People often pursue multiple, competing goals, striving to achieve desired outcomes, while avoiding undesired outcomes. Because individuals have limited time and resources, they often have to choose which goal to prioritize at any given moment. These choices are difficult, because progress toward one goal may come at the expense of progress toward others. Consider an assistant professor striving to publish a sufficient number of papers before her tenure deadline (i.e., an approach goal), while simultaneously ensuring that she does not obtain poor teaching ratings (i.e., an avoidance goal). If she prioritizes her research over the summer it might lead to a publication, but it may also increase her risk of receiving a poor teaching rating in the subsequent semester. By contrast, if she prioritizes teaching, she may be able to avoid a poor teaching rating, but would reduce her chances of obtaining a publication. The choice involves risk because a single action can have a number of potential consequences. The processes by which people make decisions in these types of dynamic and uncertain environments are poorly understood (Weber & Johnson, 2009).

Until recently, the field lacked a formal theory that explains the process by which people make decisions in the face of competing goals. Formal theories are needed, because their descriptions of psychological phenomena are more precise than verbal theories (Busemeyer & Diederich, 2010). They provide a mathematical representation of the hypothetical processes thought to be responsible for observed phenomena (Maccorquodale & Meehl, 1948). Moreover, formal theories are capable of generating falsifiable predictions, which enable the field to make cumulative progress (Busemeyer & Diederich, 2010; Lewandowsky & Farrell, 2011; Roberts & Pashler, 2000). Vancouver, Weinhardt, and Schmidt (2010) took the initial steps toward a formal theory of multiple-goal pursuit by developing the multiple-goal pursuit model (MGPM), which is a cognitive model of approach goal striving. The model integrates control theory accounts of self-regulation (Carver & Scheier, 1998) and classic, subjective expected utility accounts of decision making (von Neumann & Morgenstern, 1947;
Vroom, 1964). Vancouver and colleagues (Vancouver et al., 2010; Vancouver, Weinhardt, & Vigo, 2014) have demonstrated that this model is able to account for the effects observed in existing empirical studies of multiple-goal pursuit, including the effects of incentives and the tendency for people to switch priority from the a goal with more progress needed to attain the goal to one with less progress needed to attain the goal as a deadline approaches.

The MGPM lays the foundation for developing a general theory of multiple-goal pursuit. However, it has only been applied to relatively simple choice problems, in which each action has only one potential consequence. Moreover, the decision mechanism within the model is derived from subjective expected utility theory (von Neumann & Morgenstern, 1947), which has been superseded by more sophisticated theories of decision making (Busemeyer, 2015). Furthermore, the model does not yet describe the mechanisms of avoidance goal pursuit. Avoidance goals are internal representations of undesired states in contrast to approach goals, which are internal representations of desired states (Austin & Vancouver, 1996). Finally, although there is a range of strategies that people can use while pursuing multiple goals (Orehek & Vazeou-Nieuwenhuis, 2013), the model predicts that most people will tend to work on the goal in the worst position at any given point in time and therefore switch priority frequently. Studies have shown that at least some people tend to work on the goal in the best position and thus not switch priority until it has been achieved (e.g., Schmidt, Dolis, & Tolli, 2009). The MGPM has not yet been used to account for the latter strategy.

We address these issues by (a) integrating the MGPM with decision field theory (DFT; Busemeyer & Townsend, 1993; Roe, Busemeyer, & Townsend, 2001), so that it provides a more sophisticated explanation of the complex choices encountered during multiple-goal pursuit, (b) extending the MGPM to account for avoidance goals, and (c) demonstrating that the model can account for individual differences in prioritization strategy. The resulting model, which we call the MGPM*, explains the process by which people make complex choices involving risk or uncertainty, while striving for approach and/or avoidance goals.

To evaluate the model, we first present a simulation study in which we used the MGPM to generate a set of predictions regarding the effects of goal type (i.e., approach/avoidance) and risk on prioritization. We then test these predictions in an experiment. The empirical data from the experiment demonstrate that goal type and risk exert systematic effects on goal prioritization. We also show that the effects of these manipulations vary across individuals in a way that is consistent with the predictions of the MGPM*. Further, we demonstrate that the MGPM* provides a better account of the data than the original MGPM, and that the major extensions of MGPM* from the original model are justified.

**The Multiple-Goal Pursuit Model**

The MGPM (Vancouver et al., 2010) is a cognitive model based on a control theory account of goal pursuit (e.g., Carver & Scheier, 1998; Lord & Levy, 1994; Powers, 1973; Vancouver, 2008). Control theory represents goal pursuit in terms of feedback control systems. The goals that people pursue may be a feature of the external world, such as publishing a certain number of papers to achieve tenure; or internal to the person, such as keeping emotions in check. According to control theory, the tendency to act on a goal is determined by the discrepancy between the perception of the current state of the variable being controlled and a reference state for that variable (i.e., the goal). For example, if our assistant professor has a goal of publishing 10 papers to obtain tenure, and has published five to date, the discrepancy is five. In the case of an approach goal the aim is to reach the goal, which eliminates the discrepancy.

According to the MGPM, the choice between competing goals is determined by comparing the subjective expected utilities of acting on each goal and then selecting the goal with the highest expected utility. Expected utility is a label commonly used in the field of decision making (Busemeyer, 2015). It represents the multiplicative combination of a subjective sense of probability (i.e., expectancy) and a subjective sense of value (i.e., utility). These same concepts can be found in motivational theories such as expectancy theory (Vroom, 1964), although the labels for the constructs vary. For example, utility is often referred to as valence or value in motivational theories (e.g., Kanfer, 1991). In the MGPM, utility is referred to as valence. Valence is the product of the discrepancy and gain, which is the weight that represents the importance of the goal to the individual. Gain can be affected by internal and external factors, such as the value or framing of incentives associated with obtaining the goal.

The other component of expected utility is expectancy, which in the MGPM is derived by comparing a subjective sense of the resources required to achieve the goal, and a subjective sense of the resources available. The subjective sense of resources required (e.g., time needed) is based on the discrepancy and a belief regarding the resources it takes to reduce the discrepancy. This belief is developed with experience, but is potentially biased as well (Vancouver et al., 2014). In the empirical protocols used to test the MGPM, the resource was time and the availability of that resource was determined by a deadline. Because the discrepancy and the amount of resources available (e.g., the time to a deadline) change over time, the valence and expectancy of the goal also change over time, which means that they are dynamic. The MGPM predicts that as long as one perceives that there is sufficient time available to meet the goals and the goals’ importance are equal, individuals will tend to prioritize the goal with the larger discrepancy. However, as the deadline approaches, the model predicts that people will prioritize the goal with the smaller discrepancy, because the perceived likelihood of achieving the goal with the larger discrepancy will have decreased.

In support of these predictions, studies have demonstrated that people switch priority from the goal with the largest discrepancy to the one with the smallest discrepancy as a deadline looms (Louro, Pieters, & Zeelenberg, 2007; Schmidt & Dolis, 2009), though with a preference for the goal with the higher incentive if differential incentives exist (Schmidt & DeShon, 2007). These studies also showed individual differences, which the MGPM could account for via differences in the free parameters in the model. For example, people who were more sensitive to the time available demonstrated an earlier preference reversal. More recently, Vancouver et al. (2014) added a learning component to the MGPM, which explains how people learn to anticipate the effects of environmental disturbances on goal progress and form beliefs regarding resources needed to achieve the goal.
Integration and Unification

An advantage of formal models is that they can be developed progressively and be extended to account for a broader range of empirical phenomena. This process involves identifying the factors that limit the explanatory power of the model, and modifying the model to address those factors, often by integrating mechanisms from other psychological theories. This process of systematic integration and unification facilitates the cumulative development of knowledge and is regarded as the hallmark of a mature science (Anderson et al., 2004; Hempel, 1966; Newell, 1990; Steel & Konig, 2006). It also provides a way of addressing the so-called “replication crisis” in psychology (Open Science Collaboration, 2015; Yong, 2012). The crisis is in part attributable to the fact that research is often not cumulative. Emphasis tends to be on effects that are counterintuitive and challenge conventional thinking, rather than the systematic development and testing of theories that can account for the benchmark phenomena within a field. In this paper, we focus on different types of choices, goals, and strategies to broaden the range of phenomena the model can explain.

Types of Choices

The original MGPM has only been applied to relatively simple choice problems. In these choices, each action has a single known consequence. For example, in the Schmidt and DeShon (2007) experimental paradigm, participants had to create class schedules for students from two different colleges. There was a line of students from each college, and the participants had to create class schedules for every student in each line. When they completed a schedule for a student, the number of students in line for that student’s college would always decrease by one, reducing the discrepancy between the current state and goal state for the line. Furthermore, the original MGPM assumes that the person develops an expected utility based on the consequence of an action in relation to a single goal. For example, the model determines the expected utility of working on a schedule for a student from College A based on the discrepancy for College A. However, choices often involve more than one potential consequence. Furthermore, these consequences often need to be considered in relation to more than one goal. For example, the assistant professor in our ongoing example cannot be certain that she will obtain a publication if she prioritizes her research over the summer. She also needs to consider the possibility that prioritizing research may or may not lead to a poor teaching rating, and thus that the potential benefit for the research goal could come at the cost of the teaching goal.

The MGPM needs a more sophisticated decision mechanism to account for the types of complex choice problems described above. The decision mechanism within the original MGPM is derived from classic theories of decision making, such as subjective expected utility theory (SEU; Edwards, 1954) and its derivatives, such as expectancy theory (Vroom, 1964). Classic theories assume that people make decisions by comparing the expected utilities of various actions, and selecting the action with the highest expected utility. An SEU model provides a reasonable first approximation for performance on relatively simple choice problems, such as those to which the MGPM has been applied to date. However, it is unlikely to account for performance on more complex problems. Studies have consistently demonstrated that people violate many of the assumptions of SEU theory, and there is a wide range of empirical phenomena for which SEU theory and its derivatives cannot account. For example, people do not always choose the option with the highest expected utility (Edwards, 1955; Mosteller & Nogee, 1951), and preferences for options may reverse depending on time pressure (Dror, Basola, & Busemeyer, 1999) or the method by which choices are elicited (Johnson & Busemeyer, 2005). Furthermore, choices are influenced not only by differences in expected utilities, but also by the degree of uncertainty involved in a decision (e.g., Busemeyer, 1985). Finally, SEU models assume that people make choices rationally by systematically assessing the likelihood and value of all the potential consequences of each action. However, humans have limited information processing capacity, and do not always fully consider the consequences of their actions (Fu & Gray, 2006).

To provide a more sophisticated explanation for the types of complex choices encountered during multiple-goal pursuit, we extend the MGPM by integrating it with DFT (Busemeyer & Townsend, 1993). DFT was developed in response to the limitations of classic decision theories and is capable of accounting for behavior on complex choice problems, such as those involving risk and uncertainty. This theory is a member of a class of decision models known as sequential sampling models (Brown & Heathcote, 2008; Donkin, Brown, Heathcote, & Wagenmakers, 2011; Ratcliff & McKoon, 2008). Sequential sampling models provide a dynamic, cognitive explanation for how people make decisions. They describe how the preference for a given course of action evolves over time as one considers the different consequences associated with each action.

Types of Goals

There are several different types of goals that people can pursue. One important distinction is between approach and avoidance goals. An approach goal is defined as a desirable state individuals wish to reach, whereas an avoidance goal is defined as an undesirable state from which individuals wish to keep away. Despite a long history of research on approach and avoidance motivation (e.g., Brown, 1948; Hull, 1938; Lewin, 1935), surprisingly little research has examined the role of avoidance goals in a multiple-goal pursuit context. Research that has focused on avoidance goal pursuit has examined the causes and effects of avoidance goal pursuit, but has largely failed to consider how the process itself works. For example, Elliot and Church’s (1997) hierarchical model of approach and avoidance achievement motivation identifies antecedents (e.g., motivation, expectancy) and consequences (e.g., performance) of pursuing avoidance as compared to approach goals. Other work focuses on understanding how personality influences whether people pursue approach or avoidance goals (e.g., Elliot & Thrash, 2002). Gable’s (2006) theory of approach and avoidance social motivation describes how dispositional motives and the features of one’s social environment influence the type of goals one pursues. Although this work reveals factors that influence goal adoption and outcomes associated with pursuing different types of goals, it provides little insight into the factors that influence motivation or decision making during that pursuit.

Carver and Scheier (1998) argue that different psychological processes are required for the pursuit of approach and avoidance goals. An important difference between approach and avoidance
lies in the dynamics of valence. When pursuing approach goals, valence should decrease as one moves closer to the goal. However, when pursuing avoidance goals, valence should increase as one moves closer to the goal, because the goal is an undesired state. These arguments suggest that the decision-making architecture for approach and avoidance goals may not be the same. We enable the MGPM* to account for avoidance goals by modifying the valence, expectancy, and expected utility functions within the original MGPM.

Strategies

Studies of multiple-goal pursuit have shown that there are individual differences in the way that people prioritize goals (Orehek & Vazeou-Nieuwenhuis, 2013; Schmidt, Dolis, & Tolli, 2009). These studies have all used approach goals, and have shown that some people tend to work on the goal with the largest discrepancy at a given point in time. In an approach context, the goal with the largest discrepancy is the one in the worst position, because it is the furthest from attainment. The dynamic pattern that emerges from this behavior is one in which the person switches back and forth between goals as the relative discrepancy changes (referred to as the “concurrent strategy”). Other people tend to work on the goal that has the smallest discrepancy (i.e., the goal in the best position). The dynamic pattern that emerges from this behavior is one in which the person works on one goal until it has been, or is close to being, achieved (referred to as the “sequential strategy”). Although the original MGPM has been used to explain the concurrent strategy, it has not yet been used to account for the sequential strategy. In this paper, we examine the different strategies people use when pursuing approach and avoidance goals, and assess whether the MGPM* can account for each one. The results of our study show that there are individual differences in strategies among people pursuing approach goals, but not among people pursuing avoidance goals, and that the MGPM* can account for these effects.

Decision Field Theory

To enable the MGPM* to account for the more complex choice problems encountered during multiple-goal pursuit we integrate the MGPM with DFT (Busemeyer & Townsend, 1993). DFT is a sequential sampling model developed to explain the mechanisms involved in decision making under risk and uncertainty. The theory is capable of accounting for a wide range of empirical phenomena that could not be explained by any one previous theory, including violations of stochastic dominance, violations of independence between alternatives, the relationship between choice probability and decision time, the effects of time pressure on choice accuracy, and the effects of changes in risk or uncertainty on choice probability (Busemeyer & Townsend, 1993).

There are several reasons why DFT is the ideal candidate for integration with the MGPM. First, DFT is a formal, dynamic model of decision making that describes how goals influence decision making. Like the MGPM, it assumes that the subjective value of acting on a goal changes as the person makes progress toward or away from that goal (Busemeyer, Dimperio, & Jessup, 2006). This makes DFT amenable to integration with the MGPM, because they share the same basic assumptions. Second, it provides a general account of decision making involving any number of goals, actions, and consequences, whereas the original MGPM only addresses choices between two actions where each action only affects one goal. Thus, DFT enables the MGPM* to generalize to more complex situations than the MGPM. Third, DFT was developed to explain how people make choices involving risk or uncertainty, which is one type of complex choice problem we seek to understand in this paper. Finally, DFT provides an explanation of the internal dynamics of the decision process, because it describes how preferences develop over time and eventually produce a choice. By contrast, the original MGPM treats the decision process as static.

DFT assumes that people make a choice between two or more actions. Actions can have any number of possible consequences, and each consequence may be considered in relation to one or more goals. In our ongoing example, the assistant professor faces a choice between two actions for the summer: focusing on research or focusing on teaching. There are at least four potential consequences of each action. For example, if she focuses on her research, she might: (a) succeed in getting a paper published, but receive a poor teaching rating in the following semester; (b) succeed in getting a paper published, without receiving a poor teaching rating; (c) fail to get the paper published, and receive a poor teaching rating; or (d) fail to get the paper published, without receiving a poor teaching rating. Some of these consequences may not be fully considered by the decision maker, particularly if the decision is being made rapidly or the preference for one option dominates the others.

DFT uses the term motivational value to describe the attractiveness of a consequence. Motivational value is a function of two factors: the need to act on each goal and the quality of the consequence in relation to each goal (Busemeyer, Dimperio, & Jessup, 2006; Busemeyer, Townsend, & Stout, 2002). The need to act is a function of the discrepancy between the current state and the goal. Quality refers to the degree of satisfaction that a consequence provides with respect to a particular goal. In the goal pursuit context, quality is proportional to the change in discrepancy that would occur if that particular consequence arose.

To make the example more concrete, Table 1 displays the qualities associated with the assistant professor’s research and teaching goals. As can be seen, having the paper accepted would have a quality of one with respect to the research goal because it brings our assistant professor one paper closer to achieving her goal of publishing 10 papers. Having the paper rejected would have a quality of zero with respect to the research goal because it brings her no closer to the undesired state that she is poor teaching rating; (c) fail to get the paper published, and receive a poor teaching rating; or (d) fail to get the paper published, without receiving a poor teaching rating. Some of these consequences may not be fully considered by the decision maker, particularly if the decision is being made rapidly or the preference for one option dominates the others.

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<table>
<thead>
<tr>
<th>Quality</th>
<th>Research goal</th>
<th>Teaching goal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Paper published</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Paper not published</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Poor teaching rating received</td>
<td>0</td>
<td>-1</td>
</tr>
<tr>
<td>Poor teaching rating not received</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
striving to avoid. Receiving a poor teaching rating would have a quality of −1 with respect to the teaching goal because it brings her one course closer to the avoidance goal. Thus, the motivational value of having the paper accepted will be larger when she is a long way from her research goal. The motivational value of receiving a poor teaching rating will be larger (i.e., more negative) when she is close to the undesired teaching goal.

DFT assumes that when comparing actions, individuals cannot simultaneously attend to all of the possible consequences of each action, because they have limited information processing capacity. Therefore, individuals shift their attention between possible consequences as they deliberate over the decision (Busemeyer & Townsend, 1993; Busemeyer & Diederich, 2002; Roe et al., 2001). According to DFT, at each point in time the person considers one potential consequence of each action. The probability of a person paying attention to a consequence at a given point in time is referred to as the attention weight. The attention weight reflects the perceived likelihood of a consequence occurring if a particular action is selected.

For example, Table 2 displays four possible consequences associated with prioritizing teaching or research as well as possible attention weights associated with each consequence. In this example, when considering the consequences of prioritizing research, the assistant professor is most likely to pay attention to the possibility of publishing a paper, but receiving a poor teaching rating. When considering the consequences of prioritizing teaching, she is most likely to pay attention to the possibility of receiving a good teaching rating, but not publishing a paper.

At each point in time, the person compares the consequences being attended to for each action. This comparison results in a momentary perception of the relative attractiveness of each action, which is referred to as the momentary attractiveness. Unlike expected utility in the MGPM, which only varies in response to changes in the environment, momentary attractiveness also varies as the person considers different consequences of an action—consequences that are considered sequentially as the person makes the decision. For example, our assistant professor might consider that if she prioritizes research, she may get a publication without receiving a poor teaching rating, whereas if she prioritizes her teaching, she may avoid obtaining a poor teaching rating, but will not get a publication, either. At that point in time, prioritizing research work would be more attractive to the assistant professor than prioritizing teaching. Thus, the momentary attractiveness of focusing on research would be positive, whereas the momentary attractiveness of focusing on teaching would be negative. When the assistant professor shifts her attention to alternative consequences, the momentary attractiveness of each action changes. For example, the assistant professor may then consider the possibility that if she prioritizes research, she may get a publication, but at the cost of receiving a poor teaching rating. At this point in time, focusing on research would become less attractive.

Within DFT, the transitory momentary attractiveness of each action cumulates during the sampling process to determine a preference. For example, if the assistant professor continues to focus on consequences that make focusing on research appear more attractive than focusing on teaching, her preference for prioritizing research will increase over time. If she then focuses on consequences that make prioritizing teaching appear more attractive, her preference for prioritizing teaching will start to increase. She will continue to shift attention between different consequences while comparing the actions, until the preference for one of the actions exceeds a threshold. At this point, the action for which preference breached the threshold is selected.

The threshold represents the strength of preference required before one is willing to select a course of action. Lower thresholds generally lead to faster, but less accurate decisions. Higher thresholds generally lead to slower, but more accurate decisions (Brown & Heathcote, 2008; Ratcliff & McKoon, 2008). Use of the threshold parameter therefore enables DFT to naturally accommodate both rapid (i.e., heuristic) and slow (i.e., analytic) decision making. Thresholds have been shown to relate to stable factors (e.g., need for closure; Brown, Rae, Bushmakin, & Rubin, 2015) that influence how cautious or urgent individuals are when making decisions. However, this parameter can also be influenced by environmental factors such as perceived time pressure (Dror et al., 1999).

Figure 1 shows an example of the sequential sampling process as the assistant professor considers the potential consequences of the different courses of action. When making a choice between two actions, preference is expressed on a bipolar continuum, with positive values indicating a preference for one action and negative values indicating a preference for the other action. As can be seen, her preference for focusing on research versus teaching was initially equal (i.e., preference had a value of zero). As deliberation (i.e., sampling) proceeded, preference first accumulated in the negative direction (i.e., in favor of prioritizing teaching). However, as deliberation continued, preference started to accumulate in the positive direction (i.e., in favor of research). Eventually, preference breached the threshold in the positive direction and the assistant professor decided to prioritize research.

### Development of the MGPM

In this section, we introduce the MGPM*. Like the MGPM, the MGPM* assumes that individuals monitor the discrepancy between their current state and their goal. The discrepancy and the importance (i.e., gain) of the goal together determine the valence of acting on the goal. The person also monitors resources (e.g., time) available and the expected resources required to reach the goal, and the difference between these influences the expectancy of reaching the goal. Valence and expectancy combine to determine the expected utility of the goal, which represents one’s motivation to act on the goal at a given point in time. As summarized in Table 3, the MGPM* introduces several modifications to the MGPM to enable the model to explain more complex choice problems, and to account for the effects of avoidance goals.

---

**Table 2**  
*Example of Possible Attention Weights for the Consequences of Prioritizing Teaching Versus Research*

<table>
<thead>
<tr>
<th>Priority</th>
<th>Paper published</th>
<th>Paper not published</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prioritize research</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poor teaching rating received</td>
<td>.50</td>
<td>.25</td>
</tr>
<tr>
<td>Poor teaching rating not received</td>
<td>.20</td>
<td>.05</td>
</tr>
<tr>
<td>Prioritize teaching</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poor teaching rating received</td>
<td>.05</td>
<td>.10</td>
</tr>
<tr>
<td>Poor teaching rating not received</td>
<td>.25</td>
<td>.60</td>
</tr>
</tbody>
</table>
Like DFT, the MGPM assumes that people do not have sufficient capacity to systematically assess the expected utility of each action when those actions have multiple possible consequences. Instead, people deliberate over the decision, considering the various consequences sequentially. The attractiveness of a consequence, referred to as motivational value, is determined by the potential change in discrepancy for each goal (i.e., qualities) and the expected utilities of those goals. At a given point in time, the person considers one potential consequence for each action. The relative attractiveness of each consequence being considered determines the momentary attractiveness of the actions. As the person considers different consequences over time, they develop preferences for the different actions. The person continues to consider different consequences until preference for one action reaches a threshold, at which point that action is selected.

Figure 2 provides a graphical summary of the MGPM. The figure summarizes a dynamic process involving goals a and b, where actions x and y are being considered and where each action has consequence 1 and 2. The figure is divided into three layers. The first layer, expected utility of goals, illustrates the mechanisms that determine the expected utility of acting on each goal. In this layer, \( U_a \) and \( U_b \) denote the expected utility of goals a and b respectively. The second layer, motivational value of consequences, illustrates how the expected utility of acting on each goal combines with the quality of each consequence to determine the motivational value of the possible consequences for each action. In this layer, \( M_{a1} \) and \( M_{a2} \) denote the possible consequences of action x, whereas \( M_{b1} \) and \( M_{b2} \) denote the possible consequences of action y. The third layer, choice of action, illustrates how the motivational values and the attention weights combine to influence the choice process. In the subsections that follow we provide the mathematical specification for the model.

**Discrepancy**

Like the original MGPM, the MGPM assumes that goals are reference values or standards, and that the person compares the current state of the variable (s) to the goal (g) to determine a discrepancy. The sign of the discrepancy is determined by whether or not the reference value has been surpassed. We define the discrepancy as positive when the reference value has not been surpassed, so that it decreases as the current state moves closer to the reference value. This definition enables the MGPM to be applicable across a range of goal pursuit scenarios. We have used the example of the academic trying to publish at least 10 papers (an approach goal), while ensuring that she does not receive more than 3 poor teaching ratings (an avoidance goal). This example is a scenario in which the person is trying to ensure that a variable is greater than or equal to its reference value (for the approach goal) and trying to prevent a variable from reaching or exceeding its reference value (for the avoidance goal). In these situations, the discrepancy is calculated by subtracting the current state of the variable from the goal (\( d = s - g \)). A positive discrepancy occurs when the variable’s value is less than the goal, which in this scenario means that the goal has not yet been surpassed.

Of course, other scenarios are possible. In some situations, a goal is surpassed when the variable’s value drops below the reference value. An example is a manager trying to bring the number of safety incidents down to an acceptable level. This is an approach goal, because it is a desired state that the person is striving to achieve. However in this case, the discrepancy is calculated by subtracting the goal from the current state (e.g., if there are currently 10 incidents per month, and the goal is 5, then the discrepancy is +5). The same is true if the person is trying to prevent the variable from reaching or falling below the reference value, such as a manager trying to prevent the firm’s capital reserves from falling below a particular level. This represents an avoidance goal, because the person is trying to prevent the system reaching an undesired state. In this case, the discrepancy is positive when the starting capital reserve level is above the goal, and it decreases as the capital reserves are drained away.

**Valence**

The MGPM assumes that the valence of an approach goal decreases as the person moves closer to the goal. Consider the example of the assistant professor aiming for 10 papers before her tenure deadline. When she only has one paper, the valence of acting on that goal will be high, but as she gets more papers and thus closer to achieving her goal, the valence of acting on the goal will reduce. In contrast, the valence of an avoidance goal should increase as one moves closer to the goal (Carver & Scheier, 1998). When the assistant professor has not yet received any poor teaching ratings, the valence of acting on the teaching goal will be low, because she is a long way from the undesired state. However, if she starts getting poor teaching ratings, the valence of acting on that goal should increase. To account for this relationship, we introduce an intercept parameter (b), which represents the valence of acting on the goal when the current state is equal to the goal. For approach goals, we assume that the intercept is zero such that the valence decreases as the person gets closer to the goal. Thus, for approach goals like those considered by the MGPM the intercept need not be included in the valence formula. However, to handle...
### Table 3
**Summary of Extensions Made by the MGPM* From the MGPM**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Conceptual definition</th>
<th>MGPM</th>
<th>MGPM*</th>
<th>Rationale for extension</th>
</tr>
</thead>
<tbody>
<tr>
<td>Valence (V)</td>
<td>Subjective immediate value of acting on goal</td>
<td>Positive function of discrepancy, with an implied intercept of 0</td>
<td>Negative function of discrepancy for avoidance goals, with an intercept greater than 0</td>
<td>Needed to account for avoidance goals</td>
</tr>
<tr>
<td>Gain (κ)</td>
<td>Importance of goal</td>
<td>Lower bound of 0</td>
<td>Can take on negative values for avoidance goals</td>
<td>Needed to account for avoidance goals</td>
</tr>
<tr>
<td>Expectancy (E)</td>
<td>Perceived likelihood of reaching goal</td>
<td>Scaled from 0 upward</td>
<td>Constrained to be between 0 and 1</td>
<td>Bounded scale needed for avoidance goals</td>
</tr>
<tr>
<td>Expected Utility (U)</td>
<td>Motivation to act on goal</td>
<td>Positive function of expectancy</td>
<td>Negative function of expectancy for avoidance goals</td>
<td>Needed to account for avoidance goals</td>
</tr>
<tr>
<td>Quality (q)</td>
<td>Potential change in a goal discrepancy if consequence occurs</td>
<td>Not included in original MGPM</td>
<td>Part of more sophisticated account of the choice process</td>
<td>Needed to account for complex choices</td>
</tr>
<tr>
<td>Motivational Value (M)</td>
<td>Attractiveness of consequence</td>
<td>Not included in original MGPM</td>
<td>same as above</td>
<td>same as above</td>
</tr>
<tr>
<td>Attention Weight (w)</td>
<td>Probability of attending to a particular consequence</td>
<td>Not included in original MGPM</td>
<td>same as above</td>
<td>same as above</td>
</tr>
<tr>
<td>Momentary Attractiveness (A)</td>
<td>Attractiveness of action based on consequences being considered at given point in time</td>
<td>Not included in original MGPM</td>
<td>same as above</td>
<td>same as above</td>
</tr>
<tr>
<td>Preference (P)</td>
<td>Cumulative evaluation of action based on past momentary attractiveness</td>
<td>Not included in original MGPM</td>
<td>same as above</td>
<td>same as above</td>
</tr>
<tr>
<td>Threshold (θ)</td>
<td>Strength of preference required to select an action</td>
<td>Not included in original MGPM</td>
<td>same as above</td>
<td>same as above</td>
</tr>
</tbody>
</table>
avoidance goals an intercept greater than zero is required. The MGPM also includes a gain parameter to represent the importance of the goal. In the MGPM, the gain parameter was positive. In the MGPM, the gain parameter is negative for avoidance goals. Because of this, valence associated with an avoidance goal increases as the person gets closer to the goal (see Figure 3). Finally, we assume that valence cannot fall below 0. The MGPM defines valence (V) as follows:

\[ V_k(t) = \max[b_k + \kappa \cdot d_k(t), 0]. \]  

(1)

The subscript \( k \) denotes the goal and \( t \) denotes the time. Thus, \( V_k(t) \) represents the valence of goal \( k \) at time \( t \).

**Expectancy**

Expectancy has traditionally been conceptualized as the subjective likelihood of an event occurring (Edwards, 1954; Vroom, 1964). When represented mathematically, expectancy is traditionally bounded between zero and one, with zero indicating that the occurrence of the event is impossible and one indicating that the event is certain. A value of 0.5 indicates that there is a 50% chance that the event will occur, which is the point of maximum uncertainty. The original MGPM did not represent expectancy as a subjective probability. In particular, it had no upper limit. This representation creates difficulties when dealing with avoidance goals. Specifically, to deal with avoidance goals we bound expectancy by zero and one. Bounding expectancy in this way allows us to treat it like a subjective probability in which the likelihood of an event not occurring is equal to one minus the likelihood of the event occurring. To accomplish this bounding we use a logistic function. Logistic functions are commonly used in neural network models to constrain function outputs to a particular range (Hill, Marquez, O’Connor, & Remus, 1994) and are used in psychophysical models to describe how people respond to changes in stimulus intensity (Wichmann & Hill, 2001).
The MGPM defines the expectancy (E) of reaching a desired or undesired state given the resources available. As with the MGPM, we assume time is the key resource. Hence, the time required (TR) is subtracted from the time available (TA). The difference is weighted by a time sensitivity parameter (γ) that represents the individual’s sensitivity to the difference between TA and TR. These elements are placed in a logistic function to obtain the bounded expectancy values needed to represent both approach and avoidance goals. The full equation is as follows:

\[ E_k(t) = \frac{1}{1 + \exp[-\gamma (TA_k(t) - TR_k(t))]}. \] (2)

Equation 2 provides a convenient way to capture the effects of uncertainty associated with goal pursuit and time. According to this function, expectancy should approach one as the difference between TA and TR becomes larger because the person should become more certain of reaching the goal in the time available. Expectancy should approach zero as the difference between TA and TR becomes smaller because the person should become more certain of not reaching the goal in the time available. Expectancy should equal 0.5 when TR equals TA, because this is the point of maximum uncertainty, when the chances of reaching the goal before the deadline are equal to the chances not reaching it by the deadline. Thus, this equation also provides an improvement on the original MGPM, because it assumes that when the time required to reach the goal is equal to the time available, a person should expect a 50/50 chance of reaching a goal. By contrast, the original MGPM assumed that the expectancy of reaching the goal should be 0 in this situation.

We assume that time sensitivity may be influenced by both individual differences and environmental factors. For example, differences in impulsiveness may produce differences in time sensitivity (Monterosso & Ainslie, 1999; Vancouver et al., 2010). Differences in the flexibility of a deadline might also influence the sensitivity to time (e.g., preparing a conference presentation compared to preparing the first submission of a paper). Higher values of γ mean that expectancy, and therefore an individual’s decision, is more sensitive to the difference between the time available and expected time required (see Figure 4). Likewise, lower values of γ indicate a lower level of sensitivity. In the Simulation of the MGPM section, we demonstrate that variability in time sensitivity can account for individual differences in whether people display the concurrent or sequential strategies.

We should note that the MGPM’s time sensitivity parameter is conceptually similar to the ‘time gain’ parameter in the MGPM. Both parameters influence the relationship between time and expectancy. The difference between the two parameters is that time sensitivity reflects sensitivity to the difference between TA and TR, whereas time gain reflects sensitivity only to TA. We made this change so that the parameter would still have a meaningful effect.

Figure 3. Valence as a function of discrepancy for approach and avoidance goals.

Figure 4. Expectancy as a function of the difference between time available and time required, and time sensitivity (γ). See the online article for the color version of this figure.
after the addition of the logistic function. When using this function, multiplying the parameter with the difference between TA and TR produces clear effects on expectancy (see Figure 4), whereas multiplying the parameter only with TA has effects that are much more difficult to interpret.

Following the MGPM, we define TR as the product of discrepancy and expected lag (α). TR is dynamic because discrepancies can change. Expected lag is a belief regarding the time needed to move one unit of discrepancy closer to the goal. Expected lag can change based on experience with the task (Vancouver et al., 2014) or environmental cues (e.g., there may be only one opportunity per semester for our assistant professor to obtain teaching ratings). The expected time required is defined as follows:

\[ TR(t) = d(t) \cdot \alpha(t). \] (3)

**Expected Utility**

According to the MGPM, a goal’s expected utility is the product of valence and expectancy. However, this equation needs modification to account for the fact that high expectancies likely adversely affect the expected utility of avoidance goals. Expectancy is positively related to the expected utility of an approach goal because a high expectancy indicates a high likelihood of reaching the desired goal. Expectancy should be negatively related to expected utility of an avoidance goal because the person is trying not to reach the goal. There are a number of ways that this idea could be implemented within a model. A simple way is to define expected utility using separate equations for approach and avoidance goals. For approach goals, expected utility (U) is defined as follows:

\[ U_i(t) = V_i(t) \cdot E_i(t). \] (4a)

For avoidance goals, expected utility is positively related to the expectancy of not reaching the goal in the time available. Because we have modified the specification of expectancy to include an upper bound of one, expectancy can be treated like a probability. The expectancy of not reaching the goal is therefore equal to one minus the expectancy of reaching the goal. The expected utility of acting on an avoidance goal is therefore defined as follows:

\[ U_j(t) = V_j(t) \cdot [1 - E_j(t)]. \] (4b)

**Motivational Value**

DFT assumes that motivational value is a function of quality (i.e., the perceived impact of a consequence on goal progress) and discrepancy. The expectancy of achieving a goal is not represented in DFT, because the problems DFT has addressed are not the type where expectancy is likely to have a strong influence, such as the satisfaction of hunger or safety (e.g., Busemeyer & Diederich, 2002; Busemeyer et al., 2006). However, people need to consider the likelihood of goal attainment when dealing with achievement goals, because there is no point spending time pursuing a goal that is unachievable (Schmidt & Dolis, 2009; Vancouver et al., 2010). The MGPM therefore assumes that the motivational value of a consequence is a function of quality and the expected utility of acting on the goal. Thus, the motivational value of having the paper accepted will be higher to the extent that it is possible to achieve the goal of 10 papers in the time remaining before the tenure deadline. The MGPM defines the motivational value of an actor as follows:

\[ M_{ij}(t) = \sum U_i(t) \cdot q_{ij}(t). \] (5)

The subscripts i and j denote the action and consequence respectively. Thus, \( M_{ij}(t) \) represents the motivational value of consequence j of action i at time t.

**Attention**

According to DFT, the focus of attention at a given point in time is determined stochastically. For each action, each consequence has a probability that the person will attend to it, which is referred to as the attention weight (\( w_{ij} \)). DFT assumes that the attention weight is related to the probability of the consequence occurring—people are more likely to pay attention to the most likely consequences. For example, our assistant professor may believe that if she focuses on her teaching, she will avoid receiving a poor teaching rating. She is therefore more likely to pay attention to this possibility when considering the consequences of focusing on teaching. This assumption is supported by eye tracking studies demonstrating that when making decisions with consequences that vary in their probability of occurring, people fixate more on outcomes that are more probable (Fiedler & Glückner, 2012). The attention allocated to a particular consequence of an action at a given moment is referred to as the momentary attention and is denoted \( W_{ij}(t) \). Momentary attention can only be allocated to one consequence per action. Thus, \( W_{ij}(t) \) is equal to either 1 (denoting attention allocated) or 0 (no attention allocated), and the total attention allocated across all consequences for a particular action at any given moment equals 1 (i.e., if \( W_{ij}(t) \) for consequence j of action i = 1, \( W(t) \) for all other consequences of action i must be 0).

**Momentary Attractiveness**

The momentary attractiveness (A) for each action is determined by the motivational value of the consequence that is being attended to at that moment. For example, the momentary attractiveness of focusing on research would be higher when the assistant professor considers the possibility that she might get a publication, than when she considers the possibility that she might not get a publication. The momentary attractiveness of focusing on teaching would be higher when the assistant professor considers the possibility of receiving a good teaching rating, than when she considers the possibility of receiving a poor teaching evaluation. Following DFT, the MGPM defines momentary attractiveness as follows:

\[ A_i(t) = \sum W_{ij}(t) \cdot M_{ij}(t). \] (6)

According to the above equation, the momentary attractiveness of action i at time t is equal to the motivational value of the consequence that is being attended to at that time, because the

---

1 The construct we refer to as momentary attractiveness is referred to as valence by decision field theory. We relabeled this construct because the MGPM also includes a valence construct that is formally distinct from the valence construct in decision field theory.
momentary attention for that consequence will be equal to 1, whereas the momentary attention for other consequences will be equal to 0.

Preference

Following DFT, the MGPM\textsuperscript{*} assumes that preference ($P$) changes over time according to the following equation:

$$P(t) = P(t-1) + [A_1(t) - A_2(t)].$$

In our example, $A_1(t)$ represents the momentary attractiveness of prioritizing research and $A_2(t)$ represents the momentary attractiveness of prioritizing teaching. Positive values of preference therefore indicate that prioritizing research is preferred, whereas negative values indicate that prioritizing teaching is preferred. The $P(t-1)$ term in the equation means that preference is a variable with memory (i.e., it is a dynamic variable; Vancouver et al., 2010). It moves from its last value based on the differences in the actions' momentary attractiveness at a given point in time.

Simulation of the MGPM\textsuperscript{*}

In this section, we generate predictions for the MGPM\textsuperscript{*} by conducting a simulation study (Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013). In this study, we simulate the model under different conditions and examine the emergent behavior of the model in each one. The results of the simulation represent the model’s predictions. We test those predictions in an empirical study described in the next section.

We constructed the simulation study to address three specific research questions. Each research question corresponds to an aim of the paper. The first research question relates to how prioritization is influenced by avoidance goals:

*RQ1*: How does prioritization differ when pursuing two approach goals, two avoidance goals, or one approach and one avoidance goal?

The second research question relates to the complexity of prioritization decisions. The decision we examine in this paper is one where actions can involve risk. We examine prioritization as a function of whether the outcomes of actions are risky or certain. By risky, we mean that actions have more than one possible consequence, but that the person knows the probability that each consequence will occur. By certain, we mean that each action has one consequence that is guaranteed to occur. The second research question is as follows:

*RQ2*: How does prioritization differ when actions are risky compared with when actions are certain?

The third research question relates to the model's ability to account for prioritization strategies. We argue that differences in strategy can be accounted for by the time sensitivity parameter in the model ($\gamma$). A high level of time sensitivity makes people more attuned to the likelihood that each goal can be achieved. As a result of this increased sensitivity, people should be more likely to make prioritization decisions based on expectancy. Thus, high levels of time sensitivity should make people more likely to work on the goal that has the greatest likelihood of attainment at any point in time, and therefore more likely to display the sequential strategy. This means that when pursuing approach goals, people should be more likely to prioritize the goal with the smallest discrepancy, and when pursuing avoidance goals, people should be more likely to prioritize the goal with the largest discrepancy. A low level of time sensitivity makes people less attuned to the likelihood that each goal can be achieved. As a result, people should be less likely to make prioritization decisions based on expectancy. Thus, low levels of time sensitivity should make people more likely to work on the goal that has the highest valence at any point in time and to display the concurrent strategy. Therefore, the third research question is:

*RQ3*: How does the time sensitivity parameter influence prioritization strategy?

Simulation Method Description

We created a simulation study that mirrored the task that we used in the experiment described subsequently to validate the model’s predictions. This experimental task required the participant to make a series of prioritization decisions while pursuing two goals (referred to as Goal A and Goal B). Participants were assigned one approach and one avoidance goal (henceforth, ‘approach–avoidance’), two approach goals (‘approach–approach’), or two avoidance goals (‘avoidance–avoidance’). The task required participants to make a series of choices between two actions. Each action prioritized one goal at the expense of the other, for example, by providing the opportunity to make progress toward one goal, while missing out on the opportunity to make progress toward the other. We varied the level of risk associated with the actions. In the risky condition, the action had two possible consequences, with an equal probability of occurring if the action was selected. In the certain condition, the action had one certain consequence if the action was selected.

Simulating a computational model typically involves fixing the parameters to specific values (see Table 4). The choice of these values can be important because the parameters influence the behavior of the simulation. If parameters are fixed to values that are not observed in the population of interest, the behavior of the simulation may not reflect the process under investigation. Fortunately, some parameter values can be selected based on the fact that they are reasonable given the task environment. This was the

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Specified values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b$</td>
<td>Intercept of valence function</td>
<td>$b_{\text{approach}} = 0$</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>Goal importance (gain)</td>
<td>$\kappa_{\text{approach}} = 0$, $\kappa_{\text{avoidance}} = 1$</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Time sensitivity</td>
<td>$N(.33, .25)$</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Expected lag</td>
<td>2</td>
</tr>
<tr>
<td>$w$</td>
<td>Attention weights</td>
<td>Equal to objective probability of outcomes</td>
</tr>
<tr>
<td>$\theta$</td>
<td>Threshold</td>
<td>$N(.71, .34)$</td>
</tr>
</tbody>
</table>

*Note.* The notation $N(x, \gamma)$ indicates that the value is sampled from a normal distribution with $\mu = x$ and $\sigma = \gamma$. 

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case for the valence intercept, gain, expected lag, and attention weight parameters. We fixed the valence intercept to 0 for approach and 5 for avoidance, and the gain parameter to 1 for approach goals and −1 for avoidance goals. These values were reasonable because they ensured that the overall level of valence would be approximately equal for approach and avoidance goals. We fixed the expected lag to 2. This value was reasonable because on average it would take two units of time to reduce each discrepancy by one unit in this task. We fixed the attention weights to equal the objective probabilities of the consequences, which was reasonable because DFT predicts that the probability of attending to a consequence relates to the probability of that consequence occurring.

In contrast to the above parameters, we did not have a priori estimates of time sensitivity and threshold, because these values vary across individuals. We therefore simulated a range of values for these parameters to ensure the simulation results were robust. A common method for ensuring robust results is to run multiple simulations where parameter values are sampled randomly from a distribution that reflects the variability of that parameter in the population of interest (i.e., Monte Carlo). The results can be collapsed across simulations to illustrate the behavior that is most likely to occur in that population. We used this method to generate time sensitivity and threshold parameters. We identified the distribution of these parameters by fitting the MGPM to data from a previous study of multiple-goal pursuit (Ballard, Yeo, Vancouver, & Neal, 2013) where the parameters for each participant were estimated. In the previous study, the time sensitivity parameter had a mean of 0.33 and a standard deviation of 0.25. The threshold parameter had a mean of 0.71 and a standard deviation of 0.34. We used these values to generate the sampling distributions for each parameter in the simulation study (with the constraint that neither parameter could have a negative value).

We ran one million simulations in MATLAB for each goal type (approach–approach, avoidance–avoidance, or approach–avoidance) crossed with risk combination (risky vs. certain). Each simulation included 10 decisions. The model predicted the probability of selecting the action that prioritized Goal A. We simulated the actual decision by randomly sampling from a uniform distribution with a minimum of 0 and a maximum of 1. If the sampled value was less than the predicted probability of prioritizing Goal A, the model prioritized Goal A, if not, the model prioritized Goal B. The dependent variable of interest was the action selected, because this indicated which goal was being prioritized. This method ensured that, over a large number of observations, the proportion of times the model selected the action that prioritized Goal A would match the predicted probability of prioritizing Goal A (and vice versa for Goal B).

We examined research questions 1 and 2 by examining how the likelihood of an action being selected (and thus a particular goal being prioritized) varied according to the goal type and risk manipulations. We examined research question 3 by examining how the likelihood of selecting an action differed depending on the value of the time sensitivity parameter. To do this, we grouped the simulations according to the time sensitivity parameter value. Simulations were classified as very low time sensitivity if the value of the time sensitivity parameter was below the 25th percentile, low time sensitivity if the value was between the 25th and 50th percentiles, high time sensitivity if the value was between the 50th and 75th percentiles, and very high time sensitivity if the value was above the 75th percentile. We examined the simulation results for these four groups separately.

Simulation Results and Discussion

Previous research on multiple-goal pursuit has plotted prioritization effects as a function of relative discrepancy. For example, Schmidt and DeShon (2007) plotted prioritization as a function of whether a goal’s discrepancy was larger than, equal to, or smaller than, the discrepancy for the other goal. We do the same for the approach–approach and avoidance–avoidance conditions. For the approach–avoidance condition, we plot the predictions as a function of the time (represented as decision number). Discrepancy has opposing effects for approach and avoidance goals and, as a result, these effects cannot be interpreted if the data are plotted as a function of relative discrepancy.

The simulation results revealed that goal type, risk, and time sensitivity had an interactive influence on prioritization (see Figures 5, 6, and 7). To simplify the presentation of this interaction, we present the results in two stages. We first present the results for the approach–avoidance condition. We then present the results for the approach–approach and avoidance–avoidance conditions.

Approach–Avoidance

Figure 5 shows the proportion of times the model selected the action that prioritized the approach goal as a function of the time, risk, and individual differences in time sensitivity. In general, the model initially prioritized the approach goal. Over time, however, priority shifted from the approach goal to the avoidance goal. This pattern emerged because at the start of goal pursuit there was a relatively large distance to cover before either the desired or the undesired state would be reached. In this situation, the valence of acting on the approach goal is relatively high, whereas the valence of acting on the avoidance goal is relatively low. Over time, as the model got closer to the approach goal, the valence of acting on the approach goal decreased. At the same time, the model also got closer to the avoidance goal, because the avoidance goal had not been initially prioritized. The valence of acting on the avoidance goal therefore increased. This change in valence eventually caused the expected utility of acting on the avoidance goal to exceed the expected utility of acting on the approach goal, prompting a shift in priority.

The shift in priority from approach to avoidance also depended on risk. The effects of time were stronger when the consequences of actions were certain than risky. When the consequences of actions were certain, initial preference for the approach goal was stronger and the shift from approach to avoidance more pronounced than when the consequences were risky. This result emerged because attention is variable when actions are risky because of the multiple possible consequences. However, attention is less variable when actions are certain because there is only one consequence. The heightened variability in attention when deciding between risky actions made the choices at a given point in time less predictable.

Finally, time sensitivity had only a weak influence on prioritization. When actions were risky, there was virtually no difference in prioritization as a function of time sensitivity. When actions
were certain time sensitivity appeared to influence the timing of the shift in priority from approach to avoidance. When time sensitivity was lower, the switch in priority from approach to avoidance occurred earlier; when time sensitivity was higher, the switch in priority occurred later. This result emerged because lower levels of time sensitivity represent less sensitivity to the deadline, which increases the likelihood of switching priority before the approach goal is achieved.

Approach–Approach and Avoidance–Avoidance

For the conditions in which both goals are of the same type, we refer to each goal as simply Goal A or Goal B. Figures 6 and 7 show the proportion of times the model selected the action that prioritized Goal A as a function of risk, relative discrepancy, and time sensitivity when pursuing two approach goals (see Figure 6) or when pursuing two avoidance goals (see Figure 7). Goal type and time sensitivity both influenced the direction of the relationship between relative discrepancy and prioritization, whereas risk influenced the strength of these relationships.

In the approach–approach condition, the model most often prioritized the goal with the larger discrepancy when time sensitivity was lower, but prioritized the goal with the smaller discrepancy when time sensitivity was higher. Thus, the model produces behavior that is consistent with the concurrent strategy when time sensitivity is low, because it prioritizes the goal with the lowest likelihood of achievement, and switches priority

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**Figure 5.** Proportion of times the model selected the action that prioritizes the approach goal as a function of time, risk, and time sensitivity when pursuing one approach and one avoidance goal. See the online article for the color version of this figure.

**Figure 6.** Proportion of times the model selected the action that prioritizes Goal A as a function of the relative discrepancy, risk, and time sensitivity when pursuing two approach goals. See the online article for the color version of this figure.
between goals as relative discrepancy changes. However, the model produces behavior consistent with the sequential strategy when time sensitivity is high, because it prioritizes the goal with the greatest likelihood of attainment, and it tends to prioritize that goal until it is achieved.

In the avoidance–avoidance condition, a different pattern emerged. The model most often prioritized the goal with the smaller discrepancy at almost all levels of time sensitivity. This pattern is consistent with the concurrent strategy because it prioritizes the goal with the lowest likelihood of achievement. The pattern held unless time sensitivity was very high and actions were certain. In this case, the model exhibited a weak tendency to prioritize the goal with the larger discrepancy. This difference in the predominance of each strategy between the approach–approach and avoidance–avoidance conditions emerged because expected utility is more sensitive to differences in valence when valences are lower. Valence had a stronger effect in the avoidance–avoidance condition than in the approach–approach condition, because valence is initially relatively low when pursuing avoidance goals, but relatively high when pursuing approach goals. As a result, the model was more likely to prioritize the goal that was worse off in the avoidance–avoidance condition than in the approach–approach condition.

Finally, risk influenced the strength of these relationships. The interaction between goal type, relative discrepancy, and time sensitivity was stronger when actions were certain compared with when they were risky. Once again, this effect was attributable to the heightened variability in attention when actions were risky compared with when actions were certain. Because of this heightened variability in attention, choices were less predictable when actions were risky.

Empirical Test of the MGPM

Having generated predictions for the MGPM regarding the effects of goal type, risk, and time sensitivity on prioritization, we now test those predictions empirically. We made several hypotheses based on the simulation results. We begin with hypotheses for the approach–avoidance condition. In this condition, we focus on the effects of time and risk, because the simulation study revealed that these are the strongest predictors of prioritization. We made the following hypotheses:

**H1:** When pursuing one approach and one avoidance goal, people will shift priority over time from the approach to the avoidance goal.

**H2:** The shift in priority over time from the approach to the avoidance goal will be more pronounced when actions are certain than when they are risky.

We also made hypotheses for the approach–approach condition. In this condition, we focus on the effects of relative discrepancy, risk, and time sensitivity, because the simulation study revealed that all three are strong predictors of prioritization. We made the following hypotheses:

**H3:** When pursuing two approach goals, people with lower time sensitivity will be more likely to prioritize the goal with the larger discrepancy (i.e., the concurrent strategy), whereas people with higher time sensitivity will be more likely to prioritize the goal with the smaller discrepancy (i.e., the sequential strategy).

**H4:** The two-way interaction between relative discrepancy and time sensitivity described in H3 will be stronger when actions are certain than when they are risky.

Finally, we made hypotheses for the avoidance–avoidance condition. In this condition, time sensitivity influenced the magnitude of the effect of relative discrepancy, but not the direction of that effect. Our hypotheses are as follows:

**H5:** When pursuing two avoidance goals, people with higher time sensitivity will show a stronger tendency to prioritize the
goal with the smaller discrepancy (i.e., the concurrent strategy) than people with lower time sensitivity.

*H6:* The two-way interaction between relative discrepancy and time sensitivity described in H5 will be stronger when actions are certain than when they are risky.

In addition to examining whether the predictions of the MGPM* are supported, we also examine whether the empirical results can be accounted for by the original MGPM. Demonstrating that the MGPM* provides a better account of the data than the previous model is important because the increased complexity of the MGPM* can only be justified if the model has superior explanatory power. Thus, if the MGPM* does not provide a better account of the data, the original MGPM should be preferred on the grounds of parsimony. We therefore systematically compare the MGPM*’s ability to explain the empirical results to the MGPM. We also compare the MGPM* to two other alternatives to justify the integration of DFT and the introduction of the valence intercept.

**Method**

**Participants**

The sample consisted of 91 participants (46 males, 43 females, and 2 participants for whom gender was not specified) with ages ranging from 17 to 53 ($M = 20.82, SD = 6.31$). Seventy-two of these individuals were undergraduate students at an Australian university who participated for course credit. The other 19 were members of the university community who were recruited from a mailing list and given $20 compensation. There were no systematic differences as a function of sample concerning the predicted relationships. We therefore collapsed across samples for the analyses.

**Experimental Task**

We used the air-traffic control microworld (ATC-LabAdvanced, Fothergill, Loft, & Neal, 2009; see Figure 8) to design a task suitable for testing the MGPM*. During each trial, aircraft entered one-at-a-time from the left side of the screen. As each aircraft entered the screen, a dialogue box appeared asking the participant to assign the aircraft to one of two routes: the upper route or the lower route. Participants were asked to assign the aircraft to one of the two routes before it crossed a vertical line on the screen, which coincided with the time that the subsequent aircraft entered the sector. The participant could assign the aircraft to either route. If the participant failed to assign an aircraft to a route in the interval required, the participant would forfeit their opportunity to assign the aircraft to a route, the crossing would be regarded as unsuccessful, and the decision would be coded as a missing observation. This penalty encouraged participants to make a decision before the aircraft reached the point at which the routes diverge.

Once the participant made a route assignment decision, they had no control over the aircraft’s subsequent position. In some trials, military aircraft flight paths (i.e., indicated by light gray strips) intersected the upper and/or lower routes. The military flight paths always originated in the airspace between the upper and lower routes. The military flight paths followed one of three randomly determined trajectories. An aircraft crossing was successful if it crossed the screen along its designated route without breaching separation with a military aircraft (i.e., without coming within 5 nautical miles of it) and unsuccessful if it did breach separation. A scale marker was provided in the bottom right corner of the screen.

![Figure 8. Screenshot of the ATC task. In the condition shown, the upper route goal is approach and the lower route goal is avoidance. Moreover, assigning an aircraft to the upper route is risky, whereas the lower route is certain. See the online article for the color version of this figure.](image-url)
Manipulations

Goal type and risk were manipulated using a 4 (approach/approach; avoid/avoid; approach/avoid; avoid/approach) \( \times 4 \) (risky/risky; certain/certain; risky/certain; certain/risky) experimental design. Goal type was manipulated between participants, whereas risk was manipulated within participants.

**Goal type.** Goal type was manipulated by framing the goal as an approach goal or as an avoidance goal. For an approach goal, participants started each trial with zero points and were told to “achieve a score of 5 or more.” Points were gained for every aircraft that successfully crossed the route. No points were gained if the aircraft did not successfully cross the route or the route was not chosen. For an avoidance goal, participants started each trial with 10 points and were told to “avoid a score of 4 or less.” Points were lost for every aircraft that did not successfully cross the route or when the route was not chosen. No points were lost for aircraft that successfully crossed the route. The goal types were crossed, creating four conditions: both routes had approach goals, both routes had avoidance goals, the upper route had an approach goal and the lower route had an avoidance goal, or the upper route had an avoidance goal and the lower route had an approach goal.

To reinforce the desirability of the approach goals, participants received 25¢ per goal achieved. To reinforce the undesirability of the avoidance goals, participants lost 25¢ per goal they failed to achieve. Participants with two approach goals began with no money but could gain a much as 50¢ per trial; whereas participants with two avoidance goals began with $8 but could lose as much as 50¢ per trial. Participants in conditions where the routes had different types of goals began with $4 but could only gain 25¢ at most or only lose 25¢ at most per trial.

**Risk.** There were four risk conditions: both routes risky, both routes certain, risky upper route and certain lower route, certain upper route and risky lower route. Risky routes were those that intersected a military flight path. On risky routes, the aircraft had a 50% chance of breaching separation with a military aircraft and a 50% chance of crossing successfully. Participants were told these probabilities ahead of time. Certain routes were those that were not intersected by a military flight path. On certain routes, the aircraft had no chance of breaching separation with a military aircraft (i.e., a 100% chance of successfully crossing).

We designed the scoring system so that objective value for choosing a route was constant regardless of risk (see Appendix B). For example, for routes with approach goals the expected points gained or choosing the other route. This scoring system also ensured that approach and avoidance goals were equivalent, such that participants had the same chance of gaining/not losing the required number of points for goal success, regardless of goal type.

**Time sensitivity.** Time sensitivity was estimated for each participant by fitting the MGPM* to their data.

**Procedure**

Participants were randomly assigned to a goal type condition and presented with task instructions. They then completed a practice trial followed by 16 experimental trials. Participants were told the total number of trials to expect before beginning the experiment. Before each trial, they were told which routes would be risky (i.e., which routes would be intersected by military flight paths in that trial) and which certain as well as the probabilities and scoring consequences of successfully or unsuccessfully crossing each route. Ten aircraft were presented in each trial. The first aircraft in each trial entered the screen immediately, with each new aircraft entering every 19 seconds. The goals and cumulative scores for the upper and lower routes were presented in the top-left and top-right hand corners of the screen respectively for the entire trial. Each trial lasted approximately 4 min 30 sec and ended after the tenth aircraft exited the sector. After each trial, a feedback screen was presented for 15 seconds indicating whether the participant’s goals were achieved. The risk manipulation was randomized across trials with each participant experiencing each risk combination condition four times. After the experiment, participants received their compensation and cumulative monetary incentive.

**Model Fitting**

We used MATLAB to fit the MGPM* to the observed data. We fixed the valence intercept, gain, expected lag, and the attention weights to the values shown in Table 2. These were the same values that were used for the simulation. However, we estimated the value of the time sensitivity and threshold parameters because they were expected to vary across individuals. We estimated these parameters by identifying the values that maximized the likelihood of the observed decisions (using the simplex algorithm implemented by MATLAB’s ‘fminsearch’ function). The model was fit separately to each participant. Therefore, each participant provided a unique estimate of time sensitivity \( (M = 0.21, SD = 0.19) \) and threshold \( (M = 0.49, SD = 0.77) \). For every decision made by the participant, the model predicted the probability that the participant would select the upper and lower routes. We henceforth refer to these predicted probabilities as the 'fitted values' because they represent the choice probabilities generated by the model after it has been fitted to the participant’s decisions.

**Results**

We first report the results of statistical analyses that we used to examine whether the predictions of the MGPM* were supported. We also qualitatively evaluate the model-data fit by plotting the fitted values against the data. We then compare the fit of the MGPM* to the MGPM and to two other alternative models to examine whether the extensions made to the model were justified.

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2 With any maximum likelihood method, a single case in which the model predicts a participant’s choice with a probability of 0 would make the model infinitely unlikely. Therefore, following Rieskamp (2008), all predicted choice probabilities were constrained to a minimum of 0.01 and a maximum of 0.99 for the model fitting.
Statistical Tests of Hypotheses

We tested the hypotheses by running a series of logistic mixed effects models that controlled for the random effects of trial and participant. These analyses were run in R using the ‘glmer’ function within the ‘lme4’ package (Bates, Maechler, Bolker, & Walker, 2014).

Hypotheses 1 and 2. We tested Hypotheses 1 and 2 by running a logistic mixed effects model on the subset of participants in the approach–avoidance condition. The dependent variable in this model was whether or not participants prioritized the approach goal (1 = yes, 0 = no). The fixed effects in the model were time elapsed, risk, and the interaction between time elapsed and risk. To examine the interaction between time elapsed and risk, we also included the trial-level random effect of time elapsed. Time elapsed was represented by the order in which each decision was made (i.e., the first decision was coded as 0; the second was coded as 1; etc.). Risk was coded such that 1 indicated that both actions were risky and 0 indicated that both actions were certain (see Figure 9). Inspection of the fitted values shows that, in general, the MGPM accurately captured the effects of time and risk. However, the MGPM appears to underestimate the strength of the tendency to initially prioritize the approach goal when both actions are risky.

Hypotheses 3 and 4. We tested Hypotheses 3 and 4 by running a logistic mixed effects model on the subset of participants in the approach–approach condition. The dependent variable in this model was whether or not participants prioritized the upper route (1 = yes, 0 = no). The fixed effects were relative discrepancy, risk, time sensitivity, and the three-way interaction between these variables, and the three-way interaction. To examine these interactions, we also included the trial-level random effect of relative discrepancy, and the participant-level random effects of relative discrepancy and risk. Relative discrepancy was calculated by subtracting the discrepancy for the lower route from the discrepancy for the upper route goal at each time point. Positive relative discrepancies indicated that the discrepancy for the upper route was larger than the discrepancy for the lower route. We did not analyze observations in which one or more goals had been achieved or failed, because the effect of relative discrepancy cannot be interpreted in these cases.

We tested Hypothesis 3 by examining the two-way interaction between relative discrepancy and time sensitivity. This interaction was significant. Figure 10 shows the proportion of cases in which individuals prioritized the upper route in the approach–approach and avoidance–avoidance conditions as a function of relative discrepancy, risk, and time sensitivity. For the purposes of plotting the effects of time sensitivity in Figures 10 and 11, participants

<table>
<thead>
<tr>
<th>Condition</th>
<th>Effect</th>
<th>Coefficient</th>
<th>SE</th>
<th>Corresponding hypothesis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Approach–Avoidance</td>
<td>Intercept</td>
<td>1.80*</td>
<td>.10</td>
<td>H1</td>
</tr>
<tr>
<td></td>
<td>Time elapsed</td>
<td>-.38*</td>
<td>.02</td>
<td>H1</td>
</tr>
<tr>
<td></td>
<td>Risk</td>
<td>-.51*</td>
<td>.08</td>
<td>H1</td>
</tr>
<tr>
<td></td>
<td>Time elapsed × Risk</td>
<td>.13*</td>
<td>.02</td>
<td>H2</td>
</tr>
<tr>
<td>Approach–Approach</td>
<td>Intercept</td>
<td>.06</td>
<td>.28</td>
<td>H3</td>
</tr>
<tr>
<td></td>
<td>Relative discrepancy</td>
<td>2.28*</td>
<td>.22</td>
<td>H3</td>
</tr>
<tr>
<td></td>
<td>Time sensitivity</td>
<td>.67</td>
<td>.86</td>
<td>H3</td>
</tr>
<tr>
<td></td>
<td>Risk</td>
<td>-.10</td>
<td>.25</td>
<td>H3</td>
</tr>
<tr>
<td></td>
<td>Relative discrepancy × Time sensitivity</td>
<td>-6.37*</td>
<td>.63</td>
<td>H3</td>
</tr>
<tr>
<td></td>
<td>Relative discrepancy × Risk</td>
<td>-2.15*</td>
<td>.22</td>
<td>H4</td>
</tr>
<tr>
<td>Avoidance–Avoidance</td>
<td>Intercept</td>
<td>.51</td>
<td>.17</td>
<td>H5</td>
</tr>
<tr>
<td></td>
<td>Relative discrepancy</td>
<td>-1.53*</td>
<td>.20</td>
<td>H6</td>
</tr>
<tr>
<td></td>
<td>Risk</td>
<td>-.22*</td>
<td>.07</td>
<td>H6</td>
</tr>
<tr>
<td></td>
<td>Relative discrepancy × Risk</td>
<td>.003</td>
<td>.08</td>
<td>H6</td>
</tr>
</tbody>
</table>

Note. An asterisk indicates that a coefficient differs significantly from 0 at p < .05. H5 could not be examined because of lack of variability in time sensitivity in avoidance–avoidance condition. The model run on the approach–avoidance condition had the form: \( \text{Logit(Probability of Selecting Route with Approach Goal)} = \beta_0 + \beta_1(\text{Time Elapsed}) + \beta_2(\text{Risk}) + \beta_3(\text{Time Elapsed} \times \text{Risk}) + \gamma_0 + \gamma_0(\text{Time Elapsed}) + \epsilon \). The model run on the approach–approach condition had the form: \( \text{Logit(Probability of Selecting Upper Route)} = \beta_0 + \beta_1(\text{Relative Discrepancy}) + \beta_2(\text{Time Sensitivity}) + \beta_3(\text{Risk}) + \beta_4(\text{Relative Discrepancy} \times \text{Time Sensitivity}) + \beta_5(\text{Relative Discrepancy} \times \text{Risk}) + \beta_6(\text{Relative Discrepancy} \times \text{Time Sensitivity} \times \text{Risk}) + \gamma_0 + \gamma_0(\text{Relative Discrepancy}) + \gamma_0(\text{Time Sensitivity}) + \gamma_0(\text{Risk}) + \gamma_0 + \gamma_0(\text{Relative Discrepancy}) + \epsilon \). The model run on the avoidance–avoidance condition had the form: \( \text{Logit(Probability of Selecting Upper Route)} = \beta_0 + \beta_1(\text{Relative Discrepancy}) + \beta_2(\text{Risk}) + \beta_3(\text{Relative Discrepancy} \times \text{Risk}) + \gamma_0 + \gamma_0(\text{Relative Discrepancy}) + \epsilon \). In these three equations, \( \beta \) indicates a fixed effect, \( \gamma \) indicates a participant-level random effect, \( \epsilon \) indicates a trial-level random effect, and \( \epsilon \) indicates the decision-level error.
were classified as “higher” time sensitivity if their time sensitivity parameter value was above the median (0.22), and “lower” time sensitivity if their value was below the median. Because the median split was applied across the entire sample, the number of participants in each category could differ within goal frame conditions. In the approach–approach condition, 7 participants were classified as higher time sensitivity and 18 were classified as lower. Consistent with Hypothesis 3, participants with lower time sensitivity tended to prioritize the goal with the larger discrepancy, whereas participants with higher time sensitivity tended to prioritize the goal with the smaller discrepancy.

We tested Hypothesis 4 by examining the three-way interaction between relative discrepancy, time sensitivity, and risk. This interaction was significant. Consistent with Hypothesis 4, the two-way interaction between relative discrepancy and time sensitivity was stronger when the consequences of actions were certain than when they were risky. In fact, when one or more actions were risky there appears to be no effect of relative discrepancy for the high time pressure group and only a weak effect for the low time pressure group. Visual inspection of the fitted values suggests that the MGPM accurately captures the effects of relative discrepancy, risk, and time sensitivity in the approach–approach condition.

![Figure 9](image1.png)

**Figure 9.** Proportion of times participants selected the action that prioritizes the approach goal as a function of time and risk when pursuing one approach and one avoidance goal. Observations were collapsed across time sensitivity values. The points indicate participant proportions (with standard error). The lines indicate the fitted values of the MGPM collapsed across participants. See the online article for the color version of this figure.

![Figure 10](image2.png)

**Figure 10.** Proportion of times participants selected the upper route as a function of relative discrepancy, risk, and time sensitivity when pursuing two approach goals. In this condition, 18 participants were in the lower time sensitivity group and 7 were in the higher time sensitivity group. The points indicate participant proportions (with standard error). The lines indicate the fitted values of the MGPM collapsed across participants. See the online article for the color version of this figure.
Hypotheses 5 and 6. In the avoidance–avoidance condition, there was very little variability in time sensitivity. For all 22 participants in this condition, time sensitivity was below the 50th percentile (thus all were in the lower time sensitivity group), and 20 of them had a parameter value of 0. Because of the restriction of range in this condition, it was inappropriate to examine the effect of time sensitivity. We therefore only examined the effects of relative discrepancy and risk.

We analyzed the effects of relative discrepancy and risk by running a logistic mixed effects model on the subset of participants in the avoidance–avoidance condition. The dependent variable in this model was whether or not participants prioritized the upper route (1 = yes, 0 = no). The fixed effects were relative discrepancy, risk, and the interaction between relative discrepancy and risk. To examine the interaction between relative discrepancy and risk, we included the trial-level random effect of relative discrepancy. As expected, there was a negative effect of relative discrepancy, suggesting that participants tended to prioritize the goal with the smaller discrepancy. As can be seen in Figure 11 this tendency was strong even when both actions were risky. As a result, the interaction between relative discrepancy and risk was not significant. Inspection of Figure 11 suggests that the fitted values in the avoidance–avoidance conditions are fairly accurate when one or both of the actions has a certain outcome. However, the MGPM* appears to underestimate the strength of the tendency to prioritize the goal with the smaller discrepancy when both actions are risky.

Model Comparisons

In this section, we compare the fit of the MGPM* to the original MGPM (Vancouver et al., 2010) and to two other simpler alternatives. A good model achieves a balance between fit and parsimony. The original MGPM is simpler than the MGPM*. To justify the increase in complexity, the MGPM* must provide a more accurate description of the data than the MGPM. We therefore first compare the MGPM* to the MGPM. However, demonstrating that the MGPM* provides a better account of the data does not necessarily mean that the addition of the avoidance intercept parameter and the sequential sampling component are both justified. It is possible that an increase in the model’s ability to explain the data is attributable to one of these extensions, but not the other. We therefore follow up the comparison of the MGPM* to the MGPM by comparing the MGPM* to alternatives that isolate one of these extensions. These comparisons enable us to evaluate the evidence for each extension independently.

We compared the models using the Bayesian Information Criterion (BIC; Schwartz, 1978). We used the BIC because the models were not nested. Therefore, it was not appropriate to use traditional significance tests such as the likelihood ratio test to compare the model fits. The BIC is a well-established model selection criterion that accounts for both fit and parsimony and can be used for comparing non-nested models. We used the BIC in preference to other criteria used to compare non-nested models (e.g., the Akaike Information Criterion), because the BIC applies a harsher penalty for model complexity, and therefore provides a stronger test of a hypothesized model when it is being compared against simpler alternatives as is the case here. The BIC is interpreted by examining the difference in BIC values for the models being compared. A difference in BIC values of 5 or more indicates “strong” evidence in favor of the model with the lower value, and a difference of 10 or more indicates “very strong” evidence (Raftery, 1995).

Comparison of the MGPM* with the original MGPM. We implemented the original MGPM by specifying a model identical to the one presented by Vancouver et al. (2010). Vancouver et al. estimated a parameter in the original MGPM, referred to as time gain, that determined the relationship between the subjective perception of time available and the objective amount. We also estimated this parameter from the data when fitting the MGPM. For participants in the approach–avoidance condition, we also estimated gain for the avoidance goal to account for the possibility

![Figure 11](image-url)
that the effects of goal framing could be explained by differences in goal importance. For example, research has indicated that people are more motivated by the threat of negative outcomes than the opportunity to achieve positive outcomes (Highhouse & Johnson, 1996; Kahneman, Knetsch, & Thaler, 1991; Tversky & Kahneman, 1991). These findings suggest that avoidance goals may be more important than approach goals. We fixed gain for the approach goal to 1, because only one free parameter was required to examine whether gain differed between goals. In the approach–approach and avoidance–avoidance contexts, the value of the gain parameter does not affect the model predictions because it is assumed equal for the two goals and cancels out. For participants in these conditions, we fixed gain to 1 for both goals. We estimated the relevant parameters using the same procedure that we used to estimate the parameters of the MGPM (described in the “Model Fitting” section above).

For each participant we calculated the BIC difference. Positive values indicated evidence in favor of the MGPM and negative values indicated evidence in favor of the MGPM. The BIC differences favored the MGPM for 90% of participants (M = 44.77). For 77% of participants, the evidence in favor of the MGPM was in the strong or very strong ranges (i.e., >5). Only 2% of participants yielded BIC differences that indicated strong evidence in favor of the original MGPM (i.e., <5). These results suggest that, in general, the MGPM provides a better account of the experimental data than the MGPM.

Comparison of the MGPM with two other alternatives.

Although we have shown that the MGPM provides a better account of participants’ prioritization decisions than the MGPM, we still do not know whether both of the extensions—the integration of DFT and the introduction of the valence intercept—are needed in their own right to explain prioritization. We therefore examine two other alternative models to assess these extensions in isolation.

The purpose of testing Alternative 1 was to examine whether the more sophisticated choice mechanism from DFT is required to account for prioritization. We therefore created Alternative 1 to be identical to the MGPM, except that it did not include the sequential sampling component of the model. Instead, it simply assumed that the goal with the higher expected utility is always prioritized (and that if the expected utilities are equal, the probability of prioritizing each goal is 0.5). Support for Alternative 1 would provide a better account of the experimental data than the MGPM.

The purpose of testing Alternative 2 was to examine whether the valence intercept (and the corresponding assumption that valence increases as one moves closer to an undesired state) is necessary to account for prioritization of avoidance goals. We created Alternative 2 to be identical to the MGPM, except that the valence of acting on an avoidance goal is defined in the same way as for an approach goal. Specifically, for approach and avoidance goals, the valence intercept was fixed to 0, and gain was constrained to be positive. As with our implementation of the MGPM, we allowed for differences in gain between different types of goals by estimating gain for the avoidance goal among participants in the approach–avoidance condition while fixing gain for the approach goal to 1. As before, we fixed gain to 1 for both goals for participants in the avoidance–avoidance condition. We did not consider participants in the approach–approach condition for this comparison, because the MGPM and Alternative 2 are identical when no avoidance goals are present. Support for Alternative 2 would suggest that the valence intercept is not necessary to account for prioritization, and the variability in gain between approach and avoidance goals is sufficient to account for the observed pattern of results.

The BIC differences favored the MGPM over Alternative 1 for 99% of participants (M = 167.02), with all of these participants in the strong to very strong range. The BIC differences favored the MGPM over Alternative 2 for 89% of participants (M = 22.64), with 68% of participants in the strong or very strong evidence range. These findings suggest that the MGPM provides a better account of the data than either alternative model and that the two major extensions are justified.

Discussion

Our aim was to (a) extend the MGPM to provide a more sophisticated explanation that accounts for the complex choice problems encountered during multiple-goal pursuit, (b) enable the model to account for avoidance goals, and (c) demonstrate that the model can account for individual differences in prioritization strategy. The extended model, the MGPM, is an integration of the original MGPM (Vancouver et al., 2010) and DFT (Busemeyer et al., 2006; Busemeyer & Townsend, 1993) that explains how people prioritize when pursuing different combinations of approach or avoidance goals where actions involve risk or uncertainty and when actions can impact progress for more than one goal. In a simulation study, we demonstrated that the MGPM predicts differences in prioritization as a function of goal type, risk, and time sensitivity.

The predictions of the MGPM corresponded with the behavior observed. As predicted, individuals who pursued one approach and one avoidance goal tended to switch priority from the approach goal to the avoidance goal over time. Among those pursuing two approach goals, time sensitivity interacted with relative discrepancy in the manner that was predicted. Participants with a low value for the time sensitivity parameter tended to prioritize the goal with the larger discrepancy, which is consistent with the concurrent strategy. Participants with a high value for the time sensitivity parameter tended to prioritize the goal with the smaller discrepancy, which is consistent with the sequential strategy, but only tended to do so when both actions were certain. Everyone who pursued two avoidance goals tended to display the concurrent strategy by prioritizing the goal with the smaller discrepancy. As predicted, these effects were stronger when the consequences of both actions were certain, compared to when one or more of the actions were risky, except in the case of those pursuing two avoidance goals. We also showed that the MGPM provided a better account of participants’ prioritization decisions than the original MGPM and that the major extensions to the model could be justified. In the following sections, we discuss the theoretical, empirical, and practical contributions of this paper, highlight potential limitations, and suggest avenues for further research.

Contributions to the Multiple-Goal Pursuit Literature

The MGPM generalized the original MGPM to include avoidance goals. Moreover, it generated novel predictions that, in gen-
eral, were supported by the data. The predictions regarding goal type converge on the notion that, if expectancy is held constant, people are more likely to prioritize the goal with the higher valence. The model assumes that valence decreases as you get closer to a desired state (i.e., an approach goal), but increases as you get closer to an undesired state (i.e., an avoidance goal). As a result, people simultaneously pursuing one approach and one avoidance goal tended to prioritize the approach goal earlier and the avoidance goal later. The prediction emerged because the valence, and therefore the expected utility of acting on the avoidance goal, is lower when the goal is further away, and is therefore outweighed by the expected utility of acting on the approach goal.

It is important to note that the nature of the approach-to-avoidance priority shift may differ when the initial states for the goals differ. For example, if the initial state for the avoidance goal was closer to the undesired state, the priority shift could occur earlier (or not at all), because the expected utility of acting on the avoidance goal would be higher.

The MGPM’s prediction regarding risk is that the tendency to prioritize a particular goal should be stronger when actions have more certain consequences. This prediction is a direct consequence of incorporating DFT into the MGPM (Bussemeyer & Townsend, 1993). According to DFT, people pay attention to the most likely consequences of their actions. As risk levels increase, people pay more attention to a range of different consequences. This creates more variability in preferences over time, which weakens the effect of a goal’s expected utility. As a result, people make noisier decisions. SEU theory cannot account for this tendency for decisions to become noisier as variability in possible consequences increases (Bussemeyer, 1985). We observed this effect of risk in the approach–avoidance and approach–approach conditions. Indeed, for participants in the approach–approach condition with higher time sensitivity parameter values, the effect of relative discrepancy disappeared when one or more action did not have certain consequences. These findings provide strong support for replacing the choice function in the original MGPM with the sequential sampling process described by DFT when predicting complex choices.

Although the predictions of the MGPM were largely supported, we did not find the expected effect of risk in the avoidance–avoidance condition. In this condition, people demonstrated a consistent tendency to prioritize the goal with the smaller discrepancy regardless of risk. As a result, the model did not provide a close fit to the data when participants were pursuing two avoidance goals and actions were risky, as it did in other conditions. Furthermore, although the model correctly predicted the direction of the effect of risk in the approach–avoidance condition, it overestimated the strength of the effect. The shift in priority from approach to avoidance over time was stronger than predicted by the model when both actions were risky. These findings illustrate the value of using formal models, because it is clear when a model cannot account for the direction or strength of effects observed in the data. One explanation for the lack of an effect of risk in the avoidance–avoidance condition is that people focus their attention more narrowly in the presence of avoidance goals (Förster, Friedman, Özelsel, & Denzler, 2006; Friedman & Förster, 2005). Allocating attention in this way would mean that attention fluctuates less when actions have multiple possible consequences, and would therefore weaken the effect of risk. The MGPM might account for this by assuming that, when avoidance goals are present, attention is not necessarily allocated in line with the objective probability of the possible consequences.

Finally, the MGPM provides a formal explanation for individual differences in prioritization strategy. We observed a mix of behavioral patterns among participants pursuing two approach goals, with some participants displaying the concurrent strategy and others displaying the sequential strategy. Individual differences in strategy were reflected in the time sensitivity parameter. According to the MGPM, when time sensitivity is higher, people are more likely to make prioritization decisions based on expectancy. As a result, people will tend to display a sequential strategy: They will generally work on the goal with the greatest likelihood of attainment and continue to do so until that goal is sufficiently close to achievement. When time sensitivity is lower, people are less likely to make prioritization decisions based on expectancy. As a result, people will tend to display a concurrent strategy by working on the goal with the highest valence, and switch priority between goals as relative position changes.

Goal Framing Versus Incentive Framing

In the experiment presented here, we used incentives to reinforce the desirability of the approach goals and the undesirability of the avoidance goals. It is therefore reasonable to ask whether the effect of the manipulation of goal type was due to the framing of the goals or the framing of the incentives. However, if our results were attributable to incentive framing, then the original MGPM should be able to account for the effect of the experimental manipulation. This is because the original MGPM assumes that incentives influence goal importance (and therefore prioritization) via the gain parameter. Our model comparisons revealed that the original MGPM did not explain participants’ decisions as well as the MGPM. We also examined an alternative model (Alternative 2), which was identical to the MGPM except that it did not contain the valence intercept—the extension to the valence function that we argued was required to account for the effect of goal type. This alternative model could not account for the effect of the experimental manipulation either. Furthermore, the results of the current study are consistent with an unpublished study that manipulated only goal framing (Ballard et al., 2013). This study replicated the finding that people pursuing two avoidance goals tend to prioritize the goal with the smaller discrepancy, and people pursuing an approach and avoidance goal tend to shift priority over time from the approach to the avoidance goal. Collectively, these findings suggest that the effect of the goal type manipulation observed in the current study was not simply due to incentive framing.

Nevertheless, we still view incentive framing as an important avenue for future research. It would be useful to manipulate goal framing and incentive framing independently to examine their interaction. Such a manipulation was not feasible in our study because of the complex design (our goal type × risk manipulation had 16 unique combinations). However, it would be possible to examine the Goal frame × Incentive frame interaction without manipulating risk. We predict that incentive frame should influence the strength of the effect of relative discrepancy, and that the MGPM will account for the effect using the gain parameter.

3 Details available from the authors.
Schmidt and DeShon (2007) showed that people pursuing two approach goals showed a stronger tendency to prioritize the goal in the worse position when incentives were framed as losses compared to gains. They argued that the effect of relative discrepancy was stronger in the former context because of loss aversion (Kahneman & Tversky, 1979)—people are more sensitive to potential losses than gains of equivalent magnitude. If so, then gain should be stronger when goals have incentives that are framed as losses, regardless of whether the goal is approach or avoidance (Vancouver et al., 2010).

**Practical Applications**

There are a number of potential applications of the findings of this study in situations that require individuals to manage multiple goals. The finding that people shift priority from approach to avoidance goals over time may be particularly important in safety critical industries, such as mining, aviation, or medicine, where people have to effectively manage safety and productivity goals. Productivity is typically framed as an approach goal, whereas safety is typically framed as an avoidance goal (e.g., ensuring that the number of incidents does not exceed a specified level over a given period). Our results suggest that framing productivity and safety goals in this manner may lead people to prioritize productivity over safety. One way to encourage people to prioritize safety may be to frame safety as an approach goal. This is consistent with a growing interest in the safety literature on promoting behaviors that make the work environment safe, rather than preventing behaviors that make it unsafe (Neal & Griffin, 2006). In aviation, for example, there has been a shift away from ‘conflict detection and avoidance,’ which is an avoidance goal, toward ‘separation assurance,’ which is an approach goal (Durso & Manning, 2009; Loft, Bolland, Humphreys & Neal, 2009).

The current study provides insight into different ways to influence how individuals or teams allocate resources when managing multiple tasks. There are many situations in which people need to prioritize the allocation of resources. Common examples include project management and task scheduling. Under some circumstances, the best strategy is to prioritize the task with the greater amount of work required because it ensures that progress is made on both. Under other circumstances, the best strategy is to focus on the task with the least amount of work required, to ensure that at least one task is completed by the deadline (Ballard, Yeo, Neal, & Farrell, 2016). Our findings suggest that these choices are sensitive to the way that the goals are framed and the level of uncertainty that employees have regarding the potential consequences of their actions. For example, if a manager wants employees to use the concurrent strategy, it would make sense to frame the goals in avoidance terms and to enhance the level of certainty regarding the consequences of actions. For example, certainty may be enhanced by reducing the number of distractions in the work environment or allocating particular times to work exclusively on that task. However, in many cases, uncertainty will be unavoidable. Our results imply that people will not show strong preferences for one strategy over the other when there is a high level of uncertainty. This may well be adaptive because it means that people are more flexible in the way they prioritize goals in an uncertain environment (Hannah & Neal, 2014).

The lack of variability in strategy in the avoidance–avoidance context is interesting from a practical perspective because it implies that conflict between avoidance goals creates a psychologically “strong” environment that limits the potential for individual differences to be expressed (Sydner & Ickes, 1985). This finding has implications for understanding how managers can use different types of goals to enhance team performance. Strong situations can enhance cooperation because they provide clear behavioral norms (de Kwaadsteniet, van Dijk, Wit, & de Cremer, 2006). However, too much homogeneity among team members can lead to poor group decision making (Olson, Parayitam, & Bao, 2007). In the end, goal framing may not provide a one-size-fits-all solution for optimizing strategies among individuals and teams. However, our results highlight the need for managers to be aware of the implications that goal frame has on strategy.

**Additional Considerations and Avenues for Future Research**

One issue that should be considered is the assumption that the subjective immediate value (i.e., valence) of acting on a goal is always a linear function of the discrepancy. Both the MGPM and DFT share this assumption and are able to account for a broad range of empirical phenomena (Busemeyer et al., 2006; Vancouver et al., 2010, 2014). However, this assumption may not always hold. For example, if the assistant professor is told that she will lose her job if she does not publish 10 papers before her tenure deadline, the valence of publishing her tenth paper could be just as high as the valence of publishing her first. In this case, valence may be more accurately described as a step-function that drops only after the tenth paper is published. Alternatively, Heath, Larick and Wu (1999) have made arguments that suggest the valence function may be nonlinear, following the form described by prospect theory (Kahneman & Tversky, 1979).

It is worth noting that the MGPM cannot explain how well or how poorly people make decisions during multiple-goal pursuit. This type of examination requires evaluating people’s decisions against a normative model (Baron, 2004, 2012). Recent work has extended a normative model of decision making to the multiple-goal pursuit context and found that people depart from optimal prioritization in systematic ways depending on whether they are pursuing approach or avoidance goals (Ballard et al., 2016). By comparing the MGPM’s predictions to this type of normative model, it would be possible to assess the extent to which the MGPM predicts departures from optimality. In doing so, future work may be able to use the MGPM to explain why people exhibit biases in decision making during multiple-goal pursuit.

**Applicability of the MGPM**

The MGPM can be applied to different types of multiple-goal environments. In some cases, goals are directly in conflict with each other such that progress toward one goal precludes the possibility of progress toward another goal. In other cases, it is possible to make progress toward both goals at the same time. In this experiment, we assumed that a person could make progress toward an approach goal if this goal was prioritized, but could not make progress towards the goal that was not prioritized. Likewise, the person could prevent themselves from moving toward an
avoidance goal if the avoidance goal was prioritized, but was guaranteed to move closer to it if the goal was not prioritized. However, the MGPM\(^*\) can also be applied to environments in which actions may simultaneously benefit multiple goals or when the probabilities of making progress toward goals are different. Research has shown that the effects that emerge in these types of environments are similar to the ones observed in the experiment presented above. Ballard et al. (2013) compared prioritization patterns in environments in which actions could simultaneously benefit both goals versus when they could only benefit one goal at a time, and found few differences between the two environments. Furthermore, the qualitative pattern of prioritization when actions had an 80\% chance of benefitting a goal was similar to the pattern when actions only had a 50\% chance.

Although we only examined prioritization involving two goals, the model can be applied to any number of goals. The MGPM\(^*\) can also be generalized to choices involving more than two actions in the same way as DFT (see Roe et al., 2001)—by assuming that the preference state for each action undergoes a separate accumulation process, and that preference for one action suppresses preference for the other actions. In this way, the MGPM\(^*\) can account for the fact that people take longer to decide between three or more actions than they do to decide between two (Busemeyer & Diedrich, 2002; Onken, Hastie, & Revelle, 1985). The MGPM\(^*\) can also be generalized to decisions involving uncertainty, rather than risk, by assuming that attention weights change as people learn the likelihood of different consequences. Moreover, we only examined an environment in which disturbances affected the consequence of an action. However, there are other types of disturbances. The MGPM\(^*\) can be generalized to situations in which disturbances may affect the time it takes for the consequence of an action to become apparent, or alter the state of the variable being controlled in the absence of any action being carried out (Vancouver et al., 2014).

It is important to recognize that some of the parameters included in the original MGPM and DFT were not addressed in this paper. All of the parameters from each theory are relevant to the MGPM\(^*\) and are important for understanding decision making during multiple-goal pursuit more generally. For parsimony, however, we focused this paper on parameters that we believed were most important to understanding the effects of approach–avoidance framing and risk on prioritization. Here we discuss additional parameters and provide suggestions for how they might be incorporated in future research.

For example, the original MGPM includes an expected lag bias parameter that represents individuals’ beliefs regarding the rate of progress that can be achieved when working toward a goal. This parameter is potentially important for understanding a source of optimism or pessimism in expectancy. The model presented in this paper assumed that, when someone is completely ignorant of the difference between the time available and the expected time required to reach the goal (i.e., when $\gamma = 0$), expectancy would always equal 0.5. However, incorporation of the bias parameter would explain how a person who is optimistic about the achievable rate of progress might have an expectancy of greater than 0.5, or how a pessimistic person might have an expectancy of less than 0.5.

DFT includes self-feedback parameters that produce a return to baseline phenomenon in which memory for preferences decays over time (i.e., ‘leaky’ accumulation). It also includes lateral inhibition parameters that produce ‘suppression,’ whereby preference for one action is inhibited by preference for another action. These parameters are particularly relevant for understanding choices involving more than two actions (i.e., Roe et al., 2001). Busemeyer and Townsend (1993) also introduce an approach–avoidance gradient parameter. This parameter enables the model to account for the fact that people take longer to decide between actions with undesirable consequences than they do to decide between actions with desirable consequences (Busemeyer & Townsend, 1993; Houston et al., 1991). We did not address this parameter because it has little effect on choice probabilities (see Figure 9 in Busemeyer & Townsend, 1993). However, this parameter will be important for future research seeking to model the relationship between goal framing and the time it takes to make a prioritization decision.

Conclusion

The MGPM\(^*\) represents a step forward in the development of a formal, unified theory of multiple-goal pursuit. We demonstrated that the MGPM\(^*\) can explain how people make prioritization decisions when pursuing different combinations of approach and avoidance goals, and when the consequences of actions vary in their level of risk. We hope that the MGPM\(^*\) will be used as a foundation for continued development of a general theory of motivation and decision making that explains the importance of goals in navigating the complexity and uncertainty of one’s environment, and, in doing so, helps to build a stronger bridge between basic psychological science and organization studies.

References


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(Appendices follow)
Appendix A

Formula for Calculating Choice Probability

We followed Busemeyer and Townsend’s (1993) formula for calculating the probability of selecting one action from a set of two, when the model assumes no initial preference bias (i.e., \( p(0) = 0 \)). We calculated the probability of selecting action 1 (\( a_1 \)) in favor of action 2 (\( a_2 \)) as follows:

\[
p_r(a_1, a_2) = \frac{1}{1 + \exp\left(-2 \cdot \frac{A_1(t) - A_2(t)}{\sigma(t)} \right)}.
\]

where \( A_1(t) \) and \( A_2(t) \) are the expected momentary attractiveness for actions 1 and 2 and \( \sigma(t) \) is the standard deviation of the difference in their momentary attractiveness at a given point in time. We have denoted these variables as time varying to express the fact that their values change from decision to decision during multiple-goal pursuit. However, in line with Busemeyer and Townsend (1993), we assume that their values do not change within a single decision episode. Following Rieskamp (2008), we assume that the decision maker always chooses a threshold that is proportional to \( \sigma \). Thus, the threshold \( (\theta) \) is expressed in units that represent the standard deviation of the momentary attractiveness.

The expected momentary attractiveness for a given action is defined as follows:

\[
\overline{A}_i(t) = \sum_{j} w_{ij} \cdot M_{ij}(t).
\]

The standard deviation of the difference in momentary attractiveness is defined as follows:

\[
\sigma(t) = \sqrt{\sum_{ij} [M_{ij}(t) - \overline{A}_i(t)]^2}.
\]

Thus, the standard deviation of the difference in momentary attractiveness represents the square root of the total variance in consequences across both actions. Note that Busemeyer and Townsend’s (1993) formula also accounts for the covariance in consequences of different actions. We did not include this term because there was no covariance in the consequences of the actions in the experiment presented in this paper. Because the standard deviation of the difference in momentary attractiveness was 0 in the condition in which both actions had certain consequences, the choice probabilities for this condition could not be calculated unless a small constant was added to the variance of the valence difference. Thus, we added \( 10^{-5} \) to the output of Equation A3 when computing variance in the momentary attractiveness difference for all choices to avoid having to divide by zero. This constant had no visual effect on the predictions for the other conditions. Conceptually, this constant can be seen as additional variability in attention attributable to off-task activities (Roe et al., 2001).

Appendix B

Summary of Scoring System

<table>
<thead>
<tr>
<th>Risk level</th>
<th>Action selected</th>
<th>Upper route</th>
<th>Lower route</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Risky</td>
<td>Certain</td>
<td>Risky</td>
</tr>
<tr>
<td></td>
<td>Outcome</td>
<td>Success</td>
<td>Failure</td>
</tr>
<tr>
<td>Probability of occurrence</td>
<td>50%</td>
<td>50%</td>
<td>100%</td>
</tr>
<tr>
<td>Goal type</td>
<td>UR approach/LR approach</td>
<td></td>
<td></td>
</tr>
<tr>
<td>UR Points</td>
<td>2</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>LR Points</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>UR avoidance/LR avoidance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UR Points</td>
<td>1</td>
<td>-1</td>
<td>0</td>
</tr>
<tr>
<td>LR Points</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
</tr>
<tr>
<td>UR approach/LR avoidance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UR Points</td>
<td>2</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>LR Points</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
</tr>
<tr>
<td>UR avoidance/LR approach</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UR Points</td>
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<td>-1</td>
<td>0</td>
</tr>
<tr>
<td>LR Points</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Note. UR = Upper route; LR = Lower route.