Dynamic Goal Choice when Environment Demands Exceed Individual's Capacity:

Scaling up the Multiple-Goal Pursuit Model

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Abstract

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Dynamic Goal Choice when Environment Demands Exceed Individual's Capacity: Scaling up the Multiple-Goal Pursuit Model

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Navigating the complexities of life where one must managing multiple goals, where one's status vis-a-vie those goals are constantly changing, and where limited resources undermines the ability to pursue all of one's goals simultaneously, creates a thorny problem for individuals as well as psychologists trying to understand how individuals manage this process. Recently researchers have started to use computational modeling to better understand the dynamic processes involved in multiple-goal pursuit. However most models and research are limited in a way that (a) they have assumed that people use a normative decision strategy, and (b) focused on the pursuit of two goals. Whereas in real life people often need to juggle more than two goals, decision-making literatures suggested that people may not always adopt the normative strategy. The present study aims to advance our knowledge by (a) scaling up the existing model on multiple-goal pursuit to more than two goals, (b) proposing a two-stage decision mechanism involving a range of heuristic to analytic strategies, and (c) developing nine computational models to represent the possible ordering of these strategies over time to explain individuals' behavior. I conducted an experiment to test the models' predictions. The results showed that individuals tended to use more heuristic strategies compared to more analytic strategies, and tended to switch from a more heuristic to more analytic strategy if they switched. The decision strategy represented in a model that represented people as starting with the simplest heuristic strategy (i.e., decide based on goal with the largest discrepancy) and then switching to the least complicated analytic strategy (i.e., decide based on goal discrepancy weighted by goal importance) received the strongest support. Theoretical and practical implications, as well as future directions, are discussed.

Dedication

To my husband and parents

Acknowledgments

I would first like to thank my advisor Dr. Jeffrey Vancouver for guiding me through my study. This dissertation would have not been possible without his support and advice. His passion, enthusiasm, and belief in science and research have been a great source of inspiration and motivation to me. His high standard for the quality of work has encouraged me to pursue the perfection of the work. I feel very fortunate to have the opportunity to work with him and I could not have imagined having better advisors for my graduate study.

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Introduction

Goals are considered an important concept driving much of human behavior (Austin & Vancouver, 1996). Moreover, individuals appear to make numerous decisions on how to allocate limited resources across multiple goals (Schmidt & DeShon, 2007; Wrosch, Scheier, Miller, Schulz, & Carver, 2003). For example, people may need to deal with multiple goals at work (e.g., multiple projects) while meeting the needs of their family and their own health and well-being. Yet, much of the research theorizing on goals has focused on the processes involved in pursuit of a single goal (Kernan & Lord, 1990; Locke & Latham, 2002). Relatively little is known about how multiple goals and commitments are managed.

Recently, however, researchers have begun to seek to understand the processes involved in multiple-goal pursuit (see Unsworth, Yeo, & Beck, 2014, for a review of theories and research in this area). This research has considered various factors that influence goal choice when pursuing multiple goals. It also revealed the importance of considering the joint effect of these factors on goal choice in a dynamic goal pursuit process where goal pursuit typically changes the states of variables (e.g., goal progress) related to the goals as well as the states of variables related to the processes of goal regulation (e.g., resources available, beliefs regarding goal pursuit).

Because of the complexities inherent in understanding dynamic phenomena, there has been limited empirical work examining the dynamics of goal pursuit. A few exceptions include the work of Schmidt and Vancouver (e.g., Schmidt & DeShon, 2007; Vancouver, Putka, & Scherbaun, 2005). In addition, these scholars have turned to computational models as a way to represent and examine the theories they are considering. For example, Vancouver and colleagues (Vancouver, Weinhardt, & Schmidt, 2010; Vancouver, Weinhardt, & Vigo, 2014) developed a computational model integrating different mechanisms (e.g., goal-choice, goal-striving, and learning) to explain findings that previous theories could not explain. However, these efforts are in their infancy and much more needs to be done. For example, one of the limitations of multiple-goal pursuit studies and theories is that they have only considered the pursuit of two goals (e.g., Erez, Gopher, & Arzi, 1990; Kernan & Lord, 1990; Klein, 1989; Schimidt & DeShon, 2007; Vancouver et al., 2010, 2014). It is not clear whether the findings from these studies and the theories developed to understand them will extrapolate to contexts where more than two goals are pursued.

The question of extrapolation is salient because individuals' only have limited cognitive resources (Simon, 1956). The current models of dynamic multiple-goal pursuit (i.e., Vancouver et al., 2010) often assume that individuals use a normative procedure to make decisions. That is, these models assume that individuals consider the subjective expected utility (SEU) of each choice and select the one with the maximized value of SEU. Here SEU is a function of multiple factors, including the goal-performance discrepancy, subjective value of the goal to the individual, and the expectancy to complete the goal. However, calculating the SEU of each goal and the means to meet the goals can become computationally intense (Gigerenzer & Gaissmaier, 2011), and thus it is not clear how generalizable the SEU approach is to more complex multiple goal striving contexts like those associated with pursuing more than two goals.

Indeed, decision research has found that individuals use various choice strategies depending on task demands (Abelson & Levi, 1985; Payne, 1982). Although it may be important to consider all related information before making the decision, in many cases (e.g., complex task, increase in alternative options, etc) people tend to save effort by ignoring some of the information and make the decision using heuristic strategies (i.e., making decisions only based on a portion of the available information). Though efficient, some researchers argue that heuristic strategies often lead to less than optimal choices (Payne, Bettman, & Johnson, 1993; Shah & Oppenheimer, 2008). This effort-accuracy trade-off demonstrates that people are adaptive to environments (Payne, Bettman, & Johnson, 1988). Therefore, given that managing and working on multiple goals might tax one's limited resources, the primary issue examined in this dissertation involves the question of scaling up the existing two-goal pursuit model to a three or more goals pursuit model with more complex decision rules.

Besides the issue of resources applied to deciding what to do, another issue is the resources one expends on goal striving. Indeed, one of the things likely relevant when individuals pursue one or more goals is the rate of one's actions. For example, in one of the few studies examining individual's multiple goal choice behavior, subjects were asked to perform either clerical tasks (e.g., Kernan & Lord, 1990) or scheduling tasks (e.g., Schmidt & DeShon, 2007; Schmidt & Dolis, 2009; Schmidt, Dolis, & Tolli, 2009) where there were individual differences in the rate of one's action. This difference in rate is likely to influence one's decision-making. For example, in a study where individuals needed to work on two scheduling goals, the choice patterns were different between those who were able to complete both goals and those who were only able to achieve one goal (Vancouver et al., 2010). In addition, the rate of change to a variable one is acting on is not the only influence on the variable in question. Outside factors, called disturbances, can also change the state of a variable. It is not uncommon that some goals in life are associated with constant negative disturbance. For example, a course where new material is presented requires one to keep spending time attending to and studying the material to maintain a desired standing. Similarly, eating is required to counter the drain on calories and drinking is required to counter water loss. Because people only have limited resources, pursuing a goal with high negative disturbances might drain one's resources needed in the pursuit of other goals. However, little research has examined how these kinds of negative disturbance would affect one's goal choice in a multiple goal pursuit context. Thus, the second issue in this dissertation considers how people pursue multiple goals in a highly demanding situation where negative disturbances are affecting the goals one is pursuing. I refer to the variables to which the goals refer with greater negative disturbance as variables with *high decay*, whereas variables with smaller negative disturbance as variables with *low decay*.

Given the above, the objective of the current study is to further develop the formal efforts via scaling up a computational model on two-goal pursuit (Vancouver et al., 2010) to more than two goals. Successful scaling up will allow the model to account for more complex situations where individuals need to allocate their limited resources across a multitude of goals. A situation of particular interest is where the pursuit of one goal can undermine the pursuit of multiple other goals. Moreover, I seek to maintain conceptual parsimony by adopting the basic structure from the models of self-regulation developed by Vancouver and colleagues (Vancouver, 2008; Vancouver et al., 2010; Vancouver et al., 2014).

Towards these ends, I first review the literature on multiple-goal pursuit and the major components in Vancouver and colleagues' multiple-goal pursuit model (MGPM). Then I expand their model to allow it to handle more than two goals. Because the new model aims to examine individuals' choice behavior in a demanding multiple-goal condition, it is possible that individuals would adapt to such situations and adopt a different decision rule (Payne et al., 1988). Therefore, I justify and develop a series of plausible variants of MGPM with different decision strategies that might explain one's choice behavior. Finally, I describe a lab experiment to compare the models' predictions.

Current State of the Literature on Multiple-Goal Pursuit

As noted above, past research on motivation has largely focused on processes involved in single-goal pursuit during a single performance episode. For example, goal setting theory (Locke & Latham, 1990), which is one of the most prominent theories of motivation in I/O psychology (Latham & Pinder, 2005), claims that individuals' action is regulated by goals. In particular, the research finds that specific, difficult goals lead to increased effort and therefore better performance than an easy or "do your best" goal. Moreover, feedback about goal progress helps individuals determine whether to increase, maintain, or decrease effort toward that goal.

However, in real life individuals often juggle multiple goals and tasks (Austin & Vancouver, 1996; Diefendorff & Chandler, 2011; Locke & Latham, 2002). Under conditions of multiple-goal pursuit individuals often face goal conflict, which may require them to strategically allocate their limited resources across multiple goals (Emmons & King, 1988). It would be unwise to apply blindly findings from the single goal literature to multiple goal situations (Unsworth et al., 2014), because previous goal pursuit literature was based on obtaining variances in goal choice between people on one goal, when it should be about the variances in choices across multiple goals within each individual.

As researchers have begun to examine the mechanisms involved when individuals pursue conflicting goals, the majority of empirical studies on multiple-goal pursuit have focused on resource allocation or goal prioritization. That is, researchers try to understand why and how individuals would allocate their limited resources to a certain goal and not another (Unsworth et al., 2014). Two lines of research are relevant here, self-regulation goal theories and decision-making theories (Diefendorff & Lord, 2008; Matsui, Okada, & Mizuguchi, 1981; Vancouver et al., 2010).

Self-Regulation Goal Theories

Based on goal-setting theory mentioned above, a basic finding is that harder goals lead to higher performance (Locke & Latham, 1990). This finding is consistent with self-regulation theories of goal-striving processes. Goal striving theories, often rooted in control theory (Carver & Scheier, 1998; Klein, 1989), are also called self-regulation theories because they highlight the dynamic process individuals use to regulate a desired state or goal (Vancouver et al., 2005). An important element of the theory is that decisions are affected by one's progress towards the goal (i.e., goal-performance discrepancy), which is likely changing over time (Vancouver et al., 2005; 2010). According to self-regulation theories, individuals tend to prioritize the goal with the largest discrepancy (Unsworth et al., 2014). Nonetheless, empirical findings are mixed regarding how discrepancy influences one's choice behavior. For example, Kernan and Lord (1990) found that when all else is equal, greater priority is given to the task with *smaller* goal-performance discrepancy, whereas Schmidt and DeShon (2007) found that the opposite was true, though this depended on time left to accomplish the goal. That is, they found that individuals tended to prioritize the task with *larger* goal-performance discrepancy unless a deadline was approaching.

Decision-Making Theories

Self-regulation theories of goal pursuit borrow much of their theorizing about goal choice from decision making theories (Vancouver, 2000). In applied psychology the most prominent decision theories are expectancy-value (E-V) models (Campbell & Pritchard, 1976; Kanfer, 1990; Klein, Austin, & Cooper, 2008). According to E-V models, people choose the option with the highest motivational force (Vroom, 1964) or expected utility (Fishburn, 1970), which is conceptualized as a multiplicative function of subjective impressions of expectancy and value. Expectancy refers to a belief in the probability or feasibility that a certain outcome will be achieved, and value reflects the desirability or importance of that outcome for the individual (Donovan, 2003; Steel & Konig, 2006; Van Eerde & Thierry, 1996). In many decision theories, *value* is an objective construct and *valence* or *utility* are its subjective counterparts. In the current study, I use *value* for the objective construct, which reflects the consequences tied to a goal. A common way to affect the value of a goal in organizational settings is via financial incentive (Schmidt & DeShon, 2007). However, individuals may react differently to the same incentive, and *incentive sensitivity* is used to reflect this individual difference. The subjective association of an incentive to a goal and the utility that incentive has, along with other associated outcomes is presumed to determine the *importance* of the goal, which is also called *error sensitivity* (Hyland, 1987; Schmidt & DeShon, 2007) or *gain* in the control theory literature (Jagacinski & Flach, 2003; Vancouver et al., 2010).

E-V theories predict that people compare the expected utilities of options (e.g., goals to pursue) and choose the one with the highest assessment. For example, Matsui and colleagues (1981) found that harder goals led to better performance only when adopted and the harder goals were adopted only when the valence for the goal was high enough to compensate for the lower expectancy of such goals. However, a limitation of most E-V theories is that they focus on one-time choices among options, where expectancy and valence are viewed as constant. Yet, in real life making choices between several goals repeatedly over time is common. Some researchers argue that expectancy and valence are also likely to change over time as one makes progress on a goal (e.g., Vancouver et al., 2010). Indeed, when integrating decision-making theories with goal theories, researchers argued that expectancy at any time is positively determined by the discrepancy that remains to be eliminated and the resources (e.g., time) remaining to do so, whereas valence should be a function of discrepancy weighted by goal importance. For example, a goal has total expectancy but no subjective value if it has been already achieved (i.e., discrepancy has been reduced to zero; Vancouver et al., 2010).

Therefore, in a multiple-goal pursuit situation an individual's behavior is likely influenced by several factors, where some factors (e.g., valence and expectancy) are a function of others (e.g., discrepancy). For such complex and dynamic phenomena, it is difficult to understand the process simply by "thinking about" them (Cronin, Gonzalez, & Sterman, 2009). To address this problem, Vancouver et al. (2010) developed a computational model of multiple-goal pursuit. In next section I review how these core concepts are represented in MGPM.

A Formal Model on Multiple-Goal Pursuit

Computational models are formal (e.g., mathematical) representations of theories that take the form of computer programs that can be simulated (Taber & Timpone, 1996). They are often used to translate the processes, interactions, or relationships depicted in traditional verbal theories into mathematical representations and computer programs (Busemeyer & Diederich, 2010). Formal models make transparent the logic and details involved in a theory (Farrell & Lewandowsky, 2010). Moreover, by solving the math or simulating a model, one can test whether a theory works as proposed and make specific predictions based on the theory (Adner, Polos, Ryall, & Sorenson, 2009).

There are different architectures for computational models. Some models are nonmathematical and logic-based algorithms, such as ACT (adaptive control of thought; Anderson, 1983). In contrast some models are mathematical models, such as connectionist models, agent-based models, and control theory models, to name a few (Weinhardt & Vancouver, 2012). There are some hybrid models which are combinations of logic-based and mathematical-based models, such as ACT-R (adaptive control of thought-rational; Anderson et al., 2004) and CLARION (connectionist learning with adaptive rule induction online; Sun, 2006). Different computational architectures are suitable for modeling different processes. For the current study, I adapt MGPM, which is a control theory model. The basic architecture of the MGPM is control theory's negative feedback loop (Vancouver, 2008), which is used to form many different self-regulatory agents (see Figure 1) that represents the dynamic process of multiple-goal pursuit. Self-regulatory agents refer to the elements of the negative feedback loop in the agent-environment border (i.e., the gray, round-cornered rectangle in Figure 1). In the following section, I first use a goal-striving process as an example to illustrate how this agent works. Then I describe how this agent is adapted to represent other components in multiple-goal striving (i.e., expectancy, valence, and choice).

Self-regulation agent: Goal-striving example. Goal striving refers to the process of goal pursuit (Kanfer, 1990) and is often referred to as self-regulation because one is regulating some perceptions of a variable to align with a self-held desired perception (i.e., goal) associated with that variable (Vancouver & Day, 2005). Among different approaches used to understand goal-striving, one prominent set of self-regulation theories are those derived from control theory (Powers, 1973). The version of control theory that Vancouver (2008) proposed included a comprehensive computational approach representing the dynamic goal-striving process. Figure 1 represents the central concept in this dynamic process theory: the discrepancy-reducing, negative feedback loop. Discrepancy refers to the difference between a desired perception of a variable state, often called the goal level, and one's perception of the current state of a variable, which comes from an input function that translates external stimuli into internal perceptions. Discrepancy drives individuals to act upon a variable in such a way as to reduce the discrepancy via the output function. It is called a negative feedback loop because the output of this agent reduces the discrepancy.

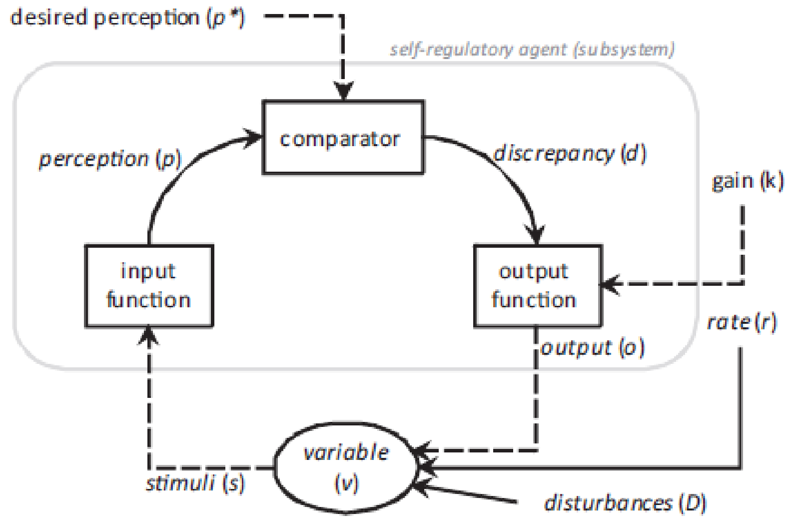

Figure 1. Self-regulatory agent as part of negative feedback loop.

In Figure 1, each box represents a function of the variables pointing to it. I start with the input function for the purpose of illustration. In particular, the input function represents, mathematically, how the variable state (v) is translated into a signal within the system. This signal is called a perception. For example, if the variable of interest is one's weight, then the reading of one's current weight from a scale would serve as the input that the function would presumably translate isomorphically. Thus, in this simple example, the following equation can represent the input function.

$$p = v \tag{1}$$

In the comparator function the perception is compared with a goal or desired perception (p*). The desired perception is also referred to as the reference signal (Powers, 1973) or goal level (Vancouver et al., 2005). For example, if one's current weight is 160 lbs., and the desired weight is 140 lbs., the discrepancy is 20 lbs. Researchers often call this difference error or discrepancy (d; Vancouver et al., 2014). The discrepancy value is key; it represents how much work needs to be done to achieve the goal (Vancouver, 2008). The output of the comparator function is typically assumed to be asymmetric, where negative discrepancies are truncated. For example, if one's current weight is 135 lbs, and the goal is to maintain weight at or below 140 lbs, then the discrepancy is -5 lbs, indicating no action is needed to lose any weight and thus a value of zero would be passed on to the output function. A simple version of the relationship can be represented through the equation below:

$$\text{If } (p^* - p) > 0\text{, then } d = (p^* - p)\text{; else, } d = 0 \qquad (2)$$

Specifically, this equation means that the discrepancy is forwarded only if the current state is short of the desired level ($d > 0$). All negative discrepancies ($d < 0$) are truncated at 0, indicating no action is needed (Vancouver et al., 2010). Positive discrepancy values drive people to take action to reduce the gap between current state and goal. However, the action that one may take not only depends on the magnitude of the discrepancy, but also the value or importance of the goal (Vancouver et al., 2010). This "weighing process" is realized in the output function, where the output (o) is a multiplicative function of the discrepancy and weighting term called goal importance (k). Goal importance magnifies or attenuates one's reaction to the discrepancy. For example, given two tasks with similar discrepancies, one is likely to respond more quickly or vigorously to the task with higher importance. This output determines the goal's valence in the MGPM. This valence is dynamic because the discrepancy changes due to one's action over time.

$$o = kd \quad (3)$$

In a simple system, the output (o) is translated to actions that change the state of the variable over time at some rate (r) of effect (Vancouver et al., 2010; 2014). Rate can be either influenced by individual differences (e.g., ability, strategy, etc.) or environmental factors (e.g., the effectiveness of the tools one uses to complete a task), depending on the nature of the task (Vancouver et al., 2010). Moreover, the influence of one's action and its effectiveness does not happen in a vacuum. The state variable (v) is dynamic and its value is determined by the individual's actions (o) and disturbances (D). The dynamics of the state can be represented by a standard linear system:

$$V_{(i+1)}\text{-}V_{(i)} = AV_{(i)} + ro_{(i)} + D_{(i)} \quad (4)$$

where A describes the impact of the current state on the state dynamics and the subscript i is the time index. In the current study, I assume that the change in the state does not depend on the current state, thus A is 0. This reduces equation (5) to:

$$V_{(i+1)}\text{-}V_{(i)} = ro_{(i)} + D_{(i)} \quad (5)$$

For example, the rate (r) might represent the speed at which an individual typically burns calories when doing ten push-ups. The negative feedback loop is completed through the effect of output (o) on the state of the variable.

The self-regulatory agent can be used as a basic building block to explain various processes involved in multiple-goal pursuit process (Vancouver et al., 2010). For example, one agent, called the expectancy agent, represents how one considers the possibility of achieving a goal. Another agent, called the choice agent, represents how one chooses one goal over the other. A third type of agent, called the learning agent, represents the process by which one learns from experience. In the following section, I describe how the self-regulatory agent is applied to the goal-choice processes.

Dynamic goal-choice processes. As mentioned earlier, most theory on goal choice uses some form of expectancy-value (E-V) models, where people make decisions based on the expected utility of each option. More specifically, the expected utility is often conceptualized as a multiplicative function of expectancy and valence. Although almost every theory of goal choice adopts an E-V perspective (Klein et al., 2008), some empirical studies have failed to confirm that people's choice behavior matches the theory's predictions (Van Eerde & Thierry, 1996). Some researchers argue that it might be due to the fact that E-V theories fail to capture the dynamic nature of expectancy and value (e.g., Steel & Konig, 2006).

For example, Vancouver et al. (2010) argued that expectancy should be conceived in a dynamic way because the actions people take as well as changes occurring in the environment, including the mere passage of time, are likely to affect the factors that determine expectancies. Therefore, presenting expectancy as a static concept may limit one's understanding of individuals' behavior over time. To address this limitation, Vancouver et al.'s MGPM formally models the dynamics of expectancy (see Figure 2). In particular, they introduced the concept of *expected lag*, which is one's belief in the time it takes to change a variable by a unit of discrepancy given a unit of action. For example, expected lag might correspond to the speed at which one believes he or she can write a page of a manuscript, where the goal is a completed manuscript. They suggested this expected lag is a critical factor used to determine expectancy for a goal. Specifically, they argued that an expectancy agent multiplies a goal agent's discrepancy by expected lag to create a perception representing the time one needs to reduce the discrepancy. This time needed is compared to time available (e.g., time to deadline) to form an expectancy. Note that changes with discrepancy, the passage of time, and possible changes to expected lag as one becomes more familiar with the task will all result in changes to expectancy over time.

For example, if one believes it takes 10 minutes to write a page and one needs to write 10 pages to achieve a goal, then the person would perceive needing 100 minutes (i.e., 10 * 10). This perception reflects three sources of dynamics for the expectancy belief. First, the discrepancy may change over time due to action (e.g., writing pages), disturbances (e.g., an editor rejects a page) or expected lag beliefs changing as one becomes a more efficient writer or just a better sense of his or her rate of writing. Meanwhile, in cases where time is limited (i.e., the task has a deadline), the perception of time needed is compared against the time available. Note that the time available is most certainly changing over time when a deadline exists. Finally, the difference between time needed and time left provides an estimated possibility of reducing the discrepancy before the deadline. In particular, larger positive values of expectancy indicate a higher possibility of reaching a desired state given the available resource (e.g., time). A negative value of expectancy indicates one believes one cannot reach the desired state given the resources left.

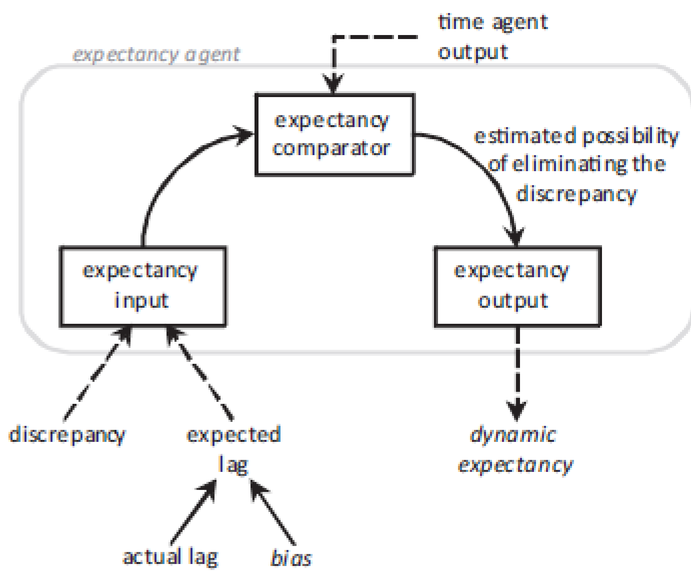

Figure 2. The expectancy agent.

In a similar vein, Vancouver et al. (2010) argued that the valence of a particular task is not fixed across time. They proposed that this valence is a multiplicative function of both (a) the goal importance parameter, which is a function of the traditional notion of value (e.g., the consequences associated with an outcome) and (b) the discrepancy for the goal. Specifically, they argued that the progress that remains to be made on a goal reflects the need to work on that goal. Considering a highly valued goal, if there is no discrepancy, one is unlikely to work on that goal since it is not needed unless there is a disturbance that moves the variable from its desired state. Note that this multiplicative function is the output function of the self-regulatory agent. However, when used for goal choice, as opposed to goal striving, they labeled that output *dynamic valence*. The dynamic valence of a goal increases as one moves further from a goal and decreases as one moves closer to the goal, even though the importance of achieving the goal might remain constant over time (Vancouver et al., 2010; Ballard et al., in press).

In line with classic decision-making theories (e.g., Vroom, 1964), though with the addition of dynamics, the MGPM conceptualized the input function of the choice agent as the product of expectancy and valence of a task. As mentioned earlier, they called this product subjective expected utility (SEU). When one needs to work on two tasks, the comparator function of a choice agent represents how an individual chooses one task over the other. Specifically, the SEU of one task is subtracted from the SEU of the other task, and the sign of the difference indicates which goal will be selected (see Figure 3). If the SEU for both tasks are the same, then the model will randomly select between the two.

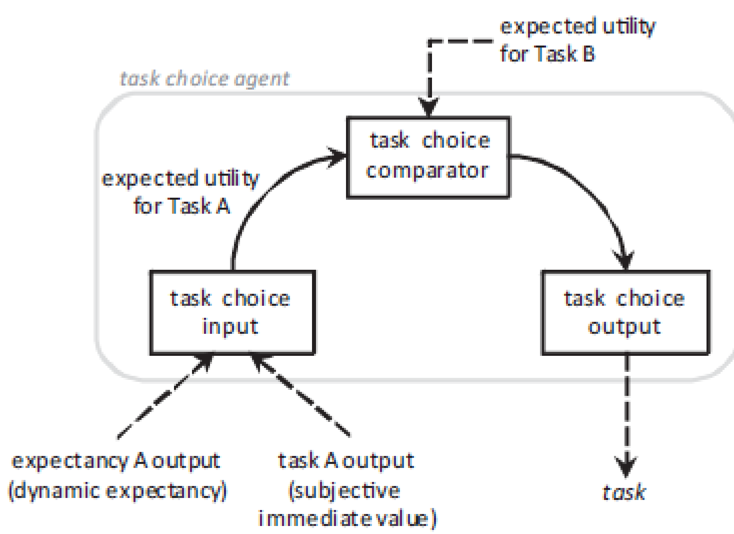

Figure 3. The choice agent.

Vancouver et al. (2010) showed that the MGPM (the complete model is shown in Figure 4) can account for the mixed empirical findings mentioned earlier. In particular, researchers often find that individuals tended to spend more resources on the task with the larger discrepancy, which is consistent with self-regulation theory (e.g., Carver & Scheier, 1998; Klein, 1989; Powers, 1973). However, when considering the role of time in predicting goal prioritization, Schmidt and DeShon (2007) found that individuals tended to spend more time working on whichever goal had the larger discrepancy only when the deadline was not too close. Yet, some of these individuals would switch their effort to the task with smaller discrepancy as the deadline approached. The MGPM not only reproduced this reversal effect, but also explains why the reversal effect might occur. In particular, they examined the relative expectancy differences and valence differences of the two tasks over time. Their simulation results demonstrate that the relative differences in the valences of two tasks were greater than the relative differences in the expectancies early on. However, as the deadline approached, the differences between expectancies of the two tasks become more salient and eventually outweighed the effect of valence.

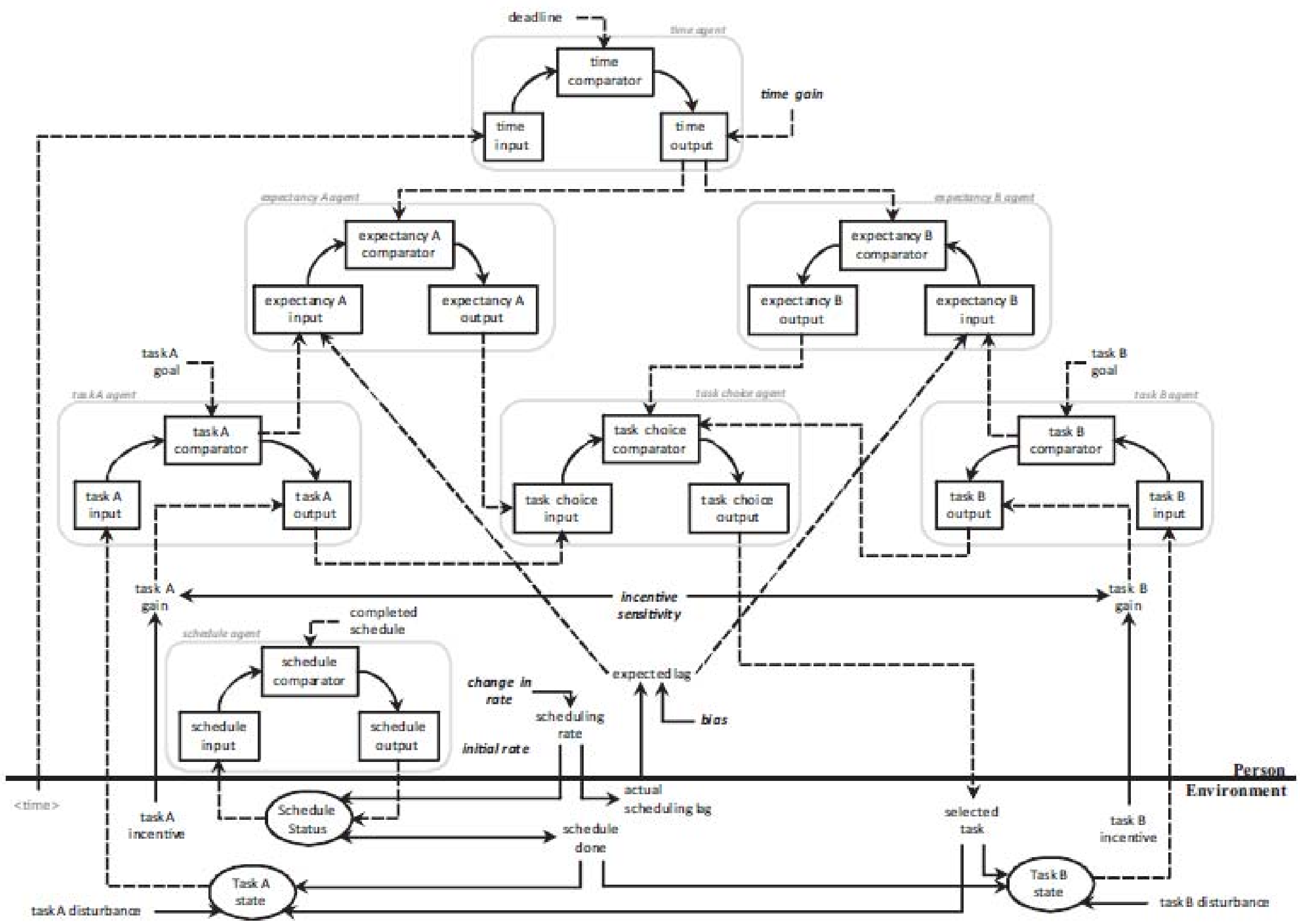

Figure 4. The MGPM from Vancouver et al. (2010).

Vancouver et al. (2010) was the first attempt to formally model the dynamic process of multiple-goal pursuit by integrating goal theories and decision theories. As the authors pointed out, there are many modifications to the model that are needed if it is to account for more phenomena related to multiple goal pursuit. For example, they suggested the inclusion of learning elements to account for how individuals learn expected lags and the effects of an uncertain environment, as well as how these learned elements can affect goal decisions.

For example, the MGPM originally assumed that individuals had a perfect knowledge of their rate and a perfect estimation of the time they need to complete the task (Vancouver et al., 2014). However, individuals must learn this knowledge and it often takes time for individual to develop it. Toward that end, scholars suggest that individuals often update such beliefs based on past performance (Bandura, 1997; Porter & Lawler 1968). Moreover, some researchers (e.g., DeShon & Rench, 2009; Louro, Pieters, & Zeelenberg, 2007; Schmidt & DeShon, 2007) found that individuals would work on tasks where the goal is already met. Although the MGPM did not capture this pattern of behavior, Vancouver et al. (2010) suggested that individuals might learn over time to predict that disturbances might occur to the variable for which one has a goal and use this information to offset their perception of the current state of the task.

To understand the processes individuals use to estimate expectancy based on the learned expected lag and to predict the effect of uncertain disturbances, Vancouver et al. (2014) extended the MGPM with the addition of learning agents. In particular, they adopted a connectionist version (Thomas & McClelland, 2008) of the delta-learning rule

(Widrow & Hoff, 1960). The delta-learning rule assumes that individuals learn from the differences between a predicted and observed state of a variable and corrects a weight used in the prediction based on a fraction of this difference. The delta-learning rule is a specific variation of the negative feedback loop of goal theories used in the MGPM, which Vancouver et al. (2014) called a learning agent. Moreover, they used two of these learning agents in the MGPM. One represented how the rate of one's action (i.e., expected lag) might be learned, and the other represented how unpredictable environmental disturbances might be learned.

Specifically, for the agent used to learn expected lag, individuals compare the differences between the time they believe they needed using expected lag and discrepancy, and the time actually needed to reduce a discrepancy. The agent updated the expected lag belief by incorporating the miscalibration weighted by learning rate, which reflects how fast individual learn from the miscalibration. For the learning agent to learn disturbances, individuals compare the differences between the predicted state of a variable and the actual state, taking into consideration whether they acted on the variable in that round. The learned value thus represented an expected change to the variable from outside forces per time step and it was used to offset the perception of the current state of the variable.

To assess the MGPM with learning agents, Vancouver et al. (2014) simulated the model. The simulation results were consistent with previous empirical findings that the original model could not explain (Vancouver et al., 2010). For example, the simulation results were consistent with the observation that individuals in the Schmidt and DeShon

(2007) study continued working on goals that are already achieved. The simulation results also demonstrate that the model is capable of representing how people learn about the time needed to complete a task as well as the sporadic disturbances (Vancouver et al., 2014). More generally, this extended MGPM represents how “mental models” of the environment and the individual are developed and how it is linked to goal-striving processes. Below, I describe how I adapt this extended MGPM to account for a more complex goal-pursuit condition with more than two goals.

Expanding the Multiple-Goal Pursuit Model

In this section, I first described how I adapted the learning agent in the MGPM to the current study. Then I expanded the MGPM to account for multiple goal pursuit with more than two goals. In particular, I proposed three input functions for the choice agent that represent levels of analytic processing when making decisions. Finally, I described a protocol to examine when and if the different functions are used when one is pursuing three goals in an onerous context (i.e., one where not all the goals can be met or maintained over time).

Adaptation of the Learning Agent

In many situations people may learn the rate with which their actions affect the state of the variable of interest. In the MGPM, this was represented in a process that compared the change in the state of a variable that occurred as the result of an action to the expected change and adjusted expected change to align with observed change. In this way, one was learning the effect of one's action. However, if disturbances are also constantly affecting a variable, then the change in the state of a variable after an action includes not only the effect brought on by the action, but also the effect of the disturbance. Thus, one's belief about his or her rate of effect likely includes the effectiveness of one's action and decay. Note the rate belief resembles the inverse of expected lag in the MGPM, and I assumed that individuals use change in task state after one acts to learn the effectiveness of their actions on each goal. If true, individuals are actually learning a rate of change that combines two forces (e.g., effect of actions minus decay).

The process by which individuals learn this rate in the models is the same described by Vancouver et al. (2014). In particular, individuals predict the level of goal progress after their action and compare this value with their actual level of goal progress after the action. The discrepancy between actual state and estimated state of the variables represents prediction error. If this discrepancy is greater than zero, it means the person underestimates his or her rate; if the discrepancy is less than zero, it means the person overestimates his or her rate. Individuals adjust (i.e., learn) their estimates of rate based on this discrepancy (i.e., prediction error) weighted by learning rate, which ranges from zero to one. In particular, a learning rate equal to zero indicates that the individual will not learn from the experience, whereas learning rate equals to one means that the individual will totally trust and learn from one's experience. For example, if someone predicts that he or she would finish writing ten pages a day (i.e., estimated rate), but writes six pages (i.e., actual rate), then the discrepancy, four pages, would be the prediction error. If the learning rate for this person is 0.5, he or she would update the estimated rate for next day to eight (e.g., 10 + (6-10) * 0.5 = 8).

Extension of Choice Agent: Cascading Choice Agent

For the extended model, I maintain the basic structure and logic of the MGPM, and extend it to handle choosing among more than two goals by cascading multiple choice agents. Recall, the choice agent in the MGPM compares the SEU of two goals to determine which goal to pursue. I choose to represent two choice agents, though it is more likely information is cycled through a single agent. I represent two agents to more clearly illustrate the flow of information. That is, the first choice agent determines which of two goals to continue to consider. The next compares the winner of the previous comparison with another. The last choice agent in the cascade thus determines the goal to be acted upon. Following the decision-rule in the MGPM, the two choice agents form a cascading choice agent where the SEU of Task A is compared with that of Task B, the winner of the two is passed on to the second choice agent and compared with the SEU of Task C (Figure 5). If the SEU of all three tasks are the same, the model will randomly select one of the three tasks.

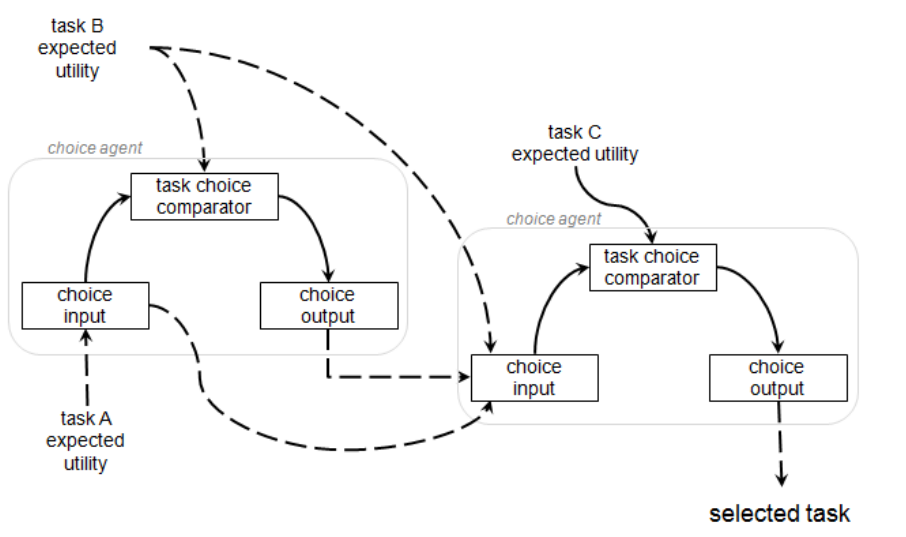

Figure 5. Cascading choice agent.

As presently configured (Vancouver et al., 2014), the choice agent in MGPM considers a relatively sophisticated amount of information. That is, knowing expected utilities requires people to search for information and do computations, both of which cost time and effort (Gigerenzer & Gaissmaier, 2011). Yet, individuals' cognitive resources are limited and may not be available for making thorough decisions among multiple goals, especially when pursing several goals at once. Moreover, the notion that resources might be taxed may play an important role in understanding multiple-goal pursuit (Kanfer & Ackerman, 1989; Vancouver & Tischner, 2004). For example, when scaling up beyond two goals, more goal-related information and possible comparisons come along. This raises the question of whether people consider all the information (e.g., discrepancy, valence, expectancy) when making a goal pursuit decision. In next section, I propose decision rules that might be more adaptive in a resource limited condition other than the SEU-based decision rule used in MGPM.

The Two-Stage Decision Mechanism: Integrating Heuristic and Analytic Strategies

The decision-making strategy represented in the MGPM is an integration of classic decision-making theories and goal theories. In that strategy, a decision is made to pursue the winner of a comparison of SEUs of available options (Beach & Connelly, 2005), where its components, expectancy and valence, are both influenced by how far one is from the goal (i.e., discrepancy) over time. Of some import, it is useful to note that the SEU is a variant of the expected utility (EU) model, which is often seen as a normative strategy (Payne et al., 1988). The EU model assumes that individuals make decisions without constraints of time, knowledge, and computational capacity (Martignon, 2001). The EU and SEU are also compensatory strategies in that low values on one dimension (e.g., expectancy) can be compensated for by high values on another dimension (e.g., value).

However, there is a large literature in psychology that invalidates the normative model as descriptive of human behavior and suggests that people do not always act in a normative way (Beach & Mitchell, 1978; Diefendorff & Lord, 2008; Einhorn & Hogarth, 1981; Hastie, 2001; Klein et al., 2008; Thaler, 1994). Indeed, according to dual-processing theories, there are two different systems of information processing. System 1 is associated with automatic, low effort, and rapid processing, whereas System 2 is labeled with controlled, high effort, and slow processing (Evans, 2008). Different researchers have proposed various names for the two modes of thinking, such as heuristic vs. systematic (Chaiken, 1980), heuristic vs. analytic (Evans, 2006), intuitive vs. analytic (Hammond, 1996), just to name a few. In this dissertation, I use *heuristic* and *analytic* to refer to these two types of strategies. That is, similar to System 1 heuristics refer to computationally simple models that allow one to quickly find good, feasible solutions and "…when compared to standard benchmark strategies… can be faster, more frugal, and more accurate at the same time" (Gigerenzer & Todd, 1999, p.22). Heuristic strategies are often seen as non-compensatory because they do not require tradeoffs between values on different dimension. In other words, heuristic strategies do not consider all available information to make a decision (Chu & Spires, 2003).

Although only considering a subset of the information, heuristic strategies do not necessarily lead to less accurate results (Payne et al., 1993). Indeed, researchers have examined the accuracy of different heuristics such as hiatus heuristic (Wübben & Wangenheim, 2008), lexicographic rules (Luce, 1956), elimination-by-aspect (Tversky, 1972), adaptive toolbox (Gigerenzer & Todd, 1999), and so on. Evidence from different domains, such as bail decisions (Hastie & Wittenbrink, 2006), consumer choice (Hauser, Ding, Gaskin, 2009), emergency medicine (Cook, 2001), and others support the notion that heuristics may outperform analytical methods in certain situations (Gigerenzer & Gaissmaier, 2011). Moreover, according to Gigerenzer and Gaissmaier (201), heuristic strategies are often used for decision making, whereas analytic strategies are only used as the exception.

Whereas individuals have a strategy repertoire with both analytic and heuristic strategies, the pressing question is which strategy individuals would choose to use and when. Cost-benefit theories of decision strategy have emerged to describe how individuals adaptively make choices in various situations (e.g., Beach & Mitchell, 1978; Payne et al., 1993). According to these cost-benefit theories, individuals trade a strategy's accuracy (i.e., benefits) against its demand for mental effort (i.e., cost), and choose the strategy that yields the optimal result. Decision-making researchers have argued that the selection of strategies depends on the characteristics of the task and decision maker, where task characteristics can be further divided into characteristics that are inherent in the decision problem and those in the decision environment (Beach & Mitchell, 1978). Indeed, previous research has shown that when making a decision, individuals would choose different strategies depending on various factors such as task demands (Payne, 1982), time pressure (Payne et al., 1988), and learning (Rieskamp & Otto, 2006).

The research on decision making strategy switching is mixed. Most studies show that individuals move from more analytic strategies to more heuristic strategies over time. However, similar to the limitation of most E-V theories (i.e., focusing on one-time choice), most of the studies examining how individuals select from a repertoire of strategies are also static in nature. That is, even though individuals are asked to make choices repeatedly under different conditions, each choice is independent from the other. Little is known about whether individuals would change the strategies they use during goal-striving process, and if so, when they would make such change. Therefore, in this dissertation, I consider the possibility that the strategy one uses might change over time. In particular, I consider moving from a more analytic to a more heuristic strategy and vice versa.

The adaptive decision strategy: From analytic to heuristic. The idea that one might move from an analytic to heuristic strategy is based on the research on self-regulatory resource depletion (Baumeister, Bratslavsky, & Muraven, 1998). In particular, researchers argue that decision-making requires effort that consumes individuals' limited resources and thus reduces the resources available for subsequent self-control, which in turn impairs rational reasoning and decision making (Vohs, 2006). Several empirical studies have demonstrated this pattern (e.g., Muraven, Tice, &Baumeister, 1998; Schmeichel, Baumeister, & Vohs, 2003; Vohs et al., 2008). In most of the studies, researchers found that individuals performed worse on a second task that required willful self-regulation if the first task they performed required willful self-regulation.

For example, Vohs et al. (2008) found that participants who were asked to make repeated choices regarding the courses they would take spent less time studying for an upcoming test than those who did not make those decisions. In another lab study, they found that participants who were instructed to make choices about a psychology course persisted shorter on a subsequent spatial design task than did participants who were not asked to make many choices. Similar findings were also found in a field study where researchers found that shoppers who reported having made more choices early that day performed worse on arithmetic problems than those who reported having made fewer prior decisions. Therefore, in a dynamic goal-pursuit situation, it is likely that making many decisions in an early stage would deplete one's limited resources, which in turn would trigger one to switch to a heuristic strategy that requires less cognitive resources.

Further evidence for this shift in strategy can be drawn from research on the cost-benefit framework (Payne et al., 1988). In particular, extant research suggests that individuals may change the decision strategy from analytic to heuristic when under constraints. One constraint that attracts interests of many researchers is time. Research has shown that under time pressure, individuals tend to rely on the information they felt to be most important (Zakay, 1985). For example, Einhorn (1970) suggested that non-compensatory strategies may be cognitively simpler and require the use of less information. Zakay (1985) investigated the relationships between time pressure and the type of decision process and found that the influence of time pressure decreased the use of analytic strategies. Payne et al. (1988) examined the effect of several contextual factors (e.g., time pressure, alternative options, etc.) on the use of decision strategies. They also found that people only considered a subset of information and changed their information processing strategies under time pressure.

Although most aforementioned studies manipulate this time pressure in terms of the amount of time one has to make a decision, it is possible that one may feel time pressure as one approaches the deadline as well. Therefore, I propose to add a time threshold into the MGPM that could determine the shift from an analytic strategy to a heuristic strategy. In particular, this time threshold is a free parameter in the model, which reflects an individual difference in the extent to which one would tend to switch the decision strategy. The value of this time threshold parameter ranges from zero to one, where zero indicates that the individual would switch to a heuristic strategy on the first day, and one indicates that the individual would use an analytic strategy until the last day (i.e., Day 100). The value of this time threshold parameter can be influenced by numerous factors, including mental fatigue and time pressure mentioned above. However, this dissertation focuses on whether and when this switch of strategies occurs. Examining the source of this variation in time threshold is beyond the scope of this dissertation.

The adaptive decision strategy: From heuristic to analytic. Although the studies mentioned above seem to imply that the default strategy people use is analytic, and people switch to heuristic when they get tired, it is also possible that people would normally use heuristic strategies and switch to analytic strategies only when being triggered by some stimulus. In his book on "Thinking, Fast and Slow," Kahneman (2011) argues that because of the limited capacity of humans, people tend to avoid deliberative thinking because it is very costly and would leave less cognitive resources available for other activities. People only invoke the deliberative and logical thinking when it is necessary. For example, it might be easy for a driver to talk to the passengers when he or she drives on an empty road. However, both the driver and the passengers would tend to stop talking when the driver is trying to find the way or passing a truck on a narrow and busy road. Indeed, numerous studies have found that individuals are motivated to minimize effort in decision-making (Todd & Benbasat, 1994). Therefore, it seems possible that people might start with heuristic strategies and shift to a more analytic thinking only when needed when pursuing multiple goals.

Moreover, because characteristics of task environments become noticeable only after some information has been processed (Payne, Bettman, & Luce, 1996), it is less likely that individuals would adopt an analytical strategy in the beginning of the goal pursuit. In other words, individuals need time to learn about the task and environment to gather all the information to make decisions analytically.

Therefore, I propose a different order of strategy use. That is, individuals may start from heuristic strategies and switch to more analytic strategies as needed. For the purposes of this dissertation, the function of this switching variable is the same as the one in the first decision-rule. That is, it is based on the amount of time a person has spent on the task. However, in these models a zero time threshold indicates that one would adopt an analytic strategy in the beginning, and time threshold of one indicates that one would not adopt analytic strategies until the deadline. As mentioned above, many factors may affect the value of this parameter. However, in the current model I only represent where one would switch from heuristic strategies to analytic strategies, instead of modeling what factors trigger this process.

Different degrees of heuristics to analytic strategy. In the original MGPM, individuals were represented as making decision based on SEU, which was a multiplicative function of valence and expectancy, and where valence was a multiplicative function of discrepancy and goal importance. In other words, there are three pieces of information one could possibly consider when pursuing a goal. Of these, the discrepancy from the goal was involved in all of them. Thus, the simplest decision rule would be discrepancy only, followed by discrepancy weighted by goal importance (i.e., valence), followed by discrepancy weighted by goal importance and expectancy (i.e., SEU). Rather than assuming that heuristic and analytic are the only two choices, I assume that the degree of analytic processing can vary. In particular, in this relatively simple context it can take on three values (i.e., discrepancy, valence, & SEU). Therefore, systematic combination yields six variants of the MGPM (see Table 1). For example, the decision rule represented in Model 1 indicates that individuals first consider the discrepancy, goal importance, and expectancy of each goal to make a choice, and at some point they switch to only compare the discrepancy of each goal to make a choice. In addition, there are three nested models with single decision rules when the time threshold parameter takes on certain value. For example, Model 7 is a special case of Model 1 and 3 where time threshold is zero, and a special case of Model 4 and 6 where time threshold is one.

Table 1

Nine Variants of the MGPM

Model	Decision rule
From analytic to heuristic	
Model 1	SEU – d
Model 2	SEU – valence
Model 3	Valence – d
From heuristic to analytic	
Model 4	d – SEU
Model 5	Valence – SEU
Model 6	d – valence
3 nested models	
Model 7	d only
Model 8	Valence only
Model 9	SEU only

Note. SEU = subjective expected utility; d = discrepancy.

Simulations of Nine Proposed Models

To compare the nine variants of the MPGM, the models were implemented in simulations set up based on the protocol used by Harman et al. (2011). Below, I describe the protocol, the parameters used in the simulation, followed by the simulation results.

The Context Represented in the Simulation

Computational models of dynamic processes of human decision making often need to include a representation of the context if the decisions affect the context within the time frame represented by the model. For example, if task progress, which is a contextual variable, both affects and is affected by decisions, then the effect of the decisions on task progress needs to be included in the model. This is the case here. That is, the MGPM assumes that decisions made at one time affect the context used to make subsequent decisions. Fortunately, this context can be relatively easy to represent if the protocol used to test the model is relatively simple. The Harman et al. (2011) protocol is relatively simple and, with a few modifications, could be used to assess the relative quality of the nine proposed models.

The Harman et al. (2011) protocol involved asking participants to assume the role of a student taking three courses and having the time to allocate study time to only one of those courses in each simulated day. As a global goal, participants are told to try to achieve the final averaged GPA as high as possible for the semester represented. More specifically, participants are asked to obtain a good standing for each of three classes (i.e., Psychology, Modern Fiction, and Applied Math), which are assumed to translate into three goals (i.e., one grade goal for each class). Class standing represents the grade they would have in the class at any one time based on their knowledge acquisition. Within this context is some inherent dynamics. That is, over the semester the knowledge needed to maintain standing increases such that not studying for the class will lower one's acquired knowledge (i.e., one will get further and further behind on the material). This drop in acquired knowledge is a type of disturbance to the acquired knowledge construct and is referred to as the rate of decay. The rate is constant across time and occurs each day for all classes regardless of the choice, but it is a function of the class. In particular, one class has a high decay (-6), which represents the idea that a lot of new material is presented such that one can get further behind on acquired knowledge relatively quickly compared to the two class that have low decay (-3).

Meanwhile, the effect of decay can be countered by an individual choosing to study for a class. In particular, for each of 100 "days" represented in the paradigm the participant can pick one of the classes to "spend time studying the material." Spending time studying will raise one's acquired knowledge by nine points, regardless of the class; however, since the decay still applies, this means an improvement of only three or six points for the high and low decay classes, respectively. To achieve a high average GPA they need to obtain a high grade in each class by the last day. That is, in the current paradigm participants are told 100 days represents an academic semester (i.e., a deadline).

To provide information on where they stand in each goal (i.e., class standing) a 100-point scale anchored by "A" at the top and "F" at the bottom and with an indicator of current standing is presented to the participants (see Figure 6). The initial statuses of all three goals are the same (i.e., 83, which represents a grade of A). Change to each standing depends on choice and external disturbances (i.e., decay). In particular, the status on each goal (i.e., the cumulative increase or decrease of the state) is displayed throughout the task.

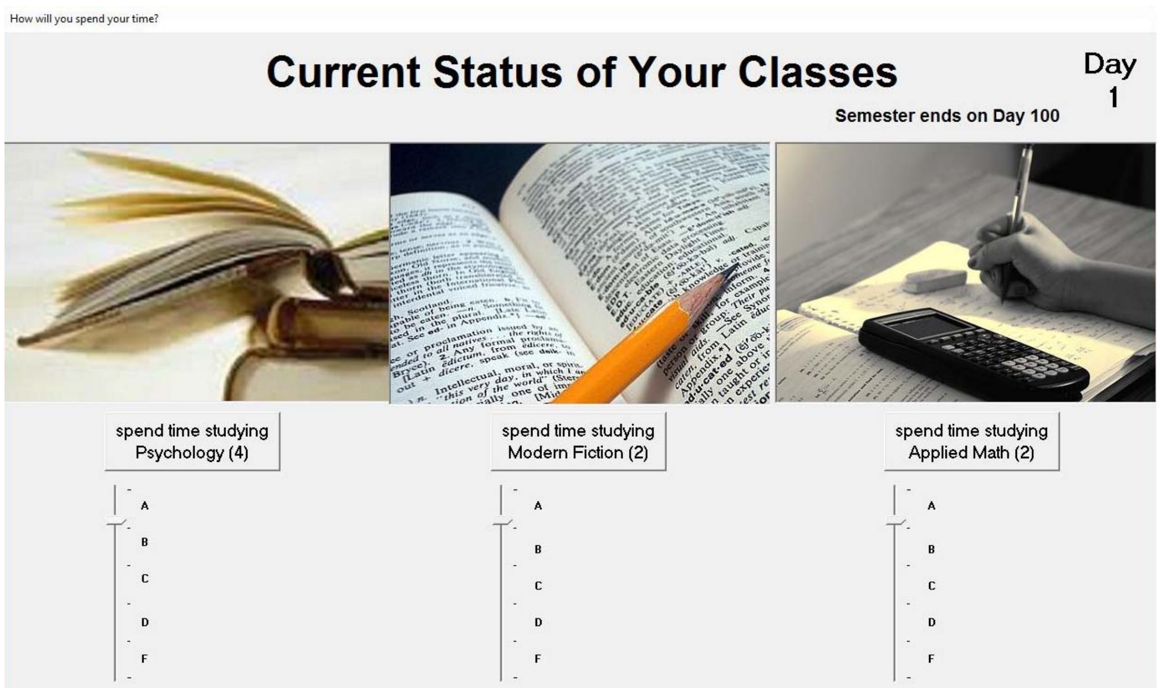

Figure *6*. A screenshot used in the paradigm.

Moreover, one class (i.e., Psychology) is presented as more important (i.e., four credits) than the other two classes (i.e., two credits). This operationalizes an importance difference among the courses that should be reflected in the goal importance parameters necessary for examining the valence part of the models. In addition, as noted one of the courses, randomly determined for each participant, has a higher decay rate (i.e., decrease by six if not chosen). In the models tested, this difference in decay would be reflected in the belief in rate and thus relative expectancies if discrepancies were the same. This manipulation, therefore, allows me to assess that element of the models.

Simulation Set Up

To illustrate the differences in predictions that each model makes, I simulated each model based on the protocol. Specifically, some parameter values come directly from the protocol. For example, the goals were each set to 100 to reflect the assigned goals for the participants (e.g., the grade for a class). The initial states were set as 83 for all three goals. For one class standing, a disturbance of nine was used (i.e., the class with high decay), whereas for the others the disturbance was set to six (i.e., the classes with low decay). The effectiveness of action (i.e., choice to spend time studying) on a class standing was set to nine for all the standings.

In the MGPM, goal importance is a function of task incentive and incentive sensitivity (Vancouver et al., 2010). In the current study, task incentive is represented by the credit hours of each class. Specifically, to manipulate goal importance, Psychology should be the most important goal for all participants because they are told that "the credit hours for each course are four credits (Psychology), two credits (Modern Fiction), and two credits (Applied Math)." These were also the parameter values used for the gain parameters for the different classes/goals in the models.

A few other parameters were time-invariant constants that might be different among individuals (Vancouver, 2008; Vancouver et al., 2010), where all but one were assumed to be the same for this study. These parameters include learning rate, initial estimated rate, incentive sensitivity, and time threshold. All these parameters are listed in

Table 2. In particular, learning rate was set to 0.04, which is consistent with the findings from Vancouver et al. (2014). Initial estimated rate was set to five, representing one's belief that after choosing to spend time on a course, the standing on that course will increase five units on a 100-point scale. Incentive sensitivity reflects how individual weights the differences in credits. It is set to one in the current simulations. Time threshold reflects the time when individual would switch to a different decision rule. This was the one free parameter in the model. For the simulations, the range of this time threshold parameter was varied from zero to one, where zero indicates the individual would switch to a different strategy from the beginning, and one indicates the individual would not adopt a new strategy until the deadline. The analysis of variations of this parameter, called sensitivity analysis, is presented in a later section. For illustrative purposes, the time threshold was set to 0.5 in the current simulations, indicating the individual adopts one strategy during the first 50 days and switch to another strategy during the last 50 days. The MATLAB codes used to program the model are reported in Appendix A.

Table 2

Parameter Values Specified for the Model Simulation

Parameter	**Default value**	**Values tested**	**Meaning**
Learning rate	0.04	0, 1	Degree of change in belief given difference between a prediction and an observation
Initial estimated rate	5	1, 10	Initial belief regarding the effect of one's action
Incentive sensitivity	1	0.5, 1.5	The extent to which one scales goal importance in the mind
Time threshold	0.5	0, 1	The extent to which one switches to a different strategy

Simulation Results

To demonstrate that the protocol can distinguish the models, I presented individuals' status on all three goals over time. I chose to analyze individual's status on the goals as opposed to choice behavior because modeling choice behavior results in 100 points with value of either zero (i.e., not being chosen) or one (i.e., being chosen) for each goal. It is difficult to observe the pattern for 300 points fluctuating between zero and one for three goals. On the other hand, simulating individual's status over time demonstrated a clear pattern of the status change of each goal, which is easy to compare with experimental data. More importantly, control theory based views of self-regulation assume that it is the states of the variables that drive behavior, not actions (Powers, 1973).

Because the two less important classes (i.e., Modern Fiction and Applied Math) both have two credits, the simulation results are the same when they have the same decay. Therefore I only present the simulation results of one case where the less important variable with high/low decay. Figure 7 shows the simulation results of all nine models when a variable with high decay is less important, and Figure 8 shows the simulation results of all nine models when a variable with high decay is the most important goal. In both figures, I use $G_{a,b}$ to represent each goal in different conditions. In particular, "a" represents goal importance whereas "b" represents the decay associated with that variable. For example, $G_{2,3}$ represents the less important variable (i.e., two credits) with a decay of three. In Figure 7, all models demonstrate different patterns of data that allow them to be distinguished from each other. In Figure 8, all models demonstrate distinguishable features except Model 5 (i.e., valence - SEU) and Model 9 (i.e., SEU only). This is because during the first 50 "days", the quantities of valence and SEU are nearly proportional to each other. Therefore making decisions based on valence or SEU yields the same results. However these two models can be distinguished in Figure 7 where a variable with high decay is less important.

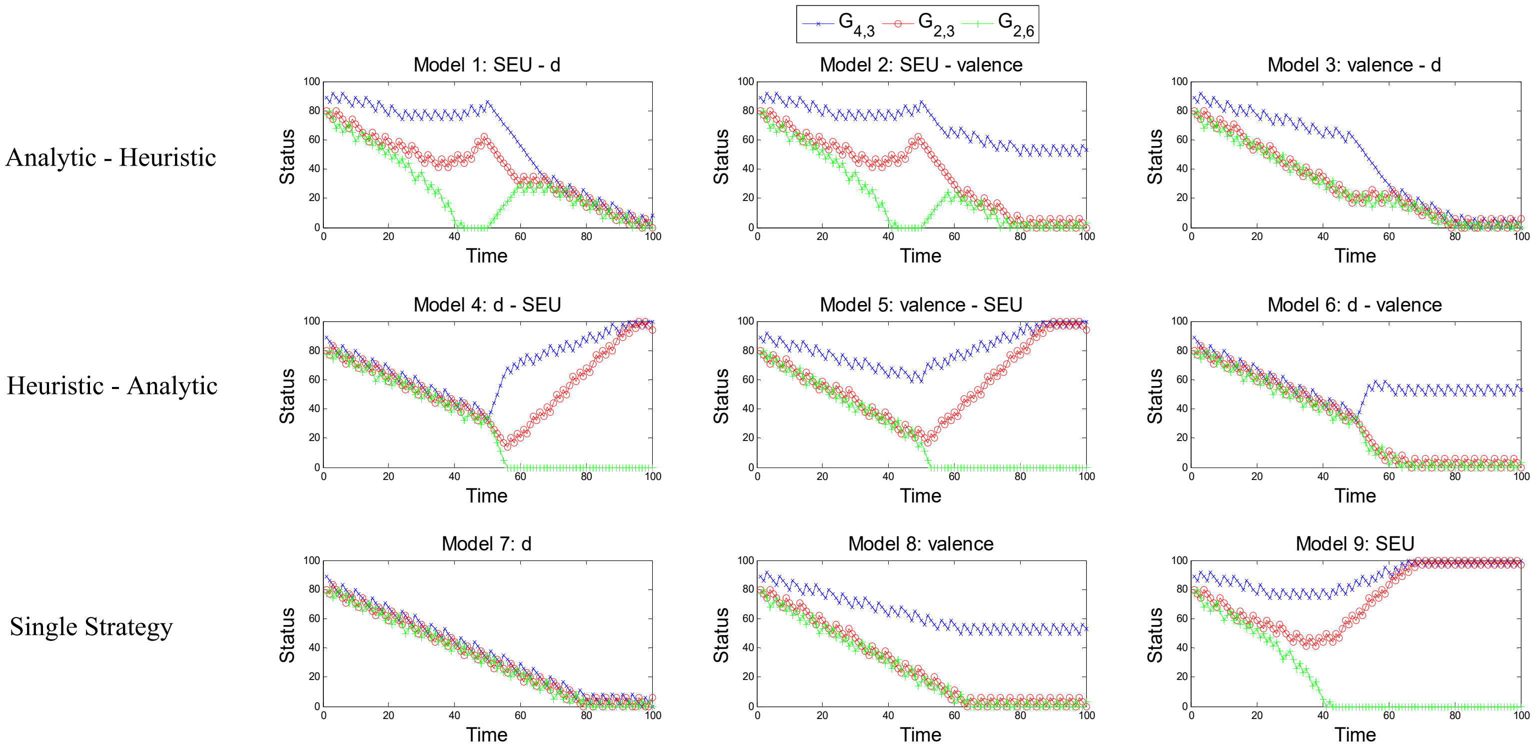

Figure 7. Simulation results when the variable with high decay is less important.
Note. SEU = subjective expected utility; d = discrepancy.
$G_{2,3}$: the less important variable with low decay.
$G_{2,6}$: the less important variable with high decay.
$G_{4,3}$: the most important variable with low decay.

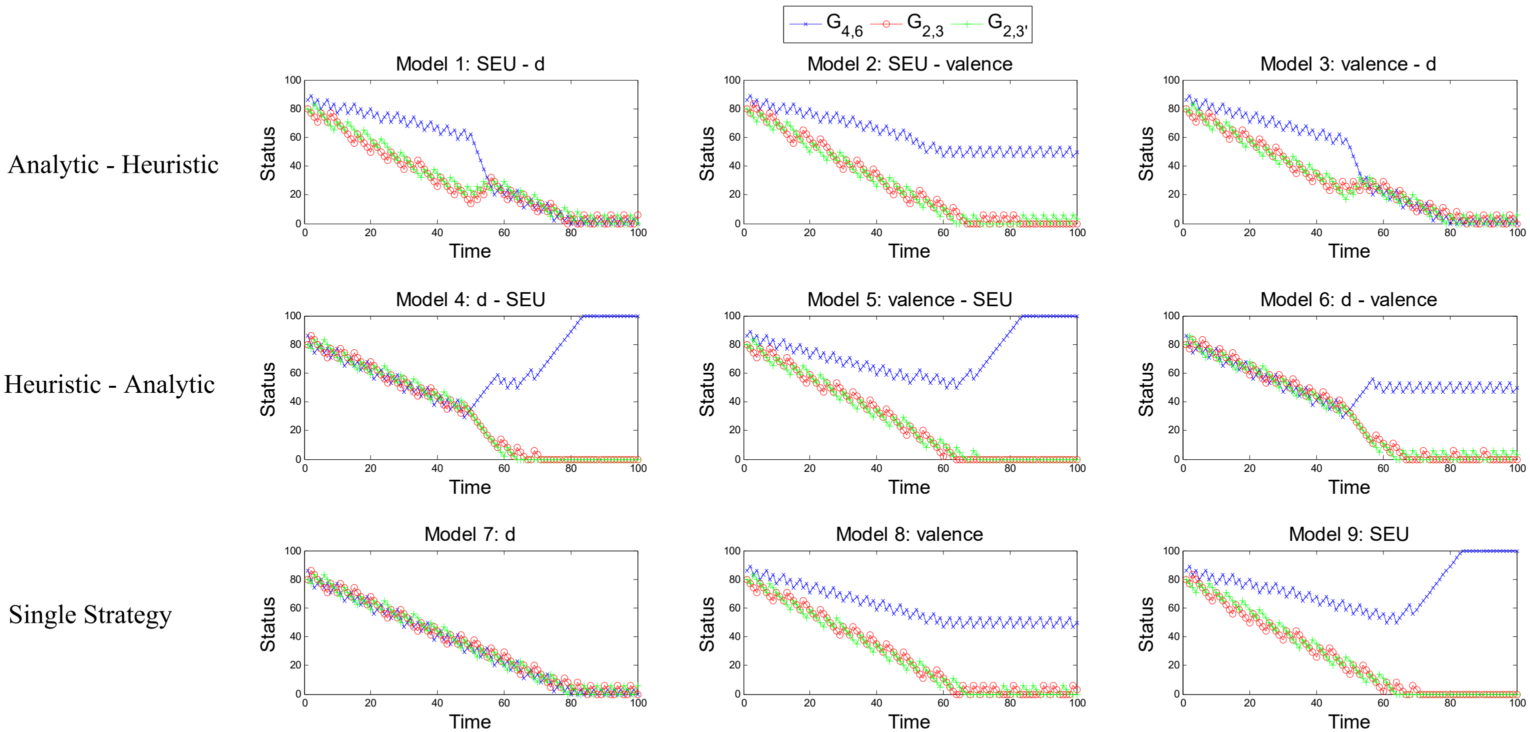

Figure 8. Simulation results when the variable with high decay is the most important.
Note. SEU = subjective expected utility; d = discrepancy.
$G_{2,\,3}$: one of the less important variables with low decay.
$G_{2,\,3'}$: the other less important variable with low decay.
$G_{4,\,6}$: the most important variable with high decay.

Sensitivity Analysis

In the sensitivity analysis, the purpose was to evaluate the effect of each parameter when they take on different values within the context of the protocol represented in the models. I list all the parameters examined and the specific values assessed in Table 2, including learning rate, initial estimated rate, incentive sensitivity, and time threshold. Except for time threshold, the patterns of the simulation results reported above were robust within the range of values tested. That is, different values on those parameters (i.e., learning rate, initial estimated rate, incentive sensitivity) did not change the patterns of behavior produced by all models dramatically given the present paradigm. It does not mean that these parameters are unimportant and they are likely to influence individual's behavior in other contexts. Time threshold, on the other hand, determines when the behavior switch occurs. Thus, the status trajectories vary with the time threshold. Take Model 6 (when a variable with high decay is less important) as an example. In this case a sensitivity analysis is shown in Figure 9 where the time threshold takes the value of 0.25, 0.50, and 0.75. As can be seen, increases in time threshold move the switch later in the time line. Therefore when fitting the models with experiment data in this study, I fix the values of learning rate (i.e., 0.04), initial estimated rate (i.e., 5), and incentive sensitivity (i.e., 1) to the default value and consider time threshold as the only free parameter. In particular, setting incentive sensitivity to one removes that parameter from the model because it is a weight factor of goal importance.

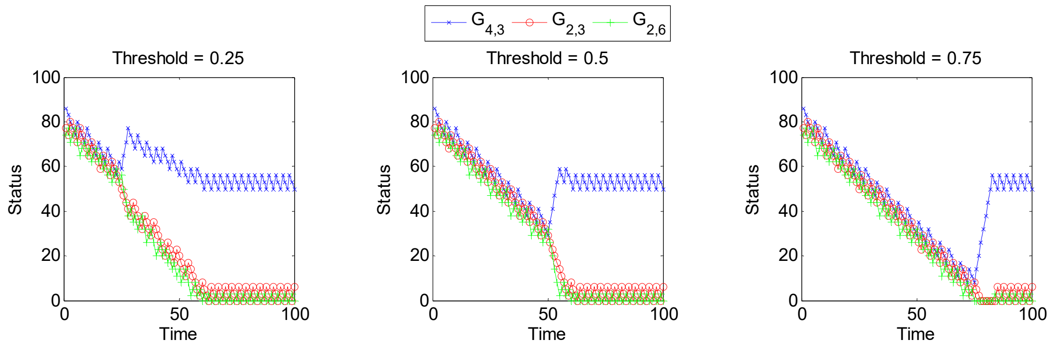

Figure 9. Sensitivity analysis for time threshold.
$G_{2,\,3}$: the less important variable with low decay.
$G_{2,\,6}$: the less important variable with high decay.
$G_{4,\,3:}$ the most important variable with low decay.

Empirical Test of the Models

In the sections below, I describe an experiment in which participants make repeated decisions regarding allocating resources (i.e., time) among three goals. Goal importance and decay associated with each goal are manipulated. I compare the ability of the nine variant models explaining the empirical data. All the models are tested with the experiment data.

Method

Participants

Participants were seventy-six undergraduate students (48 males, 28 females) with age ranging from 18 to 24 years (*M* = 18.92, *SD* = 1.19) recruited from Psychology Pool for Human Subjects Research at Ohio University during the last week before final's week. Subjects were randomly assigned to one of the three experimental conditions.

Procedure

A revised version of the computer game (i.e., SimLife) was used. SimLife is a computer game developed by Vancouver, González-Vallejo, Weinhardt, Harman, and Phillips (2010). Figure 6 shows an example of the screen participants saw. As described earlier, in the game, participants were told that they have a set schedule of classes, studying, and work that leaves them two hours of free time each day that they can choose to spend on one of the three classes (i.e., Psychology, Modern Fiction, and Applied Math). Participants made 100 choices, simulating the number of days in an academic semester. After each choice, participants were shown a 5-second slide show of pictures representing the class they had just selected to simulate the passage of time. The status of each goal was calculated on a 100 point scale with visual feedback varying continuously along the scale (i.e., the status of a goal improves when it is selected and decreases when not chosen). Grade for each class (i.e., A – F) was scaled along the 100 point scale (e.g., 0 – 20 for F, 21 – 40 for C, etc). Individuals' choice and status were recorded over the 100 trials. After the experiment, participants were debriefed.

Manipulations

Variable with high vs. low decay. As noted above, goal condition was manipulated as which class standing was instantiated as the variable with high decay. Participants were randomly assigned to three groups. In each group, one variable was set with high decay (i.e., a decay of six each time), whereas the other two variables were set with low decay (i.e., a decay of three each time).

Goal importance. Goal importance was manipulated across goal. Psychology was always presented as the most important class for all participants. This was accomplished by telling participants that "the credit hours for each course are two credit (Modern Fiction), two credit (Applied Math), and four credits (Psychology)." This goal importance information is also available on the button for each class (see Figure 6). Before participants started, they were asked to identify one of the classes as the most important based on the information provided in the instructions, which serves as a manipulation check (see detailed instructions in Appendix B).

Data Analysis

To evaluate the models, I used MATLAB to fit each model to the empirical data. In particular, all models were fitted with the empirical data at the individual level using a least squares procedure. The free parameter being estimated was the time threshold for Models 1 through 6. The other parameters were fixed to the default values given in Table 2. Model fitting results were analyzed based on prediction error and parameter estimation.

Results

Manipulation Check

Participants were expected to choose Psychology as the most important class. Sixty nine (90.8%) of the participants selected Psychology as the most important class among the three. Two (2.6%) participants selected Modern Fiction and five (6.6%) participants selected Applied Math as the most important class among the three. The behaviors of these seven participants were examined in relation to how they reported the relative importance among three classes as well as the assigned importance. The fitting results were similar in both conditions because their behaviors fit Model 7, where one makes decision based on discrepancy alone. Therefore the relative importance for each goal had little impact on their behaviors, and they were not excluded from the dataset.

Further evidence for the effect of manipulation was from the analysis of individuals' average status on each variable over time (Figure 10). The trajectories of status were similar when Modern Fiction and Applied Math were associated with high decay, which was different from the trajectories of status when Psychology was associated with high decay. The mean final status for each class on a scale of 1 to 100 for each condition is shown in Table 3. The corresponding letter grades were listed in the parentheses. When participants failed Modern Fiction and Applied Math in all three conditions, on average they received a D for Psychology when Psychology was associated with high decay and a C for Psychology when Modern Fiction or Applied Math was associated with high decay. There was a statistically significant difference in final average point between conditions as determined by one-way ANOVA, $F(2, 73)$ =

5.90, $p = .004$. A Tukey post hoc test revealed that the average points for all classes when Psychology had high decay ($M = 14.90$) was significantly lower comparing to the average points when Modern Fiction had high decay ($M = 29.77$, $p = .013$) and when Applied Math had high decay ($M = 30.18$, $p = .010$). There was no statistically significant difference in the average points between conditions when Modern Fiction and Applied Math had high decay ($p = .996$). These findings are consistent with a previous study which adopted the similar protocol (e.g., Harman et al., 2011).

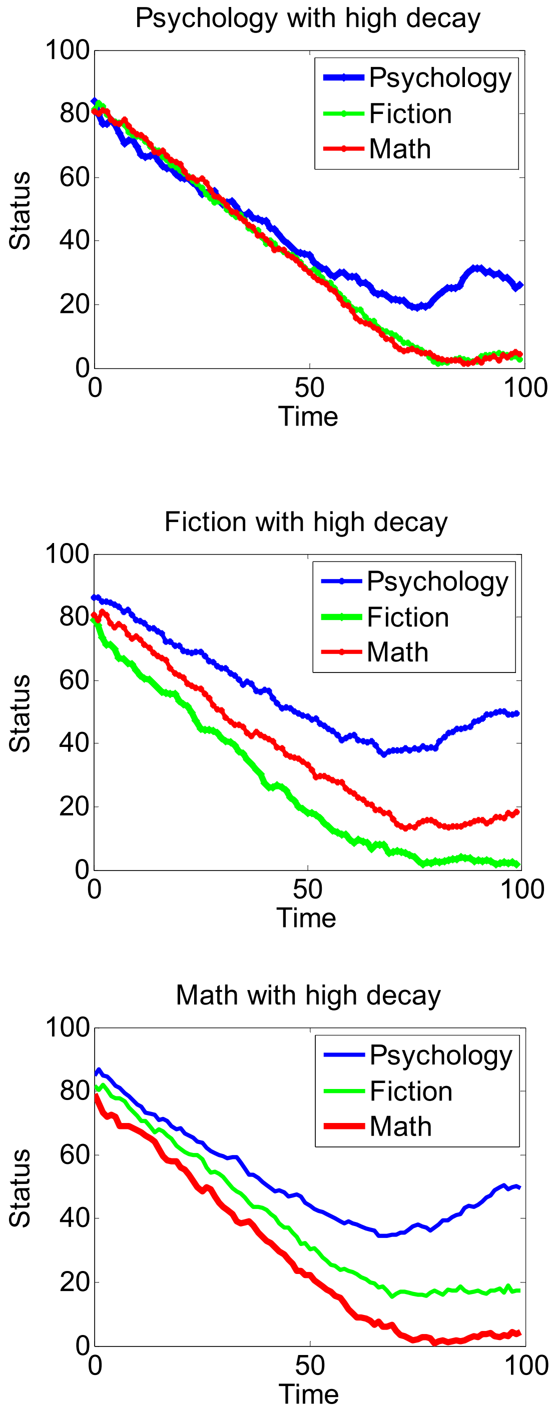

Figure 10. Status on each class over time in three conditions.

Table 3

Final Status of Each Class

Class	Class with High Decay		
	Psychology	Modern Fiction	Applied Math
Psychology	26.23 (D)	49.52 (C)	49.56 (C)
Modern Fiction	2.88 (F)	1.68 (F)	17.28 (F)
Applied Math	4.27 (F)	18.36 (F)	4.32 (F)
Average Point (GPA)	14.9 (0.5)	29.77 (1.0)	30.18 (1.0)

Note. The mean final status for each class (row) is shown in each condition (column) Letters in parentheses in first three rows are the grades translated from the points for each class.

Goodness of Fit Analyses

Using a minimization algorithm implemented in MATLAB, I estimated time threshold parameter to minimize the prediction error. In particular, Root Mean Square Error (RMSE) was used to represent the prediction error. RMSE was calculated by the square root of the variance of the residuals. Exhaustive search method was used to find the optimal parameter value. That is, for every possible time threshold (0, 0.01, 0.02 ... 1), the RMSE was calculated. The time threshold value that led to the lowest RMSE was chosen to be the best fitting parameter value. The reasoning behind choosing exhaustive search is that the set of possible time thresholds is finite and rather small. Thus, exhaustive search can be finished quickly, and it guarantees to find the global optimum. The codes used to determine fit are reported in Appendix C.

To compare models, the model prediction error (i.e., RMSE) on individual's state on each variable was calculated for each individual. The model that had the smallest error for each individual was designated as the winning model. If more than one model had the same minimal RMSE, it is coded as multiple winning models. In particular, there were six cases where Model 1 and 3 fit an individual's data equally well. The time threshold was the same for both models with a value of 0.01. This indicates that both models predict that individual switched to the heuristic strategy (i.e., discrepancy) after the first day. These six cases were coded as winning models under "Multiple Models" in Table 4.

Note that Models 7 – 9 are nested models within some of Models 1 – 6. Therefore, when any single decision strategy model (i.e., Model 7, 8, or 9) was the winning model, there were four other winning models. For example, when Model 7 (i.e., discrepancy only) was the winning model, any model includes this strategy was also a winning model automatically. That is, Model 1 (i.e., SEU - d) and 3 (i.e., valence - d) were winning models with time threshold equaled to zero, and Model 4 (i.e., d - SEU) and 6 (i.e., d - valence) with time threshold equaled to one. In this case, instead of designating multiple winning models, Model 7 was coded as the winning model because it had fewer parameters and was more parsimonious. Same was true for Model 8 and Model 9 when they were the winning models. The number of times each model won and the percentage of each model won are shown in Table 4.

Table 4

Numbers of Times Each Model Fit an Individual's Date Best

Model	Decision-rule	# of times each Model won	% of times each Model won
From analytic to heuristic			
Model 1	SEU – d	3	3.95%
Model 2	SEU – valence	3	3.95%
Model 3	Valence – d	2	2.63%
From heuristic to analytic			
Model 4	d – SEU	12	15.79%
Model 5	Valence – SEU	10	13.16%
Model 6	d – valence	36	47.37%
3 nested models			
Model 7	d	4	5.26%
Model 8	Valence	0	0
Model 9	SEU	0	0
Multiple Models		6	7.89%

Note. SEU = subjective expected utility; d = discrepancy.

To assess whether some models did better than others in terms of their probability of being the best fitting model for individuals, I used Cochran's Q (Cochran, 1950). This omnibus test was significant, $\chi^2(8) = 107.65$, $p < .001$. Because there was a significant omnibus effect, I used McNemar's test to determine which model won significantly more often than the other models (McNemar, 1947). Model 6 won the most and it was found to have won significantly more often than all the other models ($p < .001$). Model 8 and 9 did not win in any cases, and were found to have won significantly less often than Model 1, Model 3, Model 4, Model 5 ($p < .05$), and Model 6 ($p < .001$). There were no significant differences in the number of times Models 1, 2, 3, 4, 5, and 7 won. This analysis showed that Model 6 predicted individuals' behavior the best among all models. Moreover, the results favored the decision strategy where one switched from a heuristic to an analytic strategy.

However, for any individual, one model might win over other models by having a slightly smaller value of RMSE due to chance. For example, there was one individual where Model 1 (i.e., SEU – d) had the lowest RMSE (i.e., 6.2), whereas Model 7 (i.e., discrepancy only) also showed close RMSE (i.e., 6.36). More importantly, for this person, the time threshold for Model 1 was 0.04, indicating that if that person indeed adopted the decision strategy in Model 1, he or she was very likely to start using the "discrepancy only" rule (i.e., Model 7) very early on. Due to the small difference between the RMSE between the two models, Model 1 might essentially have won just by chance. To determine whether there were significant differences on the prediction errors among models with the same number of parameters, I used Friedman test. F-test was used to compare the full models and reduced models. In addition, R^2 was also calculated for each individual for each model. Comparison of R^2 yielded similar results as the comparison of

RMSE. Median (IQR), minimal, maximal RMSE and Median (IQR) R^2 for all nine models was listed in Table 5.

Table 5

Model Fitting Results

Model	Median of RMSE	Min of RMSE	Max of RMSE	Median of R^2
From analytic to heuristic				
Model 1 (SEU – d)	12.33 (10.68)	3.88	28.64	0.77(0.37)
Model 2 (SEU – valence)	14.56 (7.75)	6.12	23.54	0.66 (0.36)
Model 3 (Valence – d)	10.14 (5.63)	3.88	41.03	0.85 (0.15)
From heuristic to analytic				
Model 4 (d – SEU)	10.03 (6.72)	3.88	18.23	0.86 (0.19)
Model 5 (Valence – SEU)	13.29 (7.37)	5.93	20.98	0.72 (0.31)
Model 6 (d – valence)	7.86 (3.69)	3.88	40.88	0.91 (0.08)
3 nested models				
Model 7 (d)	12.72 (12.65)	3.88	48.83	0.73(0.46)
Model 8 (Valence)	15.79 (7.81)	6.12	41.03	0.64 (0.37)
Model 9 (SEU)	39.27 (19.93)	10.03	51.13	-0.81(2.04) [a]

Note. Numbers in parentheses in second and fifth column are the interquartile range.
SEU = subjective expected utility; d = discrepancy.
[a] We note that it is possible to have negative R^2 values if the mean predicts better than a model.

For the comparison among models with the same number of parameters, there was a statistically significant difference in RMSE of Models 1 – 6, $\chi^2(5) = 75.32$, $p < 0.001$, and a statistically significant difference in RMSE of Models 7 – 9, $\chi^2(2) = 80.95$, $p < 0.001$. Post hoc analysis with Wilcoxon Signed Rank tests was conducted with a Bonferroni correction applied, resulting in a significance level set at $p < 0.001$. For the comparisons among Model 1 – 6, Model 6 (i.e., d – valence) had the lowest RMSE and was significantly better than Model 1 – 5 ($p < 0.001$). This finding suggested that, on average, Model 6 fit the data best.

Models 4 and 3 had the second and third lowest RMSE. The RMSE of both models were significantly smaller than the RMSE of Models 1, 2, and 5 ($p < 0.001$), but there was no significant difference in RMSE between Models 4 and 3 ($p > .05$). The RMSE of Model 1 was not significantly smaller than the RMSE of Models 2 and 5 ($p > .05$). The RMSE of Model 5 was significantly smaller than the RMSE of Model 2 ($p < 0.001$). This finding in general supported the order of decision strategy that individuals first adopt a heuristic strategy and switched to an analytic strategy at a later time. This finding also suggested that models including strategy of discrepancy and valence fitted the data better than other combination of strategies.

For the comparisons among Model 7 – 9, there was no significant difference in RMSE between Model 7 and Model 8 ($p > .05$). Both the RMSE of Model 7 and 8 were significantly smaller than the RMSE of Model 9 ($p < 0.001$). Again, this finding further supported the notion that individuals considered discrepancy and/or valence, but not SEU when making decisions.

To further compare the full models (i.e., Model 1– 6) and reduced models (i.e., Model 7 – 9), a standard F-test was used. For the comparisons between full models and reduced models, F-test results showed that Model 1, 3, 4, and 6 performed significantly better than Model 7 – 9 ($p < .001$). Model 2 and Model 5 performed significantly better than Model 8 and Model 9 ($p < .001$), but not Model 7 ($p > .05$). This finding suggested that overall adding a parameter (i.e., time threshold) significantly improved the prediction power of the model. In addition, a common component of Model 1, 3, 4 and 6 is discrepancy, whereas Model 2 and 5 include strategy of valence and SEU. This finding indicates that heuristic strategy explained the data better than analytic strategy.

Analyses of Estimated Parameter Values

In this section, I examined the time threshold values for each model when they fit best with individual's data. In particular, the median and 25^{th} and 75^{th} percentiles of best fitting time thresholds for Model 1 – 6 were shown in Table 6. To further examine the characteristics of this parameter, I plotted the histogram of the best fitting time threshold for each model when it won. Figure 11 showed the frequency distribution of time threshold in each model when it won.

Table 6

Parameter Estimation Results for Time Threshold

Model	Decision-rule	Number of Individuals	Median of Time Threshold	25th Percentiles	75th Percentiles
From analytic to heuristic					
Model 1	SEU – d	9	0.01	0.01	0.04
Model 2	SEU – valence	3	0.36	0.28	N/A[a]
Model 3	Valence – d	9	0.01	0.01	0.39
From heuristic to analytic					
Model 4	d – SEU	12	0.76	0.56	0.95
Model 5	Valence – SEU	10	0.83	0.64	0.91
Model 6	d – valence	36	0.75	0.63	0.84

Note. SEU = subjective expected utility; d = discrepancy.

[a] 75th percentile for Model 2 is not available because there were only three cases where Model 2 fit the sample well.

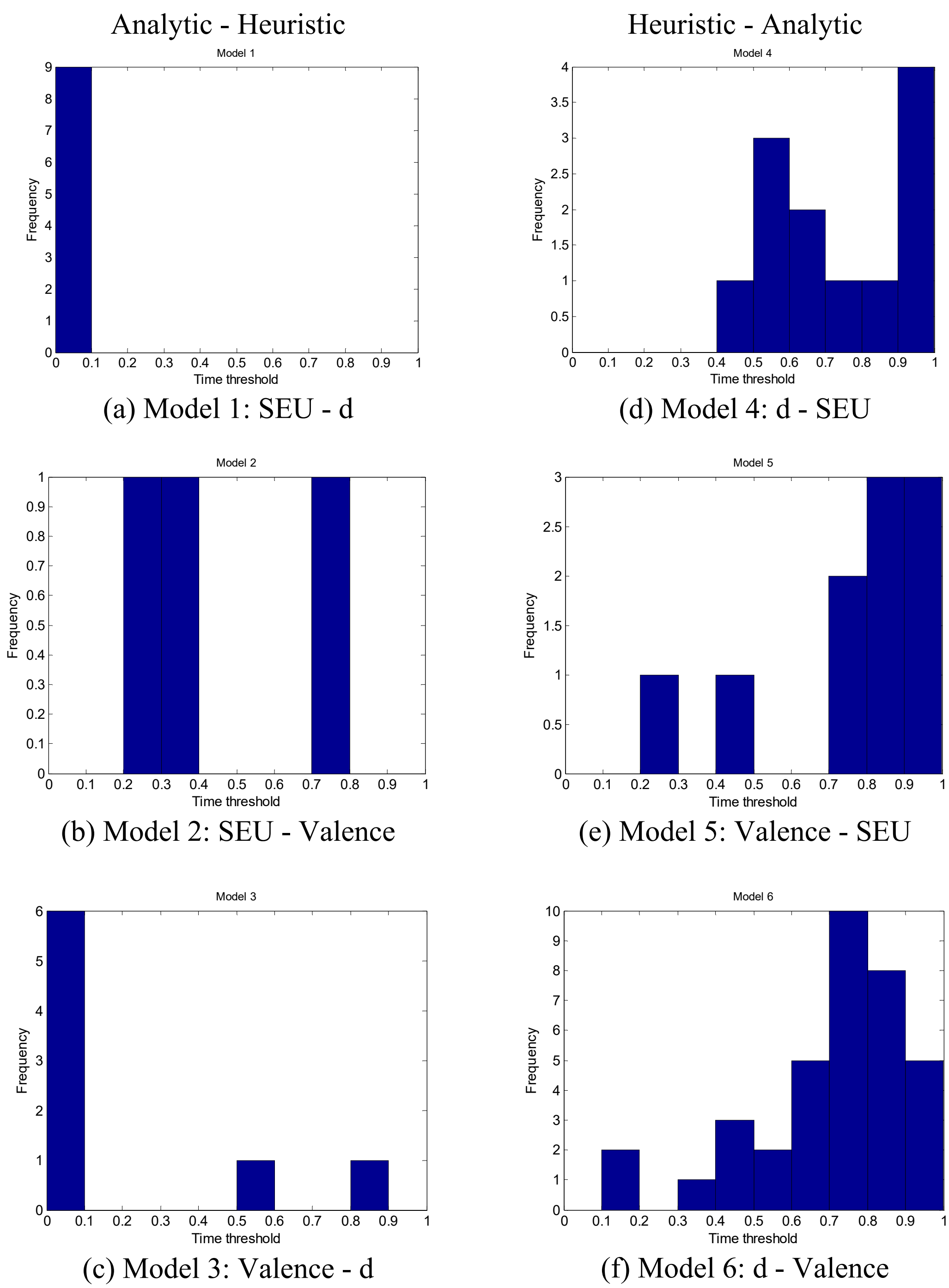

Figure 11. Frequency distribution of time threshold in Model 1 – 6 for winning models listed in Table 4.
Note. SEU = subjective expected utility; d = discrepancy.

In Model 1 and 3 the median time threshold was 0.01, indicating that for those who fit well by Model 1 and 3, they switched after the first day and spent the rest of their time using a heuristic strategy (i.e., discrepancy) till the end. Therefore, the analytic strategy (i.e., SEU or valence) was not truly represented when each model fit well with individual's data. It is likely that Model 1 and 3 won over Model 7 (i.e., discrepancy only) by chance. For Model 2, although there were some variations in the time threshold, given the small sample size (i.e., 3 cases) when Model 2 fit the data best, it is possible that Model 2 predicted the data best by chance as well.

The distributions of time threshold in Model 4, 5 and 6 were negatively skewed, indicating a late switch from heuristic to analytic strategy. In Model 4, 50% of the switching happened after Day 67 and 25% of the switching happened during last five days. In Model 5, 60% of the switching happened after Day 79 and 20% of the switching happened during the last ten days. In Model 6, 83.3% of the switching happened after Day 50 and 47.2% after Day 75. Based on above findings, it seemed that participants mostly adopted the decision strategy of a combination of comparing discrepancy and valence, though when to use which varies by individual.

To further examine whether individuals switched at a different time when the variable associated with high decay was the most important comparing to when it was less important, I plotted the frequency distribution of time threshold in Model 1 – 6 for winning models in each condition (Figure 12). Although the numbers of winning models were too few by condition to make any strong conclusions, especially for Models 1, 2, and 3, it does not appear that condition had a large impact on time threshold values. For example, for Model 6, which wins most often, the majority of participants switched during Day 70 to 90 (i.e., time threshold with a value from 0.7 to 0.9) regardless of condition. Figure 12 also illustrates that when Psychology had high decay participants tended to use the decision strategy in Model 6 (i.e., d - valence), but when Modern Fiction or Applied Math had high decay the participants tended to use the decision strategies in Model 4 (i.e., d - SEU) or Model 5 (i.e., valence - SEU).

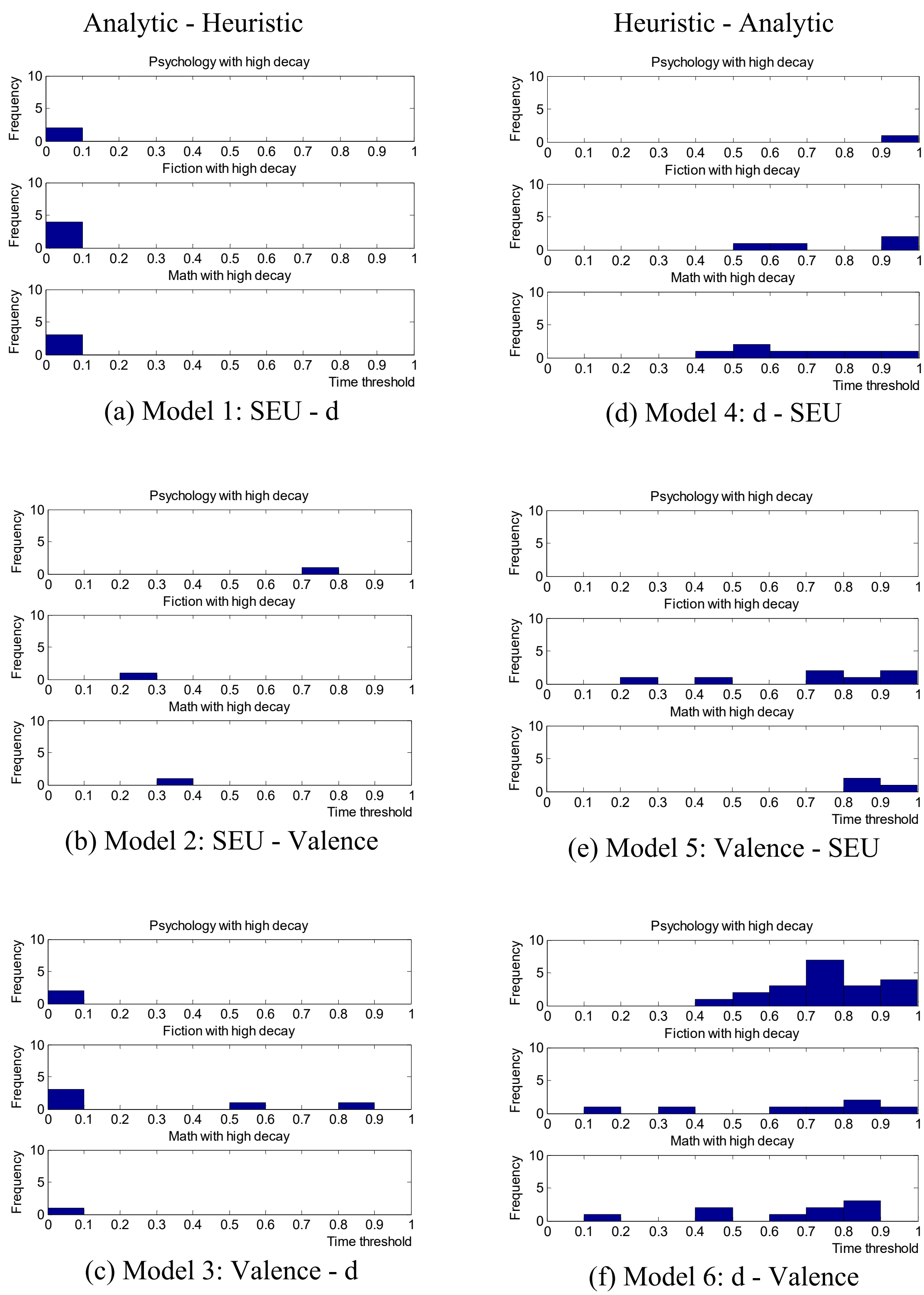

Figure 12. Frequency distribution of time threshold in Model 1 – 6 by condition.
Note. SEU = subjective expected utility; d = discrepancy.

Discussion

This dissertation aimed to better understand how individuals make decisions regarding how to allocate one's limited resources (i.e., time) when pursuing multiple goals. Despite the growing number of studies on multiple-goal pursuit behavior, most have only focused on the pursuit of two goals. The first purpose of the study was to show that a model of goal choice between two goals could be expanded to a model of goal choice among multiple goals via cascading choice agents. The findings supported the expansion of the model.

The second purpose was to determine if the sophistication of the choice agents would vary over time. That is, by extrapolating to contexts where more than two goals are pursued, the current study tried to answer the question: what kind of decision strategy do people use when they pursue multiple goals in a demanding situation where all the goals could not be met? In particular, I proposed a two-stage decision mechanism involving a range of heuristic to analytic strategies, and developed nine computational models to represent the possible ordering of these strategies over time to explain individual's behavior. In general, the results showed that individuals use more than one strategy when facing a demanding situation (i.e., more than two goals, constant decay for each variable, and insufficient resources available to maintain all the goals). Moreover, individuals tended to use more heuristic strategies (i.e., discrepancy and valence) compared to more complex strategy (i.e., SEU), and tended to switch from more heuristic to more analytic strategy if they switched. The decision strategy represented in Model 6, which predicted that people would start with the simplest heuristic strategy (i.e., discrepancy) and switch to the least complicated analytic strategy (i.e., valence) received the strongest support. Below, I discuss the theoretical and practical implications of this paper, as well as potential limitations and future research directions.

Theoretical Implications

The current study makes several contributions to theory. First, the finding of multiple strategy use is important because models of multiple-goal pursuit have up until now assumed a single decision strategy. That is, they assumed that individuals would make decisions based on the same standard over time. Although previous computational models on multiple-goal pursuit have received support from empirical data, the findings of the current study suggested that individuals tended to start with a heuristic strategy and switch to an analytic strategy at a later time.

Also of interest, the findings from the current study appear to challenge the simple heuristic vs. analytic dichotomy of decision strategy. That is, many theories of cognition refer to two systems or processes (e.g., Gigerenzer & Todd, 1999; Kahneman, 2011). Yet, this study examined different degrees of heuristic to analytic strategy based on components of the self-regulatory agents found in control theory (e.g., Vancouver, 2008). In particular, the three pieces of information one could possibly consider when pursuing a goal can be seen as heuristic (i.e., discrepancy), semi-analytic (i.e., valence), and fully analytic (i.e., SEU). The findings showed that individuals are most likely to adopt the heuristic and semi-analytic strategy, instead of the most complicated analytic strategy. However, this finding does not necessarily mean that individuals do not consider SEU at all when they make decisions. Indeed, there were six individuals whose data fit best with

Model 4 (i.e., d – SEU) and ten individuals whose data fit best with Model 5 (i.e., valence – SEU). These differences could be due to stable individual differences like need for cognition, which is an intrinsic motivation to engage in effortful cognitive thinking (Cacioppo & Petty, 1982). Researchers argued that individuals high in need for cognition actively search and process information thoroughly, whereas those who are low in need for cognition often rely on simple cues and adopt heuristics to make judgments (Petty, Briñol, Loersch, & McCaslin, 2009). Future research might examine if need for cognition predicts which model fits the best.

The differences in selecting different degrees of heuristic to analytic strategy could also be due to motivations evoked by the experiment. The experimental task I used in this study may not be a high-stakes task for participants, reducing the likelihood they adopt a complicated strategy. On the other hand, it is possible that the task is high-stakes, but not taken seriously by the sample collected in this study. That is, the sample was collected during the week before final exams. It is possible that on average these participants are less conscientious and less engaged in the experiment than volunteers at the beginning of a semester. However, previous research has shown that even in high-stakes contexts people may still prefer using noncompensatory decision rules (i.e., heuristic strategies) (e.g., Kahn & Baron, 1995). Nonetheless, it is still possible that collecting sample at a different time or under different incentive systems would yield a different distribution of results in terms of the use of decision strategies (see Payne et al., 1993).

Of some interest, though participants were juggling three goals, the context of this present study was fairly simple. For example, choices only affected one of the three goals directly (i.e., they indirectly affected status on the other goals via the application of the constant decays). Moreover, the decision context did not require the consideration of how choices might vary outcomes or goals the individual might have concerns about. That is, the paradigm did not represent the kind of complex decision space that the Ballard et al. (2016) model sought to represent when they integrated the MGPM (Vancouver et al., 2010; 2014) with decision field theory (Busemeyer & Townsend, 1993). Indeed, it may be the kind of information processing represented in System 2 (Evans, 2008). That is, though the decision strategies could vary, all might be variations of System 1 processing. Thus, a dichotomy of processing may still be reasonably assumed, but that the level or type of processing that distinguished them is not well captured by the discrepancy, valence, or SEU strategy distinctions.

Last but not least, the current study advances our knowledge of why people do not always behave in ways that optimizes some higher level metric (i.e., rationally). Literatures on judgment and decision making suggested that there are different mechanisms that would lead individuals deviate from normative behaviors (Shafir & LeBoeuf, 2002). In the present study I found that individuals achieved lower average GPA if the most important goal (i.e., Psychology) was associated with high decay. When a less important goal (i.e., Modern Fiction or Applied Math) was associated with high decay, the participants spent less time on it and focused on the other two goals. This resulted in a higher average GPA at the end. This finding indicates that participants were too sensitive to high decay when it is associated with a more important goal. That is, they spent more time on Psychology although it could not compensate for the overall loss on all three classes. If they were able to stop allocating resources to Psychology because of its high decay, they could have achieved a higher average GPA. In contrast, when the goal with high decay was not the most important goal, individuals were able to realize that spending time on such goal could not compensate for their overall GPA and focused on the other two goals with low decay. Harman et al. (2011) found similar results and they argued that this deviation from rationality is likely due to one's unwillingness to abandon an important goal, perhaps due to the individual's emotional attachment to it. The findings of current study provided evidence that this deviation is likely due to the use of decision strategies. Future research could further develop the models by adding variables and processes that could represent how emotion might influence one's choice behavior.

Practical Implications

The current study provided evidence on how individuals make decisions repeatedly among competing goals. This finding has two major implications on a practical level. First, by understanding how individuals adopt different information and use them to make decisions, practitioners can structure the information in certain ways to trigger different strategies used by individuals to achieve desirable outcomes (Gigerenzer & Todd, 1999). For example, if one wants people to keep making progress on multiple goals, making the goals of equal or similar importance would lead them to focus on their progress and how far they are from each goal. On the other hand, if one wants people to make progress on a certain goal, increasing the importance of that goal might be an option, but it might not result in behavior change unless the individual experiences difficulty pursuing multiple goals. That is, goal importance, as reflected in valence for the goal, only became relevant after some time. Presumably, time allowed the individual to see the limits to their resources and that is what spurred a more analytic decision strategy.

Another practical implication relates to the development of assistive tools that help people make more rational decisions. Although the decision strategy in Model 6 (i.e., discrepancy – valence) was the best model regarding how well it fit with the experiment data, it is by no means the best model if one's goal is to achieve the highest average performance across the three classes. As shown in Figure 6, models that adopt the most complicated analytic strategy (i.e., Model 4, 5, and 9) showed the optimal results regarding final status across three classes. However these analytic strategies might tax one's cognitive resources that could be used to perform the task and encouraging the use of analytic strategy might not be optimal. Therefore practitioners could consider develop assistive tools that make the rational decisions for individuals so that those individuals could focus their limited resources on the task itself. For instance, in the current study, if the information of current and final average GPA were available, it is possible that participants could use such information directly to make decisions without exploiting their limited resources. Therefore, in an education setting, academic advisors can assist students to balance among multiple course goals to achieve desirable GPA in a semester. Similarly, in workplace where employees often face multiple goals to accomplish, managers can use tools to manage goals for employees and help them increase efficiency and achieve optimal performance.

Limitations and Future Research Directions

The results of current study extended our knowledge by using computational models to understand more complex scenarios of multiple-goal pursuit. There are several limitations with the current study, some of which might be addressed in future research. These limitations and future research ideas are presented below.

First, when it comes to assessing the use of more or less complex decision strategies, it is important to point out that the paradigm, though more complex than many (i.e., dynamic context; three goals instead of just one or two), was still fairly straightforward. Likewise, the decision strategies in the proposed models are relatively simple. That is, I assumed that individuals only switch from one strategy to another. It is possible that the actual decision processes involve more than two stages. For example, one may first make decisions based on discrepancy, then valence, and finally SEU. On the other hand, I assumed that the change of strategy only moves in one direction (i.e., from analytic to heuristic, or heuristic to analytic). It is possible that one might change decision strategies in both directions depending on various situations. A more comprehensive model will help explain why one moves back and forth through different degrees of information processing. I also assumed that individuals would use the same decision strategy across the goals. This assumption is reasonable in the current study because all three goals were quite similar in the sense that they were all academic goals. However, it is likely that individuals would pursue multiple goals that are different in nature (e.g., work goals, life goals, etc). This raises the question that whether the decision strategy in Model 6 (i.e., d – valence) would still hold in different situations. Future research could examine this issue by including different types of goals and incorporating new decision strategies in the model.

Moreover, both theoretical and empirical research is needed to further examine what factors might influence the timing of the switch of decision strategies. The timing of when individuals switch the strategy they use could be influenced by both internal factors (e.g., how sensitive one is to time and deadlines) and external factors (task complexity, time pressure, etc.; Payne et al., 1988). In the current study, I did not speculate on or include such factors in the computational models because they would likely qualitatively differ when considering factors that moved one from analytic to heuristic decision strategies as compared to heuristic to analytic. Given the findings support the unidirectional move from heuristic to analytic with the type of context represented, further work could focus on examining such factors.

For example, one speculation is that expectancy notions play a role in determining what choice is made when more complex information processing is used, but also when the more complex information processing is engaged. One way to examine such a thesis is to vary deadlines and assess sensitivity to time. Sensitivity to time is the *time gain* parameter in MGPM (Vancouver et al., 2010). Time gain with a value of one indicates a perfect perception of how much time left before the deadline, which was assumed for this dissertation. Time gain with a value greater than one indicates one would perceive more time before the deadline whereas time gain with a value less than one indicates one would perceive less time before the deadline (Vancouver et al., 2010). This change in perception of available time would likely result in change in expectancy, which in turn influences SEU for each variable. If this difference in SEU was reflected in the change of choice behavior, we could learn better regarding when individuals would adopt the full analytic strategy (i.e., SEU).

Other than individual differences, contextual factors could also influence the use of heuristic vs. analytic strategies. For example, Payne (1976) found that task complexity influenced how individuals process information and thus how they choose from multiple alternatives. In particular, he found that individuals seek to use heuristics as the decision situation became more complex. This perspective leads to the hypothesis that in a three goal pursuit scenario the heuristic strategies would dominate, which is what was found. It would be interesting to see if the heuristic strategies became even more prevalent as the number of goals or other information processing factors increase. For example, Payne et al. (1988) found that the increases of time pressure resulted in the change of the speed of information processing and strategies use (i.e., more heuristic as time pressure increased). Yet, other added factors, like varying deadlines, may increase the use of analytic strategies of the information processed in heuristic strategies (e.g., a work-on-what-is-due-next strategy). Future research should add such individual and contextual factors into the model to explain more phenomena.

Furthermore, although the findings supported that one may first adopt heuristic strategies and switch to more analytic strategies later, the current study did not directly test why the participants chose this order of strategy use. It is likely that they did so because they wanted to save their limited mental capacity and only switched to analytic strategy when needed. An alternative explanation is that they needed time to learn about the decision space before they can apply more complicated analytic strategy (e.g., efficiencies beliefs are needed to assess SEU). Yet, the information needed to compute SEU is rather straightforward and easy to learn. Given the fact that most participants switched to the SEU analytic strategy when they were near the deadline if they ever did, it is more likely that the approaching deadline made them switch to a more analytic strategy, rather than their sense of comprehending the task only reach a desired level near the end. Nonetheless, assessing these alternative explanations would be useful.

Last but not least, there are more substantial additions to the models that can broaden our understanding of the empirical phenomena related to multiple-goal pursuit. For instance, the models in the current study were built on a cognitive perspective. I did not include other types of variables like affect in the proposed models. Yet, research shows that affect variables are likely to influence how one prioritizes goals (Custers, 2009). In future work, researchers might consider the interaction effect of affective and cognitive variables on decision-making. Moreover, the proposed models represented the processes of goal-choice and goal-striving under the assumption that individuals accepted all three goals. It is possible that individuals may abandon a few goals in the beginning and only focus on the rest or lowered goal levels over time, especially when there are a lot more goals than one can handle. However, data from a previous study (Harman et al., 2011) suggested that participants would not abandon goals in the current paradigm. Moreover, I choose not to attempt to model processes that affect goal level because they would likely add a significant layer of complexity to the modeling. Indeed, computational models of goal level change exist (Scherbaum & Vancouver, 2010; Gee, Vancouver, & Neal, 2017), but they address somewhat different contexts than the one presented here. That is, much research has focused on goal commitment and goal disengagement and some implies it could be adaptive and beneficial for individuals to disengage or lower their goals (e.g., Wrosch et al., 2007). For example, if a goal is too difficult to obtain, abandoning that goal can free up the limited resources to other goals that might be more valuable or promising. It can also reduce the negative emotions induced by failures from pursuing that unattainable goal (Latham, 2007).

Conclusion

Previous computational models of multiple-goal pursuit assumed that individuals use one decision strategy to choose between two goals. The present study advances our understanding of multiple-goal pursuit by scaling up the MGPM to considering multiple goals and incorporating the possibility that more than one decision strategies might be used over time. The findings shed some light on the dynamic decision-making in a demanding situation where one does not have the resources to meet all the goals. The expansion of MGPM demonstrates how the model can be integrated with decision-making theories and allows us to explore more complex situations of multiple-goal pursuit in the future.

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Appendix A: Codes for Specifying the Computational Model in MATLAB

Below are the codes for simulating Model 6. The codes for the other eight models are the same except the decision strategy. Variables labeled with letter G are related to Psychology (e.g., perceived_G_current_M1 refers to the current perceived status of Psychology). Similarly, variables labeled with letter R and F are related to Applied Math and Modern Fiction, respectively.

```
for i = 1:Num_step

    perceived_R_current_M1 = max(ceil(x_perf_R_current_M1*Num_scale/100),1);
    perceived_F_current_M1 = max(ceil(x_perf_F_current_M1*Num_scale/100),1);
    perceived_G_current_M1 = max(ceil(x_perf_G_current_M1*Num_scale/100),1);

    perceived_R_past_M1 = max(ceil(x_perf_R_past_M1*Num_scale/100),1);
    perceived_F_past_M1 = max(ceil(x_perf_F_past_M1*Num_scale/100),1);
    perceived_G_past_M1 = max(ceil(x_perf_G_past_M1*Num_scale/100),1);


    d_R_M1 = goal_R*Num_scale/100 - perceived_R_current_M1;
    d_F_M1 = goal_F*Num_scale/100 - perceived_F_current_M1;
    d_G_M1 = goal_G*Num_scale/100 - perceived_G_current_M1;

    weighted_d_R_M1 = d_R_M1*gain_R;
    weighted_d_F_M1 = d_F_M1*gain_F;
    weighted_d_G_M1 = d_G_M1*gain_G;

    tnR = d_R_M1/x_eff_R_current_M1;
    tnF = d_F_M1/x_eff_F_current_M1;
    tnG = d_G_M1/x_eff_G_current_M1;

    exp_R = gamma*(100 - i) - tnR;
    exp_R = max(exp_R,0);

    exp_F = gamma*(100 - i) - tnF;
    exp_F = max(exp_F,0);

    exp_G = gamma*(100 - i) - tnG;
    exp_G = max(exp_G,0);


    eu_R_M1 = d_R_M1 * gain_R * exp_R;
    eu_F_M1 = d_F_M1 * gain_F * exp_F;
    eu_G_M1 = d_G_M1 * gain_G * exp_G;
```

```
   y_eff_R_M1 = perceived_R_current_M1 - perceived_R_past_M1;
   y_eff_F_M1 = perceived_F_current_M1 - perceived_F_past_M1;
   y_eff_G_M1 = perceived_G_current_M1 - perceived_G_past_M1;

   if i > t_threshold

      if (weighted_d_G_M1 >= weighted_d_R_M1) && (weighted_d_G_M1 >=
weighted_d_F_M1)

         choice_R_M1 = 0;
         choice_F_M1 = 0;
         choice_G_M1 = 1;

      elseif weighted_d_R_M1 == weighted_d_F_M1

         rand01 = rand;
         if rand01 >= 0.5
            choice_R_M1 = 1;
            choice_F_M1 = 0;
            choice_G_M1 = 0;
         else
            choice_R_M1 = 0;
            choice_F_M1 = 1;
            choice_G_M1 = 0;
         end

      elseif weighted_d_R_M1 > weighted_d_F_M1

         choice_R_M1 = 1;
         choice_F_M1 = 0;
         choice_G_M1 = 0;

      else

         choice_R_M1 = 0;
         choice_F_M1 = 1;
         choice_G_M1 = 0;

      end

   else

      if (d_G_M1 >= d_R_M1) && (d_G_M1 >= d_F_M1)
```

```
        choice_R_M1 = 0;
        choice_F_M1 = 0;
        choice_G_M1 = 1;

    elseif d_R_M1 == d_F_M1

        rand01 = rand;
        if rand01 >= 0.5
            choice_R_M1 = 1;
            choice_F_M1 = 0;
            choice_G_M1 = 0;
        else
            choice_R_M1 = 0;
            choice_F_M1 = 1;
            choice_G_M1 = 0;
        end

    elseif d_R_M1 > d_F_M1

        choice_R_M1 = 1;
        choice_F_M1 = 0;
        choice_G_M1 = 0;

    else

        choice_R_M1 = 0;
        choice_F_M1 = 1;
        choice_G_M1 = 0;

    end

end

x_perf_R_next_M1 = x_perf_R_current_M1 + eff_R*choice_R_M1 + decay_R;
x_perf_F_next_M1 = x_perf_F_current_M1 + eff_F*choice_F_M1 + decay_F;
x_perf_G_next_M1 = x_perf_G_current_M1 + eff_G*choice_G_M1 + decay_G;

x_perf_R_next_M1 = min(max(x_perf_R_next_M1,0),100);
x_perf_F_next_M1 = min(max(x_perf_F_next_M1,0),100);
x_perf_G_next_M1 = min(max(x_perf_G_next_M1,0),100);

if delayed_choice_R_M1 == 1
```

```
        x_eff_R_next_M1 = x_eff_R_current_M1 + rate_R*(y_eff_R_M1 -
x_eff_R_current_M1);
    else
        x_eff_R_next_M1 = x_eff_R_current_M1;
    end
    if delayed_choice_F_M1 == 1
        x_eff_F_next_M1 = x_eff_F_current_M1 + rate_F*(y_eff_F_M1 -
x_eff_F_current_M1);
    else
        x_eff_F_next_M1 = x_eff_F_current_M1;
    end
    if delayed_choice_G_M1 == 1
        x_eff_G_next_M1 = x_eff_G_current_M1 + rate_G*(y_eff_G_M1 -
x_eff_G_current_M1);
    else
        x_eff_G_next_M1 = x_eff_G_current_M1;
    end

    x_perf_R_past_M1 = x_perf_R_current_M1;
    x_perf_F_past_M1 = x_perf_F_current_M1;
    x_perf_G_past_M1 = x_perf_G_current_M1;

    x_perf_R_current_M1 = x_perf_R_next_M1;
    x_perf_F_current_M1 = x_perf_F_next_M1;
    x_perf_G_current_M1 = x_perf_G_next_M1;

    x_eff_R_current_M1 = x_eff_R_next_M1;
    x_eff_F_current_M1 = x_eff_F_next_M1;
    x_eff_G_current_M1 = x_eff_G_next_M1;
```

```
    delayed_choice_R_M1 = choice_R_M1;
    delayed_choice_F_M1 = choice_F_M1;
    delayed_choice_G_M1 = choice_G_M1;

end
```

Appendix B: Experiment Instructions

The Setup

Welcome to your virtual life in SimuWorld! For the next 30 minutes you will manage a life perhaps not too distant from your current one. That is, you will play the role of a student going to college. We are interested in studying the decisions you make across a term. These decisions will have implications in the virtual world and your virtual life. We are interested in studying decision making over time, so we want you to make decisions AS YOU WOULD IN REAL LIFE. Click 'Continue' to move on.

Continue

The Setup

In this virtual world you have only three classes to worry about: a Psychology class, a Modern Fiction class, and an Applied Math class. You would like to end the semester with the highest GPA, however the classes vary in credits and relevance to your major. Specifically, Psychology is your major and is worth 4 (four) credits, whereas the Modern Fiction and Applied Applied Math classes are only worth 2 (two) credits which you are taking to meet general education requirements.

Continue

The Setup

The decisions involve managing your time across the three classes over the course of a semester. To do that, you basically must decide what to do with your spare time. Each 'day' you can only spend time studying for one class. That is, assume that you go to the classes on your schedule, work 30 hours a week to make ends meet, and sleep 8 hours a day. So you only have a few hours a day of spare time for studying. True if this were real life you might go crazy with such a busy schedule, but it is a virtual life, so buck up. The question is which class to study for each day. To help you do that, we will give you information about your current grade in each class. Click 'Continue' to see more instructions.

Continue

The Setup

This grade, or STATUS, represents the grade you would get if a final exam was given that day. That is, it represents the knowledge you have acquired relative to what you should have acquired up to that point. At the start of the simulation we assume this status in the B range for your three classes, but time will eat into that status if you do not spend time on a class. Likewise, the only way to improve your status in a class is to spend time on the class. At the end of the simulation (100 'days' from the start) is the end of the semester, so your status at the time determines your grade for the class. Click 'Continue' to move on.

Continue

The Setup

Before we begin, we want to get your opinion regarding the three classes. Specifically, we want to know which of the three (assuming you were taking all three) would be most important. Please check one of the classes in the box below.

Most important domain?

- Psychology
- Modern Fiction
- Applied Math

Continue

The Setup

Okay, you are ready to begin. If you have any questions, now would be a good time to ask the experimenter. Otherwise, press 'Continue' to begin.

Continue

Appendix C: Codes for Model Fitting in MATLAB

```
ExpDataFull = xlsread(filename, sheetname, range);
ExpDataLC = sheetname;

i_person = 1;
num_points = 100;
ExpData = ExpDataFull((i_person-1)*num_points+1:i_person*num_points,:);


rng(1)

x_range = (0:0.01:1)';

for i_model = 1:6

    switch i_model

        case 1
            for i = 1:length(x_range)
                x_i = x_range(i);
                [Simu_Results_i,Err_i] =
ParamEst_MultiModel_v1_Model1(x_i,ExpData,ExpDataLC);
                Err_vec(i,1) = Err_i;
            end
            [Err_min,index_min] = min(Err_vec);
            x_opt = x_range(index_min);
            Simu_Results = ParamEst_MultiModel_v1_Model1(x_opt,ExpData,ExpDataLC);

        case 2
            for i = 1:length(x_range)
                x_i = x_range(i);
                [Simu_Results_i,Err_i] =
ParamEst_MultiModel_v1_Model2(x_i,ExpData,ExpDataLC);
                Err_vec(i,1) = Err_i;
            end
            [Err_min,index_min] = min(Err_vec);
            x_opt = x_range(index_min);
            Simu_Results = ParamEst_MultiModel_v1_Model2(x_opt,ExpData,ExpDataLC);

        case 3
            for i = 1:length(x_range)
                x_i = x_range(i);
```

```
            [Simu_Results_i,Err_i] =
ParamEst_MultiModel_v1_Model3(x_i,ExpData,ExpDataLC);
            Err_vec(i,1) = Err_i;
        end
        [Err_min,index_min] = min(Err_vec);
        x_opt = x_range(index_min);
        Simu_Results = ParamEst_MultiModel_v1_Model3(x_opt,ExpData,ExpDataLC);

    case 4
        for i = 1:length(x_range)
            x_i = x_range(i);
            [Simu_Results_i,Err_i] =
ParamEst_MultiModel_v1_Model4(x_i,ExpData,ExpDataLC);
            Err_vec(i,1) = Err_i;
        end
        [Err_min,index_min] = min(Err_vec);
        x_opt = x_range(index_min);
        Simu_Results = ParamEst_MultiModel_v1_Model4(x_opt,ExpData,ExpDataLC);

    case 5
        for i = 1:length(x_range)
            x_i = x_range(i);
            [Simu_Results_i,Err_i] =
ParamEst_MultiModel_v1_Model5(x_i,ExpData,ExpDataLC);
            Err_vec(i,1) = Err_i;
        end
        [Err_min,index_min] = min(Err_vec);
        x_opt = x_range(index_min);
        Simu_Results = ParamEst_MultiModel_v1_Model5(x_opt,ExpData,ExpDataLC);

    case 6
        for i = 1:length(x_range)
            x_i = x_range(i);
            [Simu_Results_i,Err_i] =
ParamEst_MultiModel_v1_Model6(x_i,ExpData,ExpDataLC);
            Err_vec(i,1) = Err_i;
        end
        [Err_min,index_min] = min(Err_vec);
        x_opt = x_range(index_min);
        Simu_Results = ParamEst_MultiModel_v1_Model6(x_opt,ExpData,ExpDataLC);

  end

  Simu_Results_MultiModel{i_model,1} = Simu_Results;
```

```
    Err_min_MultiModel(i_model,1) = Err_min;
    x_opt_MultiModel(i_model,1) = x_opt;

end


for i_model = 7:9

    switch i_model

        case 7
            [Simu_Results,Err] = ParamEst_MultiModel_v1_Model7(ExpData,ExpDataLC);

        case 8
            [Simu_Results,Err] = ParamEst_MultiModel_v1_Model8(ExpData,ExpDataLC);

        case 9
            [Simu_Results,Err] = ParamEst_MultiModel_v1_Model9(ExpData,ExpDataLC);

    end

    Err_min_MultiModel(i_model,1) = Err;
    Simu_Results_MultiModel{i_model,1} = Simu_Results;

end


 [Err_BestModel,index_BestModel] = min(Err_min_MultiModel);
winner = find(Err_min_MultiModel == Err_BestModel)
```

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