A COMPUTATIONAL AND EMPIRICAL INVESTIGATION OF PRIORITIZATION DURING MULTIPLE APPROACH AND AVOIDANCE GOAL PURSUIT

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Abstract

Most decisions involve trade-offs between competing goals. For example, an academic may prioritize research over teaching by deciding to spend more time conducting experiments or writing papers. Alternatively, he or she may prioritize teaching over research by deciding to spend more time writing lectures or grading papers. Ultimately, the ability to effectively prioritize is a major determinant of success when simultaneously pursuing multiple goals. The aim of this thesis is to examine prioritization when pursuing multiple approach and/or avoidance goals. Although goal pursuit can involve approaching a desired state or avoiding an undesired state, theories of multiple-goal pursuit have only addressed approach goals. These theories have been articulated with the precision and transparency of computational models, and these models have been empirically validated. On the other hand, theories of avoidance goal pursuit have been limited to verbal descriptions, which have undergone virtually no empirical examination. Furthermore, although prioritization involves making a decision, modern theory and methodology that has facilitated our understanding of decision making has been underutilized in examinations of multiple-goal pursuit. In order to develop a deeper understanding of prioritization, I therefore incorporate into the examination of multiple-goal pursuit a) a precise conceptualization of avoidance and b) theory and methodology from the decision making literature. In Chapter 1 of this thesis, I provide a general introduction to the theory and methodology that will be drawn upon. In Chapters 2 and 3, I provide insight into how people prioritize. In Chapter 2, I increase the precision of a verbal theory of avoidance goal pursuit by articulating it as a computational model. In Chapter 3, I extend an existing model of multiple-approach-goal pursuit by incorporating the model of avoidance introduced in Chapter 2 along with a sequential sampling model of decision making. I use this model to explain how prioritization depends on the combination of approach and avoidance goals being pursued, and the level of uncertainty associated with an action’s impact on goal progress. In Chapter 4, I provide insight into how well people prioritize. I implement a normative model of decision making during multiple-goal pursuit. I use this model to demonstrate that people depart from
optimal prioritization in a risk-averse manner when pursuing multiple approach goals and in a risk-seeking manner when pursuing multiple avoidance goals. In Chapter 5, I discuss the theoretical contributions that the findings of this thesis make to our understanding of multiple-goal pursuit.
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PREAMBLE

The body of this thesis is presented as three journal article manuscripts. At the time this thesis was submitted, versions of two of the papers (Chapters 3 and 4) were published at a peer-reviewed journal. A version of the other paper (Chapter 2) was under review. Reference details for the three papers can be found in the ‘Papers Included in this Thesis’ section. Details of the candidate’s contribution to each manuscript can be found in the ‘Statement of Candidate Contribution to Included Papers’ section.
PAPERS INCLUDED IN THIS THESIS

Chapter 2: Under review at Psychological Review


Chapter 3: In press at Journal of Applied Psychology


Chapter 4: Published at Journal of Applied Psychology

STATEMENT OF CANDIDATE CONTRIBUTION TO INCLUDED PAPERS

Chapter 2
The candidate completed the literature review, computational modeling, and primary manuscript preparation. Gillian Yeo supervised the project. Jeffrey Vancouver and Andrew Neal provided feedback on the computational modeling. All co-authors helped prepare the manuscript by editing and providing feedback.

Chapter 3
The candidate completed the literature review, programming of the experimental task, computational modeling, and primary manuscript preparation. The candidate also played a major role in designing the study. Gillian Yeo supervised the project and provided feedback on the experimental design. Shayne Loft provided feedback on the design. Jeffrey Vancouver provided feedback on the computational modeling. Andrew Neal provided feedback on the experimental design and computational modeling. All co-authors helped prepare the manuscript by editing and providing feedback.

Chapter 4
The candidate completed the literature review, programming of the experimental task, implementation of the optimal model, statistical analyses, and primary manuscript preparation. The candidate also played a major role in designing the study. Gillian Yeo supervised the manuscript preparation and provided feedback on the statistical analysis. Andrew Neal also provided feedback on the statistical analysis. Simon Farrell supervised the experiment design and implementation, as well as the implementation of the optimal model. Simon Farrell also provided feedback on the statistical analysis. All co-authors helped prepare the manuscript by editing and providing feedback.
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CHAPTER 1

GENERAL INTRODUCTION

The aim of this thesis is to examine prioritization when pursuing multiple approach and/or avoidance goals. Most decisions involve the consideration of more than one goal. Moreover, the goals people pursue can be framed in different ways. Pursuing an approach goal involves moving towards a desired state; whereas pursuing an avoidance goal involves moving away from an undesired state (Carver & Scheier, 1990, 1998; Elliot & Covington, 2001). For example, an academic may have the approach goal of publishing a certain number of papers in a year and the avoidance goal of not receiving a certain number of poor teaching evaluations. Due to time or resource limitations, he or she will often have to decide between performing tasks that facilitate one goal at the expense of the other. Drafting a paper may bring the academic closer to achieving the publication goal, but may inhibit progress towards the teaching goal. Writing a lecture may bring him or her closer to achieving the teaching goal, but may inhibit progress towards the publication goal. A major determinant of an individual’s success in achieving these goals is his or her decisions about which goal to prioritize at a given point in time.

Although approach/avoidance framing is a salient feature of a goal (Elliot & Covington, 2001), research on multiple-goal pursuit thus far has only addressed approach goals. Theories of multiple-approach-goal pursuit have been articulated as computational models (Vancouver, Weinhardt, & Schmidt, 2010; Vancouver, Weinhardt, & Vigo, 2014), which provide a rigorous foundation for theory development and empirical testing (Busemeyer & Diederich, 2010; Lewandowsky & Farrell, 2011). A growing body of empirical work has identified factors that influence prioritization when pursuing multiple approach goals (e.g., Kernan & Lord, 1990; Louro, Pieters, & Zeelenberg, 2007; Schmidt & DeShon, 2007; Schmidt, Dolis, & Tolli, 2009; Schmidt & Dolis, 2009). By contrast, theories that address avoidance goal pursuit contain only
verbal descriptions which, as argued below, are often limited in their internal consistency, clarity, and testability (Weinhardt & Vancouver, 2012). Moreover, empirical studies that examine multiple-goal pursuit contexts in which one or more of the goals is avoidance are lacking. This lack of focus on avoidance goal pursuit is problematic because avoidance goals are common (Elliot & Sheldon, 1997) and the process by which people pursue avoidance goals differs to the process that governs approach goal pursuit (Carver & Scheier, 1990, 1998).

In order to examine how and how well people prioritize when one or more of the goals being pursued are avoidance, in Chapter 2, I first translate a verbal theory of avoidance goal pursuit (Carver & Scheier, 1990, 1998) into a computational model. This translation enables the theory to be incorporated into a more general model of multiple-goal pursuit, which is introduced and tested in Chapter 3. Chapters 2 and 3 provide insight into how people prioritize by examining the process by which prioritization decisions are made. In Chapter 4, I then implement a mathematical model of optimal decision making and compare people’s prioritization decisions to a normative criterion. Chapter 4 provides insight into how well people prioritize by examining if and how people’s prioritization decisions depart from optimality. This examination of prioritization requires incorporating concepts from the decision-making literature into theory and methodology relating to multiple-goal pursuit. In doing so, this thesis integrates two traditionally disparate bodies of literature.

The remainder of this general introduction consists of three sections. The first section outlines the theories of goal pursuit and decision making drawn upon, in order to explain the factors that influence prioritization. The second section describes the computational and normative modeling approaches used in this thesis, and the contributions that they make to our understanding of prioritization during multiple-goal pursuit. The third section provides an overview of the thesis chapters.

1.1 Integrating Disparate Theories to Understand Goal Prioritization

A goal prioritization decision is a choice made between actions that each favors one goal at the expense of the other goal(s). Prior work that has examined prioritization has focused on factors that represent properties of the goals themselves. This research has revealed that goal prioritization depends on factors such as the relative discrepancy between one’s current state and their goal (Kernan & Lord, 1990; Schmidt & DeShon, 2007), and expectancy of goal achievement (Louro et al., 2007; Schmidt & Dolis, 2009). However, this research fails to take into account factors unrelated to the goals themselves that influence the attractiveness of each course
of action. For example, studies of multiple-goal pursuit typically examine prioritization in environments where the impact of an action on goal progress is relatively certain. However, the impact of an action on goal progress is often uncertain. Re-writing a lecture may facilitate progress toward the goal of avoiding poor teaching ratings if the lecture is well received, but might have the opposite effect if the new lecture is poorly received. Research on decision making suggests that uncertainty in the consequences of an action influences people’s preferences for that action (Busemeyer, 1985; Busemeyer & Townsend, 1993). In order to develop a more comprehensive understanding of prioritization, I therefore integrate theory from the goal pursuit and decision-making literatures. Throughout this thesis, I use theory from the goal pursuit literature as a foundation for understanding this process. I incorporate theories and methodology from the decision-making literature in Chapters 3 and 4. In order to enact this approach, I draw on control theory (Powers, 1973), the multiple-goal pursuit model (Vancouver et al., 2010), decision field theory (Busemeyer & Townsend, 1993), and prospect theory (Kahneman & Tversky, 1979). I summarize these theories below.

1.1.1 Control Theory

Control theory (Carver & Scheier, 1990, 1998; Powers, 1973) is a general theory of goal pursuit, which describes the process as a feedback loop in which individuals continually monitor their performance and compare it to a reference value. If the reference value represents a desired state (i.e., an approach goal), the individual aims to reduce the discrepancy between his or her current state of performance and the reference value. If the reference value represents an undesired state (i.e., an avoidance goal), the individual aims to enlarge the discrepancy between his or her current state and the reference value (Carver & Scheier, 1990, 1998). Control theory claims that the magnitude of the discrepancy influences the extent to which effort must be applied. Research on approach goal pursuit has revealed that individuals allocate more resources (e.g., time, effort, attention) towards approach goals when the discrepancy between current and desired states is larger (Bandura & Cervone, 1983; Campion & Lord, 1982; Kernan & Lord, 1990). In Chapter 2, I instantiate Carver and Scheier’s (1990; 1998) control theory-based account of avoidance goal pursuit as a computational model. In Chapter 3, this model is integrated into a broader model that explains how people pursue different combinations of approach and avoidance goals.
1.1.2 **The Multiple-Goal Pursuit Model**

The multiple-goal pursuit model (Vancouver et al., 2010, 2014) uses control theory as a foundation for understanding prioritization during multiple-goal pursuit. According to the multiple-goal pursuit model, prioritization is based on a comparison of the expected utilities of acting on each goal. The expected utility is a function of valence, which represents the discrepancy; and expectancy, which represents the perceived likelihood that the goal can be attained in the time available. Consistent with the multiple-goal pursuit model, when pursuing multiple approach goals, people tend to prioritize the goal in the worst position (i.e., the goal with the largest discrepancy) as long as they believe that both goals are achievable. However, when people expect that they cannot achieve both goals, they tend to prioritize the goal in the best position (i.e., the goal with the smaller discrepancy; Louro et al., 2007; Schmidt & Dolis, 2009). In Chapter 3, I extend the multiple-goal pursuit model to address avoidance goals (using the computational model introduced in Chapter 2), and to account for uncertainty in the impact of actions on goal progress. In Chapter 4, I examine how pursuing multiple approach versus avoidance goals influences the tendency to prioritize the goal in the worst versus best position, and how these tendencies depart from optimality.

1.1.3 **Decision Field Theory**

Decision field theory is a sequential sampling model of decision making that describes the dynamic process by which preferences for various actions evolve over time when one is making a decision (Busemeyer & Townsend, 1993; Roe, Busemeyer, & Townsend, 2001). The theory states that attention fluctuates over time between potential consequences of each action. Preference for a given action increases when desirable consequences are considered, and decreases when undesirable consequences are considered. Preferences accumulate over time until preference for an action becomes strong enough to breach an inhibitory threshold, at which point the action is selected.

Decision field theory provides an explanation for the influence of uncertainty on decision making (Busemeyer & Townsend, 1993). According to decision field theory, uncertainty in the consequences of actions influences the degree to which attention, and thus preference for an option, fluctuates over time. If the consequences of actions are highly uncertain (e.g., if an academic is unsure how well a new lecture will be received), fluctuations in attention are stronger, making the accumulation of preferences more variable over time. If the consequences of actions are highly certain (e.g., if the academic has a good idea of how well the lecture will be received), fluctuations in attention are weaker, making the accumulation of preferences more
stable over time. All else being equal, individuals will therefore tend to make more consistent
decisions when there is less uncertainty in the consequences of actions. I draw on decision field
theory in Chapter 3 in order to extend the multiple-goal pursuit model, to account for decisions
involving actions with uncertain consequences that affect multiple goals.

1.1.4 Prospect Theory

Prospect theory (Kahneman & Tversky, 1979) provides an explanation of how decision making
differs when the consequences of actions are expressed in terms of gains versus losses. A
primary tenet of the theory is that individuals are risk-averse when given the opportunity to
gain and risk-seeking when faced with the threat of loss (Tversky & Kahneman, 1981). For
example, when faced with the choice between an option that offered a 100% chance of gaining
$100 and an option that offered a 50% chance of gaining $200 and a 50% chance of gaining $0,
persons should prefer the former option to the latter. However, when faced with the choice
between an option that offered a 100% chance of losing $100 and an option that offered a 50% of
losing $0 and a 50% chance of losing $200, people should prefer the latter option to the former.
In Chapter 4, I argue that the tendency for decisions expressed in terms of gains and losses,
respectively, to produce risk-averse and risk-seeking behavior, produces systematic departures
from optimal prioritization when pursuing multiple approach versus avoidance goals. I draw
on prospect theory to make predictions regarding whether pursuing multiple approach versus
avoidance goals makes individuals more likely to prioritize the goal in the worst position (a
risk-seeking tendency) versus the goal in the best position (a risk-averse tendency) relative to an
normative model.

1.2 Overview of Computational and Normative
Modeling Methodology

A contribution of this thesis is the application of computational and normative modeling to
investigate prioritization decisions. Chapters 2 and 3 implement computational models that
enhance understanding of the process by which prioritization decisions are made. Chapter 4
implements a normative model in order to examine how prioritization decisions depart from
optimality. I provide a summary of these two methods in the following sections.
1.2.1 Computational Models

Computational models are quantitative descriptions of latent cognitive processes instantiated in formal terms (Harrison, Lin, Carroll, & Carley, 2007; Weinhardt & Vancouver, 2012). A computational model will typically have a number of parameters that represent sources of variation in the psychological process that it describes. This variation can be the product of individual differences, environmental factors, or both. These parameters are meaningful both theoretically and empirically. Manipulation of parameter values through simulation may produce novel or even counterintuitive behavior, providing predictions that can be tested empirically. Model parameters can alternatively be estimated from empirical data, with their values providing useful information about the manner in which the psychological process operates under particular conditions.

Computational modeling provides a number of benefits over traditional theories, which are typically represented informally as verbal descriptions. First, computational models ensure that psychological theories are held to a high standard of internal consistency, meaning that the pattern of behavior predicted by the theory can in fact be produced from the proposed underlying mechanisms (Lewandowsky & Farrell, 2011). Because computational models require the processes that underlie psychological phenomena to be formally specified, their predictions can be evaluated through simulation, to identify whether the underlying mechanisms proposed by a theory produce the expected pattern of behavior. Thus, computational models provide a systematic way to establish a theory’s internal consistency. Because verbal theories cannot be simulated in the same manner, they are more difficult to establish as valid. Attempts to instantiate verbal theories as computational models often reveal inconsistencies between the underlying psychological mechanisms and the predicted behavioral output, demonstrating the necessity for the theory to be specified in greater detail (Fum, Del Missier, & Stocco, 2007). I make this contribution in Chapter 2 by using computational modeling to demonstrate that a literal interpretation of Carver and Scheier’s (1990; 1998) account of avoidance goal pursuit does not in fact produce the behavior Carver and Scheier predict.

Another benefit of representing theories as computational models is the ability to generate and test precise, quantitative predictions. Psychological phenomena result from complex interactions between latent constructs (McGuire, 1973; Vallacher & Nowak, 1997). This complexity often involves dynamic processes, evolving over time, with reciprocal or non-linear relationships between components. Using verbal theories, it is difficult to characterize these processes with the specificity required to predict their behavioral output with a high degree of precision. The predictive ability of these theories is thus limited primarily to verbal hypotheses about linear relationships between variables. By contrast, computational models produce
quantitative predictions that are less limited in the complexity of the behavior they can describe (Weinhardt & Vancouver, 2012). Because of their precision, the predictions of computational models tend to be more falsifiable than the more general predictions of verbal theories. Consequently, computational models are better suited to empirical testing because evidence in favor of one theory over another is more meaningful (Lewandowsky & Farrell, 2011). In chapter 3, I utilize the precision of computational modeling to develop and test quantitative predictions regarding the effects of approach-avoidance frame combination and uncertainty on prioritization.

1.2.2 Normative Models

Normative models of decision making provide an objective criterion by which to evaluate behavior (Baron, 2004, 2012). Comparing observed decisions to the decisions predicted by a normative model allows one to identify biases, which are systematic departures from optimality. Biases provide insight into the psychological process that underlies decision making (Kahneman & Tversky, 1996). For example, the finding that people are risk-averse compared to a normative baseline when making decisions involving gains, and risk-seeking compared to a normative baseline when making decisions involving losses, has enhanced our understanding of how people use reference points to guide their decisions (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981).

The normative model used in this research is expected utility theory (von Neumann & Morgenstern, 1947), which is a widely accepted model for calculating the expected value of each course of action (Busemeyer & Pleskac, 2009; Kahneman & Tversky, 1979; Keeney & Raiffa, 1976). I refer to the decision predicted by expected utility theory as the optimal decision. According to expected utility theory, the optimal decision is to select the course of action with the highest expected value. Because multiple-goal pursuit is a multistage decision context in which individuals make a series of interdependent prioritization decisions, the optimal decision at a given point in time must take into account the decisions that will be made at later points in time. I therefore use dynamic programming—a method of implementing expected utility theory for multistage decisions—to determine the optimal prioritization decisions during multiple-goal pursuit. In Chapter 4, I use this normative model to test for departures from optimal prioritization as a function of whether people are pursuing multiple approach or avoidance goals.
1.3 Overview of Thesis

The body of this thesis is composed of three papers. In Chapter 2, I translate Carver and Scheier’s theory of avoidance goal pursuit into a computational model. Carver and Scheier’s description of the mechanisms underlying avoidance goal pursuit is ambiguous because they a) use the label ‘positive feedback loop’ in a manner inconsistent with how it is traditionally defined in the systems dynamics literature (e.g., Richardson, 1991; Zeigler, Praehofer, & Kim, 2000), and b) do not specify the precise nature of the relationship between the distance from an undesired state and the intensity of avoidance behavior. Interpreting the ‘positive feedback loop’ label according to its traditional definition leads to the assumption that avoidance behavior intensifies as distance from an undesired state increases. Yet this assumption is counterintuitive, and inconsistent with previous research. On the other hand, the assumption that the intensity of avoidance behavior decreases as one moves further from an undesired state, although implying that avoidance goal pursuit is actually a negative feedback loop, is actually consistent with Carver and Scheier’s account. I implement both sets of assumptions as computational models, and show that the model representing a negative feedback loop makes predictions that are more meaningful and more consistent with the dynamic patterns of behavior predicted by Carver and Scheier, than the model representing a positive feedback loop. I conclude that the relationship between the distance from an undesired state and avoidance intensity is negative, and therefore that it is more appropriate to describe avoidance goal pursuit as a negative feedback loop.

In Chapter 3, I extend the multiple-goal pursuit model (Vancouver et al., 2010, 2014) to address avoidance goals by incorporating the negative feedback model of avoidance goal pursuit introduced in Chapter 2. I also extend the multiple-goal pursuit model to account for actions having uncertain consequences for goal progress, by incorporating decision field theory (Busemeyer & Townsend, 1993; Roe et al., 2001). This extended model is referred to as the multiple-goal pursuit model* (MGPM*). The MGPM* predicts how prioritization is influenced by the combination of approach/avoidance goals being pursued, and the level of uncertainty associated with the impact of actions on goal progress. The model is tested using an Air Traffic Control task where 91 participants either pursue one approach and one avoidance goal, two approach goals, or two avoidance goals; and where the level of uncertainty in the consequences of actions for goal progress varies. The results show that participants pursuing one approach and one avoidance goal tend to shift priority over time from the approach to the avoidance goal. Participants pursuing two approach goals tend to use one of two strategies: either focusing on the goal for which the desired state is farther away, and thus switching priority
fairly rapidly between goals (balanced strategy); or focusing on the goal for which the desired state is closer, and thus prioritizing one goal until it is attained and then switching to the other (sequential strategy). Participants pursuing two avoidance goals demonstrated the balanced strategy more frequently than the sequential strategy. Regardless of which goal tended to be prioritized, the tendency was stronger when the consequences of actions for goal progress were more certain. All of these findings are accounted for by the MGPM* model.

In Chapter 4, I examine if and how prioritization decisions depart from optimality as a function of whether people strive for multiple approach or avoidance goals. Drawing on prospect theory (Kahneman & Tversky, 1979), I predict that people have a risk-averse bias when pursuing multiple approach goals, and over-weight the value of achieving one goal compared to the value of achieving two. As a result, people are more likely than a normative model suggests to prioritize the goal in the best position. Pursuing multiple avoidance goals is predicted to produce a risk-seeking bias, in which people over-weight the value of achieving two goals compared to the value of achieving one, and are consequently more likely than a normative model to prioritize the goal in the worst position. These predictions are tested with an experimental paradigm in which participants make a series of prioritization decisions whilst pursuing either two approach or two avoidance goals. The predictions are supported.
CHAPTER 2

DEVELOPING A COMPUTATIONAL MODEL OF AVOIDANCE GOAL PURSUIT: COMPARING POSITIVE VERSUS NEGATIVE FEEDBACK CONTROL SYSTEMS

This chapter is presented as a journal article manuscript. A version of this manuscript was under review at the time this thesis was submitted.

2.1 FOREWORD

In this chapter, I commence the investigation into how people prioritize approach and avoidance goals. In order to understand prioritization when pursuing one or more avoidance goals, it is necessary to have a well-specified account of how people pursue avoidance goals. In this chapter, I provide that account by increasing the precision of an existing theory of avoidance goal pursuit and translating it into a computational model.
2.2 Abstract

This paper aims to develop a computational model of avoidance goal pursuit. To our knowledge, Carver and Scheier’s (1998) verbal account is the only theory in the literature that describes the psychological mechanisms that underlie avoidance goal pursuit, which makes it an ideal candidate to be translated into a computational model. However, Carver and Scheier’s description of the mechanisms underlying avoidance goal pursuit is ambiguous because it a) uses the label ‘positive feedback loop’ in a manner inconsistent with how it is traditionally defined, and b) does not specify the precise nature of the relationship between the distance from an undesired state and the intensity of avoidance behavior. Interpreting the ‘positive feedback loop’ label according to its traditional definition leads to the assumption that avoidance behavior intensifies as distance from an undesired state increases. Yet this assumption is counterintuitive and inconsistent with previous research. On the other hand, the assumption that the intensity of avoidance behavior decreases as one moves farther from an undesired state, although implying that avoidance goal pursuit is actually a negative feedback loop, is actually consistent with Carver and Scheier’s account. We implement both sets of assumptions as computational models and show that the model representing a negative feedback loop makes predictions that are more meaningful and more consistent with the dynamic patterns of behavior predicted by Carver and Scheier than the model representing a positive feedback loop. We conclude that the relationship between the distance from an undesired state and avoidance intensity is negative, and therefore that it is more appropriate to describe avoidance goal pursuit as a negative feedback loop. The articulation of Carver and Scheier’s account with the precision and transparency of a computational model allows us to resolve these ambiguities. We believe that a computational account of avoidance goal pursuit will facilitate the development of theory and novel predictions regarding how people pursue avoidance goals, and practical efforts aimed at enhancing work performance.
2.3 Introduction

“For the man who flies from and fears everything and does not stand his ground against anything becomes a coward, and the man who fears nothing at all but goes to meet every danger becomes rash.” - Aristotle

Humans, like all living organisms, must obtain certain things (e.g., food) and avoid other things (e.g., dangers) to survive and reproduce. As the above quote from Aristotle makes clear, individuals are well served by balancing their need to approach the desirable and avoid the undesirable. Unfortunately, the same cannot be said for the scientific literature on goal pursuit. Approach goal pursuit involves acting to achieve something desired; whereas avoidance goal pursuit involves acting to avoid something undesired. Although goal pursuit can involve either approach or avoidance, the approach context has received more empirical and theoretical attention than the avoidance context. Fortunately, this attention has led to rigorous, formal understandings of the motivational processes likely involved in approach goal pursuit. In particular, modern motivation theories explain approach goal pursuit using computational models based on the negative feedback loop architecture found in control theory (Powers, 1973; Scherbaum & Vancouver, 2010; Vancouver, Putka, & Scherbaum, 2005; Vancouver, Weinhardt, & Schmidt, 2010; Vancouver, Weinhardt, & Vigo, 2014; Vancouver & Scherbaum, 2008). In contrast, research into the process of avoidance goal pursuit is relatively scarce, and accounts of avoidance behavior have been limited to informal, verbal descriptions of motivational processes, with the positive feedback loop process described by Carver and Scheier (1998) as the most dominant.

The relative scarcity of research that has examined avoidance goal pursuit is problematic. Avoidance goals are common (Elliot & Sheldon, 1997) and the realization of undesired outcomes tends to have a stronger impact on the individual than the achievement of desired ones (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001). The ability to effectively pursue avoidance goals is therefore important. Despite its necessity, however, avoidance goal pursuit can have negative consequences for motivation, well-being, and performance (Elliot & Church, 1997; Elliot, Thrash, & Murayama, 2011). People tend to be less motivated and perform worse when pursuing avoidance goals than when pursuing approach goals (Elliot & Harackiewicz, 1996; Roskes, Elliot, Nijstad, & De Dreu, 2013). Chronic avoidance goal pursuit can contribute to the development and maintenance of depression (Trew, 2011) and anxiety (Dickson, 2006). Avoidance goal failure can also produce negative affect (Carver & Scheier, 1990, 1998). Given the importance of avoidance goal pursuit and the evidence for its potential maladaptive effects on the individual, it is critical to develop a firm understanding of how this process plays out over time.
As we will argue, this understanding is best achieved through the use of computational modeling. We therefore develop a computational model that describes the avoidance goal pursuit process. We make this contribution by implementing Carver and Scheier’s (1998) theory as a computational model. Articulating their theory in this manner allows us to resolve two sources of ambiguity in the theory. First, Carver and Scheier’s use of the label ‘positive feedback loop’ to describe avoidance goal pursuit is inconsistent with how positive feedback loops are traditionally defined in the systems dynamics literature. Carver and Scheier’s account appears to treat positive feedback loops as analogous to discrepancy-amplifying systems. However, positive feedback loops are traditionally defined as systems in which the input is positively related to the output (e.g., Richardson, 1991; Zeigler et al., 2000). Under this definition, a discrepancy-amplifying system can be either a positive or negative feedback loop. Second, Carver and Scheier do not specify the precise nature of the relationship between the distance from an undesired state, and the intensity of avoidance behavior. Interpreting the ‘positive feedback loop’ label according to its traditional definition leads to the assumption that avoidance behavior intensifies as an undesired state becomes more distant, because only a positive relationship between these two variables makes the input to the system positively related to the output. However, this assumption is inconsistent with previous research examining how people respond to threats (Mobbs et al., 2007; Ogilvie, 1987; Teghtsoonian & Frost, 1982). Moreover, we demonstrate that a model that implements this assumption predicts a pattern of dynamic behavior that is inconsistent with the pattern predicted by Carver and Scheier. By contrast, a model that assumes that the intensity of avoidance behavior decreases as the undesired state becomes more distant predicts a pattern of behavior that is more intuitive and more consistent with the predictions of Carver and Scheier. Although this model assumes that avoidance goal pursuit is a negative feedback loop, we argue that it is consistent with Carver and Scheier’s account because it conceptualizes avoidance goal pursuit as a discrepancy-amplifying system. We conclude therefore that describing avoidance goal pursuit as a positive feedback loop is inaccurate. Given that Carver and Scheier’s account is fundamental to our understanding of avoidance goal pursuit, we believe that articulating their account with the precision and transparency of a computational model will facilitate the development of theory regarding how people pursue avoidance goals.

The remainder of this article is structured as follows. First, we elaborate on the contribution the current article seeks to make to the goal pursuit literature, by highlighting the benefits of having a computational model of avoidance goal pursuit. Second, we present the theoretical foundations by summarizing Carver and Scheier’s (1998) theory of goal pursuit. Third, we present the formal specification for two alternative models of avoidance goal pursuit. The first model is based a literal interpretation of the ‘positive feedback loop’ label described by
Carver and Scheier, and therefore assumes that avoidance behavior intensifies as the undesired state becomes more distant. The second assumes that the intensity of avoidance behavior decreases as the undesired state becomes more distant, and is therefore a negative feedback loop. Fourth, we report the results of two simulation studies that examine the behavior of these models played out over time. We then discuss the theoretical and practical implications of these findings.

2.3.1 Highlighting the Importance of a Computational Model of Avoidance Goal Pursuit

In order to achieve the theoretical precision necessary to understand the avoidance goal pursuit process, we need to a) account for the dynamics of the process and b) describe the process formally. Articulating a dynamic, formal account requires the use of computational modeling. The following sections discuss these two features and provide a literature review that highlights how this level of theoretical precision is lacking in the avoidance goal pursuit literature.

Dynamic versus Static Models

A distinctive feature of a dynamic theory is the conceptualization of psychological processes as a system, which can simply be defined as “a set of interconnected elements that undergoes change” (Vallacher & Nowak, 1997). Dynamic theories are useful, in part, because they more accurately reflect the organization of psychological constructs (McGuire, 1973). Psychological phenomena are often the product of complex, recursive interactions between constructs operating within a system. Components of the system exhibit feedback, in that they both influence and are influenced by the other components (Gelfand & Engelhart, 2012). By contrast, static theories tend to focus on simple cause and effect relationships between constructs. Static theories have considerable difficulty accounting for important properties of psychological systems such as feedback, non-linearity, and sensitivity to initial conditions (Barton, 1994). For example, early theories of newcomer socialization (e.g., Van Maanen & Schein, 1979) tended to focus on cause and effect relationships between organizational characteristics, and static outcomes such as mean job performance, satisfaction, and turnover (Vancouver, Tamanini, & Yoder, 2008). However, the process of newcomer socialization involves the ongoing interaction between the newcomer, colleagues, managers, and the organization itself over time. Recognizing this mismatch between the process under investigation and the level of theorizing, more recent theories of socialization (e.g., Ashford & Cummings, 1983; Reichers, 1987) have emphasized the dynamic process by which these interactions take place, thereby representing the socialization process in a more realistic manner.
FORMAL VERSUS INFORMAL MODELS

A formal model is a quantitative description of a latent process represented mathematically. Formal models contrast with informal models, which are qualitative descriptions represented verbally. Formal theorizing requires researchers to be more precise in specifying the mechanisms that are hypothesized to give rise to particular psychological phenomena. This process facilitates theory building. Attempts to formally instantiate theories that were previously informal often reveal a lack of internal consistency, which means that the underlying psychological mechanisms do not in fact produce the behavior predicted by the theory (Fum et al., 2007). Such discoveries demonstrate the necessity for more precision in the theory’s specification. The specificity of a formal model’s predictions allows strong tests of the theory because incorrect predictions are more likely to be falsified, which in turn leads to stronger confidence in evidence that favors a particular prediction (Lewandowsky & Farrell, 2011; Roberts & Pashler, 2000).

Models that are both formal and dynamic are referred to as computational models. Computational models are particularly useful for understanding dynamic psychological systems, such as the one that governs goal pursuit. Due to the complexity of such systems, the ability to understand and make predictions about their behavior over time without the use of formal specification is often constrained by processing limitations of the human mind (Cronin, Gonzalez, & Sterman, 2009). Computational models enable the researcher to simulate these systems and to test assumptions about how the individual components within the system interact to produce the phenomena predicted by a theory (Weinhardt & Vancouver, 2012).

A REVIEW OF THE AVOIDANCE GOAL PURSUIT LITERATURE

The two previous sections have argued that a description of avoidance goal pursuit should be both dynamic and formal (i.e., the description should be articulated as a computational model). In this section, we review the avoidance goal pursuit literature and argue that research focusing on avoidance goal pursuit is relatively scarce to begin with, and the small body of existing literature tends to be static and/or informal. Thus, there is a need to develop a computational model of avoidance goal pursuit.

THE LITERATURE ON AVOIDANCE GOAL PURSUIT IS RELATIVELY SCARCE

Despite the prevalence of avoidance goals (Elliot & Sheldon, 1997), avoidance goal pursuit has received much less attention than approach goal pursuit. We searched 21 top tier journals covering areas such as organizational, social, biological, cognitive, clinical, and developmental psychology for articles containing at least one of the following five keywords: goal pursuit, goal
striving, self-regulation, goal regulation, and, approach and avoidance (i.e., the article had to have both “approach” and “avoidance” included in its keywords). The search yielded 444 articles. A large number of these articles, however, were not directly related to our conceptualization of goal pursuit. Many of these articles considered self-regulation as an outcome itself, as opposed to using it as a framework for understanding goal pursuit (e.g., Oyserman, Bybee, & Terry, 2006; Plant & Devine, 2009). Others conceptualized self-regulation as executive control (e.g., Heatherton & Wagner, 2011; Schmeichel, 2007). After eliminating articles such as these, 77 articles remained.

We first examined the six results from the Annual Review of Psychology (Carver & Connor-Smith, 2010; Diamond, 2011; Higgins & Pittman, 2008; Karoly, 1993; Lord, Diefendorff, Schmidt, & Hall, 2010; Mays, Cochran, & Barnes, 2007). Four of these articles discussed the negative feedback architecture found in control theory, which characterizes the approach goal pursuit process (Carver & Connor-Smith, 2010; Higgins & Pittman, 2008; Karoly, 1993; Lord et al., 2010). All four made explicit reference to Carver and Scheier’s work (e.g. Carver & Scheier, 1981; 1998). Though all of these articles except Karoly (1993) acknowledge avoidance goals, the majority of the discussion focuses on approach goals. The mention of avoidance goals is often limited to acknowledging that self-regulation may involve the avoidance of undesired states.

Turning to the empirical literature, we found 27 articles with studies in which participants engaged in a task with an explicit performance goal. Only one of these studies examined avoidance goal pursuit (Schmidt & DeShon, 2007). However, this study operationalized approach-avoidance in terms of incentives. People performed a scheduling task in which they had to create university class schedules for a group of students. In the approach condition, the participant was told that they would gain a gift certificate for achieving the goal. In the avoidance condition, the participant was given a gift certificate ahead of time, and told that they would lose it if they failed their goal. Regardless of the incentive condition, however, the task involved an approach goal in which one had to reduce the discrepancy between one’s current position (i.e., the number of students to be scheduled) and a desired state (i.e., having all students scheduled). Thus, this study did not directly examine the process by which avoidance goals are pursued.

Theories of avoidance goal pursuit are mostly static

Although theories of approach goal pursuit generally conceptualize the process as dynamic (e.g., Karoly, 1993; Vancouver et al., 2008; Vancouver, 2005), most theories that address avoidance goal pursuit do so in a static fashion. For example, Elliot and Church’s (1997) hierarchical model of approach and avoidance achievement motivation specifies antecedents (e.g., motivation, expectancy) and consequences (e.g., performance) of striving for avoidance
compared to approach goals. Other work focuses on understanding how personality influences whether people strive for 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 these theories have provided insight into the factors that influence goal adoption, and the outcomes associated with adopting different types of goals, they do not describe the underlying dynamic process of avoidance goal pursuit. To use Vancouver’s (2005) analogy, these theories treat avoidance goal pursuit as a black box. They predict the causes and effects of this process, but do not explain how the process itself works. Understanding the dynamics of avoidance goal pursuit requires theorizing at a lower level of abstraction.

An exception to the above is Carver and Scheier’s (1998) theory, which is described later in this article. To our knowledge, this is the only theory that attempts to provide a dynamic account of avoidance goal pursuit. Of the three previously mentioned Annual Review of Psychology articles that acknowledge avoidance goal pursuit (Carver & Connor-Smith, 2010; Higgins & Pittman, 2008; Lord et al., 2010), all three reference Carver and Scheier’s (1998) theory, though they do not provide details on the avoidance aspect of the theory. Carver and Scheier’s description of avoidance goal pursuit as a positive feedback system is the dominant, if not the only, dynamic theory of avoidance goal pursuit.

**The literature on avoidance goal pursuit is mostly informal**

The imbalance between the approach and avoidance goal pursuit literatures is also reflected in the extent to which theory has been formalized. A growing body of literature has implemented dynamic, formal (i.e., computational) models of approach goal pursuit based on control theory (e.g., Vancouver et al., 2005; Vancouver et al., 2010; 2014). These models have been used to explain why difficult goals lead to better performance (Vancouver et al., 2005), processes that may cause people to raise their goal (Vancouver & Scherbaum, 2008), how people prioritize conflicting goals (Vancouver et al., 2010) and how people formulate expectancy beliefs (Vancouver et al., 2014). However, to our knowledge, no computational model that articulates the underlying mechanisms that govern avoidance goal pursuit has been published.

**2.3.2 Theoretical Foundations: Carver and Scheier (1998)**

In this section, we summarize Carver and Scheier’s (1998) theory. We begin by summarizing their description of approach goal pursuit, because this aspect of the theory is more commonly discussed in the literature. We then summarize their description of avoidance goal pursuit. In
summarizing their description of avoidance goal pursuit, we identify the theory’s predictions about how the avoidance goal pursuit process should unfold over time. These predictions will serve as criteria by which to evaluate the two alternative models presented later in this article.

**Approach Goal Pursuit**

Carver and Scheier (1998) describe approach goal pursuit as a negative feedback control system where the individual monitors the state of a variable in the environment, and acts to reduce the discrepancy between current state and a desired reference state. The system has four components: a variable in the environment that is monitored; an input function that creates a perception of the state of that variable; a comparator function that determines the discrepancy between the perception and the reference state; and an output function that acts to reduce the discrepancy and bring the perceived current state in line with the reference state (see Figure 2.1). External effects, known as disturbances, may also affect the state of the variable. Disturbances can have either beneficial or detrimental effects, though it is most commonly the case that they move a variable away from the desired state.

The control system is considered to be a feedback loop because there is a reciprocal interaction between input and output. The output affects the state of the variable, which is input into the system and used to compute the discrepancy, which in turn influences the output. The loop is *negative* because there is a negative relationship between input and output. As the state of the variable (and thus the input) moves closer to the desired state, the discrepancy decreases, and so too does the output. The sign of the feedback loop can be determined by counting the number of negatively signed links in the loop. In a negative feedback loop, there are an odd number of negatively signed links (Richardson, 1991; Zeigler et al., 2000). Negative feedback loops tend to produce stability in the state of the system over time, because the system aims to keep the current state in line with the desired state. Thus, output ceases when the discrepancy is eliminated. Output only resumes when environmental disturbances generate a new discrepancy. Over time, this behavior keeps the system in equilibrium, with the current state at or near the desired state.
One example of approach goal pursuit is an academic aiming to submit a certain number of papers before a tenure deadline. In this case, the current number of papers published is the variable being monitored. The desired number of publications is the reference state. The aim of the process therefore is to reduce, and ultimately eliminate, the discrepancy between current and desired number of publications. The output of the system is discrepancy-reducing behavior, such as conducting experiments or drafting manuscripts. The output is positively related to the size of the discrepancy. The discrepancy behaves as an error signal that motivates the individual to engage in activities that will lead to an increase in the number of publications in order for the goal to be achieved (Lord & Levy, 1994). As the discrepancy decreases, the output also decreases because there is less need to engage in discrepancy-reducing activities. Providing support for this notion, individuals take corrective action when discrepancies exist between current and desired states. Larger discrepancies increase the likelihood (Schmidt & DeShon, 2007) and, in some cases, the strength (Kernan & Lord, 1990) of corrective action.

*Figure 2.1. A negative feedback control system with a desired reference state (i.e., an approach goal).*
**Avoidance Goal Pursuit**

Carver and Scheier’s (1998) theory states that during avoidance goal pursuit, the individual acts to *amplify* the discrepancy between the current state and an *undesired* reference state. Thus, avoidance goal pursuit functions as a discrepancy-amplifying feedback system. For example, most animals in the wild have the avoidance goal of eluding predation. They are motivated to increase the discrepancy—or distance—between their current position and that of their predator. Carver and Scheier’s account uses the label ‘positive feedback loop’ to describe avoidance goal pursuit. However, their account appears to use this term in a manner inconsistent with how it is traditionally defined. Carver and Scheier’s perspective appears to treat positive feedback loops as analogous to discrepancy-amplifying systems. For example, they state that “a positive feedback loop, in contrast, is a discrepancy amplifying system. These loops create movement away from the reference value” (Carver & Scheier, 1998, p. 18). However, the systems dynamics literature traditionally defines positive feedback loops as systems in which the input is positively related to the output (e.g., Richardson, 1991; Zeigler et al., 2000). According to this definition, discrepancy-amplifying loops can be either positive or negative. As we argue later, Carver and Scheier’s equation of positive feedback loops and discrepancy-amplifying systems creates an ambiguous picture of the relationship between the discrepancy and the output.

Consistent with the traditional definition of a positive feedback loop, Carver and Scheier claim that avoidance goals create unstable behavior over time. Unlike approach goal pursuit, in which elimination of the discrepancy causes the output to cease, the process of discrepancy-amplification has no definite point of conclusion. Avoidance goal pursuit therefore does not contain a mechanism that inhibits the output. Consequently, Carver and Scheier (1998) suggest that avoidance processes occurring in isolation are likely to exhibit a pattern of unconstrained behavior, where the avoidance behavior proceeds without limit. This prediction represents the first criterion by which we will evaluate the model of avoidance goal pursuit. Carver and Scheier (1998) predict that when operating in isolation, discrepancy-amplifying systems “push away from the undesired reference state, and awayness goes on without limit....This creates instability, as they go on forever trying to create larger and larger deviations (p. 18).” Based on the above argument, when an avoidance goal is pursued in isolation, the avoidance behavior should never cease. In other words, the output of the feedback control system should never reach zero.

Carver and Scheier (1998) argue however that avoidance goal pursuit processes typically do not exist in isolation, but instead are often constrained by the pursuit of an approach goal. When one is acting to enlarge a discrepancy between the current state of a variable and an
undesired reference state, a desired reference state is likely to be identified. By acting to reduce the discrepancy between the variable and a desired state, an individual may simultaneously engage in behaviors that facilitate avoidance of the undesired state. They offer the example of an adolescent who, in an effort to amplify differences between themselves and their parents, attempts to minimize differences between themselves and a peer group. Carver and Scheier (1998) use magnetism as a metaphorical explanation for this phenomenon (see Figure 2.2). They suggest that the process of avoiding an undesired state is analogous to the repulsion that occurs between two magnetically charged objects with the same pole. Likewise, approach is analogous to the attraction between objects with opposite poles. Just as an object travelling away from a similarly charged object in its vicinity may eventually be drawn into the magnetic field of an object with the opposite charge, avoidance of an undesired state often results in the identification and pursuit of a desired state. In this way, the approach goal may constrain the avoidance process by creating a stopping point for the avoidance behavior.


This prediction represents the second criterion by which we will evaluate the model of avoidance goal pursuit. Specifically, Carver and Scheier (1998) predict that when operating concurrently with an approach goal, a feedback control system with an avoidance goal “creates pressure toward deviation from its reference value. Moving away occurs to a point, but the
tendency is captured by the influence of a negative loop (p. 18).” We interpret Carver and Scheier’s argument to mean that a person will initially be more motivated by the avoidance goal, but as distance from the undesired state grows, the person will be more motivated by the approach goal. In other words, the output of the feedback system with the approach goal will eventually surpass the output of the avoidance feedback system.

2.4 IMPLEMENTING CARVER AND SCHEIER’S (1998) THEORY AS A COMPUTATIONAL MODEL

In this section, we implement Carver and Scheier’s theory of avoidance goal pursuit as a computational model that can be used to make predictions about the intensity of avoidance behavior in the single avoidance and simultaneous approach and avoidance goal pursuit scenarios. Carver and Scheier’s description appears to treat positive feedback loops as analogous to discrepancy-amplifying systems, which is inconsistent with the traditional definition of a positive feedback loop. We therefore create two alternative versions of the model. Both versions are discrepancy-amplifying systems, and are therefore consistent with Carver and Scheier’s account. However, only one satisfies the traditional definition of a positive feedback loop (i.e., there is a positive relationship between the input and output of the system). The other model is a negative feedback loop (i.e., there is a negative relationship between the input and output of the system).

Due to the absence of an existing computational model of avoidance goal pursuit, we draw on a computational model of approach goal pursuit in order to provide a framework for modeling the avoidance process. We therefore begin this section by summarizing the multiple-goal pursuit model (Vancouver et al., 2010) — a computational model of multiple approach goal pursuit. We then draw on this framework to create the positive and negative feedback loop models of avoidance goal pursuit. We later compare the positive and negative feedback models in two simulation studies. The first simulates the models in the single goal pursuit scenario. The second simulates the models in the simultaneous approach and avoidance goal pursuit scenario.

2.4.1 VANCOUVER ET AL.’S (2010) MODEL OF APPROACH GOAL PURSUIT

Vancouver et al.’s (2010) model is one of a series of models that provide a computational representation of approach goal pursuit (Scherbaum & Vancouver, 2010; Vancouver et al., 2005;
Vancouver & Scherbaum, 2008; Vancouver, 2008). Their model describes the factors that influence the tendency to act on a particular goal when striving for two approach goals. The model predicts that the tendency to act on a goal is determined by a complex set of factors including the magnitude of the discrepancy, time available, and incentives for goal achievement. However, at the foundation of this model is the negative feedback control system described informally by Carver and Scheier (1998). We formally describe Vancouver et al.’s representation of this feedback control system below.

The first component in the negative feedback control system shown in Figure 2.1 is the input function. The input function represents the individual’s perception ($p$) of the current state of the performance variable. In the example of the academic pursuing the publication goal, the input function may be as simple as counting the number of papers he or she has currently published. Vancouver et al., (2010) assume that there is no bias or error in this perception. They define the perception as follows:

$$p(t) = v(t), \quad (2.1)$$

where $v(t)$ represents the current state of the variable at time $t$.

The comparator determines the discrepancy ($d$) between the current state and the desired reference state. Consistent with Carver and Scheier (1998), Vancouver et al. (2010) implement an asymmetric comparator function that is sensitive only to positive discrepancies, which arise when the current state does not exceed (i.e., is less favorable than) the desired state. When the current state does exceed the desired state, no discrepancy is registered. This asymmetry reflects the fact that actions taken to move a variable in one direction are likely different from actions that might be taken to move a variable in other direction. Moreover, individuals are often motivated to reduce a discrepancy when they have not yet achieved the goal, but are not motivated to reduce discrepancies that arise when their performance exceeds their goal. Vancouver et al., (2010) define the comparator as follows:

$$\text{If } p' - p(t) > 0 \text{ then, } d(t) = p' - p(t)$$

$$\text{else, } d(t) = 0.$$

where $p'$ represents the reference state.

Vancouver et al.’s (2010) model assumes that the intensity of the behavior aimed at reducing the discrepancy is proportional to the size of the discrepancy. This behavior is referred to as the action output ($o$). The action output may also be amplified or diminished due to individual differences or situational factors that influence one’s sensitivity to the discrepancy (Carver & Scheier, 1982; Hyland, 1987). For example, if the academic were offered a greater reward for achieving the publication goal (e.g., a higher salary), he or she should be more
sensitive to the discrepancy. In this case, a discrepancy of the same size may yield a greater action output than it would otherwise (Schmidt & DeShon, 2007). Vancouver et al., (2010) define the output function as follows:

\[ o(t) = kd(t) , \]  

(2.3)

where \( k \) is a gain parameter that represents the individual’s sensitivity to the discrepancy.

The final component in the feedback loop relates the action output to the state of the performance variable. The current state is a function of the previous state of the performance variable, the current output, the rate \( (r) \) at which the discrepancy can be reduced, and environmental disturbances \( (D) \). An environmental disturbance is an externally controlled event that produces a change in the current state, for example, a computer crash that causes the loss of recent additions to a manuscript. Vancouver et al. (2010) represented the change in the state of the performance variable in continuous time. Because the simulations conducted later in this article operate in discrete time, we use the discrete form of their equation presented below:

\[ \nu(t + 1) = \nu(t) + r o(t) + D(t) . \]  

(2.4)

To demonstrate the goal pursuit behavior predicted by the above model, we simulated it using R. We generated predictions for the current state of the variable \( (\nu) \) as a function of time \( (t) \) setting both \( p' \) and \( v_0 \) to 10, such that there was no initial discrepancy. We simulated an environmental disturbance that created a discrepancy at \( t = 10 \), allowing us to examine the model’s behavior before and after a discrepancy is produced. We set \( k \) to 1 to remove any effects of discrepancy sensitivity (i.e., gain), and \( r \) to 0.05. As can be seen in Figure 2.3, the current state of the variable does not change before the discrepancy is created because the output is 0. When the discrepancy is created however, output is produced. The output decreases over time as the discrepancy is reduced. Consequently, the state of the variable increases at a diminishing rate.
2.4.2 Two Alternative Models of Avoidance Goal Pursuit

In this section, we use Carver and Scheier’s (1998) theory to create two alternative models for the single avoidance goal pursuit scenario. The positive feedback model is based on the traditional definition of a positive feedback loop and therefore assumes that the discrepancy is positively related to the output. In other words, this model assumes that the avoidance behavior intensifies as the discrepancy between one’s current and undesired state grows. Although Carver and Scheier do explicitly make this assumption, the positive relationship between the

*Figure 2.3. Current state as a function of time during approach goal pursuit where a disturbance occurs at time = 10.*
discrepancy and the output is a necessary implication of modeling avoidance goal pursuit as a positive feedback loop. We argue that because Carver and Scheier’s account treats positive feedback loops as analogous to discrepancy-amplifying systems, a discrepancy-amplifying model in which the discrepancy is negatively related to the output is also consistent with their account. As this model satisfies the traditional definition of a negative feedback loop (i.e., as a system in which the input and output are negatively related), we refer to it as the negative feedback model.

**THE POSITIVE FEEDBACK MODEL**

We make two adjustments to the model of approach goal pursuit presented above, in order to create a positive feedback model based on Carver and Scheier’s (1998) assumptions about avoidance goal pursuit. Specifically, we change the nature of the output from discrepancy-reducing to discrepancy-amplifying, and the comparator from asymmetrical to symmetrical.

First, we implement Carver and Scheier’s assumption that action during avoidance goal pursuit aims to enlarge the discrepancy between current and undesired states. In order for this assumption to be satisfied, the sign of the path from the output to the comparator must be positive. This assumption can be satisfied by modifying the comparator function so that the discrepancy is determined by subtracting the undesired state from the perceived current state (as opposed to the approach context, where the desired state is subtracted from the perceived current state). This modification has the added benefit of making the discrepancy more comparable with the approach context. In both contexts, a positive discrepancy indicates that the reference state has not been realized (i.e., for approach goals, that the current state is below the desired state; for avoidance goals, that the current state is above the undesired state). During avoidance goal pursuit, we therefore assume that positive discrepancies are ‘good’ and that negative discrepancies are ‘bad’. Large positive discrepancies indicate that the current state is far from the undesired state, small positive discrepancies indicate that the current state is near the undesired state, and negative discrepancies indicate that the undesired state has been realized and that the current state is below (i.e., less desirable than) the undesired state.

Second, we implement a symmetric (as opposed to an asymmetric) comparator. Although Carver and Scheier (1998) assume an asymmetrical comparator in the approach context, they do not make an explicit statement as to whether the comparator is asymmetrical or symmetrical when pursuing an avoidance goal. The purpose of the asymmetrical comparator in the approach context is to represent the fact that there is no need to act on the approach goal when the current state surpasses the desired state because the goal is achieved. However, this issue is not relevant in the avoidance context, because goal achievement is not obtained by eliminating the discrepancy. Indeed, a lack of discrepancy between current and undesired states
(or a negative discrepancy) is when one most needs to act on an avoidance goal. Thus, we argue that an asymmetric comparator is not appropriate for the avoidance context, and instead implement the more parsimonious assumption that the comparator is symmetric. The avoidance comparator function is formally specified as follows:

\[ d(t) = p(t) - p'. \] (2.5)

Figure 2.4 shows a feedback control system that includes the above modifications. This system represents Carver and Scheier’s account of avoidance goal pursuit with the ‘positive feedback loop’ label interpreted according to its traditional definition. As can be seen, the link between the input and comparator functions is now positive, indicating the discrepancy is determined by subtracting the undesired state from the current state (i.e., the input). This modification makes the path from the output to the comparator positive (because the three links in the chain are all positive). The feedback system is now discrepancy-amplifying—the output increases (i.e., makes more favorable) the state of the variable, which in turn increases the discrepancy between current and undesired states. As a result of these modifications, the feedback system is positive. The output produces an increase in the input, which produces an increase in the discrepancy, which in turn produces an increase in the output.
We argue that it may be inappropriate to assume a positive relationship between the discrepancy and the intensity of avoidance behavior on the basis of Carver and Scheier’s use of the term ‘positive feedback loop’. The positive feedback model is based on a literal interpretation of Carver and Scheier’s description of avoidance goal pursuit as a positive feedback loop, which is traditionally defined in the systems dynamics literature as a system in which the input is positively related to the output (Richardson, 1991; Zeigler et al., 2000). In order for a model to satisfy this traditional definition, it must assume that the discrepancy is positively related to the output. However, Carver and Scheier’s account does not provide a precise specification of the nature of the relationship between the discrepancy and intensity of avoidance behavior, so it must be assumed based on their use of the label ‘positive feedback loop’. This assumption may be inappropriate because Carver and Scheier’s description appears

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**Figure 2.4.** A positive feedback control system with an undesired reference state (i.e., an avoidance goal).
to define positive feedback loops as discrepancy-amplifying systems, which do not require a positive relationship between the discrepancy and the output. The discrepancy-amplifying system described by the positive feedback model is a positive feedback loop because the relationship between the discrepancy and output is positive. However, a discrepancy-amplifying system in which the relationship between the discrepancy and output is negative would be a negative feedback loop.

We therefore argue that Carver and Scheier’s use of the term ‘positive feedback loop’, if interpreted according to its traditional definition, may imply an assumption about avoidance goal pursuit that is inconsistent with their perspective. This assumption, that avoidance behavior should intensify as an undesired state becomes more distant, also lacks intuitive appeal. For example, it would suggest that a zebra should put more effort into avoiding a hungry lion when it is 5 miles away, than when it is 5 feet away. It is also inconsistent with evidence suggesting that the distance between oneself and something undesirable is negatively related to the intensity of one’s response to the stimulus, whether the undesired stimulus is operationalized as a feared self (Ogilvie, 1987), a photo of a threatening stimulus (Mobbs et al., 2007), or an object toward which one has a phobia (e.g., Teghtsoonian & Frost, 1982). This evidence suggests that the intensity of avoidance behavior should decrease as the discrepancy between current and undesired states increases.

The above arguments suggest that a more appropriate model of avoidance goal pursuit should be discrepancy-amplifying, but assume a negative relationship between the discrepancy and the output. The intensity of avoidance behavior should be relatively high when the undesired state is near, and relatively low when the undesired state is distant. Because the output increases as the undesired state nears, an intercept parameter \(b\) is required to represent the intensity of avoidance behavior when the current state reaches the undesired state. We define the output function of the negative feedback model as follows:

\[
o(t) = b - kd(t) .
\]  

The intercept \(b\) influences the height of the function. Higher values of \(b\) strengthen the overall avoidance output. Higher values of gain \(k\) mean that the output decreases more rapidly as the discrepancy increases.

An important implication of this modification is that it changes the sign of the feedback control system from positive to negative. As can be seen in Figure 2.5, there is now a single negative link in the feedback loop. This single negative link makes the overall sign of the feedback loop negative, meaning that this model of avoidance goal pursuit is a negative feedback control system. Because the negative feedback model is also a discrepancy-amplifying system, we argue that it is still consistent with Carver and Scheier’s description of avoidance.
goal pursuit. However, support for this model would suggest that the use of the term ‘positive feedback loop’ to describe avoidance goal pursuit is inappropriate.

Figure 2.5. A negative feedback control system with an undesired reference state (i.e., an avoidance goal).

2.5 Simulating the Positive and Negative Feedback Models

We simulated the computational models presented above in order to examine how well each one reproduced the pattern of behavior predicted by Carver and Scheier's theory. Because Carver and Scheier make predictions about avoidance goal pursuit in insolation, as well as when pursued alongside an approach goal, we ran two simulations. The first simulated the above models in the single avoidance goal pursuit scenario. The second simulated the models in the simultaneous approach and avoidance goal pursuit scenario. In order to operationalize the
simultaneous scenario required for the second simulation, we needed to extend the model to describe how people decide which goal to act on. We present those extensions prior to presenting the second simulation.

We evaluate the two models by testing the pattern of behavior predicted by each model against two criteria. The first criterion is whether the behavior predicted by the model is consistent with the predictions of Carver and Scheier’s theory. That is, we examine whether the avoidance behavior produced by the model unfolds over time in the same manner as Carver and Scheier’s theory suggests. The second criterion is whether the behavior predicted by the model is meaningful. That is, we examine whether the model’s predictions are intuitively plausible. We examine this second criterion because a model would still be useful for understanding avoidance goal pursuit even if it makes predictions inconsistent with Carver and Scheier’s theory, as long as the predictions are meaningful. Alternatively, a model whose predictions are consistent with those of Carver and Scheier, but which do not make sense, would not be a useful explanation of avoidance goal pursuit.

2.5.1 Simulation Study 1: Single Avoidance Goal Pursuit Scenario

We simulated the models in the single goal scenario in order to examine the dynamic pattern avoidance behavior predicted by each model. For each model, the initial state was set to 10 and the undesired state was set to 0. The rate was set to 0.05. The disturbance was a normally distributed random variable with a mean of -0.1 and a standard deviation of 1. Thus, on average the disturbance had detrimental effects. Gain was set to 1 so that it would have no effect on the model’s behavior. The intercept (for the negative feedback model) was set to 50 indicating the avoidance output would equal 50 if the undesired state were reached. Because the disturbance was a random variable, we needed to conduct multiple simulations in order to achieve reliable predictions. We therefore simulated each model 1000 times and averaged the predictions across simulations.

The results of the simulations suggest that the two models predict different patterns of dynamic behavior (see Figure 2.6). The positive feedback model moves the variable away from the undesired state. The movement happens at an accelerating rate, such that the state of the variable rapidly approaches infinity. This effect emerges because the action output is positively related to the discrepancy. The predictions of the positive feedback model are consistent with the predictions of Carver and Scheier’s theory. Specifically, both predict that avoidance goal pursuit results in a pattern of runaway behavior, in which the avoidance never ceases. However, we argue that the predictions of the positive feedback model do not meet the
criterion of plausibility. These predictions seem implausible because of the counter intuitive notion that avoidance behavior should intensify over time as the undesired state becomes more distant (and therefore less of a threat).

The negative feedback model also moves the variable away from the undesired state. However, the movement happens at a decreasing rate because the output gets weaker as the discrepancy grows. As the state of the variable approaches a value equal to the intercept parameter, the output of the negative feedback model approaches 0. The predictions of the negative feedback model are not consistent with the predictions of Carver and Scheier’s theory. The avoidance behavior predicted by this model slows over time and eventually ceases, whereas Carver and Scheier predict that the avoidance behavior should continue indefinitely. However, the notion that the intensity of avoidance behavior should decrease over time as the undesired state becomes more distant still makes intuitive sense. The predictions of the negative feedback model therefore meet the criterion of plausibility.
2.5.2 Simulation Study 2: Simultaneous Approach and Avoidance Goal Pursuit Scenario

We interpreted Carver and Scheier’s theory to predict that when pursuing approach and avoidance goals simultaneously, the output for the approach system should eventually exceed the output for the avoidance system. Although there is not yet a published computational framework for modeling the simultaneous pursuit of approach and avoidance goals, Vancouver et al. (2010) model the simultaneous pursuit of two approach goals. This model can be adapted to the approach-avoidance context. This model conceptualizes the process of simultaneously
striving for two goals as involving two distinct tasks, each represented by a separate feedback loop (see Figure 2.7). One of these feedback loops represents the task of avoiding the undesired state, whereas the other represents the task of approaching the desired state. For each task, the perception of the performance variable generated by the input function, the discrepancy determined by the comparator, and the action exerted by the output function, are all defined identically to the relevant models above.

Figure 2.7. A conceptual representation of the process of simultaneously pursuing two goals.

The added complexity of this model lies in the assumption that only one task can be performed at a time. Thus, even though both feedback loops may produce an output, only one of these outputs can be transformed into an action that impacts performance for one of the tasks. Vancouver et al. (2010) therefore implement a choice function that determines which task receives priority at a given point in time. Following their model, we assume that the decision of which task to prioritize is made by comparing the action outputs for the approach versus the avoidance task. That is, the extent to which the person is far away from the desired state (i.e.,
the approach goal) is compared with the extent to which the person is nearing the undesired state (i.e., the avoidance goal). The task for which the output value is larger is considered to be the task most in need of resources, and therefore it receives priority. When the output from the avoidance feedback loop is larger (e.g., due to the undesired state drawing near), avoidance becomes the priority and action is directed toward increasing the discrepancy between one’s current state on the avoidance task and the undesired reference state. When the output from the approach loop is greater (e.g., due to the desired state being far away), approach becomes the priority, and action is directed toward reducing the discrepancy between the current state on the approach task and the desired reference state. We define the choice function as follows:

\[
\text{If } o_{AP}(t) - o_{AV}(t) > 0, \text{ then } c(t) = 1
\]

\[
\text{If } o_{AP}(t) - o_{AV}(t) < 0, \text{ then } c(t) = 0,
\]

where \( c(t) = 1 \) indicates that the approach task receives priority and \( c(t) = 0 \) indicates that the avoidance task receives priority. When the outputs for the two tasks are equal \( (o_{AP}(t) - o_{AV}(t) = 0) \), priority is determined randomly. Following Vancouver et al. (2010), we assume that only the task that is prioritized receives the output:

\[
\text{If } c(t) = 1,
\]

\[
v_{AP}(t) = v_{AP}(t-1) + r_{o_{AP}}(t) + D_{AP}(t),
\]

\[
v_{AV}(t) = v_{AV}(t-1) + D_{AV}(t).
\]

\[
\text{If } c(t) = 0,
\]

\[
v_{AP}(t) = v_{AP}(t-1) + D_{AP}(t),
\]

\[
v_{AV}(t) = v_{AV}(t-1) + r_{o_{AV}}(t) + D_{AV}(t).
\]

We simulated the simultaneous approach and avoidance goal pursuit scenario in a similar manner to the single avoidance goal pursuit scenario described above. For the approach task, the initial state was set to 0 and the goal to 10. For the avoidance task, the initial state was set to 10 and the goal to 0 (so that the initial discrepancies were equal). The rates, disturbances, gains, and the intercept (for the negative feedback model of the avoidance task) were identical to the previous simulations. Once again, we produced the patterns predicted by each model by simulating them 1000 times and averaging across simulations.

The results of this simulation suggested that, as with the single avoidance goal pursuit scenario, the models predicted different patterns of behavior in the simultaneous approach and avoidance goal pursuit scenario (see Figure 2.8). The positive feedback model once again produced runaway avoidance behavior, with the output for the avoidance task and the state of the variable for this task both increasing at an accelerating rate and approaching infinity. This behavior occurred at the expense of the approach task. As can be seen in the right half of the
figure, the state of the variable for the approach task actually moved farther away from the desired state. The predictions of the positive feedback model are inconsistent with those of Carver and Scheier, who predict that the avoidance behavior should be constrained by the pursuit of the approach goal. We argue that these predictions also do not meet the criterion of plausibility. As with the single avoidance goal pursuit scenario, it seems unlikely that avoidance behavior would intensify over time as the undesired state becomes more distant, especially when another task is being neglected as a consequence of this increased intensity.

The negative feedback model predicts that as the state of the variable for the avoidance task moves further away from the undesired state, the output for the approach system surpasses the output for the avoidance system. The avoidance behavior therefore eventually ceases and the model works towards reducing the discrepancy for the approach goal. The predictions of the negative feedback model are consistent with Carver and Scheier’s prediction that avoidance behavior should be constrained by the task of pursuing the approach goal. We also argue that this criterion meets the criterion of plausibility.
Figure 2.8. Predicted state of the variable and output as a function of time for the positive and negative feedback models when simultaneously pursuing an approach and an avoidance goal.

2.6 DISCUSSION

We implemented Carver and Scheier’s (1998) theory of avoidance goal pursuit as a computational model. Although Carver and Scheier describe avoidance goal pursuit as a positive feedback loop, their use of this term (i.e., as analogous to a discrepancy-amplifying system) appears inconsistent with how it is traditionally defined (i.e., a system in which the input is positively related to the output). We therefore simulated two different versions of their theory. The positive feedback model was based on a literal interpretation of their theory. Although this model satisfied the traditional definition of a positive feedback loop, it made an assumption that was not necessarily consistent with Carver and Scheier’s perspective, namely, that avoidance behavior intensifies as the undesired state becomes further away. The negative feedback model assumed the opposite, namely, that the intensity of the avoidance behavior decreases as the undesired state becomes further away. Although this model did not satisfy the
The traditional definition of a positive feedback loop, we argue that it is still consistent with Carver and Scheier’s conceptualization of avoidance goal pursuit.

The simulations showed that in both a single avoidance goal pursuit and a simultaneous approach and avoidance goal pursuit scenario, the positive feedback model predicted that the intensity of avoidance behavior should accelerate over time, and rapidly approach infinity. This prediction is counterintuitive, and inconsistent with Carver and Scheier’s prediction that avoidance goal pursuit should be constrained by the pursuit of an approach goal. The negative feedback model, on the other hand, predicted that the intensity of avoidance behavior should decelerate over time, which, in line with Carver and Scheier’s predictions, enabled the pursuit of the avoidance goal to be captured by the approach goal. In general, the predictions of the negative feedback model were more intuitively plausible than the predictions of the positive feedback model. We conclude that the negative feedback model provides a better representation of Carver and Scheier’s theory of avoidance goal pursuit. We therefore argue that it is inappropriate to describe this process as a positive feedback loop. The negative feedback conceptualization offers an opportunity to develop new theory and predictions regarding avoidance goal pursuit. In the following sections, we discuss the contributions of this work to the goal-pursuit literature as well as the practical implications and future research directions.

2.6.1 Contributions to the Goal-Pursuit Literature

This research contributes to the goal-pursuit literature by articulating a major theory of avoidance goal pursuit as a computational model. We have demonstrated that Carver and Scheier’s verbal theory makes meaningful predictions. However, our findings suggest that a more appropriate label for their description of avoidance goal pursuit is ‘negative feedback loop’. The confusion as to whether the label ‘positive feedback loop’ or ‘negative feedback loop’ is more appropriate arises from Carver and Scheier’s account appearing to treat positive feedback loops and discrepancy-amplifying systems as one and the same. Although discrepancy-amplifying systems are often positive feedback loops, a defining property of a positive feedback loop, which is not necessarily a property of a discrepancy-amplifying system, is a positive relationship between input and output. Yet Carver and Scheier do not specify the nature of this relationship. Moreover, when this assumption is implemented in the computational model, it produces implausible predictions that are inconsistent with the dynamic pattern of behavior predicted by Carver and Scheier’s verbal account. We therefore argue that Carver and Scheier’s account is sensible, but that avoidance goal pursuit likely
satisfies the traditional definition of a negative feedback loop, rather than a positive feedback loop.

The use of the label ‘negative feedback loop’ to describe avoidance goal pursuit highlights similarities between avoidance and approach goal pursuit. Approach goal pursuit is also a negative feedback loop (Carver & Scheier, 1998; Vancouver, 2008). The key difference between these two processes is that avoidance goal pursuit is a discrepancy-amplifying system, which aims to move the variable away from an undesired state, whereas approach goal pursuit is a discrepancy-reducing system, which aims to move the variable closer to a desired state. However, both systems are negative feedback loops because the input is negatively related to the output. In other words, whether one engages in discrepancy-amplifying or discrepancy-reducing behavior, both types of behavior reduce the need for the behavior to occur subsequently. For example, avoidance behavior moves the person away from an undesired state. As a result, the undesired state is less threatening, and the avoidance behavior therefore reduces in intensity. In the same way, movement toward a desired state reduces the amount of resources required to reach that state, prompting a decrease in the intensity of subsequent approach behavior.

Clarifying the sign of the avoidance goal pursuit feedback loop has enabled us to specify precisely the nature of the relationship between the discrepancy and the intensity of avoidance behavior. Carver and Scheier’s account states that avoidance goal pursuit involves discrepancy-amplification. However, their account is not explicit in specifying how the magnitude of the discrepancy influences the rate of discrepancy-amplification (i.e., the intensity of avoidance behavior). This lack of precision is problematic, because a formal specification of this relationship is required to translate their theory into a computational model. We examined two different ways of conceptualizing this relationship. We showed that only a model in which the relationship between the discrepancy and the intensity of avoidance behavior was positive satisfied the traditional definition of a positive feedback loop. However, if we relaxed the definition of positive feedback loop and, like Carver and Scheier, treated this label as representing a discrepancy-amplifying system, then a model in which the discrepancy-intensity relationship was negative would also be consistent with their account. Assuming a negative relationship is advantageous because it is consistent with previous research (Mobbs et al., 2007; Ogilvie, 1987; Teghtsoonian & Frost, 1982). Moreover, our findings supported this model, suggesting that the avoidance behavior weakens rather than intensifies as the individual moves away from an undesired state.

Much of our understanding of the avoidance process stems from Carver and Scheier’s theory of self-regulation. Their theory has been used across disciplines to understand behavior in areas such as social (e.g., Louro, Pieters, & Zeelenberg, 2007), clinical (e.g., Trew, 2011),
organizational (e.g., Foo, Uy, & Baron, 2009), and sport psychology (e.g., Williams, Donovan, & Dodge, 2000). It is therefore critical that the theory be specified as a computational model. As with past translations of verbal theory into computational models (Weinhardt & Vancouver, 2012), our attempts to articulate Carver and Scheier’s account computationally revealed ambiguity in their theory. This ambiguity is problematic because it increases the likelihood that those wanting to understand how avoidance behavior unfolds over time either a) misinterpret the theory and make predictions that are inconsistent with Carver and Scheier’s perspective or b) make predictions that are consistent with Carver and Scheier but be less confident in their accuracy. This lack of theoretical clarity obstructs the empirical process by making it more difficult to determine whether or not observed patterns of avoidance behavior are consistent with their theory. By specifying Carver and Scheier’s description in the form of a computational model, we resolve this ambiguity and increase both the precision and the transparency of the theory. We believe this contribution will lead to more sophisticated theory that produces novel predictions, and ultimately facilitate the accumulation of knowledge regarding how people pursue avoidance goals.

2.6.2 Practical Applications

The development of Carver and Scheier’s theory of avoidance goal pursuit into a computational model has the potential to inform practice. There are many work contexts in which the ability to effectively manage avoidance goals is critical. For example, air traffic controllers must ensure that aircraft in their sector avoid breaching separation with other aircraft. Instantiating a major theory of avoidance goal pursuit as a computational model may help inform training and performance management in these contexts (Weinhardt & Vancouver, 2012). For example, decision support tools based on computational models have been used to help controllers decide whether to take action to increase aircraft separation (Loft, Bolland, Humphreys, & Neal, 2009; Vuckovic, Sanderson, Neal, Gaukrodger, & Wong, 2013). These models tend to take into account factors such as aircraft speed, position, and the workload of the controller. However, they often fail to account for the influence of the underlying avoidance goal pursuit process on the controller’s behavior. An air traffic controller’s duties are all performed in service of the goal of avoiding safety breaches, and it has been argued that decision support systems should take into the underlying goals of the decision maker (Nute, Rosenberg, Nath, & Verma, 2000). Incorporating this process into such models may therefore improve controllers’ judgments and help them make safer decisions.

The question of whether avoidance goal pursuit is a positive or negative feedback control system is important, because the two perspectives conceptualize the relationship between
discrepancy and the intensity of avoidance behavior differently and, as a result, predict different behavior. Because Carver and Scheier do not precisely specify the nature of this relationship, a model which interprets the ‘positive feedback loop’ label according to its traditional definition, and which assumes that the discrepancy-intensity relationship is positive, could be considered an accurate representation of what Carver and Scheier propose are the mechanisms underlying avoidance goal pursuit. However, because such a model predicts patterns of dynamic behavior that are counterintuitive and inconsistent with the patterns predicted by Carver and Scheier, applying a positive feedback model in a decision support system could make the system less useful. Instead, our results imply that a decision support system would be more effective if it conceptualized avoidance goal pursuit as a negative feedback loop. Consider the air traffic control example once again. A model of avoidance goal pursuit in this context might consider the current state to be the present distance between aircraft, and the undesired state to be the minimum separation standard. A negative feedback model would assume that motivation to avoid a separation breach increases as the distance between aircraft gets closer to the minimum standard. An implication of this assumption is that people should allocate more resources to managing aircraft pairs that are closer together. This tendency may have the potential to compromise performance when more than one aircraft pair is separated by a distance near the minimum standard. In this case, a given pair might have the shortest separation distance in one moment and therefore be the focus of the controller’s attention, but another pair might reach a shorter separation distance in the next moment prompting the controller to shift attention. This situation may lead the controller’s attention to switch rapidly between aircraft pairs from one moment to the next. As a result, the controller may fail to focus on a pair long enough to carry out the actions necessary to increase the separation distance. A decision support system may therefore include a component that encourages controllers to fully execute a sequence of actions for one pair before attending to the next. A firm understanding of the underlying mechanisms is therefore critical for a theory of avoidance goal pursuit to be of practical benefit.

2.6.3 ADDITIONAL CONSIDERATIONS AND AVENUES FOR FUTURE RESEARCH

In order to examine Carver and Scheier’s prediction regarding the tendency for an avoidance goal pursuit to be constrained by the pursuit of an approach goal, it was necessary to incorporate assumptions unspecified by Carver and Scheier’s theory that describe how people simultaneously pursue multiple goals. We drew on the assumptions of multiple-goal pursuit theory (Vancouver et al., 2010, 2014) because it is an existing computational model with similar
theoretical underpinnings to Carver and Scheier’s theory (i.e., control theory). However, it is important to consider whether an alternative model would produce a different pattern of behavior. For example, rather than assuming that the individual must choose between pursuing the approach goal and the avoidance goal, we could assume that the two goals are structured in a means-end hierarchy (e.g., Kruglanski et al., 2002) whereby the approach goal is a sub-goal which is used as a means to make progress away from the avoidance goal. According to this perspective, making progress towards the approach sub-goal would facilitate pursuit of the avoidance goal. Another conceptualization might assume that the approach goal is developed at a later stage of goal pursuit to replace the avoidance goal. Although both of these assumptions seem consistent with Carver and Scheier’s account, neither assumption has been implemented in a computational model. Implementing either would therefore require developing a computational framework from scratch. The simultaneous approach and avoidance goal pursuit model implemented in this research has the advantage of being adapted from the multiple-goal pursuit model (Vancouver et al., 2010), a well-validated explanation of how people manage multiple goals. Regardless of how the approach goal is implemented, however, we argue that the core assumption of the positive feedback model—that intensity of the avoidance behavior increases with distance from the undesired state—is problematic because it is counterintuitive and inconsistent with previous research. Thus, any model that describes avoidance goal pursuit in this manner will not be accurate.

It is also worth noting that the issue of avoidance motivation has been addressed in a previous formal model. Townsend and Busemeyer (1989) provide a dynamic, formal model of approach and avoidance behavior. Although this model is not based on control theory, it assumes that one’s motivation to approach or avoid is influenced by similar factors to the ones addressed here. For example, it also predicts that motivation intensity is a function of the distance to desired and undesired objects in the environment. Importantly, Townsend and Busemeyer’s (1989) model makes similar assumptions to the negative feedback model presented above. That is, it assumes that the motivation to avoid something undesired should decrease as the undesired state or object becomes further away. Thus, when played out over time, these models should produce the same pattern of emergent behavior as the negative feedback model.

Future research should seek to test empirically the predictions of the models presented in this paper. Goal pursuit is a dynamic process that unfolds over time. Thus, an appropriate empirical test requires multiple measurements of a) goal-performance discrepancy and b) an indicator of motivation such as effort, time, or resource allocation, whilst participants pursue an avoidance goal. This test can be achieved using a variety of empirical methods. For example, some research has used diary studies which elicit repeated self-report measures of the relevant
constructs (Eddington, Majestic, & Silvia, 2012; Louro et al., 2007; Righetti, Rusbult, & Finkenauer, 2010). Other research has used laboratory experiments that obtain a behavioral measure of resource allocation (Schmidt & DeShon, 2007; Schmidt et al., 2009; Schmidt & Dolis, 2009). Ideally, a combination of approaches should be used to ensure methodological generalizability.

2.6.4 CONCLUSION

We have argued that Carver and Scheier’s use of the label ‘positive feedback loop’ to describe avoidance goal pursuit is inconsistent with how positive feedback loops are traditionally defined. The use of this label creates ambiguity in understanding the precise nature of the relationship between how far one is from an undesired state and the intensity of the avoidance behavior. As we have shown, this ambiguity is problematic because computational models of avoidance goal pursuit make different predictions, depending on how this relationship is conceptualized. Using computational modeling, we have resolved this ambiguity by demonstrating that interpreting the ‘positive feedback loop’ label according to its traditional definition produces a pattern of dynamic behavior that is counterintuitive and inconsistent with the pattern predicted by Carver and Scheier’s verbal theory. We have therefore clarified that the discrepancy-output relationship should be conceptualized as negative, and have concluded that a model based on Carver and Scheier’s account is better described as a negative feedback loop. We believe that articulating Carver and Scheier’s theory with the precision and transparency of a computational model will facilitate theory development in the area of avoidance goal pursuit. We hope that this increase in precision will enable this theory to be more readily used to guide empirical and practical pursuits.
This chapter is presented as a journal article manuscript. A version of this manuscript was in press at Journal of Applied Psychology at the time this thesis was submitted.

3.1 FOREWORD

In Chapter 2, I provided a precise account of avoidance goal pursuit by articulating Carver and Scheier’s (1998) theory as a computational model. However, in order to understand how people prioritize when an avoidance goal is pursued simultaneously with approach or other avoidance goals, the model of avoidance goal pursuit introduced in Chapter 2 must be integrated into a model of multiple-goal pursuit. I achieve this integration by incorporating the model of avoidance goal pursuit into the multiple-goal pursuit model (Vancouver et al., 2010), which is a model of multiple-approach-goal pursuit. Along with the failure to address avoidance goals, another shortcoming of the multiple-goal pursuit model is the inability to account for actions having multiple uncertain consequences that impact progress for more than one goal. Rather, implementations of the multiple-goal pursuit model (e.g., Vancouver et al., 2010; 2014) have assumed that actions have certain consequences that only affect one goal. I therefore incorporate decision field theory (Busemeyer & Townsend, 1993) to explain how uncertainty in the consequences of actions, and the ability for these consequences to impact multiple goals, influences how people prioritize. I refer to this extended version of the multiple-goal pursuit model as the MGPM*. 
3.2 Abstract

We extended the multiple-goal pursuit model (Vancouver et al., 2010) to predict how goal prioritization is influenced by the combination of approach/avoidance goals being pursued and the level of uncertainty in the consequences of actions. The model was tested using an Air Traffic Control task where 91 participants pursued one approach and one avoidance goal, two approach goals, or two avoidance goals, and where the level of uncertainty in the consequences of actions for goal progress varied. Participants pursuing one approach and one avoidance goal tended to shift priority over time from the approach to the avoidance goal. Participants pursuing two approach goals tended to use one of two strategies: either focusing on the goal for which the desired state was farther away, and thus switching priority fairly rapidly between goals (balanced strategy); or focusing on the goal for which the desired state was closer, and thus prioritizing one goal until it was attained and then switching to the other (sequential strategy). The balanced strategy was more frequently observed among participants pursuing two avoidance goals. Regardless of which goal tended to be prioritized, the tendency was stronger when the consequences of actions for goal progress were more certain. All of these findings were accounted for by the model. The extended multiple-goal pursuit model (MGPM*) represents a step forward in the development of a more general theory of decision making during multiple-goal pursuit that we hope will help build a stronger bridge between basic psychological science and organization studies.
3.3 INTRODUCTION

People often pursue multiple, competing goals and, as a result, have to choose which goal to prioritize at any given moment. These prioritization decisions are often characterized by choices between actions (i.e., the means for pursuing goals) that will facilitate progress towards particular goals, whilst impeding progress towards other goals. For example, a surgeon who is struggling to perform a maneuver with limited visibility may have to choose between actions that are likely to maximize safety (e.g., by making a long incision), and actions that are likely to minimize pain (e.g., by making a short incision). Managing competing goals is demanding, and is complicated by the fact that goals can be framed in different ways and the consequences of our actions may be uncertain. For example, people are often faced with conflicts between approach and avoidance goals. An approach goal represents a desired outcome that a person strives to achieve, while an avoidance goal represents an undesired outcome that a person strives to avoid (Carver & Scheier, 1998). Moreover, uncertainty is known to have a profound impact on decision making (Busemeyer, 1985; Busemeyer & Townsend, 1993). Yet we know surprisingly little about the way that these factors influence multiple-goal pursuit. It is important to understand how people make prioritization decisions when engaged in multiple-goal pursuit, because poor choices can have significant consequences for those concerned.

Until recently, the field lacked a formal theory that explains the process by which people make these types of prioritization decisions over time. The development of a formal model of multiple-goal pursuit (Vancouver et al., 2010) represents an important step forward in understanding this phenomenon. Formal models are widely used in cognitive psychology, neuroscience (Lewandowsky & Farrell, 2011), human factors (Loft et al., 2009; Steelman, McCarley, & Wickens, 2011), and social psychology (Kruglanski et al., 2012), but are rarely used within organizational psychology. Formal models provide a more precise specification of the mechanisms underlying psychological phenomena than verbal theories (Busemeyer & Diederich, 2010; Lewandowsky & Farrell, 2011; Roberts & Pashler, 2000). Because they are described mathematically, it is possible to simulate them and derive a set of predictions that can be falsified. Simulation is particularly important when seeking to understand dynamic processes, because even relatively simple models can generate surprising emergent phenomena when run dynamically. Further, formal theories facilitate the integration of basic structures and processes from other theories, enabling the theory to account for a broader set of empirical phenomena and to be capable of better addressing real-world problems. This process of systematic unification facilitates the cumulative development of knowledge in the field and is
regarded as the hallmark of a mature science (Anderson et al., 2004; Hempel, 1966; Newell, 1990; Steel & Konig, 2006)

Vancouver et al. (2010) took the initial steps toward a formal theory of multiple-goal pursuit by developing the multiple-goal pursuit model, which is a formal model of multiple-approach-goal pursuit. The model is capable of accounting for the effects of incentives and changing expectancies as individuals attempt to make goal progress before deadlines are reached. The model also accounted for individual differences in multiple-goal pursuit behavior. Vancouver, Weinhardt, and Vigo (2014) extended this model to explain how people learn about the task context and their own capacities during goal pursuit. The multiple-goal pursuit model lays the foundation for developing a general theory of multiple-goal pursuit. However, it does not yet account for avoidance goals and has not been applied to environments in which there is varying uncertainty regarding the consequences of actions for goal progress. Moreover, the model has only been applied to relatively simple choice problems in which each action has only one potential consequence impacting a single goal.

We extend the multiple-goal pursuit model in two ways. First, we account for avoidance goal pursuit by incorporating the computational model presented in Chapter 2. We know from over 50 years of research on achievement motivation that avoidance goals are important in motivating behavior (Elliot & Church, 1997). However, to the best of our knowledge, no published work—either empirically or computationally—has examined the role of avoidance in multiple-goal pursuit. Our extension describes the mechanisms responsible for the pursuit of avoidance goals and generates predictions regarding the impact of goal frame on prioritization decisions during multiple-goal pursuit.

Second, we account for the effects of uncertainty regarding the consequences of actions, by extending the model to deal with more complex choice problems (e.g., when people are faced by choices between actions that may have multiple, though not entirely predictable, consequences in relation to multiple goals). We achieve this by incorporating a probabilistic account of the choice process derived from sequential sampling theories of decision making (Busemeyer & Townsend, 1993; Roe, Busemeyer, & Townsend, 2001). The multiple-goal pursuit model assumes that choice is determined by a deterministic function. Deterministic choice functions make a binary prediction regarding the direction of preference—they predict which action will be chosen from a set of actions. Probabilistic choice functions assume that the likelihood of choosing a particular action is determined by the strength of preference for that action (Busemeyer & Townsend, 1993). Probabilistic theories recognize that changes in the tendency to select a course of action are graded (Edwards, 1955; Mosteller & Nogee, 1951) and are therefore able to account for a large class of phenomena that are unable to be explained by deterministic theories (Busemeyer & Townsend, 1993; Rieskamp, 2008). The specific theory that
we draw on is decision field theory (Busemeyer & Townsend, 1993; Busemeyer & Diederich, 2002; Roe et al., 2001), which provides a well-validated account of decision making under uncertainty when people are faced with complex choice problems. This extension allows us to generate predictions regarding the impact of uncertainty on the strength of goal frame effects on prioritization decisions.

In summary, our aim is to extend the multiple-goal pursuit model by accounting for goal framing and uncertainty. We refer to this extended version of the model as the MGPM*. The MGPM* generates predictions regarding the effects of these variables on the likelihood of selecting actions that prioritize a particular goal. We test these predictions in an experiment in which participants make a series of choices amongst competing courses of action whilst pursuing different combinations of approach and avoidance goals, and in which the level of uncertainty regarding the consequences of those actions varies. The results suggest that the data are consistent with the extended model’s predictions, and the model provides a better account of the data than the existing multiple-goal pursuit model. Our key conclusions are that a) when pursuing one approach and one avoidance goal, people tend to switch priority over time from the approach to the avoidance goal, b) the tendency to prioritize a particular goal is stronger when the consequences of actions are certain, and c) individual differences in prioritization strategies found in previous studies, but not yet explained by the multiple-goal pursuit model, can be formally explained by the MGPM*.

### 3.3.1 Overview of the Multiple-Goal Pursuit Model

The multiple-goal pursuit model (Vancouver et al., 2010) is a computational model based on the control theory account of goal pursuit (e.g., Carver & Scheier, 1998; Klein, 1989; Lord & Levy, 1994; Powers, 1973; Vancouver, 2008). Consistent with most control theory accounts and the majority of the empirical work, Vancouver et al’s (2010) model focuses on approach goals. Control theory represents goal pursuit as a dynamic feedback control system. 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 the satisfaction of a higher-order need. According to control theory, the tendency to act on a goal is determined by the discrepancy between the current state of the variable that is being controlled, and a reference state for that variable. For example, if an assistant professor has a goal of publishing ten 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, and thus eliminate the discrepancy between the current and desired states. Larger discrepancies represent a greater need for action than smaller discrepancies. In support of these propositions, studies have shown that discrepancy between the current and
desired states is positively related to the amount of effort directed toward an approach goal (Bandura & Cervone, 1983; Campion & Lord, 1982; Kernan & Lord, 1990).

According to the multiple-goal pursuit model, the choice amongst competing goals is determined by a choice agent that compares the expected utilities of acting for each goal. The choice agent selects the goal with the highest expected utility. Consistent with expectancy X value theories (e.g., Kanfer, 1991), expected utility is determined by a multiplicative combination of valence (also called “utility” or “value”) and expectancy (Vroom, 1964). Valence represents the subjective immediate value of acting on the goal. It is equal to the product of the discrepancy and a gain parameter, which accounts for the importance of the goal to the individual. Expectancy represents the perceived likelihood the goal can be achieved in the time available. Expectancy is generated by comparing a subjective sense of the resources required (e.g., time needed) 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 in the resources it takes to reduce a unit of discrepancy; a belief that is developed with experience but also potentially biased by the individual (Vancouver et al., 2014). In the specific empirical protocols examined to test the multiple-goal pursuit model, the resource in question was time. Thus, the subjective sense of time available was a function of the objective time available and a time gain parameter, which accounted for the individual’s sensitivity to the deadline. This model results in dynamic valence and expectancy as the person makes progress towards, or away from, the goal. Thus, over time the expected utilities of the goals vary.

The multiple-goal pursuit model predicts that, as long as there is sufficient time available to meet the goals, individuals will tend to prioritize the goal with the larger discrepancy. However, as the perceived likelihood (i.e., expectancy) of achieving the goal with the larger discrepancy in the allotted time approaches zero, the model predicts that this goal with the larger discrepancy will be abandoned and priority will shift to the goal with the smaller discrepancy. 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 et al., 2007; Schmidt & Dolis, 2009), though with a preference for the goal with the higher incentive if such differential incentives exist (Schmidt & DeShon, 2007). These empirical studies also showed individual differences, which the Vancouver et al. (2010) model could account for via differences in the time gain parameter and other free parameters in the model. For example, people who were more sensitive to time pressure (i.e., had higher time gain parameter values) demonstrated an earlier preference reversal. Vancouver et al. (2010) also showed how differences in the sensitivity to incentives could translate into differences in prioritized goals based on the magnitude of the incentive. In the following sections, we present the conceptual background and mathematical specification required to extend this model to
account for avoidance goals and variations in uncertainty in the consequences of actions related
to goal pursuit.

3.3.2 Extending the Model to Account for Avoidance Goals

The MGPM* accounts for avoidance goals by modifying the discrepancy, valence, expectancy,
and expected utility components of the multiple-goal pursuit model. These modifications are
explained below.

Discrepancy

The MGPM* assumes that people may simultaneously pursue any number of approach or
avoidance goals (denoted using the subscript \(k\)). Like the multiple-goal pursuit model, the
MGPM* assumes that discrepancy \(d\) is a function of the difference between the goal state and
the current state of the variable being controlled, but in the MGPM*, the goal may be either a
desired or an undesired state:

\[
d_k(t) = g_k(t) - a_k(t).
\]  

(3.1)

where \(g_k(t)\) is the desired or undesired state and \(a_k(t)\) is the current state of the variable being
controlled at time \(t\).

Valence

The multiple-goal pursuit model assumes that the valence of an approach goal decreases as a
person moves closer to the desired state. Consider the example of the assistant professor who is
aiming for ten papers in top-tier journals before her tenure deadline. When she only has one
paper, the subjective value of acting on that goal will be high, but as she gets more papers and
thus closer to achieving her goal, the subjective value of acting on the goal will reduce. In
contrast, the valence of an avoidance goal should increase as a person moves closer to the
undesired state. The assistant professor may simultaneously aim to avoid poor teaching ratings.
She may have been told that she is unlikely to get tenure if she receives poor teaching ratings in
more than three classes during her tenure period. When she starts out, the subjective value of
acting on that goal will be low, because she is a long way from the undesired state. However, if
she starts getting poor student ratings, the subjective value of acting on that goal should
increase. To account for this relationship, the MGPM* incorporates the computational model of
avoidance goal pursuit introduced in Chapter 2. The MGPM* therefore includes an intercept
parameter \(b\) to represent the valence of acting on the goal when one’s current state is equal to
the goal. We assume that $b = 0$ for approach goals (i.e., the valence of acting on an approach goal is 0 when a desired state is reached). However, for an avoidance goal $b$ represents the maximum valence associated with the avoid goal (i.e., one’s anticipated dissatisfaction if the avoidance goal is realized). In line with the multiple-goal pursuit model, the MGPM* assumes that gain ($\kappa$) is positive when pursuing approach goals (i.e., to reflect that valence decreases as the person gets closer to the goal). However, the MGPM* assumes that gain is negative when pursuing avoidance goals (i.e., to reflect that valence increases as the person gets closer to the goal: see Figure 3.1). Finally, we assume that valence cannot fall below 0. Thus, the MGPM* defines valence ($v$) as follows:

$$v_k(t) = \max[b_k + \kappa_k d_k(t), 0].$$  \quad (3.2)

Figure 3.1. Valence as a function of discrepancy for approach and avoidance goals.

**EXPECTANCY**

In this section, we modify the expectancy component of the multiple-goal pursuit model in order to be more consistent with the traditional conceptualization of expectancy. As will be demonstrated next, this modification is also necessary to specify how expectancy influences the expected utility of acting on an avoidance goal. Expectancy has traditionally been conceptualized as the subjective likelihood of an event occurring (Edwards, 1954; Vroom, 1964). Consequently, expectancy is traditionally bounded between 0 and 1, with 0 indicating that the occurrence of the event is impossible and 1 indicating that the event is certain to occur. The MGPM* uses a logistic function to bound expectancy at 0 and 1. Logistic functions are
commonly used in neural network models to constrain function output within a particular range (Hill, Marquez, O’Connor, & Remus, 1994). This type of function is advantageous not only because there is precedent for using logistic functions, but they are also psychologically plausible—they are commonly used to describe learning behavior (e.g., Thomas & McClelland, 2008), and beliefs regarding the state of the world or the subjective magnitude of variables (e.g., Parasuraman, Masalonis, & Hancock, 2000). The MGPM* defines the expectancy \( e \) of reaching a desired or undesired state within the time available \( TA \) as follows:

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

where \( \gamma \) is a free parameter representing time sensitivity (similar to the time gain parameter in the multiple-goal pursuit model), and \( TR \) represents the person’s belief regarding time required to reach the goal, given their current velocity of approach. According to this function, expectancy is equal to 0.5 when the time available is equal to the time required to reach the goal; greater than 0.5 when the time available is more than required; and less than 0.5 when the time available is less than required. Higher values of \( \gamma \) means that expectancy, and therefore people’s decisions, are more sensitive to the difference between the time remaining and time required. Lower values of \( \gamma \) indicate a lower level of sensitivity (see Figure 3.2).

Following the MGPM, we define \( TR \) as the product of discrepancy and expected lag \( (\alpha) \). \( TR \) 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 if the goal is acted upon. Expected lag can change based on experience with the task (Vancouver et al., 2014) or environmental cues. The expected time required is defined as follows:

\[
TR_k(t) = d_k(t) \cdot \alpha_k(t)
\]
Figure 3.2. Expectancy as a function of the difference between time available and time required, and time sensitivity ($\gamma$).

**EXPECTED UTILITY**

According to the multiple-goal pursuit model, the expected utility of acting on a goal is the product of valence and expectancy. However, this equation needs modification to account for the fact that the relationship between expectancy and expected utility in the avoidance context is in the opposite direction to this relationship in the approach context. For approach goals, expectancy is positively related to the expected utility of acting on the goal because a high expectancy indicates a high likelihood of reaching the desired state. However, for avoidance goals, expectancy should be negatively related to expected utility because a high expectancy in this context indicates a high likelihood of reaching the undesired state. The MGPM therefore defines expected utility using separate equations for approach and avoidance goals. For approach goals, expected utility ($u$) is defined as follows:

$$u_k(t) = v_k(t) \cdot e_k(t).$$  \hspace{1cm} (3.5a)
For avoidance goals, expected utility is defined by taking the complement of the expectancy variable, such that an increase in expectancy produces a decrease in expected utility:

\[ u(t) = v(t) \cdot (1 - e(t)) \]  \hspace{1cm} (3.5b)

It is important to note that in order for the complement of the expectancy variable in the equation above to be meaningful, expectancy must have an upper bound of 1. Thus, the logistic transformation described in the section above (which constrains expectancy to between 0 and 1) enables the MGPM* to account for the negative relationship between expectancy and expected utility in the avoidance context.

### 3.3.3 Extending the Model to Account for Variation in Uncertainty

In this section, we describe how the MGPM* accounts for the effects of variability in uncertainty regarding the consequences of different courses of action, using a sequential sampling model of decision making. Research in the decision-making literature has shown that uncertainty regarding the consequences of an action can influence the strength of preference for that action (i.e., how likely it is to be selected). For example, Busemeyer (1985) showed that when faced with a choice between actions that differed in expected utility, people were more likely to select the action with the higher expected utility when it had a small distribution of possible consequences (i.e., relatively high level of certainty) than when it had a large distribution of possible consequences (i.e., relatively high level of uncertainty). Busemeyer showed that classical theories of human decision making that rely on deterministic choice rules, such as subjective expected utility theory, cannot account for these effects because they do not take into account the strength of preference for each action. Sequential sampling theories, by contrast, assume that decision making is a probabilistic process, in which the preference for or against an action is sampled from moment to moment, and an action is chosen when the preference for one of the available actions exceeds a threshold. Sequential sampling theories represent one of the most successful accounts of human decision making, such that they are able to account for a broad range of behavioral decision making empirical phenomena that deterministic models cannot explain (Brown & Heathcote, 2008; Busemeyer & Diederich, 2002; Ratcliff, Gomez, & McKoon, 2004; Wagenmakers, 2009).

The specific sequential sampling theory that we draw on is decision field theory (Busemeyer & Townsend, 1993). Decision field theory is a well-validated sequential sampling model of decision making. To the best of our knowledge, it is currently the only sequential sampling model that incorporates an explicit description of the mechanisms through which
goals influence decision making (although we will argue that this explanation is incomplete). Like the multiple-goal pursuit model, it assumes that the subjective value of acting on a goal changes as the person makes progress towards or away from that goal. This assumption makes decision field theory amenable to integration with the multiple-goal pursuit model. Furthermore, it provides a general account of decision making involving any number of goals, actions, and consequences. Thus, regardless of the number of these entities being considered, decision field theory provides a way of generalizing to more complex situations. Finally, decision field theory was developed to explain decision making in dynamic, uncertain environments, making it an ideal candidate for understanding how people make choices between actions with uncertain consequences.

Similar to the multiple-goal pursuit model, decision field theory assumes that when people make a choice between two or more actions (denoted $i$) they attend to the potential consequences of those actions. However, unlike the multiple-goal pursuit model, decision field theory accounts for a given action having any number of possible consequences (denoted $j$), where each consequence potentially affects progress towards one or more goals. Consider the assistant professor who is simultaneously striving to publish 10 papers in top-tier journals by her tenure deadline, whilst ensuring that she does not end up with poor teaching ratings on more than three courses over that period (see Table 3.1). Each semester, she faces a choice: whether to concentrate on her research or her teaching. Each action has a range of possible consequences. For example, if she focuses on her research, she may succeed in getting a paper published in a top-tier journal, and she may receive a good teaching rating despite not putting much effort into her teaching. Alternatively, she may succeed in getting a paper published in a top-tier journal, but she may receive a poor teaching rating. Other possibilities are that she may fail to get the paper published in a top-tier journal and receive a good or a poor teaching rating.

**Motivational Value**

Decision field theory uses the term *motivational value* ($m$) to describe the attractiveness of a consequence, which is a function of two factors: the *quality* ($q$) of the consequence in relation to each goal, and the *need to act* on each goal at the current point in time (Busemeyer, Dimperio, & Jessup, 2006; Busemeyer, Townsend, & Stout, 2002). Busemeyer and colleagues define quality as the degree of satisfaction that a consequence provides with respect to a particular goal. In the goal pursuit context, quality represents the impact of a consequence on goal progress.
Table 3.1.

An Example of Potential Consequences of the Decision to Focus on Research or Teaching and Associated Values for Quality, Motivational Value, and Attention Weights

<table>
<thead>
<tr>
<th>Action (i)</th>
<th>Consequence (j)</th>
<th>Goal (k)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Research</td>
</tr>
<tr>
<td></td>
<td></td>
<td>at least 10 papers in top-tier journals</td>
</tr>
<tr>
<td></td>
<td></td>
<td>qi,j,1</td>
</tr>
<tr>
<td>Action 1: Focus on research</td>
<td>Paper published &amp; receive good teaching rating</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Paper published &amp; receive poor teaching rating</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Paper not published &amp; receive good teaching rating</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Paper not published &amp; receive poor teaching rating</td>
<td>0</td>
</tr>
<tr>
<td>Action 2: Focus on teaching</td>
<td>Paper published &amp; receive good teaching rating</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Paper published &amp; receive poor teaching rating</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Paper not published &amp; receive good teaching rating</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Paper not published &amp; receive poor teaching rating</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: q = quality, u = expected utility, m = motivational value, w = attention weight
As can be seen in Table 3.1, having the paper accepted would have a quality of 1 with respect to the research goal because it brings her one paper closer to achieving the goal of publishing ten papers (an approach goal). Having the paper rejected would have a quality of 0 with respect to this approach goal because it brings her no closer to that goal. Receiving a good teaching rating would have a quality of 0 with respect to the teaching goal because it brings her no closer to the undesired state that she is 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. Like the MGPM*, the need to act is a function of the discrepancy between a desired or undesired state, and the current level of achievement with respect to that desired or undesired state. 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 realizing the undesired teaching goal.

We modify the specification of motivational value to account for expectancy. In contrast to the multiple-goal pursuit model and the MGPM*, decision field theory does not include an expectancy component, because the types of goals that decision field theory has addressed are not the type where expectancy is likely to have a strong influence (e.g., hunger; Busemeyer et al., 2002, or personal safety; Busemeyer et al., 2006). However, evidence suggests that individuals evaluate consequences based on both valence and expectancy when pursuing multiple performance goals (Schmidt & Dolis, 2009; Vancouver et al., 2010). The MGPM* therefore assumes that in the context of pursuing multiple performance goals, 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 ten papers in the time remaining before the tenure deadline. The MGPM* defines the motivational value of a consequence of an action as follows:

$$m_{ij}(t) = \sum_k u_k(t) \cdot q_{ijk}$$

(3.6)

According to the equation above, the motivational value of a consequence is equal to the quality of the consequence in relation to each goal, multiplied by the expected utility of that goal summed across goals. The motivational value of a consequence therefore takes into account quality in relation to each goal that is being pursued.

**ATTENTION**

Decision field theory assumes that individuals use limited attentional resources when evaluating choices and therefore cannot simultaneously attend to all of the possible consequences of an action. Thus, the theory includes an attention mechanism that switches
between considering possible consequences over time (Busemeyer & Townsend, 1993; Busemeyer & Diederich, 2002; Roe et al., 2001). Specifically, at each point in time the person considers the motivational value of one potential consequence for each action. For example, the assistant professor might initially consider the possibility that if she focuses on her research, she might get a publication in a top tier journal and receive a good teaching rating anyway, whereas if she focuses on redeveloping her course, that she might receive a good teaching rating, but miss out on a top tier publication.

The consequence that is the focus of attention at a given point in time is determined stochastically. Each consequence has a probability that the person will attend to it, which is referred to as the attention weight \( w_{ij}(t) \). Decision field theory 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, the assistant professor may believe that if she focuses on her teaching, the most likely consequence is that she will receive a good teaching rating, but miss out on a top tier publication. The attention allocated to a particular consequence at a given moment is denoted \( W_{ij}(t) \). Attention can only be allocated to one consequence at a time. 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 \( W_{ij}(t) = 1 \), \( W_{ij}(t) \) for all other consequences must be 0).

**Momentary Utility**

The momentary utility \( U_i(t) \) of an action refers to how attractive the action is at a given point in time. The momentary utility is determined by the motivational value of the consequence that is being attended to at that moment. For example, if the assistant professor were considering the possibility that if she focused on her research, she might get a top-tier publication and receive a good teaching rating, then according to the values in Table 3.1, the momentary utility of that action would be 0.6. If the assistant professor were considering the possibility that if she focused on her teaching, she might receive a good teaching rating but miss out on a top-tier publication, then according to the values in Table 3.1, the momentary utility of that action would be 0. Following decision field theory, The MGPM* defines momentary utility as follows:

\[
U_i(t) = \sum_j \left[ W_{ij}(t) \cdot m_j(t) \right].
\]  
(3.7)

---

1 The construct referred to as momentary utility by the MGPM* is referred to as valence by decision field theory. We relabeled this construct due to the fact that the multiple-goal pursuit model also includes a valence construct that is formally distinct from the valence construct in decision field theory.
**Preference**

Decision field theory assumes that preference \( P \) for each action evolves over time, as attention switches between consequences and the effects of the momentary utilities accumulate. Preference represents the cumulative effect of the momentary utilities over time. When an individual is deciding between two possible actions, the preference for one action over the other is expressed on a single bipolar continuum, in which the positive end represents a preference for one action and the negative end represents a preference for the other. For example, assume that a positive preference represents a preference for focusing on research, whereas a negative preference represents a preference for focusing on teaching. Preference changes in the direction of the most attractive action at a given moment, and the magnitude of that change is equal to the difference in the momentary utilities of the available actions. Continuing with the example of momentary utilities provided in the previous section, the preference would change by \( +0.6 \) \( (U_1(t) - U_2(t) = 0.6 - 0) \) in the direction of focusing on research.

This process continues until the preference exceeds a threshold \((\theta)\), at which point the preferred action is selected. Figure 3.3 shows an example of the sequential sampling process as the assistant professor considers the potential consequences of the different courses of action. As can be seen, the preferences for the two actions were initially equal (i.e., preference had a value of 0). Once deliberation begins, preference accumulated in favor of prioritizing teaching. However, as deliberation continued, preference started to accumulate in favor of prioritizing research. Eventually, preference for prioritizing research breached the threshold, and this action was selected. Following decision field theory, the MGPM* assumes that preference changes over time according to the following equation:

\[
P(t) = P(t-1) + [U_1(t) + U_2(t)].
\]

In our example, \( U_1(t) \) represents the momentary utility of prioritizing research and \( U_2(t) \) represents the momentary utility of prioritizing teaching.
3.3.4 Model Predictions

We simulated the MGPM* to generate predictions (i.e., hypotheses) regarding the influence of goal framing and uncertainty on the likelihood of prioritizing a given goal during multiple-goal pursuit. The experimental data that we used to validate these predictions was collected by asking participants to perform a multiple-goal pursuit task. Participants were assigned one approach and one avoidance goal (henceforth, ‘approach-avoidance’), two approach goals (‘approach-approach’), or two avoidance goals (‘avoidance-avoidance’). We also varied the level of uncertainty associated with the impact of actions on goal progress. Each goal pursuit episode involved a series of decisions where participants chose between two actions (A or B), each of which prioritized (i.e., provided an opportunity for progress for) one goal at the expense of the other. The consequences of actions with respect to facilitating goal progress were either

\[ \text{Positive Threshold: Choose to Prioritize Research} \]

\[ \text{Negative Threshold: Choose to Prioritize Teaching} \]

Figure 3.3. An example of sequential sampling process according to decision field theory.
uncertain (i.e., 50% chance of success, 50% chance of failure) or certain (i.e., 100% chance of success).

The aim of the simulation was to predict the probability of an action being selected (and thus a particular goal prioritized) according to the above manipulations. The calculations for determining these choice probabilities are presented in Appendix 3A. We used MATLAB to simulate 100,000 goal pursuit episodes of each goal frame (approach-approach, avoidance-avoidance, or approach-avoidance) X uncertainty (uncertain or certain) condition. Generating predictions via simulation requires every model parameter to be fixed to a particular value. Table 3.2 provides a summary of the specified parameter values used in the simulation. The initial preference, $P(0)$, was set to 0, which represents equal preference for each action. The valence intercept, $b$, was set at 0 for approach and 5 for avoidance so that valence would be 0 at the start of each episode for each avoidance goal, and thus make average valence comparable across approach and avoidance goal frames. The gain parameter, $\kappa$, was set to the default value of 1 for approach goals and -1 for avoidance goals, so that the valence slope for each goal type would be negative versus positive respectively. The attention weights were set to equal the objective probabilities of the outcomes, consistent with the model’s assumption that more attention is allocated to more certain outcomes. Time gain ($\gamma$) and threshold ($\theta$) were set to 0.2 and 1, respectively, as these represented moderate levels of the relevant parameter.

Table 3.2.

<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></td>
<td></td>
<td>$b_{\text{avoidance}} = 5$</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>Gain</td>
<td>$\kappa_{\text{approach}} = 1$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\kappa_{\text{avoidance}} = -1$</td>
</tr>
<tr>
<td>$P(0)$</td>
<td>Initial preference</td>
<td>0</td>
</tr>
<tr>
<td>$\omega$</td>
<td>Attention Weights</td>
<td>Equal to objective probability of outcomes</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Time sensitivity</td>
<td>0.2</td>
</tr>
<tr>
<td>$\theta$</td>
<td>Threshold</td>
<td>1</td>
</tr>
</tbody>
</table>

**Goal Framing Predictions**

We begin by presenting the predictions concerning the effect of goal frame collapsed across levels of uncertainty. We first present the predictions for the approach-avoidance context, followed by the predictions for the approach-approach and the avoidance-avoidance contexts.
**Approach-Avoidance**

The question of interest in this research is how people prioritize goals over time. In the approach-avoidance context, given that the two goals are unique in their framing, we can examine the MGPM*'s prediction concerning the effect of time elapsed on whether people prioritize the approach or the avoidance goal. Figure 3.4 shows the predicted probability of selecting the action that prioritizes the approach goal, as a function of the time that has elapsed since the start of goal pursuit. The MGPM* predicts that participants will initially prioritize the approach goal. Over time, however, priority will shift from the approach goal to the avoidance goal. At the start of goal pursuit, there is a relatively large distance to cover before either the desired or the undesired state is reached. In this condition, 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 participants get closer to the approach goal, the valence of acting on the approach goal decreases. At the same time, the participants get closer to the avoidance goal, because the avoidance goal is not initially prioritized. For this reason, the valence of acting on the avoidance goal increases. This change in valence eventually causes the utility of acting on the avoidance goal to exceed the utility of acting on the approach goal, prompting a shift in priority.
In the approach-approach and avoidance-avoidance contexts, given that the two goals are framed the same, the question of how people prioritize goals over time is best investigated by examining the MGPM*’s prediction concerning the effect of relative discrepancy on prioritization. Figure 3.5 shows the predicted probability of selecting the action that prioritizes Goal A as a function of the relative discrepancy. The MGPM* predicts that when participants pursue two approach goals, they will prioritize the goal that is furthest away from the desired state. Specifically, the probability of prioritizing Goal A will be highest when the discrepancy for Goal A is larger than the discrepancy for Goal B. The probability of prioritizing Goal A will be lowest when the discrepancy for Goal A is smaller than that for Goal B. When participants pursue two avoidance goals, the MGPM* predicts that they will prioritize the goal that is closest

Figure 3.4. Predicted probability of selecting the action that prioritizes the approach goal as a function of time when pursuing one approach and one avoidance goal.

**APPROACH-APPROACH AND AVOIDANCE-AVOIDANCE**
to the undesired state. Specifically, the probability of prioritizing Goal A will be lowest when its discrepancy is larger than that for Goal B, and highest when its discrepancy is smaller than that for Goal B. These predicted differences between the two conditions arise because the model assumes that the valence of acting on an approach goal is highest when the desired state is far away, yet the valence of acting on an avoidance goal is highest when the undesired state is close.

Figure 3.5. Predicted probability of choosing the action that prioritizes Goal A as a function of the relative discrepancy when striving for two approach goals and two avoidance goals.

The above predictions represent a tendency to prioritize the goal in the worse position (i.e., prioritize the goal with the larger discrepancy when pursuing two approach goals, or the goal with the smaller discrepancy when pursuing two avoidance goals). These predictions are consistent with empirical evidence from studies that have examined prioritization when pursuing two approach goals (e.g., Louro et al., 2007; Schmidt & DeShon, 2007). However, Schmidt, Dolis, and Tolli (2009) found that although there was a general tendency to prioritize the goal in the worse position (i.e., the goal with the larger discrepancy), there was a sub-group of participants that departed from this general tendency by mostly prioritizing the goal in the better position (i.e., the goal with the smaller discrepancy). We therefore expect there to be variability among participants pursuing two approach goals in the tendency to prioritize the goal in the worse position.

According to the MGPM*, such individual differences may be related to time sensitivity. High time sensitivity (i.e., a high value for $\gamma$) means that expectancy, and therefore the expected utility of acting on a goal, is more strongly influenced by the difference between time available
and expected time required. As a consequence of the influence of expectancy being stronger (and thus the relative influence of valence being weaker), people are more likely to prioritize the goal in the better position (i.e., the goal with the higher expectancy, but lower valence). Low time sensitivity (i.e., a low value for $\gamma$) means that expectancy, and therefore expected utility of acting on a goal, is less strongly influenced by the difference between the time available and time required. As a consequence of the influence of expectancy being weaker (and thus the relative influence of valence being stronger) people are more likely to prioritize the goal in the worse position (i.e., the goal with the lower expectancy, but higher valence). We therefore expect those who tend to prioritize the goal in the better position to have higher values of $\gamma$ than those who tend to prioritize the goal in the worse position. It is possible that there may also be individual differences in the tendency to prioritize the goal in the better versus worse position when pursuing two avoidance goals. Given that previous empirical work has not examined this context, there is no empirical evidence regarding these individual differences. However, we will determine whether such variability exists in our data. If these individual differences do exist, we would expect that such differences to also be explained by the time sensitivity parameter in the same manner.

**Uncertainty Predictions**

**Approach-Avoidance**

As shown in Figure 3.6, the MGPM* predicts that uncertainty influences the strength of the relationship between the time that has elapsed since the start of goal pursuit and prioritization. The effects of time are stronger when the consequences of actions are certain. When the impact of actions is certain, the model predicts a stronger initial preference and a more pronounced shift in priority from approach to avoidance, than when the impact of actions is uncertain. This prediction emerges because the variability in attention when consequences are uncertain produces variability in the momentary utility of the actions, and thus the accumulation of preference over time. As a result of this variability, the individual is less likely to make consistent decisions over time.
Figure 3.6. Predicted probability of selecting the action that prioritizes the approach goal as a function of time and uncertainty when pursuing one approach and one avoidance goal.

**Approach-Approach and Avoidance-Avoidance**

As seen in Figure 3.7, the MGPM* predicts that the effect of relative discrepancy on prioritization is more pronounced when the consequences of actions are certain. Once again, these predictions are consistent with a tendency to prioritize the goal in the worse position. However, these uncertainty effects should also hold among individuals who depart from this tendency by mostly prioritizing the goal in the better position. Among such individuals, the tendency to prioritize the goal in the better position should be stronger when the consequences of actions are certain.
3.4 METHOD

3.4.1 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 all analyses.

3.4.2 EXPERIMENTAL TASK

We used the air-traffic control microworld (ATC-Lab*Advanced; Fothergill, Loft, & Neal, 2009; see Figure 3.8) 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 required to select the route assignment for each aircraft before it crossed a vertical line on the screen (which also coincided with the time that the subsequent aircraft was due to enter the sector). If the participant failed to make a route assignment before required, the aircraft would turn downward and fly off the bottom of the screen and the crossing would be regarded as unsuccessful. This penalty encouraged participants to make a decision before the aircraft reached the point at which the routes diverge.

![Figure 3.8. Screenshot of the ATC task. In the condition shown, the upper route goal is approach (and uncertain) and the lower route goal is avoidance (and certain).](image)

Once the participant made a 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 possible trajectories (which was randomly determined). For the upper route, the flight path either led diagonally toward the top left of the screen (shown in Figure 3.8 for the upper route), directly upward, or diagonally toward the top right. For the lower route, the military flight path either led diagonally toward the bottom left, directly downward, or diagonally toward the bottom right. 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. The yellow symbol in the bottom right corner illustrated this distance on the screen.
3.4.3 Manipulations

Goal Framing

We manipulated goal framing using a 2 (upper route goal type: approach vs. avoidance) X 2 (lower route goal type: approach vs. avoidance) between-participants manipulation. The goal type assigned to each route was manipulated via the scoring system. Scores were tallied separately for each goal.

For approach goals, the participant began each trial with 0 points for that goal and aimed to “achieve a score of 5 or more.” Points were gained for every aircraft that successfully crossed the relevant route, while no points were gained for aircraft that were unsuccessful. For example, if the upper route goal was approach and an aircraft was assigned to the upper route, the participant would gain upper route points if the flight was successful but would not gain any points if the flight was unsuccessful. If the aircraft was assigned to the lower route instead, the participant’s upper route goal would not change regardless of the crossing outcome.

For avoidance goals, the participant began each trial with 10 points for that goal and aimed to “avoid a score of 4 or less.” Points were lost for every aircraft that did not successfully cross the relevant route; no points were lost for aircraft that were successful. For example, if the upper route goal was avoidance framed and an aircraft was assigned to the upper route, the participant would lose upper route points if the crossing was unsuccessful but not lose any points if the crossing was successful. If the aircraft was assigned to the lower route instead, the participant would lose upper route points regardless of the crossing outcome.

We used monetary incentives to reinforce the goal type manipulation. When both goals were approach, the participant began the experiment with no money in hand. However, the participant would gain 25c per goal achieved in each trial. Thus, they gained 50c for trials where both goals were achieved, 25c for trials where only one goal was achieved, and no money for trials where neither goal was achieved. When both goals were avoidance, the participant began with $8 in hand and lost 25c per goal failed in each trial. Thus, they lost 50c for trials where both goals were failed, 25c for trials where one goal was failed, and did not lose any money for trials where neither goal was failed. When one goal was approach and the other was avoidance, the participant began with $4 in hand and gained 25c for every trial where the approach goal was achieved and lost 25c for every trial where the avoidance goal was failed. Thus, the participant gained 25c for trials where both goals were achieved, lost 25c for trials where neither goal was achieved and did not gain or lose any money for trials where only one goal was achieved (because the gain and loss would cancel each other out).
Uncertainty

Uncertainty was manipulated using a 2 (upper route uncertainty: uncertain vs. certain) X 2 (lower route uncertainty: uncertain vs. certain) within-person manipulation. Therefore, there were three possible combinations of uncertainty: both routes uncertain, one route uncertain and one route certain, and both routes certain. Uncertain routes were intersected by a military flight path. On uncertain routes the aircraft had a 50% chance of breaching separation with a military aircraft and a 50% chance of crossing successfully (and participants were told probabilities of each outcome ahead of time). Certain routes were not intersected by a military flight path. On certain routes, the aircraft therefore had no chance of breaching separation with a military aircraft (i.e., a 100% chance of successfully crossing).

The scoring system was designed so that the expected points gained from crossing a route would not be affected by the level of uncertainty (see Appendix 3B). For approach goals, the expected points gained from crossing a route was equal to 1, regardless of the level of uncertainty. This was achieved by allocating 1 point for successful crossings on certain routes, 2 points for successful crossings on uncertain routes, and 0 points for unsuccessful crossings on uncertain routes or when an aircraft was assigned to the other route. For avoidance goals, the expected points gained or lost from crossing a route were equal to 0, regardless of the level uncertainty. This was achieved by keeping the score constant for successful crossings on certain routes, allocating 1 point for successful crossings on uncertain routes, and deducting 1 point for unsuccessful crossings on uncertain routes or when an aircraft was assigned to 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.

3.4.4 Procedure

Participants were randomly allocated to a goal frame condition and presented with task instructions. They then completed a single practice trial (excluded from all analyses) where their score did not count towards the monetary incentives, followed by 16 experimental trials (this many trials were needed in order to provide enough data to fit the model). Participants were told the total number of trials to expect before beginning the experiment. Before each trial, they were told which routes would be uncertain versus certain (i.e., which routes would be intersected by military flight paths in that trial), and 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 4:30 minutes 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 uncertainty manipulation was randomized across trials, with each participant experiencing each uncertainty combination condition four times. After the experiment, participants received their compensation and cumulative monetary incentive.

3.5 RESULTS

3.5.1 Quantitative Model Fits

We conducted a quantitative evaluation of the MGPM*’s predictions by fitting the model to the participant data. In the interest of parsimony, we aimed to keep the number of parameters estimated from the data to a minimum. Specifically, we fixed the $b$, $\kappa$, $w$, and $P(0)$ parameters to the values specified in Table 3.2 because they have theoretically meaningful values to which they can be constrained. In contrast, we allowed $\gamma$ (time sensitivity) and $\theta$ (threshold) to be estimated from the data.

We compared the MGPM* to two alternative models in order to test the core assumptions of our model relating to goal frame and uncertainty. The first alternative model tests our assumption relating to goal frame, namely that the valence function differs for approach and avoidance goals. More specifically, we tested the assumption that the valence of acting to avoid an undesired state is greater than zero when the undesired state is reached, and that an intercept of the valence function ($b$) is therefore required to account for prioritization in the avoidance context. Therefore, the first alternative model differed from the MGPM* such that $b$ was fixed to zero for all goals, regardless of whether they were approach or avoidance. If the MGPM*'s assumption is correct, in that there is a difference in the intercept of the valence function for approach and avoidance goals, we would expect the MGPM* to provide a better account of the data than the first alternative model.

The second alternative model tests our assumption relating to uncertainty, which is that the probabilistic choice function within the sequential sampling component of the MGPM* provides a better account of the data than the deterministic choice function used in the multiple-goal pursuit model. Therefore, the second alternative model differed from the MGPM*, such that it had a deterministic choice function that always selected the route with the higher expected utility. When the utilities of the upper and lower route goals were equal, this model assumed that each route was equally likely to be selected. As a result, the second
alternative model did not have a threshold parameter because it is not needed for the deterministic choice function.

We used MATLAB to fit the MGPM* to the observed data using maximum likelihood methods.\(^2\) This process involved estimating the \(\gamma\) and \(\theta\) parameters (or just \(\gamma\) for alternative model 2) by identifying the values that provided the closest fit between the model predictions and the observed data. This process was done separately for each participant using each of the three models, resulting in a prediction from each model for every decision made by the participant in the experiment. We then aggregated the predictions within goal frame and uncertainty conditions by averaging across trials and participants, in order to examine whether the predictions were supported. We then computed the Bayesian Information Criterion (BIC; Schwarz, 1978) associated with each model, for each of the three goal frame conditions, in order to assess the fit of the MGPM* compared to the two alternative models. 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. The model with the lower BIC value provides a better account of the data, with a difference in BIC values of 10 or more indicating “strong” evidence in favor of the model with the lower value (Raftery, 1995).

First, we report the model results comparing the MGPM* to the first alternative model. Note that comparison of the two models in the approach-approach condition is not applicable because no avoidance goals were present, and therefore the two models were identical in this condition. The BIC value for the MGPM* was lower than the BIC value for the first alternative model for both the approach-avoidance and avoidance-avoidance conditions (see Table 3.3), indicating that it provided a better account of the data than the first alternative model. Specifically, the model which assumed that the intercept of the valence function \((b)\) for avoidance goals was greater than 0 provided a better account than the model, which assumed that this parameter is equal to 0. This result suggests that the valence function differs for approach and avoidance goals, and supports the notion that the MGPM*’s intercept parameter is required to account for prioritization in the avoidance context.

\(^2\) 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.
Table 3.3.

*BIC Values for Hypothesized and Alternative Models across Goal Type Conditions*

<table>
<thead>
<tr>
<th>Model</th>
<th>Approach-Avoidance</th>
<th>Approach-Avoidance</th>
<th>Avoidance-Avoidance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. MGPM*</td>
<td>8950.3</td>
<td>4860.5</td>
<td>5101.6</td>
</tr>
<tr>
<td>2. Alternative 1 (b fixed to 0 for avoidance goals)</td>
<td>10299.0</td>
<td>Not applicable</td>
<td>5160.5</td>
</tr>
<tr>
<td>3. Alternative 2 (deterministic choice function)</td>
<td>18575.0</td>
<td>7751.7</td>
<td>6801.1</td>
</tr>
</tbody>
</table>

We next report the model results comparing the MGPM* to the second alternative model. The BIC value for the hypothesized model was lower than the BIC value for the second alternative model in the approach-avoidance, approach-approach, and approach-avoidance conditions (see Table 3.3), indicating that the MGPM* provided a better account of the data than the second alternative model. Specifically, the model that included a probabilistic choice function provided a better account of the data than a model that included a deterministic choice function. This finding supports the notion that incorporating a sequential sampling process into the MGPM* allows it to account for the effects of uncertainty.

3.5.2 Qualitative Model Results

In this section, we present a qualitative comparison of the MGPM*’s predictions with the observed data. In each section, we present the results for the uncertainty combinations (both uncertain; one certain and one uncertain; both certain).

**Approach-Avoidance**

Figure 3.9 presents the observed and predicted decisions for participants striving for one approach and one avoidance goal. Consistent with the MGPM*’s predictions, participants were more likely to prioritize the approach goal earlier and the avoidance goal later. Thus, there was a shift in priority over time from the approach to the avoidance goal. As expected, this effect was stronger when the consequences of selecting each route were certain, than when one or more routes had uncertain consequences.
Figure 3.9. Observed and predicted decisions among participants striving for one approach and one avoidance goal as a function of time and uncertainty.

**Approach-Approach**

According to the predictions presented in the introduction, when striving for two approach goals, participants should be more likely to select the action that prioritizes the goal in the worse position (i.e., for which the desired state is farther). However, in line with the findings of Schmidt et al. (2009), there is likely to be variability in this tendency, such that some participants tend to prioritize the goal in the better position (i.e., for which the desired state is closer). Furthermore, we expected these individual differences to be explained by time sensitivity. Finally, the MGPM* predicted that the tendency to prioritize a particular goal would be stronger when the impacts of actions on goal progress were certain compared to when they were uncertain.

Inspection of the data revealed that, as expected, there were individual differences in prioritization strategy among participants striving for two approach goals. Consistent with the MGPM*'s prediction, most participants tended to select the action that prioritized the goal in the worse position. As a consequence, participants in this group tended to switch back and forth between the actions that prioritized each goal and thus make progress towards both goals in parallel. We refer to this prioritization strategy as the balanced strategy. Consistent with the variability in prioritization strategy observed by Schmidt et al. (2009), the other individuals tended to behave in the opposite manner—namely, they tended to select the action that prioritized the goal in the better position. As a consequence of this strategy, participants in this group tended to repeatedly select the same action, and only switched to the action that
prioritized the other goal once the first goal had been achieved, thus making progress on one goal at a time. We refer to this prioritization strategy as the *sequential* strategy.

In order to quantify the individual differences we observed in prioritization strategies, we created an index to classify participants as having used a balanced or sequential strategy. We refer to this index as the “switch proportion”—it is the proportion of decisions in which the action selected was different to the action selected on the previous decision (excluding decisions made after one goal was achieved or failed). Higher switch proportions indicate a tendency to switch priority more frequently. Individuals were classified as balanced if they had a switch proportion of greater than 0.5, and as sequential if they had a switch proportion of less than 0.5. We then fit the observed data to our model’s predictions for the sub-groups of individuals within these two classifications.

The results of this classification and model fitting process are shown in Figure 3.10. The data are presented for the approach-approach condition, separately for the three uncertainty combinations, and separately for individuals classified as using the balanced versus sequential strategy. Of the 25 participants in the approach-approach condition, 14 were classified as balanced and 11 were classified as sequential. Thus, in support of the MGPM’s prediction regarding goal frame, there was evidence for the balanced strategy (i.e., people who tended to prioritize the goal in the worse position or in this condition, the larger discrepancy). Figure 3.10 shows that the MGPM’s predictions fit closely with the observed pattern of results for the balanced and sequential strategy users. The latter finding indicates that the MGPM can account for the observed data for both sub-groups of participants. In support of the prediction that individual differences in prioritization strategy are attributable to variability in time sensitivity, our analysis revealed that the $\gamma$ parameter was significantly higher among the sequential strategy users than among balanced strategy users, $t(23) = 5.18, p < .001$. This finding suggests that individuals who are more sensitive to time are more likely to use the sequential strategy (i.e., prioritize the goal with the smaller discrepancy), whereas individuals who are less sensitive to time are more likely to use the balanced strategy (i.e., prioritize the goal with the larger discrepancy). Finally, in support of the MGPM’s predictions regarding uncertainty, the tendency to select an action that prioritized a particular goal was strongest in the condition in which the consequences of both actions were certain. This support was found regardless of which prioritization strategy was used.
Figure 3.10. Observed and predicted decisions among participants striving for two approach goals as a function of the relative discrepancy, prioritization strategy, and uncertainty.

**AVOIDANCE-AVOIDANCE**

The MGPM* predicted that when striving for two avoidance goals, participants should be more likely to select the action that prioritizes the goal in the worse position (i.e., for which the undesired state is closer). Furthermore, this effect should be stronger when the impacts of actions on goal progress are certain, compared to when they are uncertain. We first identified whether there was variability in prioritization strategy. Our analyses revealed that of the 22 participants in the avoidance-avoidance condition, 20 could be classified as balanced (i.e., they mostly prioritized the goal for which the undesired state was closer), and 2 could be classified as sequential (i.e., they mostly prioritized the goal for which the undesired state was further away). Because of the small number of participants in the latter sub-group, we aggregated across all participants in this condition for analysis. As can be seen in Figure 3.11, the results were consistent with the MGPM*’s predictions. People tended to prioritize the goal for which
the undesired state was farther. Furthermore, as predicted, these effects were stronger when the impacts of actions were certain.

**Avoidance-Avoidance Condition**

*Both Uncertain* | *One Certain & One Uncertain* | *Both Certain*
---|---|---
![Graph showing observed and predicted decisions as a function of relative discrepancy and uncertainty.](image)

**Figure 3.11.** Observed and predicted decisions among participants striving for two avoidance goals as a function of the relative discrepancy and uncertainty.

### 3.6 Discussion

Our aim was to extend the multiple-goal pursuit model (Vancouver et al., 2010, 2014) to account for the effects of goal framing and uncertainty. The extended model, the MGPM*, achieves this by incorporating elements from Carver and Scheier’s (1998) theory of self-regulation to explain how people prioritize when pursuing different combinations of approach or avoidance goals. The MGPM* also incorporates elements from decision field theory (Busemeyer & Townsend, 1993) to explain how uncertainty in the consequences of actions influences decision making. Consistent with the MGPM*'s predictions, people generally prioritized the goal that was in the worse position. People who pursued one approach and one avoidance goal tended to switch priority from the approach goal to the avoidance goal over time. People who pursued two avoidance goals tended to prioritize the goal for which the undesired state was closer. Just over half of the people who pursued two approach goals tended to prioritize the goal for which the desired state was farther away and, as expected, the remainder demonstrated the opposite tendency. Also consistent with MGPM*'s predictions, all of these effects were stronger when the consequences of both actions were certain, compared to when one or more of the actions had uncertain consequences. In the following sections, we discuss the theoretical, empirical, and
practical contributions of this paper, highlight potential limitations, and suggest avenues for further research.

### 3.6.1 Contributions to the Multiple-Goal Pursuit Literature

The MGPM* generated novel predictions that were supported by the experimental data. The predictions regarding goal frame converge on the notion that, if expectancy is held constant, people are more likely to prioritize the goal with the higher valence (such that being further away from a desired state produces higher valence than being close; and being closer to an undesired state produces higher valence than being further away). When people simultaneously pursue one approach and one avoidance goal, they should be more likely to prioritize the approach goal earlier and more likely to prioritize the avoidance goal later. Indeed, we showed that people shifted priority from the approach goal to the avoidance goal over time. The notion that people initially prioritize an approach goal in favor of an avoidance goal may seem counter intuitive, given the evidence to suggest that people are more motivated to avoid losses than to achieve gains of equivalent magnitude (i.e., loss aversion; Novemsky & Kahneman, 2005). However, the ability to generate novel, even counter intuitive predictions is precisely the advantage of using computational models to understand behavioral phenomena. 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. Even if the MGPM* assumed greater sensitivity to losses (e.g., via an increase in the gain and/or valence intercept for avoidance goals), the model would still predict that the approach goal would be the initial priority (though adding loss aversion would make the predicted shift from approach to avoidance occur earlier). Consistent with goal frame predictions, people also tended to prioritize the goal in the worse position (i.e., the goal with the higher valence) when striving for two avoidance goals, and this was also the case for just over half of people striving for two approach goals.

The MGPM*’s prediction regarding uncertainty is that the tendency to prioritize a particular goal (e.g., the one in the worse position) should be stronger when the consequences of one’s actions are more certain. This prediction was achieved by integrating the multiple-goal pursuit model with decision field theory (Busemeyer et al., 2006; Busemeyer & Townsend, 1993) to provide a sequential sampling account of the choice process involved in multiple-goal pursuit. The multiple-goal pursuit model conceptualizes the goal prioritization decision as a deterministic choice process in which the goal with the higher expected utility is always prioritized. By integrating decision field theory, we introduced a probabilistic conceptualization
of this choice process, which allowed the MGPM* to account for the role of uncertainty in influencing how strongly a particular action is preferred. In support of the MGPM*, the tendency to prioritize the goal in the worse position (or for some participants in the approach-approach condition, the tendency to prioritize the goal in the better position) was more pronounced when both actions had certain consequences, and weakest when both actions had uncertain consequences. Uncertainty with regard to decision consequences increases these the fluctuations in attention, and creates more variability in preferences over time. Thus, decisions made between actions with less certain consequences are likely to be more variable than those made between actions with more certain consequences.

Future research should focus on the further development and testing of the MGPM*. The model can help identify methods of reducing the tendency for avoidance goals to be initially neglected when pursued alongside an approach goal. For example, the MGPM* predicts that increasing the incentive associated with the avoidance goal (i.e., the penalty for failing the avoidance goal) will reduce the initial preference for prioritizing the approach goal, and in general, make people more likely to prioritize the avoidance goal. The incorporation of decision field theory, in addition to accounting for the effects of uncertainty, also allows the MGPM* to make predictions about the influence of time pressure and its interaction with uncertainty. The model predicts that people adopt a lower threshold when they need to make faster decisions, which means that less information needs to be sampled before deciding between actions. As a result, the tendency to select a given action in favor of another is less pronounced. We also know that when making decisions amongst actions with uncertain consequences, the tendency to demonstrate a particular prioritization strategy is less pronounced. In combination, this suggests that increasing time pressure should exacerbate the effects of uncertainty, by further reducing the tendency to prioritize a particular goal.

Similar to the multiple-goal pursuit model, the MGPM* continues to provide a formal explanation for previous empirical findings regarding individual differences in prioritization strategy. Schmidt et al. (2009) found that people pursuing two approach goals varied in what strategy they used. Consistent with our model and their results, we found that just over half of the people who pursued two approach goals tended to prioritize the goal for which the desired state was further (i.e., a balanced strategy), but the remainder tended to prioritize the goal for which the desired state was closer (i.e., a sequential strategy). The MGPM* explains these strategy differences as a function of time sensitivity, such that individuals with a higher level of time sensitivity are more likely to adopt a sequential strategy, whereas those with a lower level of time sensitivity are more likely to adopt a balanced strategy. Time sensitive individuals are more influenced by the difference between the time available and the time required to reach the desired state. These individuals are motivated to prioritize the goal in the better position (i.e.,
closer to achievement), because this is the goal for which there is less time required. In other words, when time sensitivity is high, the motivation to act on the goal with less time required (i.e., the one with higher expectancy) outweighs the motivation to act on the goal with higher need (i.e., the one with higher valence), making the expected utility higher for the goal closer to achievement. The opposite is true for individuals with a lower level of time sensitivity. When time sensitivity is low, the motivation to act on the goal with higher need outweighs the motivation to act on the goal with less time required, making the expected utility higher for the goal furthest from achievement.

Given the absence of empirical work that has examined prioritization when pursuing two avoidance goals, we did not make a prediction concerning the presence of individual differences in strategy among participants in this condition. However, the data revealed a lack of variability among people pursuing two avoidance goals, with almost all participants tending to prioritize the goal for which the undesired state was closer. Not only was there a larger number of people using a balanced strategy among those pursuing two avoidance goals compared to those pursuing two approach goals, but people in the former condition also exhibited a stronger tendency to prioritize the goal in the worse position. This result is consistent with prospect theory (Kahneman & Tversky, 1979), which suggests that subjective evaluations of gains and losses may differ from their objective value. Specifically, losses tend to have a stronger impact than gains of equivalent magnitude. It is therefore possible that valence may have had a stronger influence for avoidance goals than for approach goals. This difference would lead to a greater tendency to prioritize the goal in the worse position among participants striving for two avoidance goals, which would result in participants being more likely to use the balanced strategy.

3.6.2 Practical Applications

There are a number of potential applications of the findings of this study in situations that require individuals to manage multiple goals. First we consider the finding that people shift priority from approach to avoidance goals over time. This finding may be particularly important in safety critical industries, such as mining, aviation, off-shore oil drilling, nuclear energy, or medicine, where people have to effectively manage safety and productivity goals. Traditionally, productivity goals have been framed in terms of approach, whereas safety goals have been framed in terms of avoidance. Productivity has traditionally been defined as the total output a system can achieve given a certain amount of work, and most research has focused on identifying ways to increase this output (e.g., Katzell & Guzzo, 1983; Tuttle, 1983). On the other hand, safety has historically been conceptualized as the avoidance of accidents, with most
research being focused on error reduction (e.g., Hofmann, Jacobs, & Landy, 1995; Pate-Cornell, 1990). Our results suggest that framing productivity and safety goals in this manner may lead people to initially prioritize productivity over safety, which may increase the likelihood of industrial accidents. If organizations are aiming for people to prioritize safety, one way this may be achieved is to frame this goal as approach. This perspective is consistent with a growing interest in positive psychology within the area of workplace safety that has led some managers to encourage proactive behaviors that promote a safe working environment (i.e., an approach goal), rather than discouraging mistakes (i.e., an avoidance goal; Neal & Griffin, 2006). Likewise, in air traffic control, there has been a shift towards conceptualizing the goal of keeping aircraft safely separated as ‘separation assurance’ (i.e., an approach goal), rather than ‘conflict detection and avoidance’ (i.e., an avoidance goal; Durso & Manning, 2009; Loft et al., 2009).

Now we consider the finding that the tendency to prioritize a particular goal is stronger when the consequences of actions for goal progress are more certain. Consider the example of an employee juggling two projects with a common deadline. At any given time, the employee must decide between prioritizing projects A or B. In this situation, prioritizing the project with the greater amount of work required (i.e., the one in the worse position) is an effective strategy for completing both projects because it ensures that progress is made on both. Our findings suggest the employee should be more likely to prioritize this project when there is greater certainty associated with the consequences of prioritizing each project. Thus, organizations may benefit from taking measures to enhance the certainty associated with the expected consequences of working on either project. Certainty may be enhanced, for example, by reducing the number of distractions in the work environment or allocating particular times to work exclusively on that project. Organizations can also enhance certainty in employee’s expectations for goal progress by providing feedback on how effectively the employee has worked in the past.

3.6.3 Potential Limitations and Avenues for Future Research

A potential limitation that should be considered is the use of a laboratory task with a student sample. This methodology is often criticized for lacking generalizability (Anderson & Bushman, 1997). However, criticisms of student samples confuse statistical generalizability with theoretical generalizability. Theory is critical in psychology and management, because it is the theory that allows one to generalize, not the sample (Highhouse, 2009). Human behavior is determined by a complex interaction amongst individual and situational factors. Therefore, it is
difficult to establish that findings obtained in one context will generalize to another based on statistical grounds, because it is virtually impossible to representatively sample the “true population” of participants and situations. A theory enables generalization because it explains the underlying causal mechanisms responsible for the observed results. Furthermore, theory can be tested in any sample to which the theory applies, provided the test environment allows for an assessment of the underlying processes that are incorporated in the theory, and enables experimental control (Highhouse, 2009).

Although our incorporation of decision field theory represents an important step towards understanding the factors that influence preferences during goal prioritization decisions, more work is required. In particular, the MGPM* can be applied to make predictions about the time it takes to make a decision. Decision field theory makes predictions about the relationship between approach-avoidance framing and decision time. Busemeyer and Townsend (1993) argue that the consequences of an action become more salient as the preference nears a threshold. Desirable consequences become more salient as one gets closer to making a decision, accelerating the deliberation process. Undesirable consequences are more salient, producing hesitation. Thus, decision field theory predicts longer decision times for decisions that involve avoiding undesirable outcomes than for decisions that involve approaching desirable outcomes. Future work is required to examine the implications of these phenomena on goal prioritization decisions.

3.6.4 CONCLUSION

The MGPM* represents a step forward in the development of a formal, unified theory of decision making during multiple-goal pursuit. The MGPM* accurately predicts prioritization decisions when pursuing different combinations of approach and avoidance goals, and when the consequences of actions for goal progress vary in their level of certainty. Specifically, the MGPM* a) correctly predicted that most people should prioritize the goal in the worse position, b) correctly predicted that these tendencies should be stronger when the consequences of actions are more certain, and c) provided an explanation for individual differences in prioritization strategies that have been demonstrated previously and in the current study. We hope that the MGPM* will be used as a foundation for further testing and development of the model into a general theory that will facilitate the cumulative development of knowledge and make contributions to practice. We believe the continued development and application of formal theories within the field of I/O psychology will help to build a stronger bridge between basic psychological science and organization studies.
3.7 **APPENDIX 3A**

Busemeyer and Townsend (1993) provide a formula for calculating the probability of selecting one action from a set of two, when the model assumes no initial preference bias (i.e., \( P(0) = 0 \)). The probability of selecting action A is calculated using the following formula:

\[
pr(A, B) = F \left[ 2 \cdot \left( \frac{\bar{U}_A - \bar{U}_B}{\sigma} \right) \right] \cdot \theta.
\]  \hspace{1cm} (3A.1)

where \( \bar{U}_A \) and \( \bar{U}_B \) are the average momentary evaluations for actions A and B, \( \sigma \) is the standard deviation of the difference in momentary evaluations, and \( F \) is the standard logistic cumulative distribution function: \( F(x) = 1/[1+\exp(-x)] \). 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 standard deviation units. In other words, the real threshold (i.e., in raw units) is equal to \( \theta /\sigma \).
### 3.8 APPENDIX 3B

**Summary of Scoring System**

<table>
<thead>
<tr>
<th>Uncertainty Condition</th>
<th>Option Selected</th>
<th>Upper Route</th>
<th>Lower Route</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Uncertain</td>
<td>Certain</td>
<td>Uncertain</td>
</tr>
<tr>
<td>Outcome</td>
<td>Success</td>
<td>Failure</td>
<td>Success</td>
</tr>
<tr>
<td>Rate of Occurrence</td>
<td>50%</td>
<td>50%</td>
<td>100%</td>
</tr>
<tr>
<td>Frame Condition</td>
<td>UR Approach/LR Approach</td>
<td>UR Points</td>
<td>LR Points</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>-1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
</tr>
<tr>
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<td>1</td>
</tr>
<tr>
<td></td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
</tr>
</tbody>
</table>

**Note:** UR = Upper Route, LR = Lower Route.
CHAPTER 4

DEPARTURES FROM OPTIMAL PRIORITIZATION WHEN PURSUING MULTIPLE APPROACH AND AVOIDANCE GOALS

This chapter is presented as a journal article manuscript. A version of this chapter has been published at Journal of Applied Psychology.

4.1 FOREWORD

In Chapters 2 and 3, I provided an insight into how people prioritize by articulating Carver and Scheier’s account of avoidance goal pursuit as a computational model and integrating this model, along with decision field theory, into the multiple-goal pursuit model. However, a thorough investigation of prioritization should seek not only to examine the process by which people make these decisions, but also to examine how well people prioritize in different environments. One way to examine how well people prioritize is to compare their decisions to those predicted by a normative model. Unfortunately, a normative model of decision making during multiple-goal pursuit does not exist. In this chapter, I implement a normative model of prioritization by recasting multiple-goal pursuit as a multistage decision task and using expected utility theory to determine the optimal prioritization decisions. Drawing on prospect theory, I use the normative model as the basis for examining how pursuing multiple approach or avoidance goals produces systematic departures from optimal prioritization.
4.2 Abstract

This paper examines how people’s prioritization decisions depart from optimality when pursuing multiple approach and avoidance goals. The optimal prioritization decisions were operationalized using dynamic programming, which is a mathematical model used to implement expected utility theory for multistage decisions. Drawing on prospect theory, we predicted that people have a risk-averse bias when pursuing multiple approach goals, and over-weight the value of achieving one goal compared to the value of achieving two. As a result, people are more likely than the optimal model to prioritize the goal in the best position. Pursuing multiple avoidance goals was predicted to produce a risk-seeking bias, in which people over-weight the value of achieving two goals compared to the value of achieving one, and are consequently more likely than the optimal model to prioritize the goal in the worst position. These predictions were tested with an experimental paradigm in which participants made a series of prioritization decisions whilst pursuing either two approach or two avoidance goals. The predictions were supported. This research demonstrates the value of using normative models to understand multiple-goal pursuit. It also highlights the utility of drawing on prospect theory to explain how people make prioritization decisions. Finally, the findings raise questions regarding the motivational effects traditionally associated with approach and avoidance goals.
4.3 INTRODUCTION

Pursuing multiple, competing goals is a pervasive feature of modern life. We all have to manage competing demands for our time, and are frequently faced with situations where we have to make trade-offs. Imagine you work for a consulting firm and are preparing two tenders (i.e., a bid or proposal for a competitive contract), but will only have a limited number of opportunities to work on them before they are due. You are not certain whether you can complete both to a competitive standard by the deadline. When given the opportunity to work on one of the tenders, do you a) focus on the one that’s in the best shape in the hope of winning at least one contract, but risk missing an opportunity to win both or b) focus on the one that’s in the worst shape to have a chance of winning both contracts, at the risk of winning neither? The optimal choice is the option that produces the most efficient allocation of your resources (e.g., your time; Keeney & Raiffa, 1976). Yet, identifying the optimal choice is complex because it requires anticipating the cascading effects of actions taken now on the actions that will be available in the future, and the impact of those actions on the chances for goal attainment.

Studies have recently started to examine multiple-goal pursuit, and have identified some factors that predict the way that people prioritize competing goals (Kernan & Lord, 1990; Louro et al., 2007; Schmidt & DeShon, 2007; Schmidt et al., 2009; Schmidt & Dolis, 2009). However, this work has not considered whether, how, or why these prioritization decisions depart from optimality. Comparing observed behavior to an optimal criterion for decision making allows one to identify biases, which are systematic deviations from that criterion. Biases provide insight into the psychological processes that underlie decision making (Kahneman & Tversky, 1996), which is important for advancing theoretical understanding of human behavior. Identifying biases also provides an opportunity to enhance decision making in practice. For example, decision support systems based on models of optimal decision making have been implemented to help investors overcome biases in order to have more success in the marketplace (e.g., Bhandari & Hassanein, 2012). In order to address this gap, we need to implement a normative theory of decision making during multiple-goal pursuit. Normative theories, such as expected utility theory (von Neumann & Morgenstern, 1947), represent a prescriptive standard for behavior, and their goal is to serve as a standard for evaluation rather than to predict behavior (Baron, 2004, 2012). Thus, they are ideal for examining the extent to which observed prioritization decisions are optimal.

We use expected utility theory to derive an optimal model of decision making during multiple goal pursuit, and examine whether observed prioritization decisions depart from this optimal model. We examine both approach and avoidance goals because decision-making
research suggests they may produce systemically different departures from optimality. An approach goal represents a desired state that the person strives to achieve, whereas an avoidance goal represents an undesired state that the person strives to avoid (Carver & Scheier, 1990, 1998; Elliot & Covington, 2001). The same goal can often be framed in approach or avoidance terms. For example, a consultant might strive to win contracts (approach) or avoid losing contracts (avoidance). Prospect theory (Kahneman & Tversky, 1979) predicts that people will make decisions that are risk-averse when given the opportunity to gain, yet risk-seeking when faced with the threat of loss. This effect has been demonstrated repeatedly within the decision-making literature (Kahneman & Tversky, 1983; Kuhberger, 1998; Tversky & Kahneman, 1981). However, it does not always replicate in dynamic environments (Hollenbeck, Ilgen, Phillips, & Hedlund, 1994; Slattery & Ganster, 2002; Thaler & Johnson, 1990), which raises doubts as to whether it will hold during multiple-goal pursuit. Furthermore, as will be explained later, prospect theory generates predictions that run counter to current thought within the goal pursuit literature.

We address these controversies and in doing so, challenge existing theory regarding how people pursue approach and avoidance goals; and add to the debate regarding the generalization of prospect theory to dynamic contexts. To achieve this, we first recast multiple-goal pursuit as a multistage decision process, and develop an experimental paradigm which allows the examination of optimality. Second, we use the technique of dynamic programming— a normative model of multistage decision making based on expected utility theory—to calculate the optimal decision at multiple points in time, which allows us to test whether and how observed prioritization decisions depart from optimality. We then recast prospect theory within a multiple-goal pursuit context, to generate predictions regarding the influence of approach/avoidance goal framing on departures from optimality, in terms of prioritization decisions and subjective values placed on one versus two goals. We test our predictions in an experiment in which participants must pursue two goals with a common deadline (two approach or two avoidance goals, varied within individuals), and make a series of prioritization decisions that determine the likelihood of making progress towards each goal.

### 4.3.1 Conceptualizing and Operationalizing Optimality during Multiple-Goal Pursuit

Expected utility theory (von Neumann & Morgenstern, 1947) is a widely accepted normative model for determining the expected value of various courses of action (Busemeyer & Pleskac, 2009; Kahneman & Tversky, 1979; Keeney & Raiffa, 1976). Consistent with this theory, we define the optimal decision as that which maximizes the expected value of a reward. When
pursuing two goals, there are four possible outcomes that can occur: a) both goals are achieved, b) Goal A is achieved but Goal B is not, c) Goal B is achieved but Goal A is not, or d) neither goal is achieved. Each of these outcomes has a value and probability that the outcome can be achieved. Expected utility theory in this case assumes that the individual makes the prioritization decision with the highest expected value, computed as the summed product of the rewards for each possible outcome, by the probabilities that those outcomes can be achieved if that decision is made. For example, in some situations, the optimal decision may be to prioritize the goal in the best position (i.e., the goal with the highest likelihood of attainment) because doing so would maximize the chance of achieving at least one goal. In other situations, the optimal decision may be to prioritize the goal in the worst position (i.e., the goal with the lowest likelihood of attainment) because doing so would maximize the chance of achieving both goals.

In order to identify the optimal decision at a specific point in time, we need to assess the expected impact of each possible decision on subsequent goal attainment outcomes, given the multitude of possible pathways the decision trail and associated outcomes may follow. That is, we need to account for the fact that decisions made during multiple-goal pursuit produce cumulative changes in the environment over time, and that decisions made in the future will be constrained by the decisions made previously. In the next section, we take the first step by recasting multiple-goal pursuit as a multistage decision task. In the section after, we explain how optimality can be operationalized using dynamic programming (Bellman, 1966), which is a mathematical model used to implement expected utility theory in multistage decision tasks (Busemeyer, Weg, Barkan, Li, & Ma, 2000; Johnson & Busemeyer, 2001).

**Conceptualizing Multiple-Goal Pursuit as a Multistage Decision-Making Task**

Multiple-goal pursuit can be conceptualized as a multistage decision task, because it involves a series of sequential, interdependent decisions (Rapoport & Wallsten, 1972). A stage \( t \) represents a single decision within the series. The final stage represents the last decision in the series (i.e., when 0 subsequent decisions remain). At each stage, the individual decides between a set of actions \( a \). Actions are the means by which an individual changes the environmental state \( s \), each of which has a probability of producing this change. The environmental state that eventuates after the final stage, or decision (i.e., either task success or failure), is determined by a series of actions that produce cumulative changes in the environmental state over time. When multiple-goal pursuit is expressed as a multistage decision task, a stage represents a unit of time.
with the final stage representing the *deadline*. The environmental state represents the *current level of progress with respect to each goal*.

Consider the example in Figure 4.1, which illustrates a multiple-goal pursuit process expressed as a multistage decision task. In this example, a consultant has two goals: to complete tender A and tender B in a given period of time. The 4 x 4 grid depicts 16 possible *environmental states*. We assume that the states can be represented by the number of sections of a tender that remain to be written. In the current state, there are two sections remaining for tender A and three for tender B. At each *stage* the consultant must *act* on the environment in an attempt to complete the tenders. We assume that the consultant must decide between two *actions*: either write a section of tender A or tender B. If the consultant prioritizes tender A, she may or may not be successful in completing a section. If successful, she will transition into a new state in which only two sections of tender A remain. If unsuccessful (e.g., due to being interrupted by a colleague), the tender will still have three sections remaining. Simultaneously, there may be a chance that a section of tender B is completed without input from the consultant, for example, by a colleague. Thus, there are four possible outcomes that may result from each action: 1) completing a section on both tenders, 2) completing a section of tender A but not tender B, 3) completing a section of tender B but not tender A and 4) completing a section on neither tender. Decisions made at later stages depend on the decisions made previously. If the consultant decides to work on tender A, she is likely to make progress on this tender, but risk falling even further behind on tender B. This change in the environment will have implications for the consultant’s future decisions regarding which tender to prioritize.
Figure 4.1. Example of a multistage decision task in which a consultant simultaneously strives to complete two tenders before a deadline.

The example assumes that prioritizing a tender equates to an 80% chance of a section of that tender being completed and a 20% chance of a section of the other tender being completed. The four states with numbers shown represent the four possible states that may result at the next stage given the current state. The numbers represent the probabilities of those states occurring at the next stage if tender A is prioritized.

This example can also be used to illustrate the concept of value as it applies to multistage decision making tasks. Value \((v)\) is a property of the environmental states. For the moment, we equate value with the number of attained goals. There is a distinction between the values of environmental states that are known, which are the possible outcomes that eventuate after the final stage (or after the deadline has passed), compared to values at earlier stages. After the final stage, the value of each possible environmental state is known, because it indicates how many goals have actually been achieved. For example if, after the deadline, the consultant has zero sections remaining on tender A and one section remaining on tender B, this equates to one goal achieved, or a value of one. At earlier stages, the value of an environmental state indicates the number of attained goals that can be expected given that particular state and how many decisions are remaining. For example if, with one more chance to work on a tender, the consultant has finished tender A and has only one more section remaining for tender B, then the
value of that environmental state will be somewhere between one and two, reflecting that the consultant’s final outcome will include at least one attained goal, and that given the current situation, it is possible that the consultant will attain two goals.

**Operationalizing Optimality via Dynamic Programming**

Expressing multiple-goal pursuit as a multistage decision task allows us to use dynamic programming (Bellman, 1966) to implement expected utility theory in this context. Dynamic programming is a technique used to calculate the expected value of decision options, and thus determine the optimal decision (according to expected utility theory) for each possible environmental state in each stage (Hutchinson & McNamara, 2000). The optimal decision is determined using backward induction (Busemeyer et al., 2000; Johnson & Busemeyer, 2001). Broadly, backward induction involves first calculating the optimal decisions at the final stage, because the value of the environmental states that may eventuate after the final decision are known, then using this information to determine the value of environmental states and thus optimal decisions at previous stages. Dynamic programming is widely accepted in the animal behavior literature as a method for establishing whether complex sequences of actions are optimal according to expected utility theory (Dall, Houston, & McNamara, 2004; Houston, Clark, McNamara, & Mangel, 1988; McNamara & Houston, 1986). Dynamic programming is also commonly used by decision analysts in the workplace to find optimal solutions to complex problems that involve multistage decisions, such as how to minimize financial losses after an earthquake (Yeo & Cornell, 2009) or how to most efficiently collect meteorological data (Hanlon, Stefik, Small, Verlinde, & Young, 2013).

Figure 4.2 shows how dynamic programming can be applied to the example of a consultant attempting to complete two tenders (see Busemeyer et al., 2000; Johnson & Busemeyer, 2001 for further examples) with 16 possible environmental states (between 0 and 3 sections remaining for each tender). Step 1 is to start when there are no decisions remaining (i.e., after the final stage) and identify the value of every possible environmental state at this point in time. Step 1 in Figure 4.2 shows the values of each of the 16 states. The state that represents completing both tenders by the deadline has a value of two, the six states that represent completing one tender have a value of one, and the nine states that represent neither tender being completed have a value of zero.
Figure 4.2. Dynamic programming applied to determine the optimal prioritization decisions in the multiple tender example with 16 possible states. In the diagrams representing steps 2 and 4, the expected value for prioritizing tender A is shown in the top-left corner of each square; the expected value of prioritizing tender B is shown in the bottom-right corner; and the optimal decision is in bold.

Step 2 involves moving backwards to when there is one decision remaining (i.e., the final stage). The task in this step is to identify the optimal decision for each possible environmental state in this stage. This task is achieved by calculating the expected value \( e \) associated with each possible action for each environmental state. The expected value of an action represents the number of attained goals that can be expected if a particular action is selected. The optimal decision is to select the action with the highest expected value, because this maximizes the expected number of attained goals. The expected value of each action \( e_a \) is calculated using an expected utility equation—as product of the value of an environmental state and the probability
of that environmental state occurring if the action is taken, summed across each possible environmental state that may eventuate from an action being selected:

$$e_a(t - 1) = \sum_s p_s v_s(t),$$

(4.1)

where $p_s$ is the probability of the environmental state being produced from the action, and $v_s$ is the value of that environmental state at stage $t$. Step 2 in Figure 4.2 shows the expected values for each possible action (prioritizing tender A or tender B) for each of the 16 possible states. In this example, we have assumed that the probability of completing a section on the tender that is prioritized is 0.8, and that the probability of completing a section on the tender that is not prioritized is 0.2. The top-left corner of each square shows the expected value of prioritizing tender A, and the bottom-right corner shows the expected value of prioritizing tender B. The optimal decision is in bold. Consider a consultant who has no sections remaining on tender A and one section remaining on tender B. The optimal decision for this environmental state in this stage is to prioritize tender B (expected value = 1.8), because doing so gives a higher chance of completing the final section of tender B (and thus achieving both goals by the deadline) than if he/she were to prioritize tender A (expected value = 1.2).

At Step 3, we start repeating the cycle established in Steps 1 and 2. Step 3 involves identifying the value of each possible environmental state when there is one decision remaining. When there is at least one decision remaining, dynamic programming assumes that the value of an environmental state is equal to the expected value of the optimal action (i.e., the action with the highest expected value). That is, the number of goals that can be attained given an environmental state at a particular stage should be equal to the expected number of goals produced by the optimal decision. The value of an environmental state when there is at least one decision remaining can therefore be represented as follows:

$$v_s(t) = \max_t [e_a(t)].$$

(4.2)

Step 4 involves moving backwards to when there are two decisions remaining. Like Step 2, this step involves calculating the expected value of each action for every possible state (and therefore the optimal decisions) in this stage using Equation 1. Step 4 in Figure 4.2 shows these expected values (and optimal decisions in bold) for the tender example. The process outlined in Figure 4.2 continues backward, using repeated cycles of Steps 3 and 4, until the optimal decisions have been determined for every stage.
4.3.2 Approach vs Avoidance Goals and Departures from Optimality

In this section, we use prospect theory (Kahneman & Tversky, 1979) to derive predictions regarding how people depart from the normative model of optimality as a function of whether the individual is pursuing multiple approach or avoidance goals. In the following sections, we first describe the basic tenets of prospect theory, and outline relevant theoretical and empirical divergences between prospect theory and theories of approach and avoidance motivation (e.g., Elliot & Church, 1997; Elliot & Sheldon, 1997). We then draw on prospect theory to predict biases for the goal in the best versus worst position when making prioritization decisions, which represent departures from optimality that are risk-averse versus risk-seeking respectively. These hypotheses are counterintuitive from the perspective of approach/avoidance theories. Finally, we make predictions regarding an underlying mechanism that produces these biased prioritization decisions, namely, biases in the subjective values placed on attaining one versus two goals.

Prospect Theory and Theories of Approach and Avoidance Motivation

A central prediction of prospect theory (Kahneman & Tversky, 1979) is that framing decisions as an opportunity to gain produces risk-averse behavior, whereas framing decisions as a threat of loss produces risk-seeking behavior. For example, people tend to prefer a disease prevention program in which 200 people are certain to be saved in favor of a program that has a 1/3 chance of saving 600 people (and a 2/3 chance of saving nobody). However, people tend to prefer a program that has a 1/3 chance that nobody will die (and a 2/3 that 600 people will die) in favor of a program in which 400 people are certain to die (Tversky & Kahneman, 1981). These reversals of preference as a function of framing provide evidence of departures from normative models of decision making.

Theoretically, there are similarities and differences when comparing the gain/loss distinction from prospect theory with the approach/avoidance distinction from motivation theories. On the one hand, there is conceptual overlap between these two construct domains—approach goal pursuit involves moving toward something desired which can represent a gain, whereas avoidance goal pursuit involves distancing oneself from the threat of something undesired which can represent a loss (Carver & Scheier, 1990, 1998; Elliot & Covington, 2001). On the other hand, the motivational outcomes derived from these respective theories diverge. A core tenet of prospect theory, and robust finding, is that losses loom larger than gains.
(Highhouse & Johnson, 1996; Kahneman, Knetsch, & Thaler, 2013; Tom, Fox, Trepel, & Poldrack, 2007). In other words, individuals are more motivated to avoid a loss than they are to achieve a gain of the same magnitude (i.e., loss aversion). However, in the achievement goal literature, avoidance goals are associated with weakened intrinsic motivation and persistence, whereas approach goals are associated with heightened levels of these states (Elliot & Church, 1997; Elliot & Sheldon, 1997; Elliot et al., 1996).

In terms of empirical ambiguities, prospect theory has predominantly been tested using isolated, single-stage decisions (e.g., Birnbaum, Johnson, & Longbottom, 2008; Rieskamp, 2008), and several researchers have questioned whether the heuristics used in these static contexts generalize to more realistic environments (e.g., Hogarth, 1981; March, 1996). A number of studies have provided evidence that the predictions do not always hold when tested in dynamic contexts where people make repeated decisions (Hollenbeck et al., 1994; Slattery & Ganster, 2002; Thaler & Johnson, 1990). However, prospect theory has received some support in dynamic contexts within the multiple-goal pursuit literature. Schmidt and DeShon (2007) found that when simultaneously pursuing two goals, people allocated more time to a goal that was incentivized with a loss for goal failure (taking away a gift certificate that was previously given to the participant) than a goal that was incentivized with a gain for goal achievement (giving the participant a gift certificate). Although they did not examine whether this behavior was risk-averse or risk-seeking compared to a normative criterion, this finding is consistent with the principle of loss-aversion.

**Prioritization Decisions**

Prospect theory suggests that people may prioritize suboptimally when pursuing approach and avoidance goals. With pursuing multiple approach goals, prospect theory suggests that individuals should depart from optimality in a risk-averse manner. This equates to a bias for prioritizing the goal in the best position, because doing so maintains a chance of attaining one goal while minimizing the risk of failing both goals. This expected bias should produce a tendency to be less likely than the optimal model to prioritize the goal in the worst position. When pursuing avoidance goals, the arguments suggest that individuals should depart from optimality in a risk-seeking manner. This equates to a bias for prioritizing the goal in the worst position, because doing so provides the best chance of attaining both goals despite the risk of failing both. This expected bias should produce a tendency to be more likely than the optimal model to prioritize the goal in the worst position.

These predictions run counter to current wisdom regarding approach versus avoidance motivation. Above we highlighted the association between approach/avoidance motivation, and heightened/weakened intrinsic motivation and persistence respectively. These associations
imply that a) individuals pursuing two approach goals may persist with the aim of achieving both goals, and thus show a risk-seeking bias (i.e., tendency to prioritize the goal in the worst position) whereas b) those pursuing two avoidance goals may give up on achieving both goals to focus instead on attaining at least one and thus show a risk-averse bias (i.e., a tendency to prioritize the goal in the best position). However, prospect theory generates the opposite pattern of predictions.

Hypothesis 4.1: When pursuing two approach goals, an individual is less likely than the optimal model to prioritize the goal in the worst position (i.e., will demonstrate risk-averse behavior); whereas when pursuing avoidance goals, the individual is more likely than the optimal model to prioritize the goal in the worst position (i.e., will demonstrate risk-seeking behavior).

**SUBJECTIVE VALUE PLACED ON ONE Versus TWO GOALS**

According to prospect theory, the underlying mechanism that produces the risk-averse versus risk-seeking tendencies described above is differences in subjective values of gains and losses (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981). At face value, when pursuing two goals that have equal value, the objective value of attaining two goals should be twice the value of attaining one goal. For example, if you are striving to win two tenders which both represent the same potential profit, then winning one tender is half as profitable as winning both, and winning both tenders is twice as profitable as winning only one. However, prospect theory predicts that the subjective values for attaining one versus two goals will systematically depart from objective values, depending on whether these outcomes are framed in terms of gains or losses.

Figure 4.3 shows how prospect theory’s value function can be applied to multiple-goal pursuit. As can be seen in the top-right quadrant of Figure 4.3, the subjective value of a gain is a concave function of its objective value. That is, the increase in subjective value produced by a one-unit increase in objective value gets smaller as the objective value increases. For example, the increase in subjective value is larger when the objective value increases from 0 to 1 compared to an increase from 1 to 2. As can be seen in the bottom-left quadrant of Figure 4.3, the subjective value of a loss is a convex function of its objective value. That is, the decrease in subjective value produced by a one-unit decrease in objective value gets smaller as the objective value decreases. For example, the decrease in subjective value is larger when the subjective value decreases from 0 to -1 compared a decrease from -1 to -2.
These arguments suggest that during multiple-goal pursuit, the subjective value of goal attainment outcomes differs when pursuing approach versus avoidance goals. When pursuing approach goals, the individual is operating in the domain of gains. As indicated by the concavity of the value function in this domain, the increase in value one can obtain from achieving one approach goal, compared to a baseline of achieving neither goal, should be more than half of the increase in value one can obtain from achieving two goals. This prediction represents a departure from optimality because the individual is over-weighting the value of achieving one goal relative to the value of achieving two. When pursuing multiple avoidance goals, the individual is operating in the domain of losses. As indicated by the convexity of the value function in this domain, the increase in value one can obtain from achieving two avoidance goals (i.e., failing no goals), compared to a baseline of achieving no goals (i.e., failing two goals), should be more than twice the increase in value one can obtain from achieving one goal (i.e., failing one goal). This prediction represents a departure from optimality because the individual is over-weighting the value of achieving two goals relative to the value of achieving one.

Figure 4.3. The prospect theory value function in the context of multiple-goal pursuit.
Hypothesis 4.2: When pursuing two approach goals, the subjective value placed on achieving one goal should be more than half of the subjective value placed on achieving two goals; whereas when pursuing avoidance goals, the subjective value placed on achieving two goals should be more than twice the subjective value placed on achieving one goal.

4.4 Method

4.4.1 Participants

The sample consisted of 20 participants (13 males, 7 females) with ages ranging from 19 to 61 years ($M = 27.42$, $SD = 10.09$). These individuals were recruited from a mailing list at the University of Bristol and received ten pounds as compensation as well as a small performance incentive (explained below).

4.4.2 Experimental Task

We used a task developed from the multistage prioritization paradigm (shown in Figure 4.4) that required participants to make a series of prioritization decisions aimed at maximizing points in an attempt to meet two goals. The participants’ goals were to have a certain number of ‘blue points’ and ‘green points’ at the end of each trial. At each stage in the trial, participants chose between two courses of action each of which prioritized one goal at the expense of the other. Participants pressed the left or right arrow key to indicate the option selected. They then received immediate feedback about the decision outcome. Participants were then prompted to press the space bar, after which the scores would update and the next stage would begin. Participants’ progress through each stage was displayed on the screen and the trials ceased after the specified number of stages.
In order to examine departures from optimality, we need to ensure there is sufficient variability in a) whether or not prioritizing the goal in the worse position is optimal and b) the magnitude of the difference between the two goals’ positions. For example, if the optimal decision in this task were always to prioritize the goal in the worse position, it would be impossible to determine whether individuals are more likely than an optimal model to prioritize this goal, because an optimal model would prioritize it 100% of the time. Further, even if sufficient variability in the optimal prioritization decision is achieved, the tendency to prioritize the goal in the worse position as opposed to the goal in the better position may be relatively weak if the latter is only ever in a slightly better position than the former.

To produce the variability required to test our hypotheses, we incorporated two manipulations into the design of this experiment. First, in order to induce variability in the optimality of prioritizing the goal in the worse position, we manipulated the probability of achieving both goals. When the probability of achieving both goals is high, the optimal decision is to prioritize the goal in the worse position because it maximizes the chance of achieving both goals by ensuring that more progress is made on the goal that is further from achievement, while still allowing some progress to be made on the goal that is closer to achievement. When the probability of achieving both goals is low, the optimal decision is to prioritize the goal in the better position because it maximizes the chance of achieving at least one goal by ensuring that most of the progress is made on the goal that is closer to achievement. Second, in order to induce variability in the magnitude of the difference between the two goals’ positions, we manipulated the starting score difference. This manipulation ensured that the goal in the better

Figure 4.4. Screen shot of the multiple-goal, multistage decision task (approach condition).
position was sometimes in a much better position than the other goal and at other times just slightly better. These manipulations produce 24 different types of trials across the approach and avoidance experimental conditions (see also Appendix 4A).

**Probability of Achieving Both Goals**

We manipulated the probability of achieving both goals within-participants across three levels (high vs moderate vs low). These three levels were produced by varying a) the number of decision stages in each trial so that the same number of successful actions (i.e., actions that gained a point in the approach condition or did not lose a point in the avoidance condition) were required for goal achievement, but the number of decision stages available to do so varied and b) the starting scores. There were fewer decision stages in trials with lower probability of achieving both goals. Starting scores in the approach condition were constant across the high/moderate/low levels of this manipulation, but in the avoidance condition they decreased as the number of decision stages decreased, so that the number of actions required for goal achievement (and the probability of achieving both goals) was identical to the corresponding level in the approach condition.

**Starting Score Difference**

The difference in starting scores was manipulated within-participants across four levels (0, 1, 3, and 5).

**4.4.3 Approach-Avoidance Goal Frame Manipulation and Measures**

**Goal Frame**

We used the scoring system and monetary incentives to produce a within-subjects goal frame manipulation with two levels: approach and avoidance. In the approach condition, the participants had two approach goals: to a) ‘achieve a score of 10 blue points or more’ and b) ‘achieve a score of 10 green points or more’. The goals were the same for all trials in the approach condition. Participants began the trial with fewer points than required and had to gain points. In order to accumulate points, participants had to choose between two actions: Option A or Option B. Each action prioritized a different goal, offering an 80% chance to gain a point for the prioritized goal and a 20% chance to gain a point for the non-prioritized goal. In the example shown in Figure 4.4, Option A prioritizes the blue goal and Option B prioritizes the green goal. If the action was successful with respect to a particular goal, the participant would
gain a point for that goal; if unsuccessful, the participant would not gain a point. The outcomes of actions with respect to each goal were independent of each other. Any action could result in gaining a point for both goals, gaining a point for only one goal, or not gaining a point for either goal. A goal was achieved if the participant had 10 points or more for that goal.

In the avoidance condition, the participants’ two avoidance goals were to a) ‘avoid a score of 9 blue points or less’ and b) ‘avoid a score of 9 green points or less’. Participants began the trial with more points than required, and had to minimize the loss of points in order to ensure the goals were not failed. Each action offered a 20% chance to lose a point for the prioritized goal and an 80% chance to lose point for the non-prioritized goal. If the action was successful with respect to a particular goal, the participant would not lose a point for the goal; if unsuccessful, the participant would lose a point. A goal was failed if the participant had 9 points or less for that goal.

In addition to their compensation, all participants began the experiment with an extra £4.32 and could gain or lose 3 pence per goal depending on the goal frame condition. The verbal presentation of the incentive structure reinforced the goal frame manipulation. In the approach condition, the instructions emphasized the gains associated with goal achievement. Before each trial, participants were instructed, “If you achieve both goals, you will GAIN 6 pence. If you achieve one goal, you will GAIN 3 pence. If you do not achieve either goal, you will not gain any money.” After the trial, the participant was informed that “You have gained X pence”. In the avoidance condition, the instructions emphasized the losses associated with goal failure. Participants were instructed, “If you fail both goals, you will LOSE 6 pence. If you fail one goal, you will LOSE 3 pence. If you do not fail either goal, you will not lose any money.” After the trial, the participant was informed that “You have lost X pence”.

**Individual’s Decision**

The individual’s decision corresponded to whether the participant chose the option that prioritized the goal in the better or worse position at any given decision stage, where 1 = worse position and 0 = better position. The goal in the worse position was the one with the lower score; the goal in the better position was the one with the higher score. Consistent with Hypothesis 4.1, we coded the dependent variable with a focus on the goal in the worse position to facilitate interpretation of results, because prioritization of the worst-positioned goal is a benchmark phenomenon in the literature (e.g., Schmidt & DeShon, 2007).

**Optimal Model’s Decision**

The optimal model’s decision (calculated using MATLAB’s Markov Decision Process toolbox with the dynamic programming equations as described in the introduction) at any given
decision stage was coded 1 if it corresponded with the goal in the worse position, and 0 if it corresponded with the goal in the better position.

**Control Variables**

We controlled for the trial number and the number of decisions remaining in each trial, in order to account for the passage of time.

**Subjective Value Ratio**

Hypothesis 4.2 requires the examination of a subjective value ratio compared to the optimal model’s value ratio for each of the goal frame conditions. Specifically, the subjective value ratio for this hypothesis is the ratio of the subjective value of achieving one goal to the subjective value of achieving two goals. Therefore, it is equal to the subjective value of achieving one goal divided by the subjective value of achieving two goals. A subjective value ratio of 0 indicates that no value is placed on achieving one goal; a ratio of .5 indicates that half as much value is placed on achieving one goal than is placed on achieving both goals; and a ratio of 1 indicates that as much value is placed on achieving one goal as is placed on achieving both goals. Two subjective value ratios were estimated for each participant - one for the approach condition and one for the avoidance condition. Each of these was compared to the optimal value ratio for this experiment, which is .5 because the goals were equally valuable.

For each goal frame condition, each participant’s subjective value ratio was estimated by identifying the ratio that corresponded most closely to his/her observed prioritization decisions. This estimation was achieved by using dynamic programming to calculate the normative model’s predictions under a range of possible subjective value ratios. Equations 1 and 2 were used to generate these sets of decisions. To generate the range of possible ratios, the subjective value of achieving two goals (i.e., the denominator) was fixed at 1. This was done so that the only value in the ratio that varied was the subjective value of achieving one goal (i.e., the numerator), and so that this value would be synonymous with the subjective value ratio (e.g., if the subjective value of achieving one goal—or numerator, was 0.5, the subjective value ratio would also be 0.5). The range of values we tested for the subjective value of achieving one goal was 0 to 1, in steps of 0.01. For example, for a given participant in a given condition, we first used Equations 1 and 2 to generate the decisions that the normative model would predict if the value of achieving one goal was 0 and determined how many of these decisions were in line with the participant’s observed decisions. We next generated the decisions that the normative model would predict if the value of achieving one goal was 0.01 and determined how many were in line with the participant’s observed decisions. We proceeded in this manner up to a maximum value of 1. We then identified the value of achieving one goal (and thus the
subjective value ratio) for which the normative model correctly predicted the highest number of the participant’s decisions in the relevant condition.

4.4.4 Procedure

Participants performed the task on computers in an experimental laboratory. Sessions consisted of either one or two participants. Participants in sessions of two worked at their own computers and could not easily see the activities of the other participant. An experimenter was present at all times. After being presented with instructions, participants completed two practice trials (one approach and one avoidance, both with a medium probability of achieving both goals and a starting score difference of 0). Participants then completed 144 trials which constituted six replications, or blocks, of the 24 trial types (2 goal frame x 3 probability of achieving both goals x 4 starting score difference). Trial order was randomized within each block. This design constituted 2556 decision stages in total per participant. There was a five-minute break in between blocks 3 and 4. The experiment took approximately 90 minutes to complete.

Participants were presented with information about the goals and monetary incentives prior to each trial. The participants’ goals, scores, number of decision stages remaining, and the probabilities that each action would gain or lose each type of point were displayed on screen for the whole trial. After each trial, the participants were presented with feedback reminding them of whether each goal was achieved or failed, and informing them of their monetary gain or loss for that trial. After the experiment was completed, the participant received his/her compensation and monetary incentive.

4.4.5 Analysis Strategy

Hypothesis 4.1

Hypothesis 4.1 concerns whether individuals depart from optimality in different ways depending on whether they are pursuing approach or avoidance goals. We first tested whether individuals departed from optimality per se via the main effect of goal frame (while controlling for the optimal model’s decisions). This main effect tests whether goal frame explains variance in participants’ prioritization decisions that is not explained by the optimal model—that is, the variance that represents departures from optimality. Second, we used log odds ratios to probe the nature of any departures from optimality—specifically, to test whether individuals’ decisions differed from the optimal model’s decisions in significant, yet different ways for each goal frame condition.
We examined the main effect of goal frame using a three-level multilevel logistic regression model within R. The highest level was the participant level, which had a sample size of 20. The middle level was the trial level, which had a sample size of 2880 (144 trials X 20 participants). The lowest level was the decision level, which had a sample size of 51,120 (2556 decisions per participant x 20 participants). However, prioritization could not be examined for decisions in which a) at least one goal had already been either achieved/failed or b) the scores for each goal were equal (because neither goal was in the worse position) so these cases were excluded from analyses. The total number of prioritization decisions included in the analysis was 28,278, which corresponded to inclusion of approximately 55% of decisions from any given trial. The three-level multilevel structure was created by implementing a mixed effects model and controlling for the random intercepts of trial and individual (using the ‘glmer’ function in the ‘lme4’ package).

The main effect of goal frame was tested using a three-step procedure. The individual’s decision (whether or not the participant chose the option that prioritized the goal in the worse position) was specified as the dependent variable at the decision level. In Step 1, the optimal model’s decision was entered at the decision level as a predictor of the individual’s decision. This step allowed examination of the strength of the relationship between the optimal decisions and the decisions made by individuals (i.e., the extent to which individuals’ decisions conformed to the normative model’s predictions). In Step 2, the number of decisions remaining and the trial number at the decision and trial levels respectively were entered, in order to control for the effect of time. In Step 3, goal frame was entered at the trial level as a predictor of the random intercept. We examined the increase in model fit between steps 2 and 3 in order to determine whether goal frame explained variance in individuals’ prioritization decisions over and above the variance explained by the optimal model. All predictors were specified as fixed effects and were grand-mean centered.

We determined whether the increase in fit of the model at Step 3 (compared to Step 2) was worth the increase in complexity due to the added goal frame predictor by examining the Bayesian Information Criterion (BIC; Schwarz, 1978) associated with the model at each step. The BIC is a well-established model selection criterion that accounts for both fit and parsimony. The model with the lower BIC value provides a better account of the data, with a difference in BIC values of 10 or more indicating “very strong” evidence in favor of the model with the lower value (Raftery, 1995). A reduction in BIC values from Steps 2 to 3 in this analysis would suggest that the model that includes goal frame as a predictor provides a better account of individuals’ prioritization decisions than a model that does not.

A log odds ratio was calculated for each condition to test whether and how individuals’ decisions differed from the optimal model’s decisions. The log odds ratio for each condition
was calculated by a) dividing the number of decisions (collapsed across participants) in which the goal in the worse position was prioritized, by the number of decisions in which the goal in the better position was prioritized, b) repeating step a) for the optimal model’s decisions, c) dividing the result of step a) by the result of step b), and d) taking the log of the result of step c).

The log odds ratio for each condition was tested for significance using a z-test. A negative log odds ratio suggests that individuals are less likely than the optimal model to prioritize the goal in the worse position. A positive log odds ratio suggests that individuals are more likely than the optimal model to prioritize the goal in the worse position. For Hypothesis 4.1 to be supported, the log odds ratio for the approach condition should be negative, whereas the log odds ratio for the avoidance condition should be positive.

**Hypothesis 4.2**

Hypothesis 4.2 is tested via two t-tests—one corresponding to each goal frame condition—that examine whether the individuals’ subjective value ratios differ significantly from the optimal value ratio of 0.5 (0.5 is optimal in this experiment because the goals carried equal incentives). If Hypothesis 4.2 is supported, the subjective value ratios should be significantly greater than 0.5 in the approach condition (indicating that more than half of the value of achieving both goals is placed on achieving one goal) and significantly less than 0.5 in the avoidance condition (indicating that more than twice the value of achieving one goal is placed on achieving both goals). We also examined how well the model with individuals’ subjective value ratios explained the data compared to an optimal model that assumed a subjective value ratio of 0.5, by examining the percentage of decisions correctly predicted by each model.

**4.5 Results**

**4.5.1 Descriptive Summary**

Figure 4.5 shows the average percentage of individuals’ decisions and the optimal model’s decisions in which the blue and green goals were prioritized as a function of number of decisions remaining, blue score, and green score in the approach and avoidance conditions respectively. The figures are constructed such that the diagonal running from the bottom-left to the top-right represents equal values of blue and green scores. The figure shows that the optimal model’s decisions varied as a function of the two scores and the decisions remaining. In general, when the participant was in a relatively good position (i.e., higher scores, more decisions remaining in the approach condition/fewer decisions remaining in the avoidance condition), the optimal model’s decision was most often to prioritize the goal in the worse
position because doing so maximized the chance of achieving both goals. When the participant was in a relatively poor position (i.e., lower scores, fewer decisions remaining in the approach condition/more decisions remaining in the avoidance condition), the optimal model’s decision was most often to prioritize the goal in the better position because doing so maximized the chance of achieving at least one goal.

Lending credence to our argument that departures from optimality should be evident, the figures show that individuals’ decisions were not always optimal. In the approach condition, there are several cases in which individuals tended to prioritize the goal that was closer to completion, when the optimal decision was to prioritize the goal in the worse position. For example, in the plot that represents 18-13 decisions remaining, the top-left half of the plot representing the individuals’ decisions shows a tendency to prioritize the green goal in cases where the plot representing optimal decisions indicates that the blue goal should be prioritized (i.e., above the diagonal where the blue goal is in the worse position). Likewise, the bottom-right half of the plot shows a tendency to prioritize the blue goal in cases where the optimal decision is to prioritize the green goal (i.e., below the diagonal where the green goal is in the worse position). In the avoidance condition, there are several cases in which individuals tended to prioritize the goal in the worse position, when the optimal decision was to prioritize the goal in the better position. For example, in the plot that represents 12-7 decisions remaining, the bottom-left region of the plot shows a tendency to prioritize the blue goal in cases where the optimal decision is to prioritize the green goal (i.e., above the diagonal where the blue goal is in the worse position), and to prioritize the green goal when the optimal decision is to prioritize the blue goal (i.e., below the diagonal where the green goal is in the worse position).
### Approach

- **Individuals' Decisions**
  - Blue Score vs. Green Score
  - Decisions Remaining
  - 24-19
- **Optimal Decisions**
  - Blue Score vs. Green Score
  - 18-13

### Avoidance

- **Individuals' Decisions**
  - Blue Score vs. Green Score
  - Decisions Remaining
  - 12-7
- **Optimal Decisions**
  - Blue Score vs. Green Score
  - 6-1
Figure 4.5. Average percentage of the individuals’ and optimal model’s decisions prioritizing the blue and green goals in the approach and avoidance conditions as a function of blue score, green score, and the number of decisions remaining. White tiles represent environmental states that were not included in the analysis because either a) the combination of scores did not occur at a particular decision stage for any participant, b) at least one goal had already been achieved or failed, or c) green and blue scores were equal (and thus neither goal was in the better or worse position). Above the diagonal that runs from bottom-left to top right, blue scores are lower than green scores (meaning that the blue goal is in the worse position). Below the diagonal, green scores are lower than blue scores (meaning that the green goal is the worse position).

4.5.2 **Hypothesis 4.1: Prioritization Decisions**

Hypothesis 4.1 predicts that when pursuing approach goals, an individual is less likely than the optimal model to prioritize the goal in the worse position, whereas when pursuing avoidance goals, the individual is more likely than the optimal model to prioritize the goal in the worse position. The results of the analysis used to test the main effect of goal frame are presented in Table 4.1. The BIC for the model at Step 3 was lower than at Step 2, suggesting that goal frame influences people’s prioritization decisions over and above the optimal model’s decisions, the trial number, and the number of decisions remaining. This is consistent with Hypothesis 4.1 because it demonstrates that, as expected, goal frame explained variance in people’s decisions that was not explained by the optimal model—that is, it explained variance that represents departures from optimal decision making. The negative relationship indicates that individuals were less likely to prioritize the goal in the worse position when pursuing two approach goals than when pursuing two avoidance goals.³

³ A reviewer questioned whether our results could be influenced by learning. It is possible that two practice trials may not be sufficient to become acquainted with the task or that the avoidance condition may be more difficult to learn than the approach. We therefore re-analyzed the data with the first 48 experimental trials (i.e., the first third) excluded and found that the results have the same substantive interpretation as when these trials are included. This finding suggests that learning did not influence the results, as participants would have been very familiar with both conditions by the 48th trial.
Table 4.1.

Unstandardized Regression Coefficients for Steps 1, 2, and 3 in the Models Predicting Whether or Not the Decision Prioritized the Goal in the Worse Position.

<table>
<thead>
<tr>
<th>Variable</th>
<th>BIC</th>
<th>Coefficient</th>
<th>S.E.</th>
<th>p</th>
</tr>
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<tr>
<td><strong>Step 1</strong></td>
<td>37058.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
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<td>-0.23</td>
<td>0.09</td>
<td>.011</td>
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<tr>
<td>Optimal Decisions</td>
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<td>0.69</td>
<td>0.03</td>
<td>&lt; .001</td>
</tr>
<tr>
<td><strong>Step 2</strong></td>
<td>36745.9</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td>0.33</td>
<td>0.09</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Optimal Decisions</td>
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<td>0.72</td>
<td>0.03</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Trial Number</td>
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<td>-0.004</td>
<td>0.001</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Number of Decisions Remaining</td>
<td></td>
<td>-0.05</td>
<td>0.003</td>
<td>&lt; .001</td>
</tr>
<tr>
<td><strong>Step 3</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>0.33</td>
<td>0.09</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Optimal Decisions</td>
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<td>0.03</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Trial Number</td>
<td></td>
<td>-0.005</td>
<td>0.001</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Number of Decisions Remaining</td>
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<td>0.003</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Goal Frame</td>
<td></td>
<td>-0.44</td>
<td>0.01</td>
<td>&lt; .001</td>
</tr>
</tbody>
</table>

Analyses of the log odds ratios (LOR) revealed that in the approach condition, the individuals were significantly less likely than the optimal model to prioritize the goal in the worse position ($LOR = -0.87, SE = 0.02, z = -35.53, p < 0.001$), whereas in the avoidance condition, the individuals were significantly more likely than the optimal model to prioritize the goal in the worse position ($LOR = 0.17, SE = 0.02, z = 6.85, p < 0.001$). This pattern can be seen in Figure 4.6. The probability of prioritizing the goal in the worse position is lower among individuals compared to the optimal model in the approach condition, but higher among individuals compared to the optimal model in the avoidance condition. Thus, consistent with Hypothesis 4.1, when individuals were pursuing two approach goals, their prioritization decisions were biased in a risk-averse manner, whereas when they were pursuing two avoidance goals, their decisions were biased in a risk-seeking manner.
4.5.3 HYPOTHESIS 4.2: SUBJECTIVE VALUE RATIOS

Hypothesis 4.2 predicts that when pursuing two approach goals, the subjective value placed on achieving one goal should be more than half of the subjective value placed on achieving both goals; whereas when pursuing avoidance goals, the subjective value placed on achieving both goals should be more than twice the subjective value placed on achieving one goal. Figure 4.7 presents the subjective value ratios for the approach and avoidance conditions. The subjective value ratio was significantly higher than the optimal ratio of 0.5 in the approach condition, \( t(19) = 3.25, p = .004 \), and significantly lower than 0.5 in the avoidance condition, \( t(19) = -10.02, p < .001 \). These results suggest that individuals depart from optimality by over-weighting the value of achieving one goal in the approach condition, and by over-weighting the value of achieving both goals in the avoidance condition. The model with the individuals’ subjective value ratios
correctly predicted 68% of participants' decisions in both the approach and avoidance conditions, whereas the optimal model correctly predicted 57% and 60% of decisions in these conditions respectively. This finding provides additional support for the argument that individuals' decisions were better explained by their own subjective value ratios that departed from optimality, than they were by an optimal model with a subjective value ratio of 0.5.

![Figure 4.7](image.png)

*Figure 4.7. Subjective value ratios in the approach and avoidance conditions.*

### 4.6 Discussion

Our aim was to examine departures from optimality during multiple-goal pursuit. We integrated the multiple-goal pursuit and decision-making literatures, and examined how people departed from optimality when pursuing approach and avoidance goals. The findings suggest that people are risk-averse when pursuing approach goals, and risk-seeking when pursuing
avoidance goals. Specifically, when pursuing two approach goals, individuals over-weighted the value of achieving one goal relative to the value of achieving two, and in line with this were less likely than an optimal model to prioritize the goal in the worse position. When pursuing two avoidance goals, individuals over-weighted the value of achieving two goals relative to the value of achieving one and, in line with this, were more likely than an optimal model to prioritize the goal in the worse position. In the following sections, we discuss the contributions this work makes to the multiple-goal pursuit literature, as well as its practical implications, potential limitations, and future research directions.

4.6.1 Contributions to the Multiple-Goal Pursuit Literature

Our use of a normative theory of decision making to evaluate decisions during multiple-goal pursuit represents a new way of examining and understanding how people make prioritization decisions. Previous research in this field has tended to focus on examining factors that influence which goal is prioritized at a given point in time (Kernan & Lord, 1990; Louro et al., 2007; Schmidt & DeShon, 2007; Schmidt et al., 2009; Schmidt & Dolis, 2009). We have taken a different approach by examining how and why these prioritization decisions depart from a model of optimality.

Our approach enabled us to identify how goal frame systematically influences departures from optimality. Individuals in our research demonstrated biases when pursuing approach versus avoidance goals that challenge existing assumptions within the multiple-goal pursuit literature. Theories of approach and avoidance motivation (e.g., Elliot & Church, 1997; Elliot & Sheldon, 1997) suggest that intrinsic motivation and persistence should be enhanced when pursuing approach goals but undermined when pursuing avoidance goals. This motivational pattern is also evident in regulatory focus theory, which makes a distinction between two different regulatory foci. A promotion focus is associated with an emphasis on advancement and accomplishment, and is marked by sensitivity to gains and non-gains. A prevention focus is associated with an emphasis on responsibility and security, and is marked by sensitivity to losses and non-losses (Crowe & Higgins, 1997; Forster, Grant, Idson, & Higgins, 2001; Forster, Higgins, & Idson, 1998). For example, researchers have demonstrated links between promotion focus, and productivity and risk-taking; and between prevention focus, and safety and risk prevention (Wallace & Chen, 2006; Wallace, Johnson, & Frazier, 2009; Wallace, Little, & Shull, 2008). Indeed, in layperson terms, approach oriented people are associated with “reaching for the stars”, whereas avoidance oriented people are associated with “playing it safe”. Direct translation of these beliefs to the current context implies that individuals pursuing two
approach goals may persist with the aim of achieving both goals, and thus show a risk-seeking bias (i.e., tendency to prioritize the goal in the worst position); whereas those pursuing two avoidance goals may give up on achieving both goals to focus instead on attaining at least one and thus show a risk-averse bias (i.e., a tendency to prioritize the goal in the best position). However, consistent with prospect theory, we demonstrated the opposite pattern of results.

These counterintuitive findings emphasize the utility of drawing on theories of decision making such as prospect theory to enhance understanding of multiple-goal pursuit. They also have practical implications. For example, consider a company that is struggling to meet revenue targets—this company may prefer that their consultants err on the safe side when striving to complete applications for two different tenders so that at least one tender is successful. Previous wisdom would suggest that “playing it safe” is best encouraged by framing the goals in avoidance terms (e.g., aim to avoid losing contracts) and penalizing failure, so that the consultants focus on minimizing potential losses. Risk-taking, on the other hand, would be best encouraged by framing the goals in approach terms (e.g., aim to win contracts) and rewarding success, so that the consultants focus on maximizing potential gains. Our findings suggest the opposite—that to encourage consultants to be risk-averse, the company would be best placed framing the goals in approach terms and rewarding success, whereas to encourage consultants to be risk-seeking, the company would be best placed framing the goals in avoidance terms and penalizing failure. Indeed, there are precedents for this in industry. Safety has traditionally been framed as an avoidance goal for air traffic controllers, such that the controller’s responsibility is to detect and prevent violations of the required separation standards. Safety has been reframed as an approach goal, with the introduction of the concept of “separation assurance”, such that the controller’s goal is to assure separation between aircraft, rather than avoid violations of separation (Loft et al., 2009). Whilst this change was not informed by data, the intention was to enhance safety by encouraging risk-aversion, and is consistent with our research.

In order to operationalize prioritization optimality, we drew from the decision-making literature to conceptualize multiple-goal pursuit as a multistage decision task (e.g., Rapoport & Wallsten, 1972), and developed an experimental paradigm—the multistage prioritization paradigm—that allows examination of departures from optimality within this task environment. The multistage prioritization paradigm is comprised of a series of discrete decisions in a context in which each decision has consequences for subsequent decisions. A unique feature of this paradigm is that it specifies when the participant must make a prioritization decision—this facilitates operationalization of optimality at multiple points in time. In contrast, previous paradigms that have been used to examine multiple-goal pursuit (Schmidt & DeShon, 2007; Schmidt et al., 2009; Schmidt & Dolis, 2009) allow participants to
change priority at any point in the task—such variability would make it difficult to systematically operationalize optimality. The multistage prioritization paradigm can also be used to address previously untested assumptions in a more precise manner than existing paradigms. To date, computational models of multiple-goal pursuit (e.g., Vancouver et al., 2010, 2014) have only been tested in environments where actions facilitate progress toward one goal (though see Chapter 3 of this thesis for an exception). However, in reality, actions can affect more than one goal (e.g., supervising graduate students can facilitate both research and supervision goals). The multistage prioritization paradigm is well suited to testing models of multiple-goal pursuit in this more complex environment because it allows the experimenter to control the impact of actions on multiple goals (e.g., the points that can be gained or lost for each goal, and the probabilities of those gains or losses occurring).

Our introduction of dynamic programming to the multiple goal literature allowed us to quantify individuals’ departures from optimal prioritization decisions. This technique also has potential to augment theory building in conjunction with computational modeling. Dynamic programming models can be simulated together with computational models of multiple-goal pursuit (e.g., Chapter 3; Ballard, Yeo, Loft, Vancouver, & Neal, 2014; Vancouver et al., 2010, 2014) to compare prioritization decisions predicted by the computational model with those prescribed by an optimal model. Discrepancies between the two sets of predictions represent cases in which the computational model predicts departure from optimality. These predictions would provide strong evidence in support of the computational model if confirmed (Dobbins & Han, 2007). Experimenters seeking to test a computational model could therefore use such information to help design experiments that target decisions in which the computational and optimal models make divergent predictions. In this case, support for the computational model’s predictions would provide insight into decision-making biases that the model may help explain. Support for the optimal model’s predictions would also be useful. Given that people are unlikely to carry out the full calculus of dynamic programming each time they make a decision, results would suggest that individuals were using effective heuristics that enable them to make near-optimal decisions. Such results would justify further research to identify such heuristics.

4.6.2 FURTHER PRACTICAL IMPLICATIONS

There are many situations in which departures from optimality during multiple-goal pursuit can have significant consequences. For example, individuals and teams working across multiple projects need to prioritize the allocation of time and effort in order to meet competing deadlines. People performing process control or scheduling tasks need to prioritize the
allocation of physical resources to different components of the system. Managers need to
prioritize the allocation of tangible and intangible assets (e.g., capital, finance, human resources)
across different business units or ventures. In each case, the sub-optimal allocation of resources
increases the risk that the decision maker will not achieve one or more of their goals by the
deadline.

Understanding how people depart from optimality during multiple-goal pursuit is
practically useful, because it can be used to inform the development of interventions to improve
the quality of decision making during multiple-goal pursuit. There are a range of interventions
in which dynamic programming can be used, including training (e.g., McGinnis & Fernandez-
Gaucherand, 1994), decision support (e.g., Hanlon et al., 2013; Parasuraman et al., 2000; Yeo &
Cornell, 2009), and performance management (e.g., Anderson, 2001; Pinker & Larson, 2003). For
example, dynamic programming algorithms can be incorporated into training simulations, and
used to identify departures from optimality and provide feedback to trainees, enabling them to
learn how to prioritize optimally. Decision support systems can be developed to improve
decision making on the job. Managers may influence the way that staff members prioritize
the allocation of resources to competing goals by framing those goals in approach or avoidance
terms to induce risk-averse or risk-seeking behavior. If the goals cannot be reframed, managers
may be able to use instructions or incentives to change the relative value of the goals, or adjust
the difficulty of the goals or the deadlines, to counteract these biases.

4.6.3 Additional Considerations and Avenues for
Future Research

In order to operationalize decision optimality, it is necessary to select a criterion by which to
evaluate optimality. We used expected utility theory because it provides an objective,
mathematical tool to determine the decision that maximizes the expected reward (i.e., the
optimal decision according to our definition). However, expected utility theory is not the only
theory that offers a prescriptive standard for optimal decision making. For example, the
principle of bounded rationality states that a normative model of decision making should take
into account the information processing capabilities of the decision maker (Simon, 1952).
According to this perspective, optimal decisions do not necessarily align with the objective
criterion of expected reward maximization, because processing constraints reduce the amount
of information that is able to be incorporated into the decision. However, it is difficult to use the
principle of bounded rationality to derive a prescriptive standard for optimal decision making,
because the analyst needs to be able to quantify the amount of information to be processed and
the capacity of the human information processor. Despite over 60 years of research on human
information processing capacity, this problem still has not been solved (Gopher & Donchin, 1986; Neal et al., 2013).

In the task environment used in this experiment, the probabilities (regarding the impact of actions on outcomes) were made explicit to participants. This scenario is appropriate because there are numerous examples of decisions that are made in multiple-goal contexts in which one has a good idea of the outcome probabilities. An academic managing the competing goals of quality versus quantity with regard to their publication record will have a good idea of the probability of a particular manuscript being accepted at various outlets. A doctor managing the competing goals of treatment effectiveness versus invasiveness will have a good idea of the probabilities of various treatment options being effective. There is also evidence to suggest that animals make decisions by constructing a representation of outcome probabilities for a given action (McNamara & Houston, 1992; Stephans & Krebs, 1986). Nevertheless, the multistage prioritization paradigm could be used to implement different scenarios—for example, future researchers interested in decision making under uncertainty could design a task within our paradigm in which the probabilities are unspecified and must be learned by participants.

Another feature of our research that should be considered is the use of a laboratory task and student sample. It is often assumed that student samples lack representativeness, and the results of laboratory experiments lack generalizability. However, such criticisms confuse statistical generalizability with theoretical generalizability (Highhouse, 2009). The aim of this research is theoretical generalization—to test a set of hypotheses about how people make decisions when pursuing multiple goals. Theoretical generalization is achieved through the use of experimental manipulations and alignment between design and measurement (Anderson & Bushman, 1997; Highhouse, 2009; Locke, 1986). The protocol used in this study is therefore appropriate for drawing conclusions about generalizability, independent of the research setting. Nevertheless, replicating the current study with different tasks, settings, and samples will be necessary to identify potential boundary conditions. For example, theories of time discounting (Ainslie & Haslam, 1992; Steel & Konig, 2006) would predict that individuals may under-value a goal with a deadline that is temporally distant. Operationalizing a multiple-goal pursuit context, in which the number of decisions within which the goals must be achieved differs, would help to answer the question of whether time discounting produces departures from optimality by making individuals less likely than an optimal decision maker to prioritize goals with more distant deadlines.

Future research could also extend our examination of biased prioritization decisions by taking a deeper look at the underlying mechanisms that produce these biases when pursuing multiple approach versus avoidance goals. Understanding the dynamic process that produces biased prioritization decisions can be achieved with computational models, which have begun
to be used in the multiple-goal pursuit literature to investigate the mechanisms that govern goal choice (Ballard et al., 2014; Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013; Vancouver & Weinhardt, 2012; Weinhardt & Vancouver, 2012). For example, multiple-goal pursuit theory (Vancouver et al., 2010) predicts that motivation to prioritize a goal is a function of the distance from goal achievement and the expectancy of goal achievement. However, the influence of these two mechanisms may sometimes be unequal, and such imbalance may produce biased prioritization decisions. For example, if one is more influenced by the expectancy of goal achievement, he or she may be more likely to prioritize the goal in the best position; whereas if one is more influenced by the distance from goal achievement, he or she may be more likely to prioritize the goal in the worst position. It is possible that the biased prioritization decisions observed in this research are produced by one of these mechanisms being more influential than the other, depending on whether goals are conceptualized in approach versus avoidance terms.

4.6.4 CONCLUSION

This research has contributed to our understanding of decision making during multiple-goal pursuit. The finding that prioritization decisions and subjective values depart from an optimal model underscores the importance of taking into account what is optimal when making inferences about people’s behavior in complex, dynamic environments. Our shift in focus to examining departures from a normative theory of optimal behavior provides a new lens for goal pursuit theories. Moreover, the multistage prioritization paradigm and dynamic programming provide innovative tools for examining such factors. Together, these theoretical, empirical, and methodological contributions lay the foundation for future research and practical efforts aimed at enhancing decision making in the workplace.
### Summary of Manipulations

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<th>Goal in Better Position</th>
<th>Goal in Worse Position</th>
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CHAPTER 5

GENERAL DISCUSSION

The aim of this thesis was to examine how, and how well, people prioritize when pursuing multiple approach and/or avoidance goals. In Chapter 2, I translated a verbal theory of avoidance goal pursuit (Carver & Scheier, 1990, 1998) into a computational model. In Chapter 3, I incorporated the model of avoidance goal pursuit developed in Chapter 2 into a more general model of multiple-goal pursuit that describes how people prioritize whilst pursuing different combinations of approach and avoidance goals. In Chapter 4, I examined if and how pursuing approach versus avoidance goals produces departures from optimal prioritization. In this chapter, I integrate the theoretical implications and the findings from these respective thesis chapters. Firstly, I summarize the findings of the thesis and discuss the contributions the current work makes to the multiple-goal pursuit literature. I then address some general contributions and limitations of the computational modeling methodology. Finally, I discuss the practical implications of the findings.

5.1 SUMMARY OF FINDINGS

Chapter 2 aimed to instantiate Carver and Scheier’s (1990; 1998) verbal account of avoidance goal pursuit as a computational model. Articulating their theory in this manner allowed me to resolve ambiguities in Carver and Scheier’s account. These ambiguities arose from the fact that they a) use the label ‘positive feedback loop’ in a manner inconsistent with how it is traditionally defined and b) do not specify the precise nature of the relationship between the distance from an undesired state and the intensity of avoidance behavior. Interpreting the ‘positive feedback loop’ label according to its traditional definition (i.e. as a system in which the
input is related to the output, (Richardson, 1991; Zeigler et al., 2000) leads to an assumption that is counterintuitive and inconsistent with previous research: namely, that avoidance behavior intensifies as distance from an undesired state increases. However, Carver and Scheier appear to treat positive feedback loops as analogous to discrepancy-amplifying systems, which is inconsistent with how they are defined in the systems dynamics literature. Discrepancy-amplifying systems do not require the discrepancy to be positively related to the output. Thus, the assumption that the intensity of avoidance behavior decreases as one moves farther from an undesired state is also consistent with Carver and Scheier’s account. However, this assumption implies that avoidance goal pursuit is actually a negative feedback loop. I implemented both sets of assumptions as computational models, and showed that the model representing a negative feedback loop makes predictions that are more meaningful and more consistent with the dynamic patterns of behavior predicted by Carver and Scheier than the model representing a positive feedback loop. Instantiating Carver and Scheier’s theory with the precision and transparency of a computational model, while a contribution in itself, also allowed me to resolve these ambiguities by demonstrating that the relationship between the distance from an undesired state and avoidance intensity is negative, and therefore that it is more appropriate to describe avoidance goal pursuit as a negative feedback loop.

In Chapter 3, I used the model of avoidance goal pursuit introduced in Chapter 2 to extend the multiple-goal pursuit model (Vancouver et al., 2010; 2014) to account for avoidance goals. In Chapter 3, I also extended the multiple-goal pursuit model to account for actions having uncertain consequences for goal progress by integrating decision field theory (Busemeyer & Townsend, 1993; Roe et al., 2001). This extended model—the MGPM*—describes how people prioritize goals in multiple-goal contexts, in which they pursue different combinations of approach and avoidance goals and when actions have uncertain consequences for goal progress. As predicted by the model, participants performing a dual-goal Air Traffic Control task in which one goal was approach and one was avoidance tended to switch priority from the approach to the avoidance goal over time. Among participants performing the task with two approach goals, two strategies were used. Some participants adopted a balanced strategy, whereby they switched priority rapidly between goals. Other participants adopted a sequential strategy, whereby they prioritized one goal until it was attained and then switched to the other. Among participants performing the task with two avoidance goals, almost all participants adopted the balanced strategy. Regardless of approach/avoidance frame combination or strategy, the tendency to prioritize a particular goal was stronger when actions had a more certain impact on goal progress.

In Chapter 4, I switched focus from how people prioritize when pursuing multiple approach and avoidance goals, to examining how well people prioritize. In this chapter, I
shifted from examining how goal frame predicts prioritization decisions, to examining how goal frame predicts systematic departures from optimality. Drawing on prospect theory (Kahneman & Tversky, 1979), I predicted that people have a risk-averse bias when pursuing multiple approach goals, and over-weight the value of achieving one goal compared to the value of achieving two. As a result, people are more likely than an optimal model to prioritize the goal in the best position. Pursuing multiple avoidance goals was predicted to produce a risk-seeking bias, in which people over-weight the value of achieving two goals compared to the value of achieving one, and are consequently more likely than an optimal model to prioritize the goal in the worst position. These predictions were tested with an experimental paradigm in which participants made a series of prioritization decisions whilst pursuing either two approach or two avoidance goals. The predictions were supported.

5.2 CONTRIBUTIONS TO THE MULTIPLE-GOAL PURSUIT LITERATURE

In this section, I discuss the theoretical contributions of this thesis to the multiple-goal pursuit literature. There are two major theoretical contributions discussed in the following sections: the extension of computational models of goal pursuit to the avoidance context; and incorporation of decision-making theory into the examination of multiple-goal pursuit.

5.2.1 CONSIDERATION OF AVOIDANCE GOALS

The first contribution of this thesis is the incorporation of avoidance goals into the examination of multiple-goal pursuit. Although avoidance goals are common (Elliot & Sheldon, 1997), and pursuing approach versus avoidance goals involves distinct processes (Carver & Scheier, 1990; 1998), the multiple-goal pursuit literature has focused almost exclusively on approach goals. A general conclusion from Chapters 2, 3 and 4 is that avoidance goals exert different effects on behavior from approach goals, and these differential effects can influence how behavior plays out over time. It is therefore important to account for avoidance goals when examining prioritization during multiple-goal pursuit.

In Chapter 2, I argued that avoidance goal pursuit, like approach goal pursuit, operates as a negative feedback loop. Approach goal pursuit involves a discrepancy-reducing feedback loop, in which motivation to act on an approach goal decreases as the desired state becomes closer. Avoidance goal pursuit involves a discrepancy-amplifying feedback loop, in which motivation to act on an avoidance goal increases as the undesired state becomes closer.
(although both processes operate as negative feedback systems). This assumption served as the foundation for making predictions about how people prioritize when pursuing multiple goals with different combinations of approach and avoidance framing. In Chapter 3, I showed that a computational model of multiple approach and avoidance goal pursuit that operates according to this assumption predicts different patterns of behavior, depending on whether people pursue one approach and one avoidance goal, two approach goals, or two avoidance goals.

The empirical findings of Chapters 3 and 4 were consistent with these predictions. Chapter 3 showed that when pursuing one approach and one avoidance goal, people should initially prioritize the approach goal and later shift priority to the avoidance goal. In contrast to this relatively slow shift in priority over time, Chapters 3 and 4 showed that when pursuing two avoidance goals, people shift priority fairly rapidly between goals due to a heightened preference (relative to when pursuing two approach goals) for prioritizing the goal in the worse position. Chapter 4 revealed that this heightened tendency to prioritize the goal in the worse position when pursuing two avoidance goals was risk-seeking compared to a normative baseline because, ultimately, it made the individual more likely to achieve both goals, but also more likely to fail both goals.

In contrast to pursuing one approach and one avoidance goal or two avoidance goals, Chapters 3 and 4 showed that pursuing two approach goals does not result in a clear tendency to prioritize a particular goal. Chapter 4 showed that the overall tendency to prioritize the goal in the worse position was weaker when pursuing two approach goals, compared to when pursuing two avoidance goals. The decreased tendency to prioritize the goal in the worse position was risk-averse compared to a normative baseline because ultimately, it made the individual more likely to achieve one goal, but less likely to achieve both goals. However, the decreased overall tendency to prioritize the goal in the worse position demonstrated in Chapter 4 is likely due to the fact that, as revealed in Chapter 3, people pursuing two approach goals exhibit individual differences in prioritization strategy. Consistent with most of the existing the multiple-goal pursuit literature (e.g., Louro et al., 2007; Schmidt & DeShon, 2007; Schmidt & Dolis, 2009), some people show a tendency to prioritize the goal in the worse position. However, consistent with Schmidt et al., (2009), other people tend to prioritize the goal in the better position.

It is worth considering whether the same underlying mechanism may explain the differences in prioritization between approach and avoidance contexts, and individual differences in prioritization seen in the approach context. Chapter 3 demonstrated that the individual differences in prioritization amongst people pursuing two approach goals could be explained by variability in time sensitivity. People who are less sensitive to the time deadline are more likely to prioritize the goal in the worse position (i.e., they use a balanced strategy),
whereas people who are more sensitive to the time deadline are less likely to prioritize the goal in the worse position (i.e., they use a sequential strategy). Chapter 3 also found differences in time sensitivity among people pursuing two approach goals versus two avoidance goals. It is therefore possible that variation in time sensitivity may provide an alternative explanation for the departures from optimality observed in Chapter 4. If pursuing two approach goals makes people more sensitive to the time remaining, their subjective sense of time remaining may be less than the objective amount of time remaining (Vancouver et al., 2010). If pursuing two avoidance goals makes people less sensitive to the time remaining, their subjective sense of time remaining may be greater than the objective amount. Given the above, the decreased tendency to prioritize the goal in the worse position when pursuing two approach goals, and the increased tendency to prioritize this goal when pursuing two avoidance goals, may actually reflect optimal decision making based on a biased perception of the time remaining. These tendencies still reflect departures from optimality compared to the normative baseline. However, it is possible that the underlying bias that explains these departures has more to do with the subjective sense of time remaining than the subjective value of achieving one versus two goals.

5.2.2 Incorporation of Decision-Making Theories

The second contribution of this thesis is the integration of theories of decision making into our understanding of multiple-goal pursuit. Prioritization involves making a decision between courses of action, each of which favors one goal at the expense of the other. Thus, the decision-making literature is relevant to understanding how people prioritize. However, this literature has not been heavily featured in theories of multiple-goal pursuit. This thesis has demonstrated that theories of decision-making can enhance our understanding of multiple-goal pursuit. Specifically, in Chapter 3, I demonstrated how decision field theory enhances our understanding of the influence of uncertainty. In Chapter 4, I demonstrated how conceptualizing multiple-goal pursuit as a multistage decision, and drawing on prospect theory, can be used to explain how prioritization decisions depart from optimality.

In Chapter 3, I drew on decision field theory to explain how people decide between courses of action that have uncertain consequences for goal progress. Until now, the multiple-goal pursuit model has only been tested in environments where actions have a certain impact on goal progress. Chapter 3 showed that the uncertainty in an action’s consequences influences the likelihood of selecting that action independently of that action’s expected impact on goal progress. When deciding between two courses of action with different expected utilities, people are more likely to select a course of action with the higher expected utility when the
consequences are more certain. The existing multiple-goal pursuit model could not have accounted for this effect because it makes a deterministic prediction about which action will be selected. Decision field theory, on the other hand, makes probabilistic predictions that are able to explain the effect of uncertainty on the likelihood of selecting an action. These findings show that through incorporation of decision field theory, the MGPM* can provide a more general account of prioritization during multiple-goal pursuit that is able to explain a wider range of phenomena than the existing multiple-goal pursuit model.

In Chapter 4, I demonstrated that conceptualizing and operationalizing multiple-goal pursuit as a multistage decision enables the examination of departures from prioritization optimality. I created the multistage prioritization paradigm, in which people make a series of repeated prioritization decisions that have probabilistic impacts on goal progress. Operationalizing multiple-goal pursuit in this manner enabled the use of dynamic programming to implement expected utility theory in the multiple-goal context. Implementing a normative model of prioritization optimality represents a qualitative shift in focus from previous work, because it allows the examination of how prioritization departs from optimality, as opposed to the examination of how people prioritize. This shift in focus allowed us to define risk-averse and risk-seeking behavior in the multiple-goal context and to draw on prospect theory to make predictions about when people should exhibit each tendency. The support for these predictions demonstrates that conceptualizing multiple-goal pursuit as a multistage decision task can enhance our understanding of prioritization. Moreover, the findings of Chapter 4 indicate that prospect theory is a useful tool for understanding decision making in this context.

5.3 **Contributions and General Limitations of Computational Modeling**

A further contribution of this thesis is the application of computational modeling to examine how people prioritize goals. The model presented in Chapter 2 represents the first computational instantiation of the avoidance goal pursuit process. Incorporation of this model into the more general model presented in Chapter 3 yielded a set of novel and counterintuitive predictions, namely, that people should switch priority over time from the approach to the avoidance goal. These predictions were supported, highlighting the usefulness of computational modeling as a tool for theory building. However, like any methodology, computational modeling is not without its limitations. I discuss two of these limitations below.
One limitation pertains to the translation of verbal theories into computational models. Verbal theories are often not specified with sufficient precision to warrant a straightforward instantiation as a computational model (Kozlowski et al., 2013; Vancouver & Weinhardt, 2012). Thus, assumptions must often be made to resolve the ambiguities inherent in verbal descriptions (Vancouver et al., 2005). These assumptions can be problematic if they depart from the true intent of the original theory. In this case, the computational model being tested may not be an accurate representation of the theory; and evidence for or against the model would not necessarily reflect on the theory. For example, in Chapter 2, I pointed out that Carver and Scheier (1998) do not provide enough detail to model the process whereby avoidance goal pursuit should be ‘captured’ by approach goal pursuit. I therefore had to incorporate assumptions from the multiple-goal pursuit model (Vancouver et al., 2010) that may not have reflected Carver and Scheier’s perspective. However, the necessity for these assumptions to be made, and the ambiguity they reveal, ultimately benefits the verbal theory by encouraging more precise specification.

The second limitation pertains to the validity of the computational model as an explanation of the phenomena under investigation. Like any theory, consistency between a computational model’s predictions and empirical evidence does not guarantee that the model provides an accurate explanation of the empirical phenomenon (Vancouver et al., 2008). For example, Chapter 3 found that the predictions of the MGPM* were consistent with the prioritization decisions observed in the experiment. However, it is possible than an alternate model may provide a better explanation of these decisions. The fact that the MGPM* made a priori predictions that were confirmed provides support for it as an explanation for how people prioritize. Nevertheless, it will be important for future research to rule out alternative explanations and ensure the generality of the model by rigorously testing it in different environments, pitting it against competing models, and modifying the model when necessary.

### 5.4 Practical Applications

The findings of this thesis have implications for workplace environments that require individuals to manage multiple goals. Effective goal prioritization is particularly important in safety critical industries, such as mining, aviation, and medicine. In these work environments, mistakes or malfunction can lead to death or severe injury to people, damage to equipment and related infrastructure, or serious environmental harm. Consequently, safety is a high priority. However, a strong focus on safety may come at the expense of productivity, and vice versa. For example, individuals who are under pressure to meet production targets may be forced to cut corners and compromise their own safety or the safety of others. By contrast, individuals
focused on safety may need to slow down production to adhere to safety measures. Previous research has identified that performance targets, and expectations from management to follow safety regulations, give rise to trade-offs between safety and productivity in safety critical industries such as mining (Laurence, 2005), oil drilling (Pate-Cornell, 1990), and manufacturing (Kaminski, 2001). These trade-offs have contributed to some of the most devastating industrial disasters including the Chernobyl nuclear reactor meltdown, the Tenerife airplane collision and the Piper Alpha oil platform explosion.

Few studies have examined factors that influence both safety and productivity. These studies tend to focus on factors such as the number of hours per shift (Folkard & Tucker, 2003), organizational practices (Kaminski, 2001), or work conditions (Shikdar & Sawaqed, 2003) that influence safety and productivity at the organization level. More recent research has revealed that individual level factors, such as regulatory focus, also influence safety and productivity (McLain & Jarrell, 2007; Wallace & Chen, 2006; Wallace et al., 2009; Wallace, Little, & Shull, 2008). The findings from these studies demonstrate the practical utility of understanding factors that influence goal prioritization within individuals, over time.

Goal framing is a particularly salient aspect of safety critical work environments. Traditionally, productivity and safety have been framed in approach and avoidance terms respectively. Productivity has traditionally been defined as the total output a system can achieve given a certain amount of work, and most research has focused on identifying ways to increase this output (Katzell & Guzzo, 1983; Tuttle, 1983). On the other hand, safety has historically been conceptualized as the avoidance of accidents, with most research being focused on error reduction (Hofmann et al., 1995; Pate-Cornell, 1990). However, there are recent examples of safety and productivity goals framed in different ways. When the global financial crisis hit, some organizations shifted their focus from increasing productivity to preventing productivity losses. Similarly, a growing interest in positive psychology within the area of workplace safety has led some managers to encourage proactive behaviors that promote a safe working environment, rather than discouraging mistakes (Griffin & Neal, 2000).

Understanding the implications that different combinations of goal frames have on individuals striving for safety and productivity goals can therefore be beneficial to the development of effective performance management practices. Ideally, individuals in this context should be able to successfully manage the two goals, but will prioritize safety over productivity if both cannot be achieved. However, Chapter 3 suggests that the traditional conceptualization of productivity as an approach goal and safety as an avoidance goal may lead people to initially prioritize productivity over safety. This tendency may have harmful consequences if safety is neglected for too long. Chapter 4 suggests that framing both productivity and safety as avoidance goals may produce risk-seeking behavior, whereby people
attempt to meet both goals and therefore raise their chances of failing both. This tendency can also have harmful consequences. The findings of this thesis suggest that framing both productivity and safety as approach goals should produce the most effective decision making in safety critical environments because people will be risk-averse, and therefore less likely to compromise safety.

5.5 Conclusion

This thesis examined prioritization when pursuing multiple approach and/or avoidance goals. Chapter 2 instantiated a verbal account of avoidance goal pursuit (Carver & Scheier, 1998) as a computational model. Chapter 3 developed the MGPM*, an extension of the multiple-goal pursuit model (Vancouver et al., 2010), that incorporates the model of avoidance goal pursuit introduced in Chapter 2 and decision field theory (Busemeyer & Townsend, 1993). The MGPM* was able to explain prioritization decisions when pursuing different combinations of approach and avoidance goals and when actions have uncertain impacts on goal progress. Chapter 4 compared prioritization decisions when pursuing multiple approach or avoidance goals to a normative model, and demonstrated that goal frame produced systematic departures from optimality that were consistent with prospect theory (Kahneman & Tversky, 1979). The findings of this thesis highlight the importance of a) considering avoidance goals, b) incorporating theories of decision making, and c) implementing computational and normative models when attempting to understand multiple-goal pursuit. It is hoped that these findings serve as a foundation for future research as well as providing the opportunity to enhance decision making in the workplace.
REFERENCES


