+ Quality pattern was clearly consistent with valence model and not full model.
+ Figure 7b individual.
+ Fit significantly (p < .05) better than other model.
reviewers acknowledged, we have not integrated these theoretical perspectives very well. Moreover, despite our conceptualization of motivation as process, several have noted that our understanding of the dynamics of the processes is less refined (e.g., Dalal & Hulin, 2008; Fried & Slowik, 2004; Karniol & Ross, 1996; Mitchell & James, 2001). Part of the issue relates to the scarcity of empirical research that is both dynamic and complex (e.g., observations of behavior as individuals pursue multiple goals). Schmidt and DeShon (2007) sought to remedy that empirical gap by providing a study of multiple-goal pursuit in a controlled experimental setting. In particular, they created a protocol that allowed for changes in the state of two variables as a function of both a person’s actions and the environment, where the passage of time mattered and where changes in effectiveness (i.e., scheduling rate) could occur. Moreover, some of these changes were discrete (e.g., changes in task states; change in task worked on) and some continuous (e.g., changes in time). Their study also highlighted a theoretical gap in the existing theories. Here, we sought to remedy the theoretical gap as well as integrate existing theories via a single theoretical approach that could handle these dynamics.

In particular, we used a single information-processing architecture common to theories of self-regulation (i.e., the negative feedback loop) as well as concepts from expectancy theory (Vroom, 1964). Yet, the dynamics involved in multiple-goal pursuit presents specific challenges, particularly in the integration of expectancy theory and the role of deadlines. To accommodate these dynamics, we translated much of the static elements of expectancy theory into dynamic elements using concepts from control theory (Powers, 1973, 1978; Vancouver, 2008) and TMT (Steel & König, 2006). Moreover, the theoretical approach we took was a novel combination of approaches. That is, most goal-based self-regulation theories describe sets of goal subsystems, but they are not formal (e.g., Klein, 1989; Kruglanski et al., 2002; Lord & Levy, 1994). At the same time, more formal theories, like expectancy theory and other subjective expected utility theories, tend to be static (Luce, 1995). In particular, our approach represents a bridge between cognition and motivation (e.g., motivation as cognition), as opposed to a separation of the two (e.g., motivation vs. cognition) that Kruglanski et al. (2002) bemoaned. In addition, our theory answers a recent call to address the link between goal choice and goal striving (Klein et al., 2008), explicitly including the expectancy concept central to choice models but neglected in dynamic goal-striving models (Diependorff & Lord, 2008).

To achieve this integration, we theorized at the subsystem level (Vancouver, 2005). Using a particular subsystem architecture, the self-regulatory agent, we represented the acting and decision-making elements of the larger human system. In this way, the model realized conceptual parsimony while accomplishing conceptual comprehensiveness. Of course, we have no illusions that this model is necessarily the only one that might reproduce the effects observed. Generally, simpler models are preferred to more complex ones because the business of the theoretician is to simplify nature (Kuhn, 1962).

We should note that parsimony can vary on three levels given the approach taken here (i.e., agent-based, subsystem modeling). At one level, different types of agents or agents of more or less complexity could be described (e.g., weight times variable, as in regression models), though it is not readily apparent to us what these might look like once a dynamic perspective is taken. Moreover, on this level of complexity, the approach taken here is parsimonious (i.e., the agents are simple). Parsimony can also be a function of the number of agents required to account for a phenomenon. Here we used seven agents to account for decision and goal-striving processes. In particular, we used these agents to account for the reversal of the discrepancy effect that we thought worthy of explanation. For those not exhibiting the reversal effect, a simpler, four-agent model was rendered. Indeed, the quantitative fit results indicated that the simpler model often performed as well as the full model, indicating that the simpler model is largely sufficient. However, the simpler model does not include the expectancy construct, which much research in motivation and decision making has indicated is central for explaining behavior (Beach & Connolly, 2005; Pinder, 2008). In the future directions section, we will take up the issue of more fully testing the model when factors like expectancies are varied. Indeed, the seven-agent model rendered did not account for all the behavior patterns observed in the Schmidt and DeShon data, implying that a model with even more agents might be required. In the end, it is likely the research question at hand that will determine the level of parsimony sought in terms of the number of agents to represent. In this case, accounting for the dynamics of the reversal effect as well as the incentive effects were the central research questions; thus, we think the number of agents used is about right.

Finally, the most common understanding of parsimony is the number of free parameters in the model (Myung, 2000). We had five, but we used the simulations to reveal that, except for the rate parameters (initial and change in rate), they were not needed to account for the reversal and incentive effects. Whether all are needed will require further research. Indeed, we did not attempt to estimate all the parameters simultaneously when doing the quantitative fits because of the redundancy of the effects the parameters predict. Meanwhile, we left off parameters that might have important effects (i.e., bias terms to the input functions of the time or task agents) in order to keep the model parsimonious. These parameters might play important roles in future research on multiple-goal striving and choice discussed in the future research section.

Future Directions and Model-Inspired Research Questions

In the Model Results section, we described several criteria for evaluating models. However, an important criterion for models, like theory, is that they should inspire new research (Bacharach, 1989). In particular, good models or theories should engender predictions that can be validated against data. Here, we provide several examples of research questions that may be inspired by the current model or more substantial additions to the model given the theory from which it is derived.

Research on the current model. As noted above, although our model predicts effects found in the Schmidt and DeShon (2007) data, limitations in the protocol prevented a more complete test of the model. For example, individual differences were found in the data, but these differences were “overdetermined” by the model. That is, more than one parameter could account for some of the pattern differences. Yet these parameters are associated with individual differences that have been identified and can be measured independently. Thus, the model specifies a set of individual
difference variables that might be measured in subsequent protocols (e.g., the time gain parameter has been linked to impulsiveness; Monterosso & Ainslie, 1999) to see whether they track to behavior differences in ways consistent with model predictions.

Another major issue regarding the current model is the role of the expectancy and time agents. Our model proposes that these beliefs play a key role in goal-switching decisions. However, we could account for a plurality of the participants in Schmidt and DeShon’s (2007) equal incentives condition without the complexity that these agents add to the model. Yet, one might argue that their protocol did not emphasize expectancy issues, particularly given the fact that the two goals or tasks were identical. Perhaps a simple change in protocol (e.g., if the colleges differed in the rules to which valid schedules must conform) might result in a slower rate in scheduling for one school relative to the other, which might highlight the role of expectancy in switching. Indeed, one can use our computational model to predict behavior patterns under such conditions to confirm that such a manipulation would be diagnostic regarding the model. Indeed, we did just that and found that it produced effects similar to the incentive effects, which leads to a testable hypothesis. Alternatively, to examine the role of expectancies as well as time agents, one might operationalize two (or more) somewhat unrelated tasks (e.g., Hambrick, Oswald, Darowski, Rench, & Brou, in press) where expectancies, or perhaps deadlines, could differ.

Another example of a study with the current model would be one in which initial states of the tasks were varied in regards to their goal. When we did this within our model, an interesting discontinuous effect emerged (cf. Vancouver, More, & Yoder, 2008). Specifically, when the numbers of students in line were only moderately divergent, the model worked on the task with the greater number because of the relatively higher valence that working on this school represented. However, if the initial number of students in line for one task was set to 35 while the other was set at five, expectancies for the two tasks diverged enough that the model ignored the school with the initially longer line until it finished the school with the smaller line. This finding demonstrates that the expectancy element of the model not only holds sway as the deadline approaches but can also influence initial task choice if the discrepancy is large enough. A crucial process validity (Taber & Timpone, 1996) test of the model would be to determine if such a discontinuous effect, or the other effects predicted earlier, could be found.

More substantive additions. The examples we have cited involved a small change to the model (i.e., creating separate expected lag constants for each goal, changing initial levels of a task state). However, the model is merely an instantiation of grander theories (e.g., TMT, Steel & König, 2006; dynamic process theory, Vancouver, 2008) that might inspire other changes to the model described here. For example, one might also examine more complex input functions that uncouple the isomorphism between the state of the environment and the perception created. In particular, one might add thinking and learning elements to the input function, which Vancouver (2008) described in his theory. For instance, individuals might learn to predict that disturbances will occur to some degree over some period of time and use that to offset their perception of the current state. Such an input function essentially changes the meaning of the goal level from, for example, “having zero students needing schedules” to “having enough completed schedules to handle the students likely queuing up in the next several minutes.” These thinking and learning elements could also handle an empirical situation where feedback on one’s current state is sporadic or noisy and perhaps allow researchers to address questions related to perceptual bias and forecasting errors (Luca, 1998).

Several other issues related to multiple-goal pursuit might also be considered and added to the current model. For example, we did not model the effects after the deadline had past, including possible reactions to goal success or failure (though see Scherbaum & Vancouver, in press, for a computational model of goal changes as a result of past success). More generally, the current model does not integrate all the phases of goal process (Diefendorff & Lord, 2008), but many are not beyond the general theory. We also did not attempt to include affect variables in our model (e.g., Louro et al., 2007). Including affect presents a challenge for information-processing models, though much conceptual and empirical work has focused on integrating the affective and cognitive (i.e., information-processing) perspectives in applied contexts (e.g., the effects of mood on performance; Forgas & George, 2001). Moreover, theorists have integrated control theory or cybernetic approaches with affect processes, facilitating the ability to create computational models of the processes (e.g., Carver & Scheier, 1990; Forgas & Ciarrochi, 2002; Vancouver, 2008). In addition, attention is an issue largely neglected by Vancouver’s (2008) theory and our extension of it, though it is probably a key player in understanding multiple-goal pursuit in dynamic contexts (Kanfer & Ackerman, 1989; Vancouver & Tischner, 2004). In future work, researchers might consider whether manipulations designed to limit attentional resources reduces task switching (e.g., heavy self-regulation loads just prior to engaging in the task; Vohs et al., 2008) or whether willingness to decide among tasks drains cognitive resources from the task at hand (Borst, Taatgen, & van Rijn, 2010). At a more basic level, we should inquire as to whether certain neural structures are required to perform particular operations, structures that are limited in inputs, capacity, and output, but provide the experience and benefits of consciousness (Diefendorff & Lord, 2008). Finally, Mitchell et al. (2008) described several issues that are likely relevant to understanding multiple-goal pursuit. Those other possible effects relate to more than two goals, different types of tasks, and more. These variables remain to be considered and examined.

Regardless of the specific issue, we suspect that the computational modeling approach taken here can help. Fortunately, computational modeling has gotten much easier with advances in computer technology and software. Indeed, researchers can readily download free software from www.vensim.com (i.e., Vensim PLE), draw the model in Figure 6, and use the equations in Appendix A to reproduce the model and simulate it, which a colleague did successfully without our prompting or help. From there, researchers can explore the effect of various parameters or changes in the model, including attempts to address the theoretical extensions described, challenge the modeling efforts presented here, or address other complex theoretical problems. Examples of computational models of applied psychological issues are increasing (Harrison et al., 2007; Igen & Hulin, 2000; Lord, Hanges, & Godfrey, 2003; Scherbaum & Vancouver, in press; Vancouver et al., 2005, 2008; Vancouver & Scherbaum, 2008). As we believe our model shows, the approach is particular relevant to applied
psychologists because it shows the convergence of general (nomothetic) models of motivation coupled with parameters for individual differences and contextual variables that can affect behavior (Vancouver, 2009). This area represents a new and exciting opportunity for advancing the field theoretically as well as empirically because science makes progress by replacing good ideas with even better and more explanatory ones (Popper, 1969).

Conclusion

Schmidt and DeShon (2007) lamented the lack of theory to account for, and research to examine, multiple-goal pursuit. They worked on the research, and we worked on the theory: multiple investigators examining multiple goal pursuit using multiple theories and approaches dynamically. Despite the inherent complexity of the task, the resulting model remained largely parsimonious in that a recurring theme—the self-regulatory agent (Vancouver, 2008)—was largely able to capture the process. Yet, unlike earlier parsimonious formal theories of motivation that funneled processes through a single mechanism (e.g., Hull, 1943), the interesting results emerged from the interacting agents. Perhaps it is about time to pursue other theoretical and empirical goals, with the strategy provided here as a model.

References


### Appendix A

#### Equations for the Model

\[
\text{bias} = 0
\]

\[
\text{change in rate} = 4.83E-06
\]

\[
\text{completed schedule} = 1
\]

\[
\text{deadline} = 1,800
\]

\[
\text{expectancy A comparator} = \text{MAX(time output} - \text{expectancy A input})
\]

\[
\text{expectancy A input} = \text{expected lag} \times \text{task A comparator}
\]

\[
\text{expectancy A output} = \text{expectancy A comparator}
\]

\[
\text{expectancy B comparator} = \text{MAX(time output} - \text{expectancy B input})
\]

\[
\text{expectancy B input} = \text{expected lag} \times \text{task B comparator}
\]

\[
\text{expectancy B output} = \text{expectancy B comparator}
\]

\[
\text{expected lag} = \text{scheduling lag} + \text{bias}
\]

\[
\text{FINAL TIME} = 1,800
\]

\[
\text{incentive sensitivity} = 1
\]

\[
\text{initial rate} = 0.0212
\]

\[
\text{INITIAL TIME} = 0
\]

\[
\text{SAVEPER} = \text{TIME STEP}
\]

\[
\text{schedule comparator} = \text{IF THEN ELSE(completed schedule} - \text{schedule input}) > 0, 1, 0)
\]

\[
\text{schedule done} = \text{IF THEN ELSE(Schedule status} \leq 1, 0, 1)
\]

\[
\text{schedule input} = \text{Schedule status}
\]

\[
\text{schedule output} = \text{schedule comparator}
\]

\[
\text{Schedule status} = \text{INTEG(schedule rate} \times \text{schedule output} - \text{Schedule status} \times \text{schedule done}, 0)
\]

\[
\text{scheduling lag} = 1/\text{scheduling rate}
\]

\[
\text{scheduling rate} = \text{INTEG(change in rate, initial rate)}
\]

\[
\text{selected task} = \text{task choice output}
\]

\[
\text{task A comparator} = \text{MAX(task A input} - \text{task A goal})
\]

\[
\text{task A disturbance} = \text{PULSE}(170, 1) + \text{PULSE}(240, 1) * 3 + \text{PULSE}(510, 1) + \text{PULSE}(540, 1) + \text{PULSE}(810, 1) + \text{PULSE}(900, 1) + \text{PULSE}(1080, 1) + \text{PULSE}(1110, 1) + \text{PULSE}(1320, 1) + \text{PULSE}(1500, 1) + \text{PULSE}(1595, 1)
\]

\[
\text{task A gain} = 1 + \text{incentive sensitivity} \times \text{task A incentive}
\]

\[
\text{task A goal} = 0
\]

\[
\text{task A incentive} = 1
\]

\[
\text{task A input} = \text{Task A state}
\]

\[
\text{task A output} = \text{task A comparator} \times \text{task A gain}
\]

\[
\text{Task A state} = \text{INTEG}(-1 \times \text{schedule done} \times \text{Task} + \text{task A disturbance}, \text{initial line lengths})
\]

\[
\text{task B comparator} = \text{MAX(task B input} - \text{task B goal})
\]

\[
\text{task B disturbance} = \text{PULSE}(60, 1) + \text{PULSE}(90, 1) + \text{PULSE}(330, 1) + \text{PULSE}(450, 1) + \text{PULSE}(630, 1) + \text{PULSE}(660, 1) + \text{PULSE}(840, 1) + \text{PULSE}(960, 1) + \text{PULSE}(1260, 1) + \text{PULSE}(1350, 1) + \text{PULSE}(1440, 1) + \text{PULSE}(1623, 1)
\]

\[
\text{task B gain} = 1 + \text{incentive sensitivity} \times \text{task B incentive}
\]

\[
\text{task B goal} = 0
\]

\[
\text{task B incentive} = 1
\]

\[
\text{task B input} = \text{Task B state}
\]

(Appendices continue)
Appendix B

Calculating the Timing of a Reversal

If \( o_t \) represents the output from the time agent and the gain for the time agent equals 1, then \( o_t \) represents the time left to complete the two tasks. Also, let \( d_H \) represent the discrepancy from a task agent with a higher discrepancy level than the discrepancy \( (d_L) \) from a second task agent. Further, if two identical tasks are considered, the expected lag \( (\alpha) \) associated with both tasks can be assumed to be the same. For simplicity’s sake, we will consider a situation where the value of each task is identical, and the gains are equal to 1; thus, outputs from each task agent equal their discrepancies \( (i.e., d_H \text{ and } d_L) \). Then a point at which the decision agent’s discrepancy is 0 can be represented with the following equation:

\[
(o_t - \alpha d_H)d_H - (o_t - \alpha d_L)d_L = 0
\]  

(7)

Note the expressions within the parentheses are a representation of each expectancy agent and the entire expression to the left of the equal sign represents the decision agent. If we assume the difference between the discrepancy terms \( (i.e., d_H - d_L) \) equals 1, we can solve the above equation for \( o_t \), resulting in the following equation:

\[
o_t = 2\alpha d_L + \alpha
\]  

(8)

As can be seen, the result of this equation depends on the expected lag \( (\alpha) \) and the level of discrepancy in the task with the smallest discrepancy \( (d_L) \). For instance, if \( \alpha = 50 \) \( (i.e., \) a period of 50 s is presumed to be needed to reduce the discrepancy for one of the tasks by one unit) and the discrepancy for one task was 7 and the other 8, then the point in time at which the utilities of the two tasks are equal is 750 s from the deadline. Prior to that time, the task with the larger discrepancy has higher utility, and after that time, the task with the lower discrepancy has the higher utility. A more general form of the equation that allows for the differences between the errors to take on values other than 1 is the following:

\[
o_t = 2\alpha d_L + \alpha(d_H - d_L).
\]  

(9)

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