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On the pursuit of multiple goals with different deadlines

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Abstract

This paper presents a theory of how how people prioritize their time when pursuing goals with different deadlines. Although progress has been made in understanding the dynamics of multiple-goal pursuit, theory in this area only addresses cases where the goals have the same deadline. We rectify this issue by integrating the multiple-goal pursuit model–a formal theory of multiple goal pursuit–with theories of intertemporal motivation and choice. We examine the ability of four computational models derived from this general theory to account for participants' choices across four experiments. The models make different assumptions about how people determine the valence of prioritizing a goal (i.e., by monitoring distance to goal or time pressure), and whether the goal is subject to temporal discounting. In each experiment, participants performed a task requiring them to pursue two goals. Experiments 1 and 2 manipulated deadline and distance; Experiment 3 manipulated deadline and time pressure; Experiment 4 manipulated all three factors. Counter to the predictions of existing theory, participants generally prioritized the goal with the shorter deadline. We also observed weak, but positive effects of distance on prioritization (Experiment 2) and non-linear effects of time pressure (Experiment 3). The model that best explained participants' decisions assumed that valence is determined by time pressure and the expected utility of a goal is subject to temporal discounting. This new model broadens the range of phenomena that can be accounted for within a single theory of multiple-goal pursuit, and improves our understanding of the interface between motivation and decision making.

Keywords: multiple-goal pursuit, deadlines, prioritization, computational modeling, Bayesian methods

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Both at work and in everyday life people juggle many goals, often needing to choose which goal to prioritize at a given point in time. These choices are difficult because focusing on one particular goal can limit one's ability to make progress on other goals. To effectively manage resources, one needs to be able to identify which goals need to be prioritized and which goals can be deferred. Because goal pursuit is a dynamic process, theories of goal pursuit must explain changes in goal prioritization over time, particularly as progress is made or deadlines approach. Toward that end, Vancouver, Weinhardt, and Schmidt (2010) developed a formal, computational model, called the multiple-goal pursuit model (MGPM) that integrated concepts from static choice theories such as expectancy theory (Vroom, 1964) using a dynamic self-regulation theory (i.e., perceptual control theory; Powers, 1973). This combination allowed for concepts that have been implicated in goal choice – valence and expectancy (Klein, Cooper, & Austin, 2009) – to take on dynamic qualities that can explain how goal priority will vary over time. Valence refers to a subjective sense of the immediate value of prioritizing a goal and expectancy refers to a subjective sense of the likelihood of achieving the goal (Vroom, 1964). The model reproduced complex behavior observed in studies on multiple-goal pursuit over time (e.g., Schmidt & DeShon, 2007; Ballard et al., 2016). For example, the MGPM provided an explanation for why one generally prioritizes a goal further from realization compared to one closer to realization, and why this tendency reverses over time as the deadline becomes closer.

Although the MGPM has been useful for building an understanding of multiple-goal pursuit, it has a major limitation: it can only be used to understand goal prioritization in contexts where the different goals have the same deadline. In real life, the goals that individuals juggle tend to have different deadlines. For example, it is rare that two different projects will need to be completed by the exact same date. Thus, the MGPM in its current form may lack generality. Moreover, the insights provided by the MGPM regarding the effect of deadline on goal prioritization run in stark contrast to decades of research in the intertemporal choice and motivation literatures (e.g., Ainslie, 1975; Latham & Locke, 1975; Steel & König, 2006). In its current form, the MGPM predicts that as the deadline approaches, the individual will be less likely to prioritize the goal because he/she will be concerned by the decreasing expectancy of goal achievement. By contrast, it is well established in studies of time pressure and temporal discounting that shorter deadlines are more motivating (Hendy, Liao, & Milgram, 1997; Steel & König, 2006). This conflict between our assumptions about multiple goal pursuit and well-established conclusions from the motivation and decision making literatures suggests that our current understanding of the dynamics of multiple-goal pursuit is incomplete.

In this paper, we attempt to rectify these issues by developing and testing a theory of multiple-goal pursuit that can explain how people prioritize the allocation of their time when pursuing goals with different deadlines. We use an existing model of multiple-goal pursuit–the MGPM–as our starting point and expand this model with theory from the motivation and decision making literature. We identify two mechanisms by which deadlines might exert their effects during multiple-goal pursuit – time pressure and temporal discounting – and incorporate them into the MGPM. To examine the evidence for these mechanisms, we represent four different computational models. The first represents the MGPM in its current form, the second incorporates time pressure, the third incorporates

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The supplementary material for this paper includes all the materials, data, and code used to run the experiments, conduct the statistical analyses, and implement the computational models. The supplementary material can be retrieved from https://osf.io/hdwyn/ or by contacting the first author.

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temporal discounting, and the fourth incorporates both time pressure and temporal discounting. We examine the ability of these models to explain results from four experiments in which participants made a series of prioritization decisions whilst pursing two goals with different deadlines.

Developing an Understanding of Multiple-Goal Pursuit

Goals, which are internally represented desired states within a person or a person's environment, are a staple of theory and research on motivation and cognition (Austin & Vancouver, 1996). Much of the scholarship on goals has focused on how the properties of goals (e.g., difficulty, time frame, importance) affect performance on the goals; however, recent research and theory has focused on understanding the process of goal pursuit (for reviews, see Lord, Diefendorff, Schmidt, & Hall, 2010; Neal, Ballard, & Vancouver, 2017). A typical study in this literature uses a within-subjects design in which participants work on two or more tasks over a given time period. The participant usually can only work on one task at a time, and therefore must make a series of choices over time about which task to prioritize. This type of design allows researchers to examine the patterns of behavior that unfold over time.

For example, Schmidt and DeShon (2007) examined prioritization in a scheduling task, where participants created class schedules for two fictitious colleges. Each college had students requiring a schedule, and the goal for each was to complete a schedule for all the students requiring one within a certain amount of time. The task was difficult because the participant could only create one student's schedule at a time and, therefore, had to repeatedly choose which college to prioritize. Moreover, new students were added unpredictably to the queues across time. Schmidt and DeShon found that prioritization was generally determined based on the distance to each goal. The distance refers to the difference between the level of the performance thus far (i.e., number of students needing schedules) and the goal level (i.e., no more students requiring schedules). In this study, people generally spent more time working on the college that had more students requiring schedules. That is, at any one time the participants tended to prioritize the college with the most distant goal. However, this tendency reversed over time. As the deadline approached, people shifted toward prioritizing the college that requiring fewer schedules (i.e., the least distant goal).

Other studies have expanded on these findings (see Neal et al., 2017, for an extensive review). For example, Schmidt and Dolis (2009) found that the shift in preference from the most distant goal to the least distant goal was mediated by the expectation of achieving the goals. People often prioritized the most distant goal when they expected that both goals were achievable, but shifted to prioritizing the least distant goal when they expected that one or more goals was not achievable. Louro, Pieters, and Zeelenberg (2007) examined multiple-goal pursuit in a diary study of people striving for dieting goals. They also found a shift in how goals were prioritized depending on how close goals were to realization. Other studies have shown that when goals share a common deadline, prioritization is influenced by the way the goal is framed (as approach or avoidance; Ballard, Yeo, Neal, & Farrell, 2016), uncertainty regarding the impact of actions on goal progress (Ballard, Yeo, Loft, Vancouver, & Neal, 2016), and incentives for goal achievement (Ballard, Farrell, & Neal, 2017; Schmidt & DeShon, 2007).

Over the last decade, progress has been made towards explaining the empirical phenomena observed in these and other studies of multiple-goal pursuit. Specifically, using a control theory architecture (Powers, 1973), integrated with expectancy-value theories of motivation (e.g., Vroom, 1964), Vancouver, Weinhardt, and Schmidt (2010) developed a computational model of the dynamics of multiple-goal pursuit (i.e., the multiple-goal pursuit model, or 'MGPM' for short). This model assumes that people make prioritization decisions by evaluating the expected utility of acting on each goal and directing resources toward the goal for which expected utility is highest. Expected utility is a determined by valence (V) weighted by expectancy (E) (i.e., E x V), both of which Vancouver et al. claimed varied over time. The valence of a goal at a particular point in time during goal pursuit is a function of distance to the goal, weighted by the goal's importance. The larger the distance, the greater the subjective value of prioritizing the goal. Expectancy represents the perceived likelihood of achieving the goal. In tasks with a deadline, Vancouver et al. (2010) claimed that expectancy is a function of the difference between the perceived time available before the deadline is reached and the perceived time required to reach the goal. The perceived time required is determined by the distance weighted by one's beliefs regarding the rate at which the distance is reduced when the goal is prioritized.

One key element of the MGPM is its use of simple, self-regulatory agents to represent the information processing structure hypothesized to be involved in decision making during multiple-goal pursuit (Vancouver et al., 2010). The self-regulatory agent, which is the core of control theory (Powers, 1973), includes a comparator function that assesses the discrepancy between signals (e.g., between a goal and a perception of performance). Control theory assumes that humans are composed of a network of self-regulatory agents. This network allows individuals to navigate their world, achieve and maintain their goals, and sustain basic functioning (Powers, 1973). The MGPM included four types of self-regulatory agents based on the content of the information they process.

Figure 1 provides a simplified schematic of the model and the four agent types. In the upper left corner is the time agent, which provides a signal that represents the time available (TA) to reach the goal by comparing the current time with the deadline. To the right of the time agent is the task agent, which produces a discrepancy between the current state of progress on the task (i.e., performance) and the goal for the task. This discrepancy signal, which we refer to as distance, feeds into two functions. One function determines the valence of the goal via weighting the distance by goal importance. The other estimates the time required (TR) to achieve the goal via weighting the distance by the individual's belief in the rate by which distance is reduced when acted upon. A third agent, called the expectancy agent, compares the time remaining with the time available to create the expectancy (E) signal.

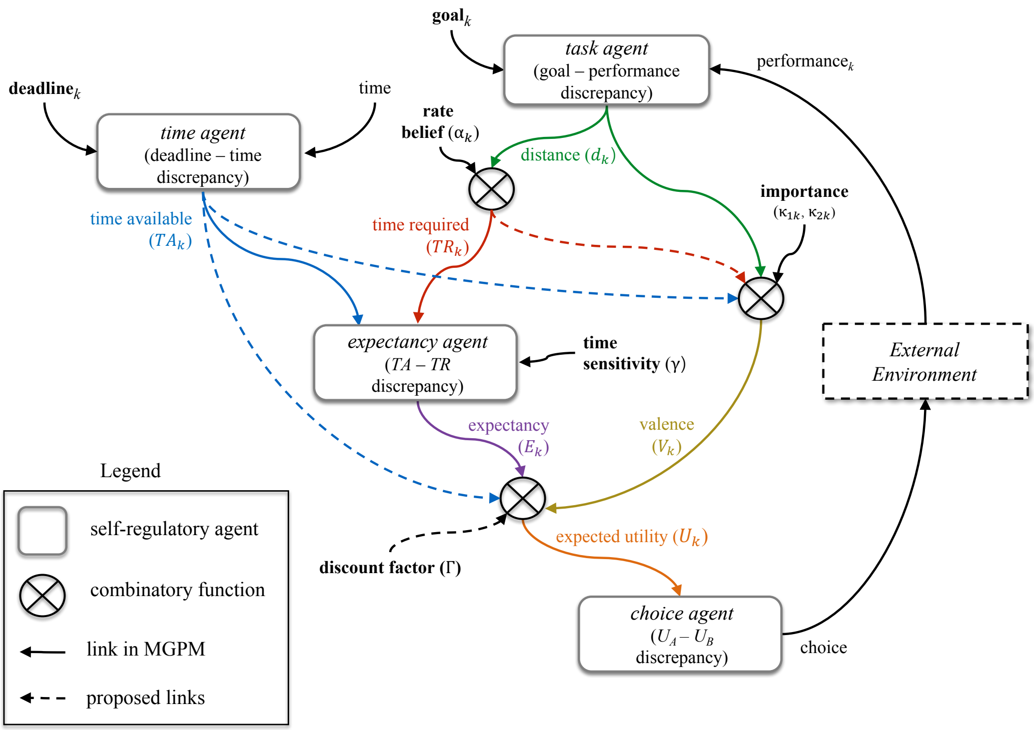

Figure 1. Schematic of MGPM. Solid lines represent existing links. Dotted lines represent proposed links. Variables in bold are assumed constant over time in contexts examined. All other variables change over time. Variables subscripted with k are assumed to vary across goal. For example, the time agent's deadline for Goal B would be different than the deadline for Goal A

In the original MGPM, the functions in the model of the individual were all simple (e.g., additive or multiplicative). For example, the comparator functions were simple subtraction functions truncated at zero. However, Ballard, Yeo, Loft, et al. (2016) suggested that such a function was an inappropriate description of expectancy, because it would mean that an individual would have zero expectancy for achieving a goal when the time available exactly matched the time required. A more realistic assumption is that individuals would likely think they had a 50-50 shot at achieving the goal in such a situation. To reflect this more realistic notion within the model, Ballard, Yeo, Loft, et al. (2016) suggested a sigmoidal function for the expectancy agent:

$$E_k(t) = \frac{1}{1 + \exp[-\gamma \cdot (TA_k(t) - TR_k(t))]}, \tag{1}$$

where γ represents time sensitivity, which determines sensitivity to the difference between TA and TR for goal k (note that k is a subscript that can take on discrete values to represent specific goals, e.g., A or B, as in Figure 1). This sigmoidal function bounds the expectancy value between zero and one and translates a zero discrepancy into 0.5.

The final self-regulatory agent is the choice agent. In the original MGPM, the product of expectancy and valence determined the expected utility (U_k) of the goal (i.e., $U_k = E_k V_k$). The choice agent simply compared the expected utilities for the goals being pursued, and passed on a signal that resulted in the goal with the highest expected utility being prioritized. Ballard, Yeo, Loft, et al. (2016) generalized the choice agent to take into account the impact of potential actions on the progress towards different goals. This generalized choice agent assumed that preference for each action evolves dynamically over time as one considers possible outcomes of the actions, and that an action is chosen when the level of preference for that action breaches a threshold.

Once a choice is made, it will usually result in some action that affects the environment. The model of the environment will depend on the nature of the task, but the environment needs to be represented in the computational model to fully capture the dynamics of the process. Examples of such representations are presented in Vancouver et al. (2010) and Vancouver et al. (2014). Indeed, an important aspect of this model is its dynamism because the signals and constructs they represent are likely to change over time. For example, progress toward a goal will influence the distance signal transmitted from the task agent. Likewise, a looming deadline will affect the time agent. These changes propagate through the information processing structure producing downstream effects on expectancy, valence, and expected utility, which can ultimately produce changes in the choices that are made.

Because the MGPM has been represented as a computational model, it can be simulated to determine if the theory can reproduce the complex effects found in the empirical literature. For example, the initial version (Vancouver et al., 2010) reproduced the shift in preference from the most to the least distant goal over time first observed by Schmidt and DeShon (2007). Simulations of the model revealed this shift resulted from goal prioritization being more strongly influenced by valence earlier in goal pursuit and expectancy later in goal pursuit. The model could also account for individual differences in the timing of the priority shift and the effects of incentives.

Since the introduction of the MGPM in 2010, additional elements have been described and tested that increase the generality of phenomena that can be explained by the model. For example, Vancouver, Weinhardt, and Vigo (2014) showed how learning elements, consistent with the control theory architecture, could be added to the original model. The learning elements provide an explanation for how beliefs about the rate of goal progress and uncertainty in the environment might form and be used during goal pursuit. More recently Ballard, Yeo, Loft, et al. (2016) added and empirically validated elements that account for both approach and avoidance goals, as well as uncertainty in the impact of actions on goal progress. Finally, Vancouver and Purl (2017) added a feedforward element to the goal pursuit model that provided an explanation for the effects of self-efficacy on performance that reconciled a debate been control theorists (Vancouver, 2005; 2012) and social cognitive theorists (Bandura, 2012; 2015).

Although this process of theory building and theory testing has enhanced our understanding of how people prioritize goals over time, there is a limitation to this work that threatens the generality of our assumptions regarding multiple-goal pursuit. The problem is that our understanding of multiple-goal pursuit is based entirely on studies where the goals have had the same deadline. As we argue below, many of the effects that deadlines exert during multiple-goal pursuit can only be observed when goals have different deadlines, and are therefore not accounted for by current theory. In the next section, we draw from other areas within the motivation and decision making literatures to make predictions about how people are likely to prioritize goals with different deadlines. We then integrate these ideas with the MGPM to develop a series of alternative models that we use to represent the mechanisms by which deadlines might influence multiple-goal pursuit.

The Effects of Deadlines on Motivation and Decision Making

There is a long history of research on the effects of time on motivation and decision making. Early research in the area of animal reinforcement learning showed that increasing the amount of time between a behavior and a reinforcer decreases the intensity of that behavior (S. H. Chung, 1965; S. H. Chung & Herrnstein, 1967). Early research on the effects of delay in humans aimed at examining how the subjective value of a reward was influenced by the time before the reward could be obtained. For example, Mischel, Grusec, and Masters (1969) asked children and adults to rate the attractiveness of rewards that could be obtained immediately, in one day, in one week, or in three weeks. The attractiveness of the reward decreased as the delay increased. This tendency is referred to as temporal discounting or delay discounting, and has been attributed to impulsiveness (Ainslie, 1975; Ainslie & Haslam, 1992).

Within the decision-making literature, a large body of work has attempted to elucidate discounting effects by studying intertemporal choice, which refers to the choice among outcomes that occur at different times (Dai & Busemeyer, 2014). A typical paradigm in this literature involves asking participants to choose between two hypothetical monetary rewards: one that is smaller, but immediate and another that is larger, but delayed. For example, Murphy, Vuchinich, and Simpson (2001) used this paradigm to determine the immediately available reward amount that was subjectively equivalent to a delayed reward of $500. As the delay for the $500 reward increased, the immediate reward that participants were willing to accept instead of the $500 decreased. Others have found that the preference for a smaller, short-term reward in favor of a larger, long-term reward reversed as the delays for both rewards increased (Green, Fristoe, & Myerson, 1994; Kirby & Herrnstein, 1995). Temporal discounting has been found to vary by the size of the reward, with smaller rewards being discounted more strongly than larger amounts (Estle, Green, Myerson, & Holt, 2006). It also varies according to whether outcomes are gains (i.e., rewards) or losses. There is also evidence that delayed losses are discounted less strongly than delayed gains (Gonçalves & Silva, 2015; Murphy et al., 2001), although Estle et al. (2006) found this effect only for smaller amounts of money. Considerable effort has gone into identifying the precise mathematical form of this relationship, with the hyperbolic model being widely used and well supported (e.g., Kirby & Herrnstein, 1995; Murphy et al., 2001; Rachlin, Raineri, & Cross, 1991)

Temporal discounting has also been observed in non-monetary contexts. For example, Odum and Rainaud (2003) examined people's preferences for delayed versus immediate food and alcohol. They found that discounting to be stronger for alcohol and food, than for money. Bashir, Wilson, Lockwood, Chasteen, and Alisat (2014) argued that discounting effects may play a role in people's responses to climate change. They showed that framing the consequences of climate change as more temporally proximal increases engagement in environmentally friendly behavior.

Understanding the effects of time on motivation was also a focus of early research in the organizational psychology and management literatures. In what is now known as Parkinson's Law, Parkinson (1958) stated that "work expands so as to fill the time available for its completion" (p. 2). This law was used to make predictions regarding the effect of deadlines during goal pursuit. Bryan and Locke (1967) gave participants a numerical addition task where the goal was to solve a certain number of problems within a particular amount of time. They found that people given just enough time to complete the task worked at a faster pace than those who had an excessive amount of time. This finding has been replicated in the field. Latham and Locke (1975) showed the logging crews exerted more effort when working under time pressure. Similarly, Peters, O'Connor, Pooyan, and Quick (1984) showed that time pressure increased performance among bank employees. More recently, Steel and König (2006) introduced temporal motivation theory, which is a mathematical theory that makes predictions about the effect of a deadline on motivation using a hyperbolic discounting function. Temporal motivation theory also includes the concepts of valence and expectancy, but they are not described as changing over time as they are in the MGPM.

These findings collectively suggest that goals with shorter deadlines should generally be more motivating than goals with longer deadlines for two reasons. First, a shorter deadline means that less time is available to complete the task, so there is greater time pressure, and thus greater need to act on the goal. Second, the prospect of goal achievement is more temporally proximal for goals with shorter deadlines, and therefore the value of achieving the goal may be discounted less. Surprisingly however, these conclusions are at odds with current representation of the multiple-goal pursuit process. Specifically, theory in this area, and research used to inform it, has only considered the effect that deadlines exert on motivation via expectancy. That is, the longer the deadline, the greater the expectancy one will have of being able to achieve the goal, and the more motivated one will therefore be to prioritize that goal (e.g., Vancouver et al., 2010). Whilst there is evidence for the role of expectancy during multiple-goal pursuit (Schmidt & Dolis, 2009), the findings discussed above suggest that the relationship between deadlines and prioritization is more complex. There is therefore a need to incorporate these insights from the motivation and decision making literatures into our understanding of multiple-goal pursuit. In the following section, we show how these ideas can be integrated.

Accounting for the Effects of Deadline during Multiple-goal Pursuit

In this section, we show how the different explanations for the motivating power of looming deadlines can be incorporated within the MGPM to provide a more complete theoretical account of how deadlines influence multiple-goal pursuit over time. We do so by considering two new mechanisms for the model. The first mechanism draws on the concept of time pressure as conceptualized within the human factors literature (Hendy et al., 1997). Specifically, it assumes that deadlines influence the goal's valence via their impact on time pressure. The second mechanism draws on temporal motivation theory (Steel & König, 2006). It assumes that deadlines influence the goal's expected utility via temporal discounting.

Time Pressure

Within the human factors literature, time pressure has been identified as an important driver of behavior in dynamic environments, and is defined as the ratio of the time required to complete a piece of work to the time that is available (i.e., TR/TA; Hendy et al., 1997). The reason why people are thought to pay attention to the time pressure ratio is because it integrates distance and time information within a single value, providing an indication of the urgency of acting on a task or goal. When this ratio is less than one, the person has more time available than required, so urgency is low. When this ratio is equal to one, the person has no spare time available, so urgency is high.

These arguments can be expressed within the MGPM by assuming that distance and time pressure are variables that people may attend to and monitor, in order to determine the valence of acting on the goal. When people are pursuing goals with the same deadline, as is the case with existing studies of multiple-goal pursuit, they likely attend to distance. In this case, distance (weighted by goal importance) is what drives valence. When pursuing goals with different deadlines, they may attend to time pressure. In this latter case, time pressure (again, weighted by goal importance) is what drives valence. These ideas can be represented as follows:

$$V_k(t) = \max[\kappa_{k1} \cdot d_k(t) + \kappa_{k2} \cdot \frac{TR_k(t)}{TA_k(t)}, 0], \tag{2}$$

where $V_k(t)$ is the valence of acting on goal *k* at time *t*, $d_k(t)$ is the distance for that goal, and κ_{k1} is a gain parameter that reflects the importance of the distance. The variable $TR_k(t)$ is the perceived time required to reach the goal. Though not shown, time required is the product of the distance and the expected lag (α), which represents the individual's sense of the average time required to reduce the distance by 1 unit. The variable $TA_k(t)$ is the perceived time available before the deadline for the goal is reached (therefore TR/TA is the perceived time pressure), and κ_{k2} is a gain parameter that represents the importance of time pressure for that goal. If the arguments presented above are correct, then κ_{k2} should equal zero when pursuing goals with the same deadline, and κ_{k1} should equal zero when pursuing goals with different deadlines. The previous versions of the MGPM are a special case of this more general model where $\kappa_{k2} = 0$.[1]

Temporal Discounting

Temporal motivation theory (Steel & König, 2006) provides a different explanation for why deadlines influence goal prioritization. This theory assumes that goals are subject to temporal discounting. When the deadline for a goal is relatively far, people 'discount' the expected utility of that goal, treating it as less important than they would if the deadline were nearer. As a result, people tend to prioritize immediate goals over more temporally distal goals, even if there is greater utility in prioritizing the distal goal.

Temporal motivation theory can be integrated with the MGPM by incorporating hyperbolic discounting within the expected utility function. Recall that expected utility is a function of valence and expectancy. Hyperbolic discounting can be incorporated within this function as follows:

$$U_k(t) = \frac{V_k(t) \cdot E_k(t)}{1 + \Gamma TA_k(t)}, \tag{3}$$

where $U_k(t)$ is the expected utility of prioritizing goal k, and Γ represents the discount factor, which represents the degree to which people discount future deadlines. Discounting is strong when Γ is high, and reduces as Γ becomes smaller. When $\Gamma = 0$, no discounting occurs. Therefore, the previous versions of the MGPM are a special case of this model where $\Gamma = 0$.

Summary and Overview of Experiments

We have argued that people generally show a tendency to prioritize goals with shorter deadlines. We described two theoretically plausible ways to account for the expected effects of deadline

[1]The valence variable in the version of the MGPM proposed by Ballard, Yeo, Loft, et al. (2016) also included an intercept parameter that represents the level of valence when the goal is reached. This parameter is assumed to equal 0 for approach goals, and be greater than 0 for avoidance goals. Because we only address approach goals in this paper, we have omitted this parameter from Equation 1 for simplicity. However, the model presented in this paper can be used to account for avoidance goals in the same way as the model described by Ballard, Yeo, Loft, et al. (2016). That is, by assuming that the intercept is greater than zero, that distance and time pressure negatively impact valence, and that expectancy negatively impacts expected utility.

and incorporate them within a control theory architecture. The first way assumes that when goals have different deadlines, people determine the valence of prioritizing a goal by monitoring time pressure. The second assumes that people temporally discount the expected utility of prioritizing goals with future deadlines. Crossing these two explanations in a 2 X 2 creates four alternative models (see Table 1). The first model is the most recent version of the MGPM (Ballard, Yeo, Loft, et al., 2016, henceforth referred to as the 'Current MGPM'). This model represents a baseline for comparison, because it assumes that valences are not based on time pressure and that goals are not subject to temporal discounting. The second model (referred to as the "Time Pressure Variant") assumes that valences reflect time pressure. The third model (the "Discounted Utility Variant") assumes that the valences are based on the distance as in the current MGPM, but that expected utilities are subject to temporal discounting. The fourth model (the "Time Pressure/Discounted Utility Variant") assumes that valences are based on time pressure, and expected utilities are subject to temporal discounting.[2]

Table 1
Summary of Models

Model	Valence Assumption	Temporal Discounting Assumption	κ_{k1}	κ_{k2}	Γ
1. Current MGPM	Valence is determined by distance.	Goals are not subject to temporal discounting.	1	0	0
2. Discounted Utility Variant	Valence is determined by distance.	Goals are subject to temporal discounting.	1	0	> 0
3. Time Pressure Variant	Valence is determined by time pressure.	Goals are not subject to temporal discounting.	0	1	0
4. Time Pressure/Discounted Utility Variant	Valence is determined by time pressure.	Goals are subject to temporal discounting.	0	1	> 0

In the sections below, we report four experiments where participants made a series of prioritization decisions whilst pursuing two goals with different deadlines. In each experiment, participants completed a computer-based farm simulation task (see Figure 2). The task was broken down into a series of trials. Each represented a single multiple-goal pursuit episode. In each trial, participants had to simultaneously manage two crops. Their objective was to ensure that the height of each crop reached a target height by the end the crop's growing season. Participants facilitated crop growth by irrigating the crops. However, only one crop could be irrigated in each week of the growing season. Thus, in each week, participants had to prioritize one crop over the other.

[2]The initial version of this manuscript included two additional temporal discounting variants. The first of these assumed that goal prioritization is a multi-attribute decision in which expected utility and time to deadline are unique attributes (see Dai & Busemeyer, 2014; Scholten & Read, 2010). The second assumed that the goals themselves were the unique attributes, and that time to deadline influenced the amount of attention paid to each one. These models and their results are available in the supplementary material.

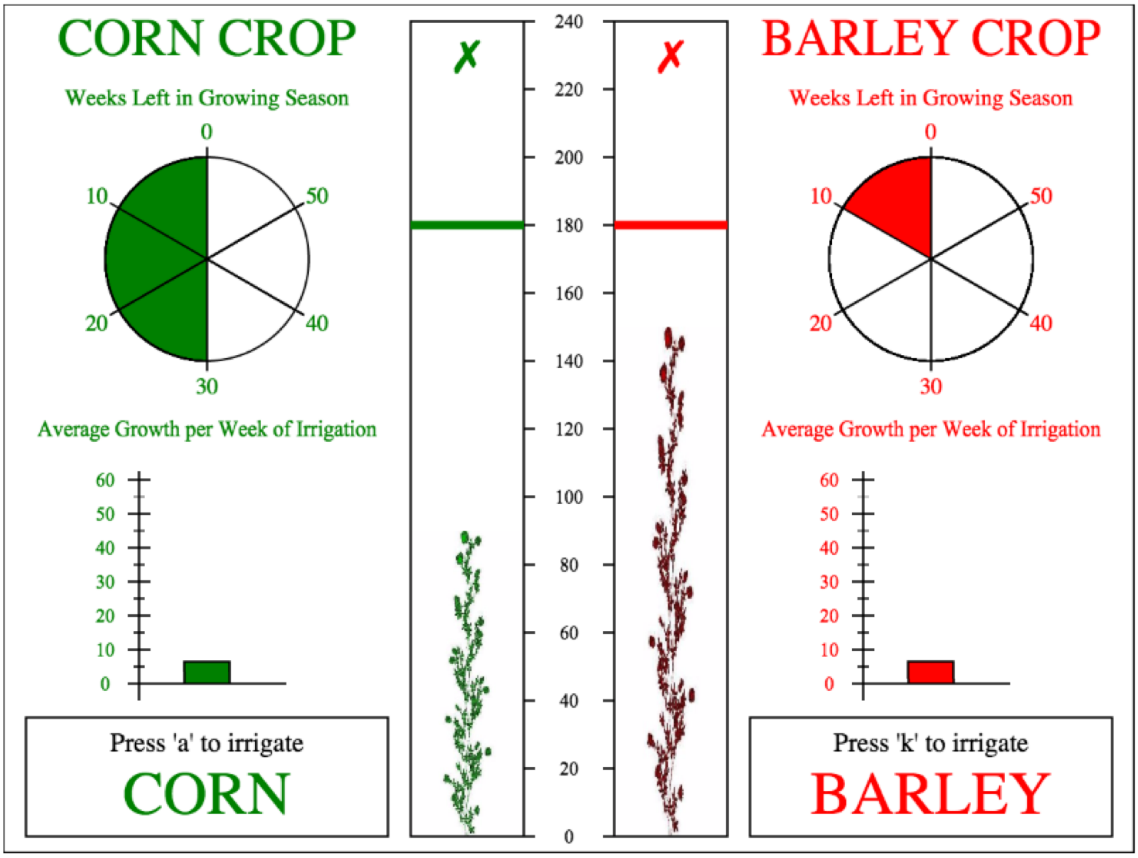

Figure 2. Screen shot of the experimental task.

The experiments were constructed to test the four competing models by manipulating deadline, distance, and time pressure. This was done by manipulating the properties of one goal (the “experimental goal”), whilst holding the properties of the other constant as a control. All four experiments manipulated deadline by varying the length of the growing season. Experiment 1 also manipulated starting distance by varying the starting height of one of the crops. The purpose of this experiment was to assess whether deadline exerts the predicted effect on prioritization. In this experiment, changes in deadline could produce changes in time pressure and the effects of temporal discounting, so it is possible that the effects could be explained either mechanism.

Experiment 2 was designed to isolate the effects of temporal discounting. It did this by manipulating starting distance, whilst holding time pressure constant via a manipulation of crop growth. In this experiment, differences in deadline did not produce differences in time pressure, so any effects of deadline on prioritization could only be accounted for by temporal discounting. Experiment 3 was designed to assess the effects of deadline and time pressure independently. In this experiment, starting distance was held constant, and time pressure was manipulated independently of deadline by varying the time required for the crop to reach its target height. This design allowed us to determine whether both mechanisms are needed to explain prioritization. Experiment 4 examined the effects of all three variables simultaneously. These studies were granted approval by the University of Queensland’s behavioral and social sciences ethical review committee (Project title: *Developing and testing a general theory of multiple-goal pursuit in dynamic and uncertain* *environments*; Clearance number: 2015000293).

The analysis will be conducted in two-parts. After each experiment, we will report the results of statistical analyses that examine the effects of the experimental manipulations on prioritization of the experimental goal. After the final experiment, we will present the analysis of the computational models. The purpose of the computational modeling was to quantitatively compare the ability of the four models described above to account for the results from the four experiments in order to gain further insight into the mechanisms that underlie prioritization. This analysis will be explained in detail after the experiments are presented.

Experiment 1

In Experiment 1, we examine how people make prioritization decisions whilst pursuing two goals with varying deadlines and distances.

Method

Participants

The sample consisted of 53 participants (35 females, 18 males) with ages ranging from 17 to 27 years (M = 19.35, SD = 2.50). All participants were undergraduates at an Australian university and participated for course credit. Five participants were excluded because they did not finish the experiment, leaving a final sample of 48 participants.

Design and Manipulations

We manipulated deadline and starting distance by varying the number of weeks in the growing season and the starting height for one crop in each trial (which we refer to as the experimental crop; the barley crop in Figure 2), whist holding these properties constant for the other crop (the fixed crop; the corn crop in Figure 2). Deadline and starting distance for the experimental crop were manipulated using a (5 x 5) within-participants factorial design, producing a total of 25 unique experimental conditions. Each of these manipulations is explained below.

Deadline. We manipulated deadline by varying the number of weeks in the growing season for the experimental crop across 5 levels (10, 20, 30, 40, and 50 weeks). The growing season for the fixed crop was always 30 weeks.

Starting Distance. We manipulated starting distance for the experimental goal by varying the starting height for the experimental crop across 5 levels (30, 60, 90, 120, and 150 cm). The distance was calculated by subtracting the starting height of the crop from the goal of 180 cm. Thus, a starting height of 30 cm corresponded to a starting distance of 150 cm, whereas a starting height of 150 cm corresponded to a starting distance of 30 cm. The starting height for the fixed crop was always 90 cm (which corresponded to a starting distance of 90 cm).

Procedure

Participants first met with the experimenter to obtain an information sheet and ask questions about the experiment. The experimenter then emailed the participant a link to the experimental task. The experiment itself was completed online, in the participants own time. However, they were encouraged to complete the experiment within 24 hours of receiving the link. Upon starting the experiment, participants were first presented with computerized task instructions. They then completed five practice trials. Participants then completed all 25 conditions (5 Deadline X 5 Starting Distance) in random order two times, with a short break halfway through. Each participant therefore completed 50 trials. We presented participants with each condition twice in an effort to increase the reliability of the data.

The heights of the crops, the target height, and the number of weeks left in the growing season were displayed on the screen throughout the trial. In each trial, the crops that the participant had to manage were randomly selected from a pool of four possible crops, which could be differentiated by the color in which it was shown on the screen (wheat - blue, corn - green, rice - red, or barley - orange). The program randomly determined the position of the experimental and fixed crops on the screen (i.e., left or right), as well as whether the experimental crop was represented by wheat, corn, rice, or barley. Participants irrigated the left crop by pressing the *a* key and the right crop by pressing the *k* key. In weeks where a participant irrigated a particular crop, the amount of growth that the crop would achieve was determined by sampling from a normal distribution with a mean of 6 cm and a standard deviation of 3 cm. In weeks where a participant did not irrigate a particular crop, its growth was determined by sampling from a normal distribution with a mean of 0 cm and a standard deviation of 3 cm. Thus, on average the irrigated crop would grow by 6 cm, whereas the average change in height for the non-irrigated crop would be 0 cm. After the participant selected a crop to irrigate, the task would immediately update to the next week, so that the participant could see how much the height of each crop had changed and make the next irrigation decision. Participants continued to make decisions until the end of the growing season, even if the target height had already been reached. Because crops had a good chance of losing height if untreated, crops that were above the target height still needed to be treated in order to prevent them from falling back below the target. The goal was achieved if the height of the crop was above the target height at the end of the growing season.

Trials where the experimental crop had the same growing season as the fixed crop (i.e., 30 weeks) ended when the common deadline was reached. Trials where the experimental crop did not have the same growing season as the fixed crop ended when the longer deadline was reached. In these trials, the crop with the growing season that finished earlier was replaced by a new crop after its growing season ended. The replacement crops were required to ensure that the participant still had to make prioritization decisions after the first deadline was reached. The presence of the replacement crop eliminated the possibility that people might prioritize the crop with the shorter growing season because they knew they would have more time work on the other crop once the shorter growing season finished. The replacement crop always imposed the same time pressure as the crop it replaced, and had a growing season of 10 weeks. Thus, when the experimental crop had a growing season of 20 weeks, it was replaced by a new crop after the 20th week of the trial. The trial would end after the 30th week, when the growing seasons for the fixed crop and the replacement crop both ended. When the experimental crop had a growing season of 10 weeks, it was replaced by a new crop after the 10th week of the trial, which was itself replaced after 20th week. The trial ended after the 30th week, when the growing season for the fixed crop and the second replacement crop ended. When the growing season for the experimental crop was longer than the fixed crop, the replacement crops would take the place of the fixed crop. We held the growing seasons for the replacement crops constant at 10 weeks so that they would not vary as a function of the deadline manipulation. The number of decisions in each trial therefore ranged from 30 to 50. Each participant made a total of 1800 decisions. Therefore, 86,400 decisions were made in total.

Results and Discussion

In this experiment, the theoretically informative decisions are those that were made before either goal or deadline had been reached. We therefore excluded all other decisions from the analyses. The total number of decisions that remained was 40,925. Figure 3 shows the proportion of choices in which participants prioritized the experimental goal as a function of experimental deadline and distance condition (the reader should attend to the observed data for now, as the results for the MGPM and Time Pressure/Discounted Utility Variant will be discussed in the 'Computational Modeling' section later in the paper). When the starting distance for the experimental goal was relatively short, extending the deadline for the experimental goal resulted in a decrease in prioritization. However, this relationship weakened as the starting distance increased and eventually reversed. When the starting distance was at its longest, 150 cm, there was a weak positive relationship between deadline and prioritization.

We examined the evidence for these effects by comparing a series of nested statistical models, using a Bayesian logistic mixed effects modeling approach implemented in R via the *blme* package (Y. Chung, Rabe-Hesketh, Dorie, Gelman, & Liu, 2013). In each statistical model, the dependent variable was whether or not the participant prioritized the experimental goal (1 = yes, 0 = no). Each model included the random effects of trial and participant. We examined the evidence for the deadline main effect by comparing the evidence for a statistical model that included the fixed effect of deadline (the deadline only model) with a null model that did not include any fixed effects. We examined the evidence for the distance main effect by comparing the evidence for a statistical model that included only the fixed effect of distance (the distance only model) with the null model. Finally, we examined the evidence for the deadline x distance interaction by comparing the evidence for a statistical model that included the fixed effects of deadline, distance, and the interaction between the two (the interaction model) with a statistical model that only included the fixed effects of deadline and distance (the main effects model). We compared the evidence for two statistical models by calculating a Bayes factor for each pair. The Bayes factor indicates the relative evidence given by the data for Model 1 versus Model 2, and can be calculated based on the difference in Bayesian Information Criteria (BIC) between the two models:

$$BF_{12} = \exp[-0.5 \cdot (BIC_1 - BIC_2)] \tag{4}$$

where BIC_1 is the lower of the two BIC values and BIC_2 is the higher. A Bayes factor of 1 indicates that the relative evidence for the two models is equal. A Bayes factor greater than 1 indicates evidence in favor of Model 1. Values between 1 and 3 can be regarded as weak evidence for Model 1, values between 3-20 as 'positive' evidence, values between 20-150 as 'strong' evidence, and values greater than 150 as 'very strong' evidence (Kass & Raftery, 1995; Wagenmakers, 2007).

The blme package by default imposes flat prior distributions on the fixed effects and uninformative Wishart distributions on the variances and covariances of the random effects. We used the default priors for the analyses reported below. As can be seen in Table 2, the Bayes factors indicated very strong evidence for the deadline only and distance only models when compared to the null model, as well as for the interaction model when compared to the main effects model. These results provide evidence for the fixed effects of deadline, distance, and the deadline x distance interaction.

In Experiment 1, we set out to examine the effects of deadline and distance on goal prioritization. As expected based on findings in the intertemporal choice and goal setting literatures, people

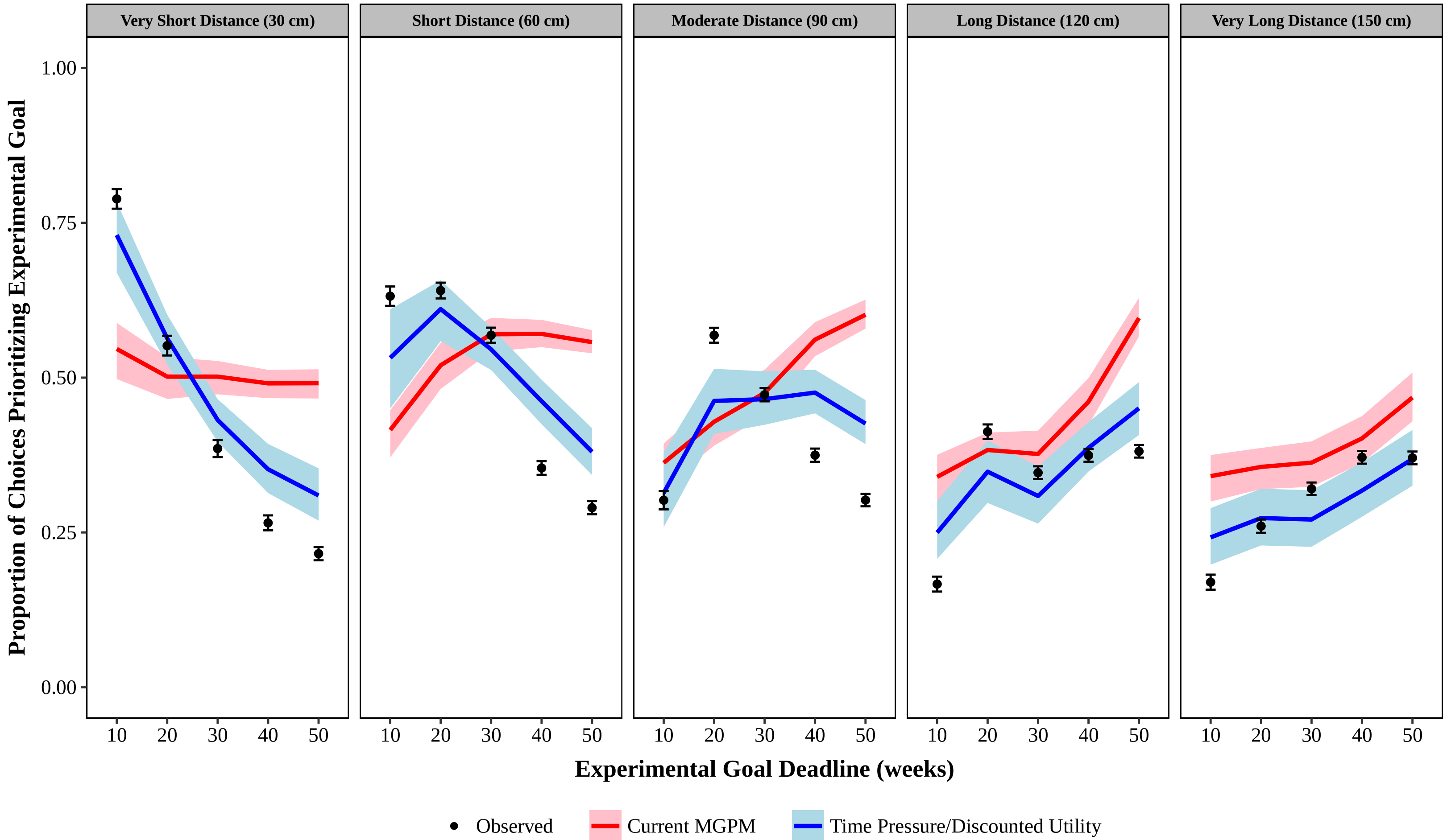

Figure 3. Choices prioritizing the experimental goal in Experiment 1 as a function of experimental deadline and distance by participants (represented by the black dots with standard error bars), the current MGPM (red), and the Time Pressure/Discounted Utility Variant (blue). The dark red and blue lines represent the average median of the distribution predicted by the model. The light red and blue shaded regions represent the average 95% credible interval.

Table 2
Fixed Effects for the Relationships Between Deadline, Distance, and Prioritization of the Experimental Goal in Experiment 1.

	Model				
Effect	Null	Deadline Only	Distance Only	Main Effects	Interaction
Intercept	−0.489	−0.040	−0.046	0.405	2.720
Deadline		−0.014		−0.014	−0.084
Distance			−0.005	−0.005	−0.029
Deadline X Distance					0.001
Bayes Factor		6.25×10^{62}	4.47×10^{68}		2.04×10^{285}

Note: The Bayes factors shown in the table reflect the difference between that model and the next simplest model. The fixed effect shown represents the posterior mode.

were generally more likely to prioritize the experimental goal when it had a shorter deadline. The only case where this effect did not emerge was when the starting distance was longer. In this case, shorter deadlines made the goal highly difficult to achieve, which likely lead to goal abandonment (Schmidt & Dolis, 2009; Vancouver et al., 2010). These results confirm that a computational model of goal prioritization should include a mechanism that can account for people's tendency to prioritize a goal more as deadlines becomes shorter, which the Time Pressure, Discounted Utility, and Time Pressure/Discounted Utility Variants all include. The results also confirm that short deadlines can reduce the tendency to prioritize the goal when much progress is needed (i.e., distance is long).

Experiment 2

In Experiment 2, we examined a context where the effects of deadline and distance are isolated from the effects of time pressure. In Experiment 1, the effects of both deadline and distance were confounded with time pressure, because increases in deadline would always reduce the time pressure. Thus, the tendency for prioritization to decrease with longer deadlines could have been due to either time pressure or temporal discounting. In Experiment 2, we isolate the effects of deadline and distance from time pressure by holding time pressure constant across all levels of the deadline and distance manipulations. This allows for a strong test of the temporal discounting component.

Method

Participants

The sample consisted of 42 participants (26 females, 15 males, and 1 participant who described their gender as "other") with ages ranging from 17 to 43 years (M = 21.28, SD = 7.14). All participants were undergraduates at an Australian university and participated for course credit. Six participants were excluded because they did not finish the experiment, leaving a final sample of 36 participants.

Design and Manipulations

We manipulated deadline and starting distance across the same levels as Experiment 1. However, in this experiment, we held time pressure constant across each cell in the design. We did this by varying the amount of growth that could be achieved when the experimental crop was irrigated so that it offset the effects of deadline and starting distance on time pressure. Specifically, the mean growth for the experimental crop when irrigated was calculated as follows:

$$growth_m = \frac{2 \cdot d}{TA}. \tag{5}$$

For example, when the experimental crop had a deadline of 30 weeks and a starting distance of 90 cm, its mean growth was 6 cm. When the experimental crop had a deadline of 10 weeks and the same starting distance, its mean growth was 18 cm. When the experimental crop had a deadline of 10 weeks and a starting distance of 150 cm, its mean growth was 30 cm. As with Experiment 1, the mean growth for the experimental crop when it was not irrigated was always equal to 0. The standard deviation of these growth distribution was always equal to the starting distance divided by the deadline (in other words, the standard deviation of the growth distribution was always one half of the mean). The configuration of the fixed crop in Experiment 2 was identical to Experiment 1. This design holds time pressure constant at a value of 1, such that the average time required to reach the goal is always equal to the time available.

Procedure

The procedure for Experiment 2 was the same as the procedure for Experiment 1. Participants in this experiment made 64,810 decisions in total.

Results and Discussion

As with Experiment 1, we only analyzed the theoretically informative decisions, which were those made before either goal or deadline had been reached. The total number of decisions analyzed was 35,682. Figure 4 shows the proportion of choices in which participants prioritized the experimental goal as a function of experimental deadline and distance condition (the reader should attend to the observed data for now, as the results for the MGPM and Time Pressure/Discounted Utility Variant will be discussed in the 'Computational Modeling' section later in the paper). In Experiment 2, there was clear negative effect of deadline, such that participants became less likely to prioritize the experimental goal as its deadline increased. Starting distance also had a weak effect, such that participants became more likely to prioritize the experimental goal as its starting distance increased.

The statistical analyses were conducted in the same manner as they were for Experiment 1. That is, we conducted a series of nested model comparisons with each model including the random effects of both trial and participant. As can be seen in Table 3, the Bayes factors indicated very strong evidence for the deadline only and distance only statistical models when compared to the null model, and strong evidence for the main effects statistical model when compared to the interaction model. These results provide evidence for the fixed effects of deadline and distance, and for the absence of an interaction between the two variables.

In Experiment 2, we set out to examine the effects of deadline and distance on prioritization in a context where deadline and distance were independent of time pressure. Consistent with the results of Experiment 1, people were more likely to prioritize the experimental goal when it had a shorter deadline. In this experiment, deadline exerted an effect even though time pressure was held constant. This result provides strong evidence to suggest that temporal discounting is needed to account for prioritization decisions when goals have different deadlines. Unlike Experiment 1, we did not find evidence of deadline and distance interaction. This is likely because time pressure was

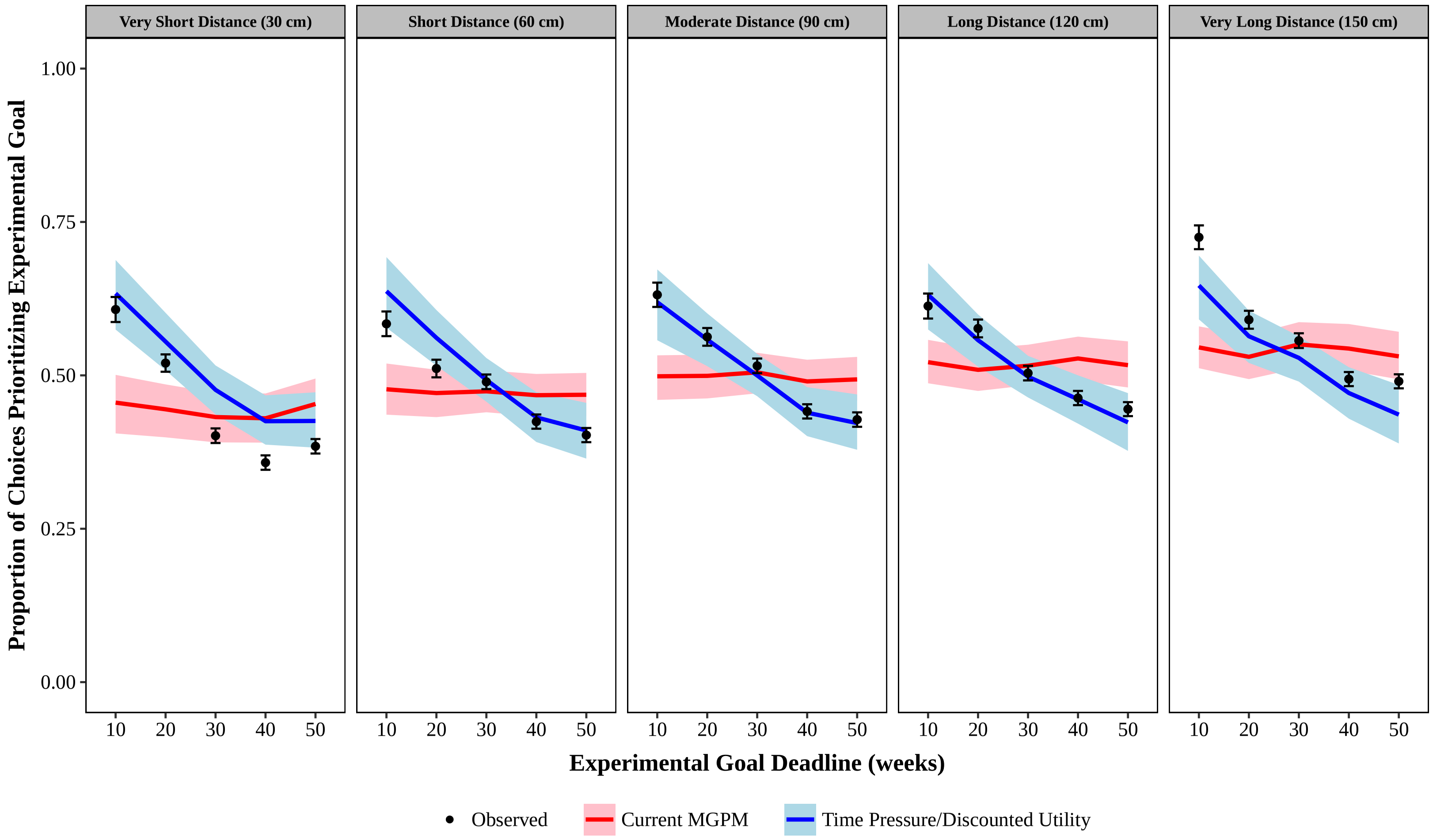

Figure 4. Choices prioritizing the experimental goal in Experiment 2 as a function of experimental deadline and distance by participants (represented by the black dots with standard error bars), the current MGPM (red), and the Time Pressure/Discounted Utility model (blue). The dark red and blue lines represent the average median of the distribution predicted by the model. The light red and blue shaded regions represent the average 95% credible interval.

Table 3

Fixed Effects for the Relationships Between Deadline, Distance, and Prioritization of the Experimental Goal in Experiment 2.

	Model				
Effect	Null	Deadline Only	Distance Only	Main Effects	Interaction
Intercept	-0.064	0.595	-0.393	0.263	0.341
Deadline		-0.019		-0.020	-0.022
Distance			0.004	0.004	0.003
Deadline X Distance					0.000
Bayes Factor		9.78×10^{105}	9.03×10^{41}		0.011

Note: The Bayes factors shown in the table reflect the difference between that model and the next simplest model. The fixed effect shown represents the posterior mode.

held constant at a moderate value, and there were no conditions where the goal was too difficult to achieve.

Experiment 3

The first two experiments showed that when people pursue goals with different deadlines they generally prioritize the goal with the shorter deadline. Experiment 1 showed that this tendency occurs when deadline impacts time pressure (as long as the goal is achievable). Experiment 2 showed that this tendency occurs even when deadline does not impact time pressure. In Experiment 3, we manipulated deadline and time pressure independently, to examine whether both mechanisms are required to account for prioritization.

Method

Participants

The sample consisted of 44 participants (26 females, 18 males) with ages ranging from 17 to 27 years (M = 19.00, SD = 1.83). All participants were undergraduates at an Australian university and participated for course credit. Two participants were excluded because they did not finish the experiment, leaving a final sample of 42 participants.

Design and Manipulations

We manipulated deadline and time pressure in Experiment 3. We manipulated deadline in the same manner as in Experiments 1 and 2. We manipulated the time pressure (TP) for the experimental crop by varying the ratio of the expected time required to achieve the goal and the deadline across 5 levels: very low ($TP = 0.25$), low ($TP = 0.5$), moderate ($TP = 1$), high ($TP = 2$), and very high ($TP = 4$). To do this, we set the mean growth for the experimental crop when irrigated to:

$$growth_m = \frac{2 \cdot d}{TP \cdot TA}. \quad (6)$$

This meant that time pressure was manipulated independently of deadline. As with Experiments 1 and 2, the mean growth for the experimental crop when it was not irrigated was always equal to 0. The standard deviation of both of these distributions always equaled:

$$growth_{sd} = \frac{d}{TP \cdot TA}, \tag{7}$$

or one half of the distribution mean. The configuration of the fixed crop in Experiment 3 was identical to Experiments 1 and 2.

Procedure

The procedure for Experiment 3 was the same as the procedure for Experiments 1 and 2. In Experiment 3, the starting distance was always 90 cm. Participants in this experiment made 75,600 decisions in total.

Results and Discussion

As with Experiments 1 and 2, we only analyzed the theoretically informative decisions, which were those made before either goal or deadline had been reached. The total number of decisions analyzed was 33,545.

Figure 5 shows the proportion of choices in which participants prioritized the experimental goal as a function of experimental deadline and time pressure condition (the reader should attend to the observed data for now, as the results for the MGPM and Time Pressure/Discounted Utility Variant will be discussed in the 'Computational Modeling' section later in the paper). At shorter deadlines, there was an inverted u-shaped effect of time pressure, such that the tendency to prioritize the experimental goal was higher when time pressure was moderate and lower when time pressure was very low or very high. At longer deadlines, people were generally less likely to prioritize the experimental goal, and the effect of time pressure was weaker (i.e, the inverted-u shape is less pronounced).

The statistical analyses were conducted in the same manner as they were for Experiments 1 and 2. Once again, we conducted a series of nested model comparisons with each model including the random effects of both trial and participant. As can be seen in Table 4, the Bayes factors indicated very strong evidence for the deadline only and time pressure only statistical models when compared to the null model, as well as for the interaction model when compared to the main effects model. These results provide evidence for the fixed effects of deadline, time pressure, and the deadline x time pressure interaction.

In Experiment 3, we set out to disentangle the effects of deadline and time pressure on prioritization, by manipulating them independently whilst holding the initial distance constant. We found that deadline and time pressure had independent effects on prioritization. Consistent with the results of the first two experiments, we found that people were generally more likely to prioritize the experimental goal when it had a shorter deadline. We also found that people were most likely to prioritize this goal when time pressure was moderate, and less likely when time pressure was too low, too high, or when the goal had a longer deadline. The results suggest that time pressure and temporal discounting both play a role, and that we need to incorporate both mechanisms within the MGPM architecture to account for people's prioritization decisions when goals have different deadlines.

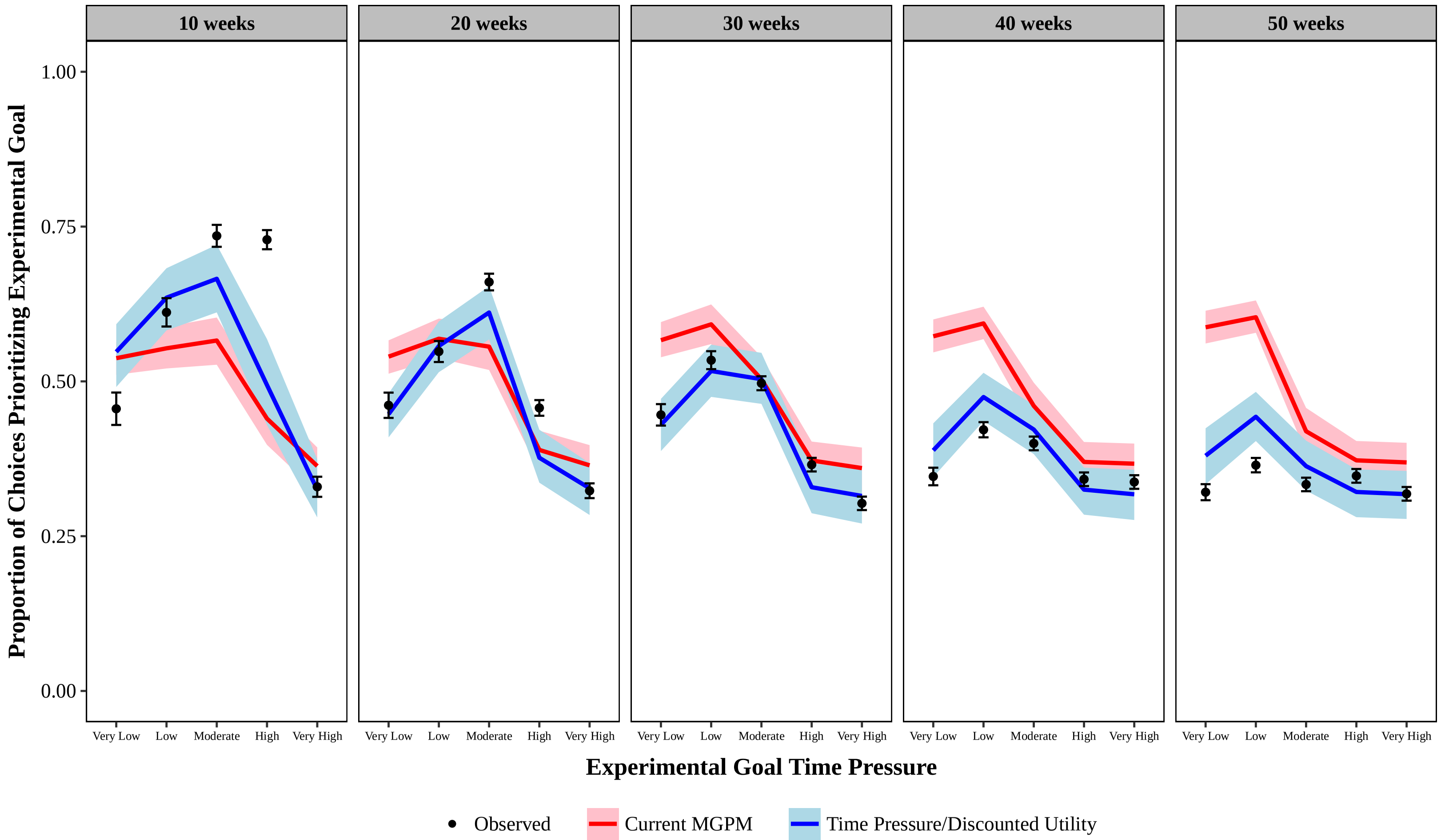

Figure 5. Choices prioritizing the experimental goal in Experiment 3 as a function of experimental deadline and time pressure by participants (represented by the black dots with standard error bars), the current MGPM (red), and the Time Pressure/Discounted Utility model (blue). The dark red and blue lines represent the average median of the distribution predicted by the model. The light red and blue shaded regions represent the average 95% credible interval

Table 4
Fixed Effects for the Relationships Between Deadline, Time Pressure, and Prioritization of the Experimental Goal in Experiment 3.

	Model				
Effect	Null	Deadline Only	Time Pressure Only	Main Effects	Interaction
Intercept	-0.384	0.396	-0.119	0.759	1.255
Deadline		-0.023		-0.025	-0.039
Time Pressure			-0.154	-0.176	-0.451
Deadline X Time Pressure					0.008
Bayes Factor		2.88 x 10^{145}	1.28 x 10^{70}		5.68 x 10^{31}

Note: The Bayes factors shown in the table reflect the difference between that model and the next simplest model. The fixed effect shown represents the posterior mode.

Experiment 4

The first two experiments examined the effects of the interaction between deadline and distance to goal on prioritization. The third experiment examined the interaction between deadline and time pressure. In the final experiment, we varied all three factors–deadline, distance, and time pressure–simultaneously.

Method

Participants

The sample consisted of 52 participants (31 females, 21 males) with ages ranging from 17 to 31 years (M = 20.31, SD = 2.89). All participants were undergraduates at an Australian university and participated for course credit. All participants finished the experiment, so no participants were excluded from the final sample.

Design and Manipulations

We manipulated deadline and distance in the same way as in Experiments 1 and 2, and time pressure in the same way as Experiment 3. We varied each factor independently across three levels. The three deadlines for the experimental goal were: 20 weeks, 30 weeks, and 40 weeks. The three starting distances for the experimental goal were: 60 cm, 90 cm, and 120 cm. The three levels of time pressure were: low ($TP = 0.5$), moderate ($TP = 1$), and high ($TP = 2$). The configuration of the fixed crop in Experiment 4 was identical to Experiments 1, 2, and 3.

Procedure

The procedure for Experiment 4 was the same as the procedure for Experiments 1, 2, and 3, with the exception that this experiment was completed in the laboratory. The factorial manipulation of deadline, distance, and time pressure produced 27 unique experimental conditions, which each participant completed twice.

Results and Discussion

As with Experiments 1, 2, and 3, we only analyzed the decisions made before either goal or deadline had been reached. The total number of decisions analyzed was 55,870. Figure 6 shows the proportion of choices in which participants prioritized the experimental goal as a function of experimental deadline, time pressure, and distance condition.

The statistical analyses were conducted in the same manner as they were for Experiments 1, 2, and 3. We focused the analysis on examining the statistical reliability of the three main effects and the three-way interaction. As with the previous experiments, we examined the main effects by comparing a statistical model containing the relevant fixed effect to a null model which did not include any fixed effects. To examine the three-way interaction, we compared a model containing all three main effects, all three two-way interactions, and the three-way interaction to a model that only included the main effects and two-way interactions. Once again, all models included the random effects of both trial and participant.

As can be seen in Table 5, the Bayes factors indicated very strong evidence for the deadline only and distance only models when compared to the null model. These findings indicate that people were generally more likely to prioritize the experimental goal when it had a shorter deadline, and that people were more likely to prioritize the experimental goal when its starting distance was longer (though this effect was weak). However, the Bayes factors also indicated strong evidence for the null model when compared to the time pressure only model and strong evidence for the model containing main effects and two-way interactions when compared to a model that additionally contained the three-way interaction. These results provide evidence for the absence of a linear effect of time pressure or a three-way interaction between deadline, time pressure, and distance. In the following section we examine the mechanisms underlying the experimental effects by assessing how well the variants of the MGPM that incorporate either time pressure or temporal discounting, or both, are able to account for the data across all four experiments.

Table 5
Fixed Effects for the Relationships Between Deadline, Time Pressure, Distance, and Prioritization of the Experimental Goal in Experiment 4.

	Model					
Effect	Null	DL Only	TP Only	Dist. Only	MEs & 2-Way Ints.	3-Way Int
Intercept	−0.140	0.910	−0.165	−0.307	1.023	0.653
Deadline (DL)		−0.034			−0.047	−0.035
Time Pressure (TP)			0.020		0.049	0.310
Distance (Dist.)				0.002	0.000	0.003
DL X TP					0.001	−0.007
DL X Dist.					0.000	0.000
TP X Dist.					−0.001	−0.004
DL X TP X Dist.						0.000
Bayes Factor		1.01 x 10^{205}	0.012	4.31 x 10^{3}		0.011

Note: The Bayes factors shown in the table reflect the difference between that model and the next simplest model. The fixed effect shown represents the posterior mode.

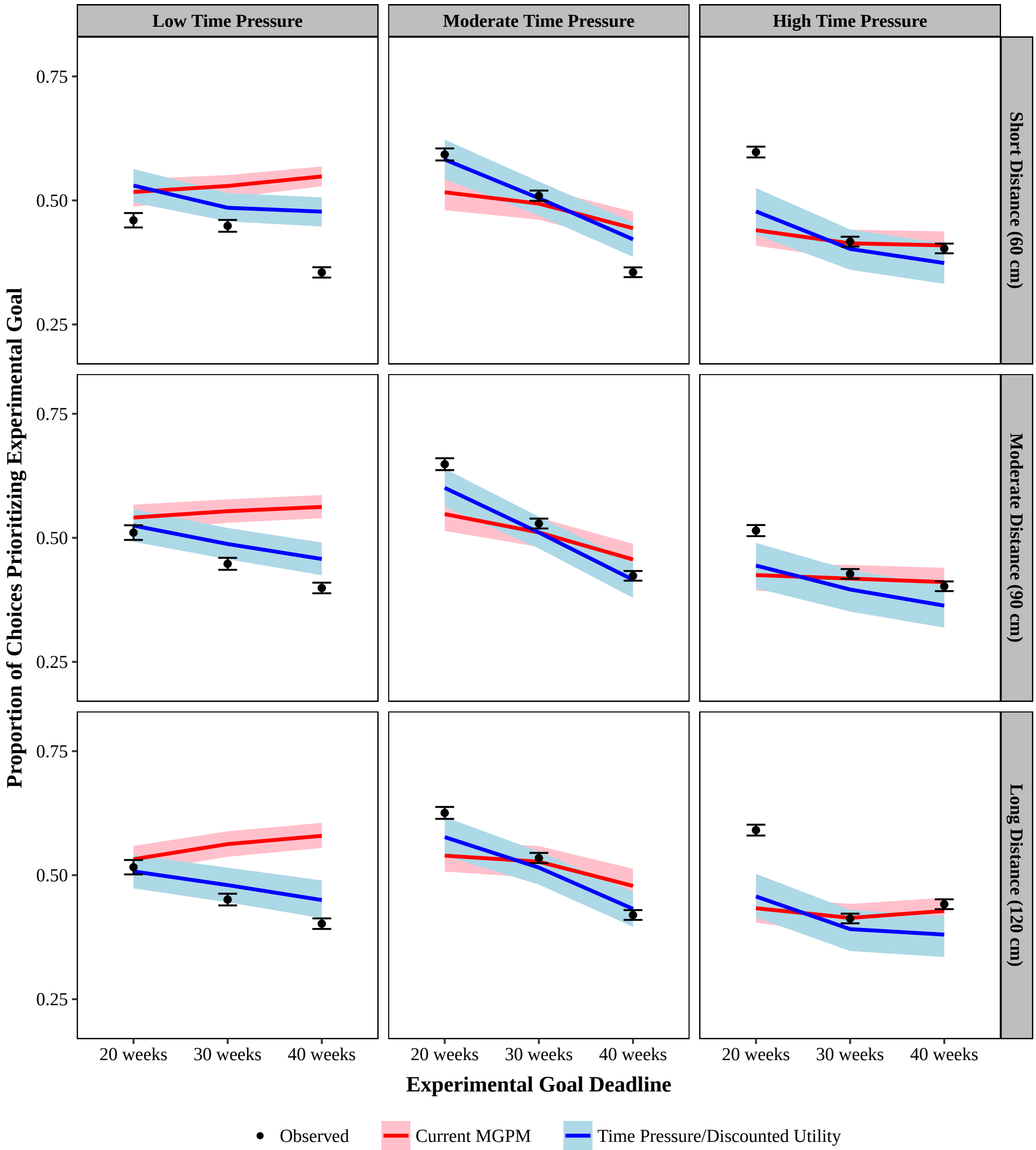

Figure 6. Choices prioritizing the experimental goal in Experiment 4 as a function of experimental deadline, time pressure, and distance by participants (represented by the black dots with standard error bars), the current MGPM (red), and the Time Pressure/Discounted Utility model (blue). The dark red and blue lines represent the average median of the distribution predicted by the model. The light red and blue shaded regions represent the average 95% credible interval

Computational Modeling

In the previous section, we evaluated whether the time pressure and temporal discounting components of the model were needed to account for prioritization of goals with different deadlines by experimentally examining the effects of time pressure and deadline on goal choice. The results provided evidence that both mechanisms are necessary. In this section, we quantitatively evaluate these mechanisms by comparing the ability of the four computational models described in the introduction to explain the experimental effects. We conducted these analyses using hierarchical Bayesian modeling. Hierarchical Bayesian modeling is a method for the analysis of computational models that can account for the multilevel structure of the data in a similar manner to how multilevel modeling does for statistical models. Because hierarchical Bayesian modeling is a relatively new methodology, we provide an overview of the procedure in the next section.

Hierarchical Bayesian Modeling

Although computational models have improved our understanding of multiple-goal pursuit, the computational modeling efforts conducted thus far in I-O psychology have typically failed to take advantage of the full information provided by the data regarding the psychological processes being investigated. The issue lies in the way the parameters from these models have been estimated. In many cases, I-O psychologists are interested in examining the parameter values for each participant, but also in making conclusions about the population-level distribution of that parameter. Yet researchers analyzing computational models typically only do one or the other. The first approach commonly used is to estimate a single set of parameters for the entire sample of participants (e.g., Lopes & Oden, 1999). This approach is analogous to a standard regression analysis. It ignores potential variability in the parameters across individuals. The second approach commonly used is to estimate a set of parameters for each participant separately (e.g., Ballard, Yeo, Loft, et al., 2016; Vancouver et al., 2010). This approach is analogous to running a separate regression analysis for each participant in the sample. It does not provide any information about the population within which those individuals are nested. Just as multilevel modeling can be important for making inferences about variability at different levels of analysis in a general linear modeling framework, hierarchical methods can also be useful when analyzing computational models.

We instantiate the models using a hierarchical Bayesian approach (see Kruschke, Aguinis, and Joo, 2012, for an introduction and demonstration of Bayesian models applied to I-O psychology). A Bayesian analysis involves combining prior knowledge about the parameters with the evidence provided by the data to make inferences about the posterior distributions of parameters (Kruschke, 2010; Lee & Wagenmakers, 2013). The posterior distribution provides information about the parameter values that are most probable after the data has been taken into account, and the level of uncertainty in the parameter value (Morey, Hoekstra, Rouder, Lee, & Wagenmakers, 2015). A hierarchical Bayesian model allows one to examine the variability in parameters at different levels simultaneously by imposing a hierarchical structure on the parameters (Rouder & Lu, 2005). Figure 7 provides a diagram of the current MGPM instantiated as a hierarchical Bayesian model. This type of diagram, introduced by Kruschke (2010), is commonly used for presenting Bayesian models. The model has a three-level structure: the population level, person level, and observation level. The model diagram is traditionally interpreted from the bottom up, starting with the data. We therefore start by describing the observation level.

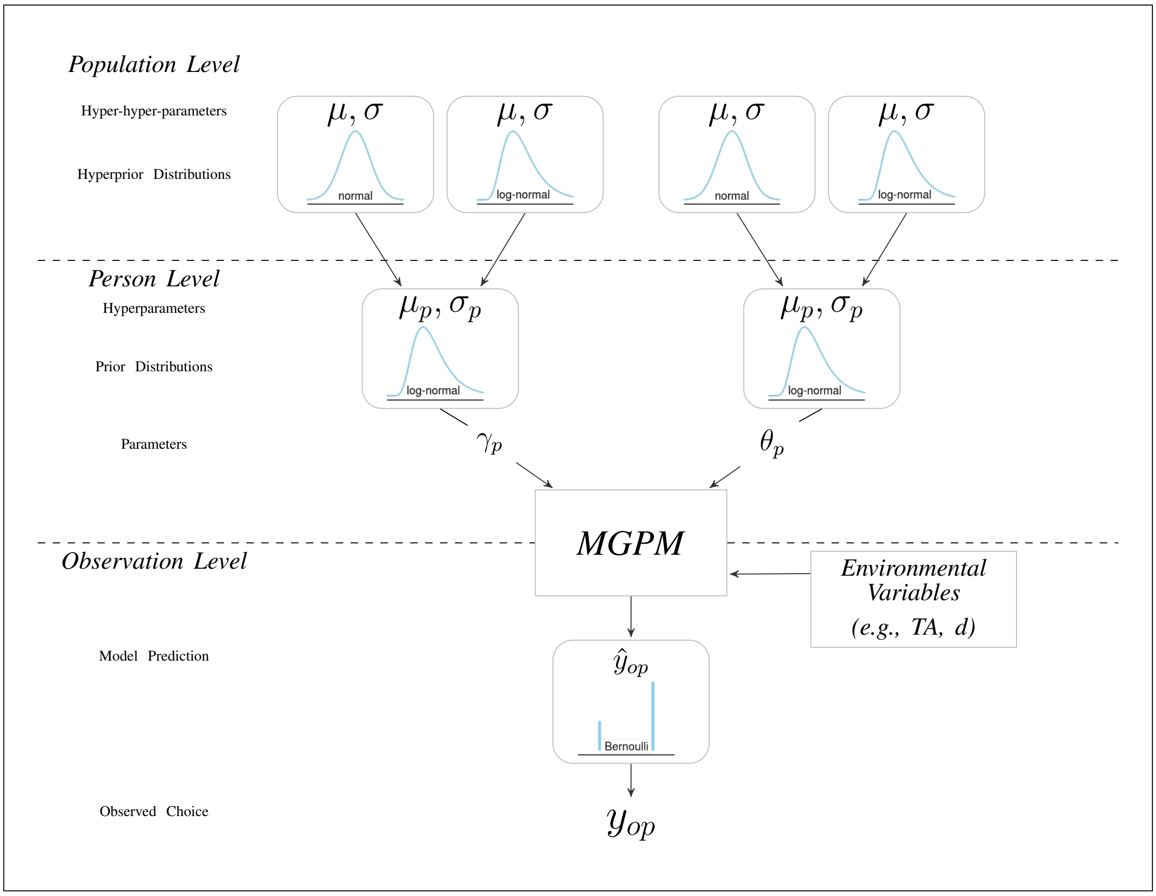

Figure 7. Diagram of MGPM instantiated as a hierarchical Bayesian model.

The Observation Level. The observation level is the level that is most proximal to the data. This level represents the variables that may vary across observations (e.g., over time). The data are denoted by y_{op}, where the o represents the observation and the p represents the person. In the experiments presented above, the observation of interest is the goal prioritized at a given point in time. These data follow a Bernoulli distribution, where $y = 1$ when Goal 1 is prioritized and $y = 0$ when Goal 2 is prioritized. The value of y is predicted by the model. In the example shown in the figure, the model is the MGPM. For simplicity, we have omitted the model details from the figure and replaced them with a single box. The arrow coming out of the bottom of the box represents the output of the model, which is the model's predicted probability that the participant prioritizes Goal 1 (denoted $\hat{y}_{op}$; the predicted probability that Goal 2 is prioritized is $1 - \hat{y}_{op}$). The arrows going into the model are the inputs to the model. The observation-level (i.e., time-varying) inputs to the model are the environmental variables such as the time available before the deadline (TA) and the distance (d).

The Person Level. The person level provides information about the participants themselves. The person-level inputs to the model are the model's parameters. The model has several parameters that may potentially vary across individuals. In this example, we model the variability in two parameters. The first parameter is time sensitivity (γ), which reflects people's sensitivity to the difference between how much time is required to achieve the goal and the amount of time available (with higher values indicating greater sensitivity). The second parameter is threshold (θ), which reflects how cautious people are in making decisions. The higher the threshold, the stronger the preference for prioritizing a goal must be before the person decides to do so. The arrows running through the time sensitivity and threshold parameters in the figure each originate from an icon that represents the prior distribution for that parameter. The prior distribution (henceforth, 'prior') represents the researcher's beliefs about the parameter before the analysis is conducted.

When specifying a prior, the researcher must make a decision about the family of distribution to use. Normal distributions are commonly used. However, an advantage of Bayesian analysis is the ease with which one can use different types of distributions. For example, normal distributions are not appropriate for γ and θ because values below 0 are not plausible for these parameters. The priors on these parameters require a distribution that only takes on positive values. We therefore use a log-normal distribution. The form of the log-normal distribution is determined by a location parameter (μ) and a scale parameter (σ). Thus, the prior distributions associated with γ and θ for each participant are each characterized by their own μ_p and σ_p values (the subscript p here denotes that the value varies across people). Parameters, such as μ_p and σ_p, that describe the prior distributions of other parameters are called *hyperparameters*. In this model, there are four hyperparameters associated with each participant: a μ_p and σ_p that describe the γ distribution, and a μ_p and σ_p that describe the θ distribution. The distributions of the hyperparameters themselves are modeled at the population level.

The Population Level. When using a hierarchical model, the researcher assumes that the hyperparameters for each person are not independent, but vary according to a particular population-level distribution. Thus, each hyperparameter has its own prior at the population-level. The prior distribution of a hyperparameter is called a *hyperprior* or *parent* distribution. These distributions characterize the uncertainty regarding the true value of the hyperparameter at the population-level before the analysis is conducted. We assume that the μ_p hyperpriors are both normally distributed, and that the σ_p hyperpriors are both log-normally distributed (because σ_p values below 0 are implausible).

The hyperprior distributions themselves each must be described by higher-level parameters, which in principle can be called *hyper-hyper-parameters*. The two μ_p hyperpriors, which are normally distributed, are each described by their own mean (μ) and standard deviation (σ). The two σ_p hyperpriors, which are log-normally distributed, are each described by their own location (μ) and scale (σ). If this third level consisted of multiple units that were nested within a higher level unit (e.g., teams within an organization), the distribution of the hyper-hyper-parameters would be modeled at a higher level. In our model, however, the third level is the highest. The hyper-hyper-parameters are therefore constants that the researcher must select before conducting the analysis. These constants need be chosen carefully, because they determine the form of the hyperprior and prior distributions, and therefore can impact the inferences drawn from the posterior distributions. Typically, researchers specify constants that produce *weakly informative* priors, which represent a high level of uncertainty regarding the true parameter value. This approach ensures that the posterior distribution is robust and not strongly influenced by the researchers prior beliefs. In some cases however, the researcher may have reason to specify constants that produce more informative priors, such as when there is a consensus among researchers regarding the true value of the parameter.

Overview of Analysis

We examined the ability of the four computational models to explain the deadline effects by estimating a set of parameters for each model based on the data from the four experiments presented above. To do this, we merged the data from each experiment presented above into a single dataset, and ran each model on the combined dataset. This method is the most appropriate way to model this series of experiments because it accounts for the fact that the participants were all sampled from the same population. This method is good practice for other reasons too. First, it allows the researcher to evaluate the model's performance across the full set of experiments in a single analysis, which enables more robust conclusions regarding the credibility of the different models (i.e. similar to a meta-analysis). Second, it prevents the model from being over-fit to any individual experiment, and therefore enables a better test of the generality of each model.

For all models, we estimated the time sensitivity (γ) and threshold (θ) parameters for each participant, because previous research has revealed that they are influenced by individual differences (Ballard, Yeo, Loft, et al., 2016). For the Discounted Utility and Time Pressure/Discounted Utility variants, consistent with previous research (e.g., Shenhav, Rand, & Greene, 2017), we assumed that the degree of discounting varied across individuals. We therefore also estimated the Γ parameter for each participant when running these models. Thus, the current MGPM and the Time Pressure Variant had two estimated parameters, whereas the Discounted Utility and the Time Pressure/Discounted Utility variants had three estimated parameters (see Appendix A for details regarding parameters that were not estimated).

We chose weakly-informative priors that do not make strong assumptions about the likely values of the estimated parameters (see Appendix B). The priors were constructed to omit values that were implausible (e.g., values below 0) or that could not be identified (e.g., high values at which changes in the parameter have no discernible effect on the model predictions). However, within the range of plausible and identifiable parameter values, the priors were not strongly biased toward a particular region of the parameter space. This configuration meant that the posterior distributions would reflect the evidence provided by the data.

There are a several open-source programming languages available for implementing Bayesian models, such as BUGS (Lunn, Thomas, Best, & Spiegelhalter, 2000), JAGS (Plummer, 2003), or Stan (Carpenter et al., in press). We implemented the models in Stan using the rstan package (Stan Development Team, 2016), which provides an R interface to the Stan program (see Appendix C for details regarding model implementation). We used Stan because it is particularly well suited to implementing more complex hierarchical models such as the MGPM (Stan Development Team, 2017). We evaluated the fit of the models using the Watanabe-Akaike information criterion (WAIC, also known as the 'widely applicable information criterion', Watanabe, 2010). The WAIC is an estimate of expected predictive error in models that are implemented using programs such as Stan that use what are referred to as *Markov chain Monte Carlo* (MCMC) methods (see Gelman, Hwang, & Vehtari, 2014, and Appendix C). Lower values indicate a better trade-off between between fit and parsimony, and therefore a better explanation of the data.

Results of Analysis

Table 6 shows the result of the model comparisons for the four experiments. As can be seen, the Time Pressure/Discounted Utility Variant was the best model overall (see Table 7 for hyper-parameter values). This model had the lowest overall WAIC value and provided the best explanation for 123 out of the 178 total participants (i.e., 69%). The next best model was the Discounted Utility Variant, which provided the best explanation for only 25 participants. However, 16 of these participants were from Experiment 2, where the Discounted Utility and the Time Pressure/Discounted Utility Variants were not easily distinguishable. All three alternative variants provided a better explanation of the empirical data than the MGPM in its current form, which is not surprising given that we observed a negative effect of deadline on prioritization in all four experiments, which the MGPM does not predict.

Table 6
Results of Model Comparisons for Experiments 1, 2, 3, and 4 Combined

Variant Name	WAIC	SE	Participants Best Fit
Current MGPM	215355.40	225.59	15
Discounted Utility Variant	210490.91	255.77	25
Time Pressure Variant	210869.59	254.97	15
Time Pressure/Discounted Utility Variant	205800.47	283.95	123

Note: The ‘Participants Best Fit’ column reports the number of participants for whom the relevant model yielded the lowest WAIC value.

Figures 3, 4, 5, and 6 show the posterior predictives from (i.e., the decisions produced by) the Time Pressure/Discounted Utility Variant and the current MGPM for Experiments 1-4 respectively. The Time Pressure/Discounted Utility Variant accurately captures the qualitative trends. In most cases, there is close correspondence between the data and the decisions generated by this model. The current MGPM on the other hand fails to capture the empirical results. This model cannot account for the data because it has no mechanism through which a looming deadline can produce an increase in the tendency to prioritize a goal.

Table 7
95% Credible Intervals on the Hyperparameters of the Time Pressure/Discounted Utility Model

Parameter	Hyperparameter	Lower Bound	Median	Upper Bound
Time Sensitivity (γ)	Location (μ)	-1.02	-0.92	-0.84
	Scale (σ)	1.39	1.55	1.72
Threshold (θ)	Location (μ)	-1.81	-1.71	-1.61
	Scale (σ)	1.02	1.14	1.27
Discount Factor (Γ)	Location (μ)	-0.02	0.00	0.02
	Scale (σ)	1.33	1.35	1.38

General Discussion

Although deadlines are an important factor influencing prioritization during multiple-goal pursuit (Schmidt & DeShon, 2007), research within the multiple-goal pursuit literature has generally focused on contexts where goals share the same deadline. The failure to consider the more common situation where deadlines differ has limited our understanding of the process by which people manage competing goals. Our aim was to evaluate the ability of a computational model to account for the effects of deadline in contexts where many aspects of goals varied. That is, one in which goals have different deadlines, different distances, and different levels of time pressure. In four experiments, we found that shortening a deadline generally increased the tendency to prioritize a goal, unless the goal became too difficult to achieve. We found the strongest support for the Time Pressure/Discounted Utility model. This model modifies two assumptions of the current MGPM. First, the model represents the idea that time pressure, as reflected by the relationship between the time required to achieve a goal and the time available, matters. Second, this model represents the idea that one's expected utility of acting on a goal is subject to temporal discounting, and therefore that deadline exerts a unique effect on prioritization over and above time pressure. In the following sections, we discuss the theoretical and methodological contributions of this paper, highlight potential limitations, and suggest areas of future research.

Theoretical Contributions

This paper advances the current understanding of multiple-goal pursuit by providing a more general account of goal prioritization. Specifically, we introduced a version of the MGPM that can explain decisions in contexts where goals have different deadlines. In all four experiments, the existing MGPM failed to reproduce the motivating effect of deadline on prioritization, whereas the generalized model provided a fairly accurate representation of the empirical trends. Thus, the improvement in explanatory power achieved by this new model goes beyond a mere increment in quantitative fit–it enables the model to explain a new phenomenon that it previously could not.

We achieved this increase in generality by making theoretically motivated modifications to two components of the MGPM. The first modification pertained to the conceptualization of valence. Valence represents the subjective immediate value of prioritizing a goal. Research conducted on multiple goal pursuit to date suggests that valence is a function of distance. Specifically, the value of acting on a goal appears to decrease as the person gets closer to that goal. We found that a variant in which valence is determined by time pressure, rather than distance, provided a better explanation of the data than the existing MGPM. This suggests that when assessing the value of acting on goals with different deadlines, people not only consider how far they are away from each goal, but also their rate of progress, and the time remaining.

The model presented here builds on the insights provided by the previous versions of the MGPM in an important way: by accounting for changes in decision making strategy depending on whether goals have different deadlines. When goals share the same deadline, there is no need to consider the rate of progress and time required. It is only when goals have different deadlines that people need to consider this additional information. These findings are similar to those obtained from relative motion judgment tasks (Law et al., 1993). When people are asked to assess whether objects on converging trajectories will collide, they typically base their judgment on the relative distance of each object from the crossing, if the objects are moving at the same speed. When the objects are moving at different speeds, people tend to base their judgment on the relative time that it will take for each object to reach the crossing (Neal, 2009). This is a more complex and cognitively demanding strategy, because the person has to integrate distance and velocity information, and they generally will not do it, unless it is necessary to accomplish the task. In the multiple goal pursuit context, it is only necessary to do so when the deadlines are different.

The second modification related to temporal discounting. Previous published versions of the MGPM have not included any temporal discounting component. Of some interest, an initial version of the MGPM (Vancouver et al., 2010) included the hyperbolic discounting function from temporal motivation theory (Steel & König, 2006), but it was removed from the published version because it was not needed to account for prioritization of goals with the same deadline and could not be tested using data from such a protocol. Indeed, one might question the notion that temporal discounting applies to multiple-goal pursuit because the types of experimental paradigms used in the temporal discounting literature do not require participants to actively pursue a set of goals. Studies of intertemporal choice reveal how much greater a future reward would need to be before its perceived value would equal the value attached to obtaining the reward immediately. Goal pursuit typically involves more than simply making a choice and then waiting for the fruits of the choice to materialize - it involves working towards a goal over time. Thus, it was very possible that our results would not have found support for the temporal discounting effect. As it turns out, though, findings did confirm that goals are treated as more valuable as their deadline draws nearer.

Of particular interest conceptually is the finding that both time pressure and temporal discounting seem to be involved in goal choice. This finding highlights the complex and sometimes complementary use of information in the process. For example, the distance between current and desired (i.e., goal) states has both a positive and negative effect on goal priority via valence and expectancy, respectively. Likewise, deadline has both a negative and positive effect on goal prioritization via valence and expectancy, respectively (see Figure 1). The time available also plays a negative role on motivation by discounting the expected utility. Thus, the model of the human decision maker arising from this research is one of a system that deftly balances a small set of factors in a way that provides an adaptive system for navigating a complex world.

Practical Applications

There are countless situations in the workplace where people juggle multiple goals, but can only allocate time or resources to one at a time. Most of the time, these goals will have different deadlines. One example is an employee working to prepare a financial performance report by the end of the year, whilst simultaneously responsible for producing weekly client briefs. The finding that people may be responsive to time pressure has implications for how to improve employee feedback. Our findings suggest that providing employees with accurate information about the pace of work that must be sustained in order to achieve the goal by the deadline (e.g., to complete the performance report by the end of the year) may be more important than providing them with information about the total amount of work to be done.

Our findings also suggest that maintaining focus on goals with longer deadlines can be challenging when they are competing against goals with shorter deadlines. The employee in the example above may find it difficult to divert attention away from the weekly client briefs, because they have the shorter deadline, even though they may be less important than the year-end report. The employee therefore runs the risk of under-prioritizing the more important task because it has the longer deadline. To optimize performance in this situation, employees need to have measures in place that encourage the allocation of time and resources to the year-end report. One such measure would be to set intermediary goals with relatively short deadlines, so that progress on the year-end report is regarded as more urgent. Another such measure would be to set aside blocks of time (e.g., two hours every morning) that are specifically dedicated to the working on the year-end report. A final possibility is to develop scheduling algorithms that help people allocate their time more effectively. Models, such as the MGPM, can be incorporated into scheduling algorithms to identify situations where people are likely to make sub-optimal decisions, and suggest alternatives.

In the longer term, the MGPM may be incorporated into larger computational models of human performance. Computational models are increasingly being used to explain or predict behavior in a range of different domains (Byrne & Pew, 2009). When used in practice, their predictions are typically generated by simulating the model using parameter values determined from previous research (rather than fitting the model to new data). Computational human performance models are used by the military for the development of interactive training simulations, acquisition of new systems, analysis of operational concepts, design of work roles, determination of staffing requirements, and management of workload. However, one of the major limitations of the current generation of human performance models is that they produce behavior that is rigid and inflexible (Pew & Mavor, 2007). The problems is that existing architectures, such as ACT-R (Anderson, 2007), lack an empirically validated theory that explains the process by which people manage competing demands on their time. The MGPM fills that gap, and therefore, has the potential to improve the quality of predictions made by the current generation of models. Whilst human performance modeling is currently a highly specialized skill, improvements in technology mean that it is becoming more accessible. We expect that it is likely to become more widely used in the future, especially in domains where people are working in collaboration with automated agents and there is a need to predict how the human is likely to behave.

Additional Considerations and Avenues for Future Research

It is important to consider the implications of the new additions to the MGPM architecture for our understanding of multiple-goal pursuit. The incorporation of the temporal discounting assumption does not fundamentally alter our understanding of this process. Nothing is lost by including this component, it merely adds another layer to the theory. In particular, in cases where a deadline does not exist or discounting is unlikely to occur, Γ would likely take on the value of zero, indicating that expected utility is not subject to discounting. However, a shift from assuming that valence is determined by distance to assuming that it's determined by time pressure when goals have different deadlines alters the theoretical statement the model makes about multiple-goal pursuit. It is therefore important to consider cases where this assumption is appropriate and where it is not. One case where people are likely to be more sensitive to the distance than to time pressure is when deadlines are flexible, such as when an academic is preparing a journal submission. In such situations, the distance may be more informative because the deadline, and therefore the time pressure, is often poorly defined. In this case, one might conceive that sensitivity to distance (κ_1) is greater than zero whereas sensitivity to time pressure (κ_2) is zero or is very small.

Another consideration is contexts with avoidance goals, which involve protecting against an undesired outcome (Ballard, Farrell, & Neal, 2017; Ballard, Yeo, B. Vancouver, & Neal, 2017). For example, one might aim to prevent debt from reaching a critical threshold. Although the model presented in this paper can be applied to avoidance goals, we only examined approach goals in the experiments. Previous work has suggested that people are more sensitive to the distance when pursuing avoidance goals (Ballard, Yeo, Loft, et al., 2016; Ballard, Yeo, Neal, & Farrell, 2016) compared to approach goals. Thus, the avoidance context may be another one where time pressure is less influential. Understanding the factors that influence sensitivity time pressure will be an important area for future research.

Another important consideration for future research is the ability to use hierarchical Bayesian methodology to construct computational models that capture multiple levels of variability. Many of the most important questions we have regarding dynamic, self-regulatory phenomena such as multiple-goal pursuit require us to understand the phenomena at multiple levels of analysis. For example, researchers often want to use computational models to quantify the degree of individual differences within a population (e.g., Busemeyer & Stout, 2002; Wallsten, Pleskac, & Lejuez, 2005), or to examine whether individuals cluster into distinct subgroups (e.g., Ballard, Yeo, Loft, et al., 2016). Researchers also often want to determine a particular component of a psychological process is sensitive to an experimental manipulation (e.g., Rae, Heathcote, Donkin, Averell, & Brown, 2014; Vancouver & Purl, 2017). The hierarchical Bayesian methodology presented in this paper provides a sophisticated way of developing and testing computational models that can answer these sorts of questions. This methodology therefore provides an opportunity for future research to bring our understanding of dynamic, self-regulatory processes to a new level.

Finally, it's important to recognize that the incorporation of both time pressure and temporal discounting as mechanisms required to account for prioritization in the face of goals with different deadlines has increased the complexity of the MGPM. The computational modeling suggested that this complexity is warranted because factors such as distance, deadline, and time pressure exert complex effects on prioritization. However, the set of models we considered in this research was not exhaustive. It is possible that there is a more parsimonious explanation for these findings, and we encourage future work that tries to identify one. The challenge of developing an accurate explanation for the process by which people manage multiple goals is one that will require a long term, collaborative effort. Ultimately, a theory can never be proven (Popper, 1959). But we can establish the credibility of different explanations by continually evaluating their ability to predict new phenomena, comparing plausible alternatives, and refining or rejecting aspects that fail to hold up under empirical scrutiny. These practices will be essential for the field to make cumulative progress.

Conclusion

The aim of this paper was to develop and test a theory of multiple-goal pursuit that accounts for people's prioritization decisions when pursuing goals with different deadlines. We showed that people faced with this scenario generally prioritize the goal with the closer deadline. To explain this behavior, we integrated the MGPM with theory from the intertemporal choice and motivation literature. The findings provided evidence for a complex, information processing architecture that incorporated deadlines in multiple ways. The result is a more general theory of multiple-goal pursuit than has been thus far achieved. We hope that these advances will spark continued interest in using computational modeling to understand dynamic self-regulatory processes that will strengthen the ties between basic psychological science and practical application.

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Appendix A
Details Regarding Fixed Parameters

The MGPM has a number of parameters that are primarily determined by the environment, as opposed to individual differences. These parameters therefore had fixed values in the analysis. In this task, expected lag (α) was $1/3$, because on average it would take one third of a week to reduce the distance to each goal by 1 cm (i.e., the distance to each goal could be reduced by 3 cm per week on average). In this task, the impact of actions on goal progress (i.e., the growth outcomes for each crop) were continuous, normally-distributed variables. In this case, the attention component of the MGPM can be modeled by assuming that quality (i.e., the perceived consequence on goal progress) is a normally-distributed, random variable. The quality distribution needs to be modeled separately for the irrigated and non-irrigated crops. The quality distribution for the irrigated crop had a mean of 1 and a standard deviation of 0.5. The quality distribution for the non-irrigated crop had a mean of 0 and a standard deviation of 0.5. The standard deviation of the quality distribution represents the extent to which attention varies across the possible consequences that each decision can have for goal progress. The quality distribution in the model was aligned with the distribution of growth outcomes in the experimental task, where the standard deviation was always 1/2 the mean growth of the irrigated crop and the non-irrigated crop always had a mean growth of 0.

Appendix B
Hyperpriors

The hyperpriors were chosen to be weakly informative. This means that they introduce a high level of uncertainty regarding the true parameter value whilst excluding values that are implausible (e.g., values below 0) or that could not be identified (e.g., high values at which changes in the parameter have no discernible effect on the model predictions). The hyperpriors for the time sensitivity, threshold, discount factor parameters are shown in Table A1. These hyperpriors were the same for each model. Note that the discount factor priors are only applicable to the Discounted Utility variants, because this parameter was fixed to 0 in the other variants.

Table A1
Hyperpriors Used in Analysis

Parameter	Hyperparameter	Hyperprior Distribution	μ	σ
Time Sensitivity (γ)	Location (μ)	Normal	-1.00	0.05
	Scale (σ)	Log-normal	0.01	0.10
Threshold (θ)	Location (μ)	Normal	-2.00	0.05
	Scale (σ)	Log-normal	0.20	0.10
Discount Factor (Γ)	Location (μ)	Normal	0.00	0.01
	SD Log (σ)	Scale	0.30	0.01

Appendix C
Details of Model Implementation

Posterior distributions for complex models such as the MGPM cannot be analytically derived. However, posterior distributions can be accurately approximated using Markov chain Monte Carlo (MCMC) methods (Kruschke et al., 2012; Lee & Wagenmakers, 2013). MCMC methods refer to a class of algorithms that can be used to generate a large number of representative samples from the posterior distribution (Kruschke, 2010). At each step in the chain, the algorithm generates sample parameter values that are in part determined by the sample at the previous step. As the number of steps in the chain increases, the distribution of sampled parameter values becomes representative of the underlying posterior distribution. Recommendations have been provided that ensure the analysis accurately approximates the posterior (e.g., Kruschke, 2010; Lee & Wagenmakers, 2013). The first is to run multiple chains with different starting values and examine whether the chains converge to the same region of the parameter space. This convergence is referred to as *mixing*, and it indicates that that samples are likely representative of the posterior. The second recommendation is to exclude the initial samples from consideration, because they are more strongly influenced by the starting point for the chain and are less representative of the posterior distribution (a process referred to as *burning in* or *warming up* the chains). Finally, to further reduce autocorrelation, it can be useful to only consider some proportion of samples in the final analysis (e.g., every 5th; a process referred to as *thinning* the chains).

For each of the models, we ran an MCMC analysis with 24 chains (with unique starting values randomly generated by Stan). Each chain had a burn in period of 500 samples. After burning in, each chain produced 250 samples. The final sample therefore contained 6000 samples (e.g., 24 chains x 250 samples per chain). We did not use any thinning because there was very little autocorrelation. The chains demonstrated good mixing, suggesting that the approximated posterior distributions are likely to be highly representative of their underlying distributions (Kruschke et al., 2012).