# Prioritisation Under Pressure: The Effect of Deliberation Time on Multiple Goal Pursuit

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This thesis was submitted in partial fulfillment of the requirements for the Bachelor of Psychological Science (Honours) at the University of Queensland

PSYC4071/PSYC4072

14th October 2020

Word count: 11,285

Assessable word count: 7,968

# Originality Statement

I, Manikya Alister, hereby certify that this thesis is my own original work. Any ideas, text or research referred to in this thesis which are not my own have been appropriately referenced. I also declare that this thesis has not been previously submitted for assessment.

Manikya Alister

13 October 2020

# Acknowledgements

To my supervisor, Dr Timothy Ballard, thank you for your guidance—I feel so lucky to have been able to work with you over the last several years. You have been so generous in the opportunities you have extended to me, from which I have learnt so much and developed interests that I never would have expected. To Scott Herbert, thank you for all of your patience while helping me navigate R, Stan, and Tinaroo. I couldn't have done it without your help. To my fellow undergrad students, thank you for all of your support and encouragement, I'm so glad to have met you all. To my partner, Kathryn, thank you for your support through these busy last few weeks before submission.

Abstract

Multiple goal pursuit refers to the process by which people strive to achieve competing goals over time. The Multiple Goal Pursuit Model (MGPM), has become the leading model of multiple goal pursuit, due to its ability to precisely describe this process across a range of contexts. However, the MGPM assumes that decisions to prioritise a goal do not change as a function of deliberation time, which is an assumption that has never been formally tested and that is not consistent with decision-making theory. This thesis aimed to refine the assumptions of the MGPM to better align with this theory, so that it can account for contexts where deliberation time varies. Across two experiments, I manipulated deadline, distance, and deliberation time using a novel task. Using a combination of statistical analyses and computational modelling techniques, I then tested the current MGPM against four novel variants of the MGPM, each based off conflicting theoretical explanations for the effect of deliberation time on decision-making. I found that participants tended to prioritise the goal with the nearest deadline unless that goal was too difficult to achieve. Further, I found that when deliberation time was reduced, the aforementioned effects of deadline and distance were still present, but people were more likely to prioritise the goal with the nearest deadline compared to when deliberation time was normal. The model which best accounted for these effects was a variant of the MGPM which assumes that people disproportionately attend to deadlines when deliberation time is reduced. This suggests deadlines may be a particularly salient cue in multiple goal pursuit, providing insight as to why goal prioritisation errors may occur in some applied settings, and how these errors could be mitigated.

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People typically pursue multiple goals at once. That is, we have at one time, more than one goal that we are working to achieve. For example, in the workplace, we may be required to both write a report and prepare a presentation. Or in our personal lives, we might want to both save for a house deposit and also go on a holiday. However, often goals like these cannot be completed simultaneously. Instead, choices must be made about how to allocate resources like time, attention, and energy, in order to balance these competing demands. The process by which people balance these demands when trying to achieve more than one goal is called *multiple goal pursuit* (Neal, Ballard, & Vancouver, 2017).

A key feature of multiple goal pursuit is that choices to prioritise a goal (i.e., *prioritisation decisions*) are dynamic, in that the preference for one goal can change over time (Neal et al., 2017). For example, people have been found to abandon goals that cannot be successfully completed before the deadline and instead, focus on more achievable goals (Schmidt & Dolis, 2009). Consequently, models of multiple goal pursuit should demonstrate how decisions to prioritise a goal vary over time, as progress is made and deadlines near. Vancouver, Weinhardt, and Schmidt's (2010) Multiple Goal Pursuit Model (MGPM), a computational model of multiple goal pursuit, offers exactly this.

The MGPM integrates theories of dynamic self-regulation (see Vancouver, 2008) to describe how decisions to prioritise competing goals vary over time. Over the last decade, the MGPM has become the dominant model of multiple goal pursuit due to its ability to account for goal prioritisation in a variety of contexts and the precision by which it describes the processes involved (Ballard, Vancouver, & Neal, 2018; Ballard, Yeo, Loft, Vancouver, & Neal, 2016;

Vancouver, Weinhardt, & Vigo, 2014). However, some of the MGPM's assumptions require further refinement to align with theory.

The MGPM assumes that decisions to prioritise a goal do not change as a function of *deliberation time*—how much time is available to decide which goal to prioritise. This assumption is not consistent with evidence, as a vast body of research suggests that when people are forced to decide quickly, they tend to adjust their decision-making strategy due to a reduction in their capacity to process information (Brown & Heathcote, 2008; Gigerenzer & Gaissmaier, 2011; Paas, Tuovinen, Tabbers, & Gerven, 2003; Palada et al., 2016; Ratcliff & McKoon, 2007; Vuckovic, Kwantes, Humphreys, & Neal, 2014; Vuckovic, Kwantes, & Neal, 2013). This suggests the MGPM might not provide a complete explanation for the effects of deliberation time on multiple goal pursuit. The current thesis aims to extend the MGPM to better align with this theory, so that it can describe how multiple goal pursuit changes as a function of deliberation time.

## The Multiple Goal Pursuit Model

The Multiple Goal Pursuit Model (MGPM) is a computational model that describes how people allocate resources while pursuing multiple, competing goals. Computational models, as opposed to conceptual models, describe the relationship between variables and constructs mathematically, rather than solely in prose. Computational models have become increasingly popular in cognitive psychology, due to the precision by which they describe cognitive processes, and the ability for their predictions to be directly evaluated against data (Lewandowsky & Farrell, 2011). The MGPM draws off theories of self- regulation (see Vancouver, 2008; Vancouver et al., 2010) which assume goals represent a desired state, and that the goal-striving process consists of continuously monitoring goal features to determine which goal should be prioritised at a given time, in order to maximise the chances of reaching the desired state (see Neal, Ballard, & Vancouver, 2017 for a review of theories of self regulation). The MGPM's ability to precisely describe and account for these self-regulatory processes has made it the foremost model of multiple goal pursuit to date.

The initial version of the MGPM, developed by Vancouver et al. (2010), demonstrated how *expectancy, valence* and *expected utility* are monitored during the goal-striving process. Valence is the subjective value of prioritising a goal. In the initial version of the MGPM, valence is a function of a goal's *importance* and *distance* to the goal (see importance and distance links to valence in Figure 1 for reference). Goal importance represents how there can be different outcomes associated with achieving different goals, which directly influences their value. For example, Vancouver et al. (2010) found that people tended to prioritise goals that were incentivised by financial rewards over those that were not (see also Kernan & Lord, 1990; Schmidt & DeShon, 2007). *Distance* in valence demonstrates how valence is also dynamic, in that valence changes as a proportion of how far a goal is from being realised. For example, all else being equal, Vancouver et al. (2010) demonstrated that participants found more value in prioritising a goal that was further from completion (i.e., required more work) compared to a goal that was nearer to completion or completed.

Expectancy refers to the perceived likelihood that a goal will be achieved. In the initial version of the MGPM, as shown in the upper left-area of Figure 1 (ignore *expectancy sensitivity* for now, this is discussed in the next section), expectancy is the discrepancy between *perceived time required* and *time available*. In the initial MGPM, perceived time required is a function of distance and *expected lag,* which relates to how quickly one believes progress can be made. Time available refers to the discrepancy between the current time and the deadline. If the perceived

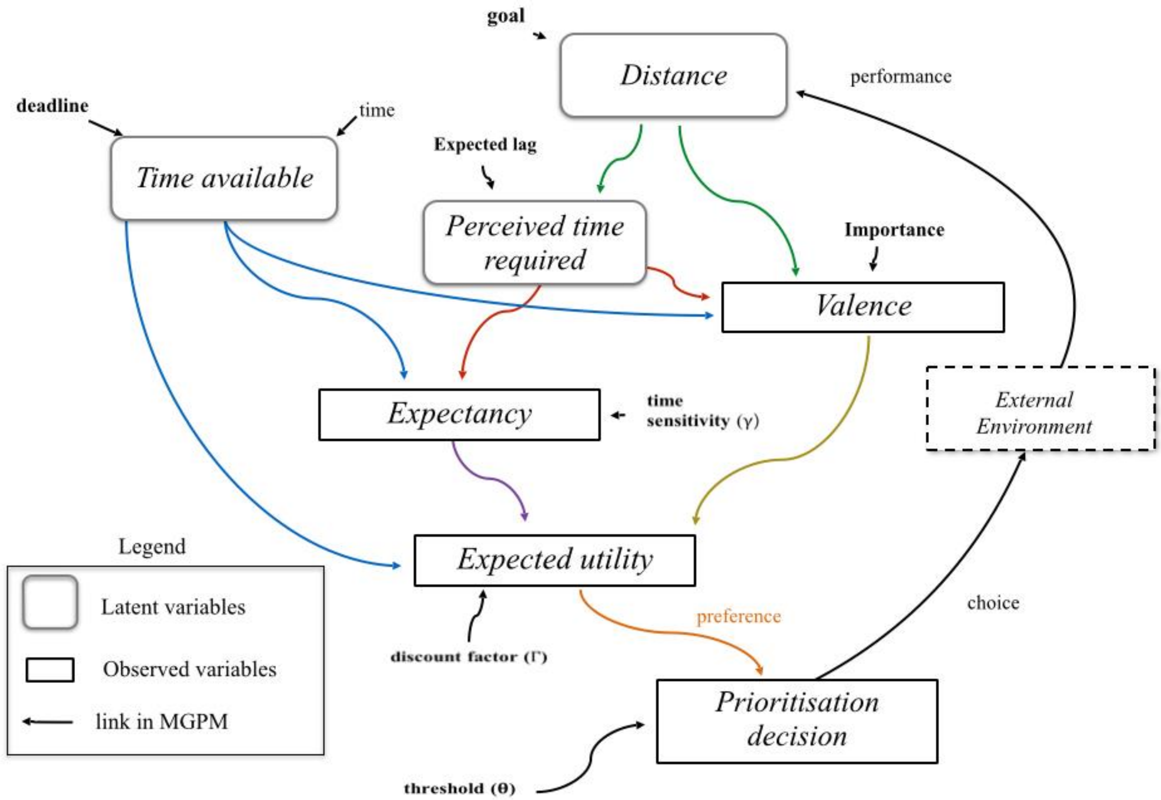


*Figure 1*. Conceptual Diagram of the Current MGPM. Variables in bold are assumed to be constant in contexts examined. All other variables vary over time. Adapted from *"*On the pursuit of multiple goals with different deadlines*" by* Ballard, T., Vancouver, J. B., & Neal, A. (2018). *The Journal of Applied Psychology*, 103(11), 1242–1264. *doi:*10.1037/apl0000304. The equations for valence, expectancy, and expected utility are in Appendix A.

time required to achieve a goal exceeds the time available before the deadline, expectancy is such that people believe that a goal is too difficult to achieve. Vancouver et al. (2010) demonstrated that when both goals were achievable, people prioritised goals based on the valence of that goal. However, once a goal was considered too difficult to achieve given the deadline, expectancy outweighed valence such that people switched to the goal that was easier to achieve (a trend also observed in Schmidt & DeShon, 2007; and Schmidt & Dolis, 2009).

Expected utility (see the bottom third of Figure 1) in the initial MGPM represents people's motivation to act on a certain goal and is a function of expectancy and valence. According to the initial MGPM, when people are deciding which goal to prioritise, they compare the expected utility of the goals and prioritise the goal with the highest expected utility.

**Subsequent Adaptions to the MGPM**

Since its initial development, the MGPM has been adapted to have more refined, theoretically relevant assumptions and has successfully accounted for multiple goal pursuit in a variety of contexts. In the first adaption to the MGPM, Vancouver et al. (2014) accounted for learning. Specifically, in the initial MGPM, calculations of expected lag (expected rate of progress towards a goal) did not consider that people would adjust their perception of time required to achieve a goal based on their rate of progress up until the current point. Vancouver et al. (2014) modified expected lag to account for the finding that if the expected rate of progress did not match with their actual rate of progress, people learnt from that experience and adjusted expected lag accordingly.

Further extending the MGPM, Ballard, Yeo, Loft, et al., (2016) accounted for different types of goals. The MGPM had previously only been tested using approach goals (i.e., goals where people try to obtain positive outcomes) and could not account for avoidance goals (i.e., goals where people try to avoid a negative outcome). However, people have been shown to be more risk-averse when pursuing approach goals compared to when pursuing avoidance goals (Ballard, Yeo, Neal, & Farrell, 2016; Kahneman & Tversky, 1979). To align with this, Ballard, Yeo, Loft et al. (2016) adjusted expectancy, valence and expected utility to explain changes in goal prioritisation as a function of goal-type.

Moreover, Ballard, Yeo, Loft, et al., (2016) integrated Decision Field Theory (Busemeyer & Townsend, 1993) into the MGPM to provide a more nuanced account of how people decide between competing goals under conditions of uncertainty. Applying Decision Field Theory, rather than prioritising the goal with the highest expected utility at any given moment, Ballard Yeo, Loft et al.'s (2016) MGPM assumes that expected utility represents a preference for a particular goal, and that preferences for each goal accumulate over time as evidence is gathered, until the preference for one goal exceeds a *threshold*, at which point it is prioritised (see the bottom third of Figure 1). This threshold is assumed to vary from person to person, and people with a higher threshold are assumed to spend more time accumulating preferences before prioritising a goal compared to those with a lower threshold. Ballard, Yeo, Loft, et al. (2016) also added *expectancy sensitivity* to the evaluation of expectancy, which is a parameter that assumes some people are more influenced by expectancy than others (located in the middle of Figure 1).

**Current MGPM**

In the most recent version of the MGPM, Ballard et al. (2018) extended the MGPM to fit contexts where goals have different deadlines. They found that nearer deadlines increase the valence of the goal and also directly increase expected utility because they are seen as more urgent than goals with a further deadline (see time available links to valence and expected utility in Figure 1). Furthermore, drawing off hyperbolic discounting in Temporal Motivation Theory (Steel & König, 2006), which suggests near deadlines are motivating while further deadlines tend to be discounted, they added a *discount factor*, which is a parameter that represents individuals' propensities for being motivated by nearer deadlines while discounting future deadlines, and directly contributes to expected utility (see the lower half of Figure 1). Using a paradigm that manipulated distance to the goal and deadline, Ballard et al. (2018) found that this model could successfully account for the observed finding that participants tended to prioritise the goal with the nearer deadline when distance was shorter (i.e., when expectancy was high) but switched to the goal with the further deadline when distance was longer (i.e., when expectancy was such that the goal was deemed too difficult to achieve).

In summary, the current MGM is comprised of four central features (as shown in Figure 1). Expectancy, which represents the perceived likelihood that a goal will be achieved. Valence, which represents a goal's subjective value. Deadlines, which represent the time available to achieve a goal. And expected utility, which is a combination of all three of the aforementioned features and represents one's preference for a particular goal. It is then assumed that preferences accumulate as each of these features are monitored until the preference for one goal exceeds a threshold, at which point it is prioritised.

## Accounting for the Effects of Deliberation Time on Decision-Making

In multiple goal pursuit, *deliberation time* refers to the amount of time available to decide which goal to prioritise. There are many contexts in which the time available to deliberate over multiple goals fluctuates. For example, a nurse taking care of two critically ill patients would have less time to deliberate over which patient to prioritise compared to a nurse caring for two stable patients. Despite this, the MGPM has only ever been tested in conditions where deliberation time is the same. Currently, the MGPM assumes that goal prioritisation does not change as a function of deliberation time. However, there is a large body of evidence to suggest deliberation time has a profound influence on decision-making, because people's capacity to process information is reduced when deliberation time is low (see Hafenbrädl, Waeger, Marewski, & Gigerenzer, 2016; Palada et al., 2016; Ratcliff & McKoon, 2007). Therefore, the predictive power of the MGPM in contexts where deliberation time fluctuates is likely to be limited. In this thesis, I investigate two leading, yet conflicting theoretical explanations for the effect of deliberation time on decision-making: speed/accuracy trade-offs and heuristics.

**Speed/Accuracy Trade-Offs**

One way in which deliberation time might influence multiple goal pursuit is through a trade-off between speed and accuracy. As I have already discussed, the threshold parameter in the MGPM allows for the assumption that people spend time accumulating evidence before prioritising a goal (Ballard, Yeo, Loft, et al., 2016). However, this threshold is also assumed to represent a trade-off between speed and accuracy, whereby when threshold is higher, it is assumed that more time is spent accumulating preferences, resulting in slower but generally more accurate decisions compared to if threshold is lower.

The MGPM assumes that this threshold does not vary as a function of deliberation time, which is inconsistent with several prominent, well-established decision-making models such as the Linear Ballistic Accumulator (Brown & Heathcote, 2008) and the Diffusion Model (Ratcliff & McKoon, 2007) which both assume that people set a higher threshold when they have more time to deliberate and a lower threshold when they have less time to deliberate. However, these models have been developed to explain static, single choice decisions and it is unclear whether these assumptions generalise to multiple goal pursuit contexts where people have to integrate a range of dynamic variables to make a sequence of decisions.

**Heuristics**

For more complex decisions, including decision-making in some applied settings, evidence has been found for the use of *heuristics*: cognitive strategies that facilitate quick decision making by ignoring a portion of available information (Gigerenzer & Gaissmaier, 2011). Using a heuristic reduces the amount of information being attended to and allows for one's mental capacity to cope with decisions that have a high demand for cognitive resources, such as decisions under time-pressure (see Gigerenzer & Gaissmaier, 2011; Hafenbrädl, Waeger, Marewski, & Gigerenzer, 2016; Todd & Gigerenzer, 2000 for reviews). While a speed/accuracy trade-off approach and heuristics both assume that as a result of time pressure, people reduce the amount of information they attend to, the key difference is that heuristics assume that people are systematically biased to attend to some information more than other information, whereas a speed/accuracy approach assumes that there is no such bias.

Over the past several decades, a range of different heuristics have been discovered that explain decision-making in a variety of both laboratory and applied settings. For example, firefighting commanders must make complex, uncertain decision under time pressure, and have been found to cope with these demands by focusing on only a few key features of the environment, while ignoring other potentially relevant information (Klein, Calderwood, & Clinton-Cirocco, 1986; Klein, Calderwood, & MacGregor, 1989). In the context of multiple goal pursuit, when deliberation time is reduced, rather than trying to systematically integrate valences, deadlines and expectancies of multiple goals over time, people might only have the capacity to fully attended to just one of either deadlines, valences, or expectancies and as a consequence, attend less to the other information. However, this is yet to be formally tested and it is unclear whether the task demands created by a relatively simple multiple goal pursuit paradigm would result in participants relying on a heuristic strategy when deliberation time is reduced.

## The Present Study

The aim of this study is to extend the MGPM so that it can account for multiple goal pursuit in contexts where deliberation time varies. This is achieved over two experiments.

## Experiment 1

Experiment 1 is a conceptual replication of Ballard et al. (2018) where I attempt to replicate their results using a novel task. This experiment is important for two reasons. Firstly, to assess the generalisability of the current MGPM and secondly, to ensure that my novel task is sensitive enough to recreate established effects. In the task, goals vary on two attributes: starting distance to the goal (how often a goal needs to be prioritised to achieve that goal) and the goal's deadline (how many opportunities there are to prioritise that goal). Specifically, this is achieved by manipulating the deadline and distance for one goal (referred to as the *experimental* goal), but always keeping the deadline and distance constant for the other goal (referred to as the *fixed* goal) to act as a control. There are three main behavioural results that would suggest Ballard et al.'s findings were replicated, denoted as hypotheses below.

**Hypothesis 1.** There will be a higher proportion of choices prioritising the experimental goal in the shorter distance conditions compared to the longer distance conditions. This is because in the shorter distance conditions, the experimental goal generally has a higher expectancy (i.e., is easier to achieve).

**Hypothesis 2.** There will be a higher proportion of choices prioritising the experimental goal when deadline is nearer compared to when deadline is further. This is because nearer deadlines create more urgency.

**Hypothesis 3.** The tendency for there to be a higher proportion of choices favouring the experimental goal when deadline is nearer will begin to reverse in the longer distance conditions. This is because goals in the longer distance conditions will seem impossible to achieve given the deadline (i.e., decreased expectancy created by longer distance will outweigh the urgency created by nearer deadlines).

**Experiment 2**

In Experiment 2, in addition to manipulating starting distance and deadline, I also manipulate deliberation time across two conditions: a normal deliberation time condition (n) which has the same deliberation time as in Experiment 1, and a reduced deliberation time condition (r) where deliberation time is reduced by two-thirds. Using this paradigm, I formally compare the Current MGPM against four novel adaptions of the MGPM described in the next section, that are each based on one of the conflicting theoretical assumptions for how deliberation time influences decision-making as discussed earlier.

**Model predictions.** A graphical representation of each prediction for the reduced deliberation time condition is in Figure 2. Table 1 outlines the assumptions of each model and how these assumptions were operationalised.

***Current MGPM.*** Participants will prioritise the goal with the nearest deadline in the shorter distance conditions, but this trend will begin to reverse in the longer distance conditions as that goal becomes too difficult to achieve before the deadline.

***MGPM with speed/accuracy trade-off.*** Decisions will become noisier in the reduced deliberation time condition. That is, there will be more variability in participants' individual responses when deliberation time is reduced compared to when it is normal because preferences will not be as strong.

***MGPM with deadline heuristic.*** There will be a higher proportion of choices prioritising the goal with the nearest deadline in the reduced deliberation time condition.

***MGPM with expectancy heuristic.*** There will be a higher proportion of choices prioritising the goal that is easiest to achieve in the reduced deliberation time condition. That is,

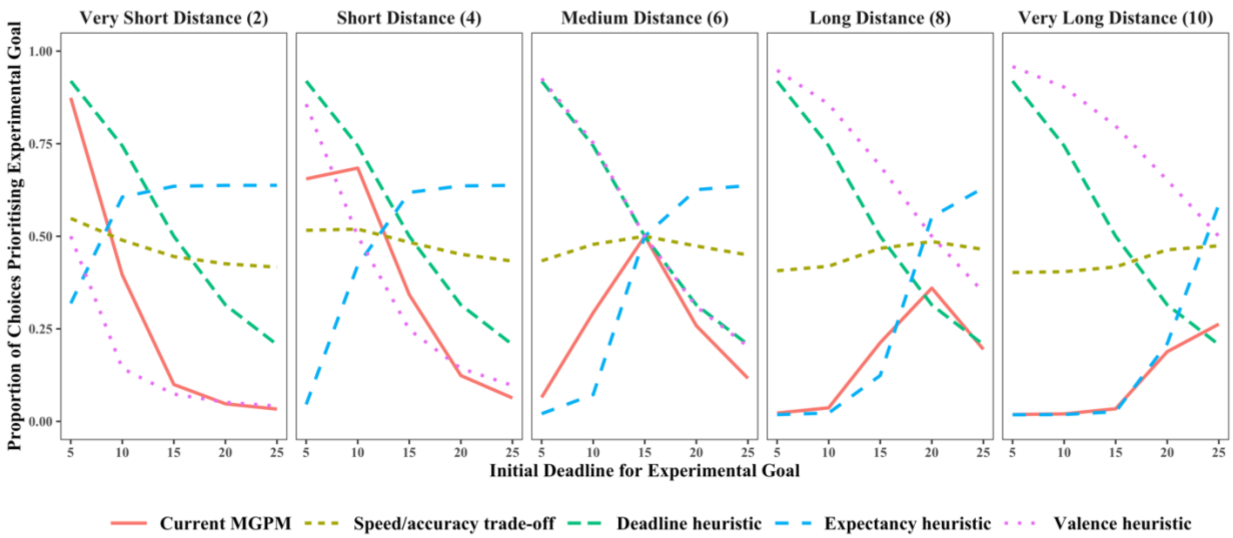


*Figure 2.* Predicted Proportion of Choices Prioritising the Experimental Goal When Deliberation Time is Reduced as a Function of the Experimental Goal's Initial Deadline and the Experimental Goal's Initial Distance. Scores on the *y* axis that are less than 0.5 represent a preference for the fixed goal, that always has a distance of 6 and a deadline of 15. Different line colours/line types represent the predictions of different models. Note that this figure is designed to facilitate understanding of the differences between each model and does not represent rigid predictions. Rather, precise predictions were estimated based on the observed data (see the Results section of Experiment 2 for more detail on how this was achieved).

the goal where the difference between time available to reach the goal and time required to reach the goal is largest.

***MGPM with valence heuristic.*** There will be a higher proportion of choices prioritising the goal that has the most subjective value. That is, the goal with the longest distance *and* nearest deadline.

Table 1

*Model assumptions and how these assumptions were operationalised across deliberation time conditions*

| Model | Assumptions | Parameter | | | |
|---|---|---|---|---|---|
| | | Expectancy Sensitivity ($\gamma$) | Discount Rate ($\Gamma$) | Threshold ($\theta$) | Valence Sensitivity ($\varphi$) |
| Current MGPM | There will be no effect of deliberation time on the goal prioritisation process. | $\gamma_n = \gamma_r$ | $\Gamma_n = \Gamma_r$ | $\theta_n = \theta_r$ | $\varphi_n = \varphi_r$ |
| Speed/ accuracy trade-off | When deliberation time is reduced, threshold will be lower such that people will spend less time accumulating evidence before deciding. | $\gamma_n = \gamma_r$ | $\Gamma_n = \Gamma_r$ | $\theta_n > \theta_r$ | $\varphi_n = \varphi_r$ |
| Deadline heuristic | When deliberation time is reduced, participants will attend less to expectancies and valences, so the relative influence of deadlines will be higher. | $\gamma_n > \gamma_r$ | $\Gamma_n = \Gamma_r$ | $\theta_n = \theta_r$ | $\varphi_n > \varphi_r$ |
| Expectancy heuristic | When deliberation time is reduced, participants will attend less to deadlines and valences, so the relative influence of expectancies will be higher. | $\gamma_n = \gamma_r$ | $\Gamma_n > \Gamma_r$ | $\theta_n = \theta_r$ | $\varphi_n > \varphi_r$ |
| Valence heuristic | When deliberation time is reduced, participants will attend less to deadlines and expectancies, so the relative influence of valences will be higher. | $\gamma_n > \gamma_r$ | $\Gamma_n > \Gamma_r$ | $\theta_n = \theta_r$ | $\varphi_n = \varphi_r$ |

Note. Parameters subscripted with n relate to that parameter in the normal deliberation time condition. Parameters subscripted with r relate to that parameter in the reduced deliberation time condition. Parameters with “=” between conditions means that these parameters were the same in each deliberation time condition for the corresponding model. Parameters with “>” between conditions means that this parameter was constrained to be a higher value in the normal deliberation time condition compared to the reduced deliberation time condition. $\gamma$ refers to the extent to which a person attends to expectancy. $\Gamma$ refers to how sensitive an individual is to the motivating effects of deadlines. $\theta$ refers to how much time an individual spends accumulating preferences before a goal is prioritised. $\varphi$ refers to the extent to which a person attends to valence and is always 1, except for in the reduced deliberation time conditions of the deadline and expectancy heuristic models.

# Experiment 1

## Method

The study protocol (i.e., hypotheses, sample, exclusion criteria, design, procedure, and analysis plan) for Experiment 1 was pre-registered at the Open Science Framework (see https://osf.io/ab8mg/).

**Contributions.** I designed the experiment with input from my supervisor, Dr Timothy Ballard. With consultation from my supervisor, I wrote, ran and interpreted all of the scripts for the statistical analyses in both experiments, and produced the figures pertaining to them using RStudio. I ran all of the computational modelling analyses and was responsible for interpreting their results and plotting their predictions and results. This thesis required in-depth knowledge of RStudio, computational modelling, and Bayesian inference which I learnt principally in my own time. These contributions apply for both experiments in this thesis.

**Participants.** Sixty-five first-year undergraduate students from the University of Queensland (49 females, 14 males, 2 did not respond) participated for course credit. The sample age ranged from 18 to 36 years ($M = 20.55$ $SD = 3.93$). In line with my pre-registered exclusion criteria, five participants were excluded because they did not finish the task, and four were excluded because they had a response rate of < 80%, leaving a final sample of 56 for analyses. Due to a technical error, the age and gender breakdown of the sample after the exclusion criteria were applied could not be ascertained. A parameter recovery analysis, which assesses whether a given sample size will produce reliable model parameter estimates, confirmed that this sample size was sufficient.

**Experimental design.** The experimental task was a dual-goal shield building task, where participants had to build a certain number of shields represented as rings around two respective planets, in order to prepare for an “impending attack”. The experiment followed a 5 (starting distance: 2 shields, 4 shields, 6 shields, 8 shields, 10 shields) × 5 (deadline: 5 opportunities, 10 opportunities, 15 opportunities, 20 opportunities, 25 opportunities) repeated measures factorial design. The manipulations were achieved by varying deadline and distance for one goal (henceforth referred to as the *experimental* goal), while keeping deadline constant at 15 and distance constant at 6 for the other goal (henceforth referred to as the *fixed* goal). Deadline represented how many opportunities (i.e., trials) there would be to achieve the goal for that planet. Starting distance represented how many shields needed to be built in order to achieve the goal for that planet. Specifically, this was operationalised by varying the *starting* number of shields for the experimental goal but having the *goal* number of shields always be 12 for both planets. The primary dependent variable was whether or not the experimental goal was prioritised. Figure 3 demonstrates how the manipulations and measures were represented in the task.

**Procedure**. Participants completed the experiment online and in their own time via a link made available to them once they registered their interest to participate. First, participants were presented with the task’s instructions and a consent form. After indicating that they had read and understood the instructions, and provided their consent to participate, participants were directed to the experimental task. After completing two practice blocks, participants began the main experiment.

During each trial, two “friendly aliens” simultaneously passed each of the respective planets. In order to build a shield, participants had to “enlist” these passing aliens by casting a net in the direction of the alien flying past the planet they wished to build a shield for. Pressing the ‘a’ key cast a net towards the alien flying past the left-sided planet and pressing the ‘l’ key

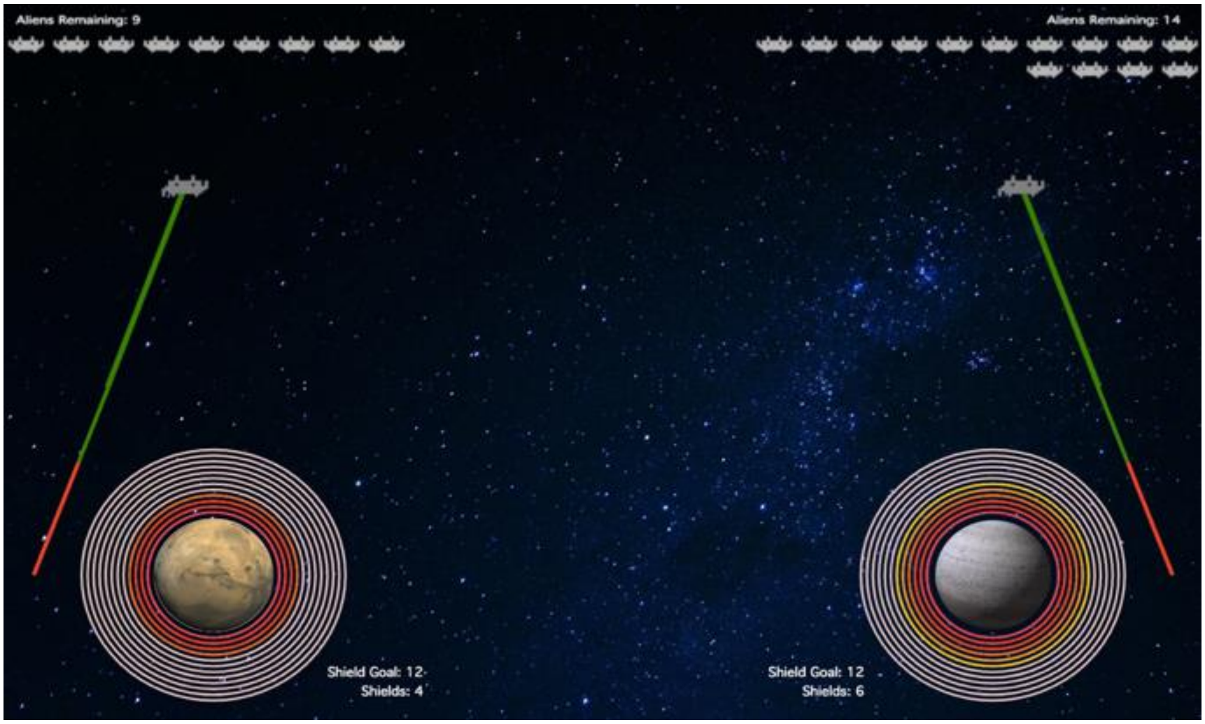


*Figure 3.* Screenshot of the Experimental Task. Deadline for each Planet was represented by "Aliens Remaining" in the top right and left-hand corners respectively. Distance to the goal could be calculated by taking the current number of shields surrounding a planet (found next to "shields" at the bottom of both planets) from the shield goal (always 12). The deadline and distance information updated each trial. The lines passing each respective planet represent the trajectory of the aliens. Participants had to decide to enlist an alien before it reached the red part of the line otherwise there would be no response in that trial.

cast a net towards the alien flying past the right-sided planet. Participants had 4.5 seconds to enlist an alien before it passed by the planet and they could only enlist one alien to build one shield for one planet at a time, so each trial participants had to prioritise one planet to build a shield for. When enlisting an alien, 20% of the time their offer was rejected, meaning no shield was built. This was to make the decisions more complex, as participants had to factor in this uncertainty when calculating how many trials it would take to achieve a goal.

The main experiment comprised of 25 blocks presented in random order, made up of each of the possible combinations of deadline and starting distance as specified in the previous section. A block in this task referred to a complete goal-striving episode, and a trial was an individual decision made within that episode. The number of trials in each block was generally determined by the goal with the longest deadline. However, on occasions where both goals were completed before a deadline, the block ended at that point. This meant participants could complete a maximum of 420 trials in the experiment, but it was possible that some participants might complete slightly fewer trials depending on their strategy.

Once a goal was achieved, that planet would turn green and it could no-longer be prioritised. However, once the first deadline elapsed, that planet was supplemented with a "replacement planet" that had the same deadline as the planet where the goal had not yet been achieved and a goal distance of 6. This replacement planet was implemented to ensure participants were still making prioritisation decisions after the first deadline ended, ruling out the potential for the goal with the shorter deadline to be prioritised simply because there would be additional time to prioritise the goal with the longer deadline once the shorter deadline elapsed. In addition to live feedback updated every trial indicating the number of aliens remaining and shields built, after every deadline written feedback would appear on the screen which advised the participant as to whether or not the goal was achieved, or how many trials were left to achieve the goal for any remaining planets. At the end of each deadline, participants had the option to take a self-paced break. Excluding the break time, Experiment 1 should have taken each participant approximately 40 minutes to complete.

**Results**

All responses after the first deadline or goal was reached (i.e., all trials including a replacement planet) were not theoretically important because the replacement planet always had the same deadline as the remaining goal, so choices were no longer influenced by the experimental manipulations. Therefore, as in Ballard et al. (2018) and in line with this study's pre-registered analysis plan, these trials were not analysed. In total, there were 11,636 trials subject to analysis. The data from Experiment 1 is presented in two sections. Firstly, I conducted a statistical analysis to see if the main effects of deadline and starting distance, and the deadline × starting distance interaction found in Ballard et al. (2018) could be replicated with my novel experimental task. Secondly, I assessed the current MGPM's generalisability to my novel task by evaluating the model's predictions against the data generated from Experiment 1.

A Bayesian approach was used to analyse the data. This combines the probability of a hypothesis before data collection (*prior probability* or just *priors*), with the observed data to create a *posterior distribution* (or just *posteriors*), which is a distribution of values that quantify support for that hypothesis (or in other words, a distribution that represents the *credibility* of that hypothesis given the evidence; Kruschke, 2014). Statistical analyses were evaluated on the basis of *95% credible intervals*. These provide an estimate of the range of values that 95% of the posterior distribution falls within, which can be used to assess the variability of the data and allows for inferences about the credibility of an effect. When evaluating statistical models (e.g., regressions), if zero falls within the 95% credible interval, it is assumed that there is no credible evidence of an effect (i.e., the hypothesis is not credible). If the 95% credible interval excludes zero, this lends support that the effect is credible.

**Statistical analysis.** To see if the statistical effects observed in Ballard et al. (2018) could be replicated, I performed a Bayesian logistic mixed effects regression analysis using the *brms* package in RStudio (Bürkner, 2017). This analysis creates a statistical model from which one can evaluate group differences (fixed effects), such as main effects or interactions, while controlling for individual differences (random effects). For this analysis, I used *brms*' default priors which assume uninformative prior distributions for both the fixed and the random effects, because I had no prior beliefs about the posterior distribution. The dependent variable was whether or not the experimental goal was prioritised (1 = yes, 0 = no) and the fixed effects were standardised distance, standardised deadline, and the standardised deadline × standardised starting distance interaction. Participant was the only random effect, accounting for the possibility of individual differences in the overall preference for prioritising the experimental or fixed goal. The results of this analysis are in Table 2 and inspection of the black points in Figure 4 allows for their interpretation visually (Ballard, Yeo, Neal et al., 2016 used a similar approach for interpretation).

Table 2

*Effects from the Bayesian logistic mixed effects regression analysis for Experiment 1*

| | | 95% Credible Interval | |
|---|---|---|---|
| Effect | Standardised Coefficient | Lower Bound | Upper Bound |
| Subject (random effect) | .26 | .20 | .34 |
| Deadline | -.47 | -.51 | -.43 |
| Starting distance | -.13 | -.17 | -.10 |
| Deadline × starting distance | .31 | .27 | .35 |

Consistent with Hypothesis 1, there was a credible main effect of deadline, such that there was a higher proportion of choices prioritising the experimental goal when it had a nearer deadline. Consistent with Hypothesis 2, there was a credible main effect of starting distance, such that there was a higher proportion of choices prioritising the experimental goal when its starting distance was shorter. Consistent with Hypothesis 3, there was a credible deadline × starting distance interaction, such that the negative effect of deadline disappeared and began to reverse when starting distance was extended. In sum, the results of Ballard et al. (2018) were replicated, as predicted.

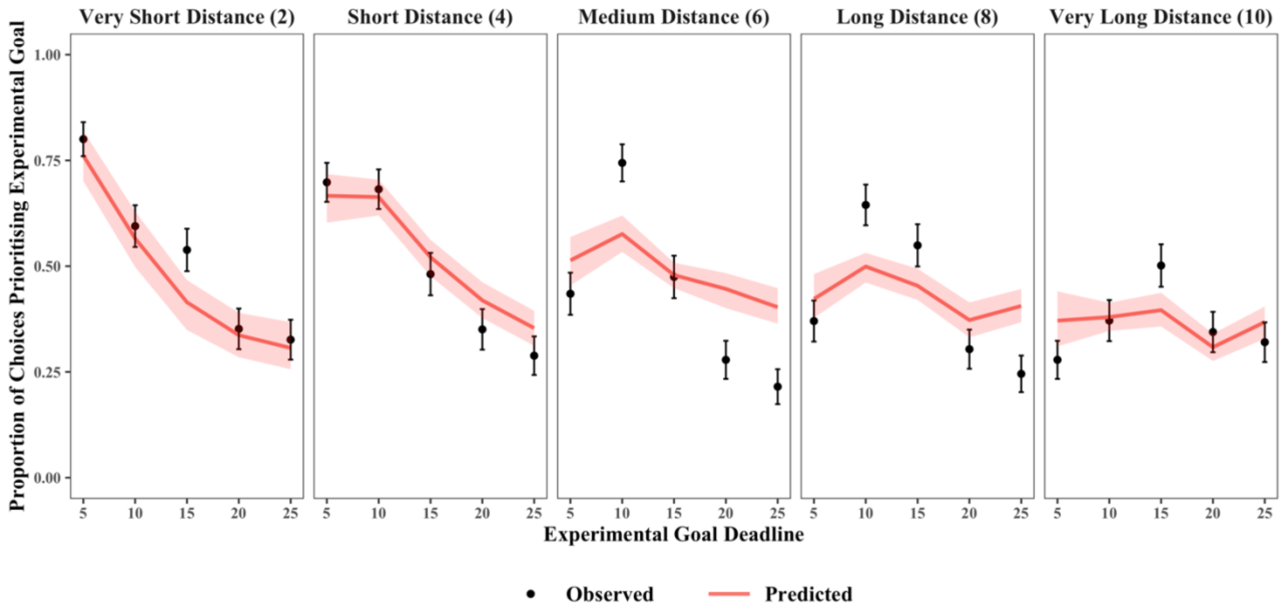


*Figure 4.* Observed Proportion of Choices Prioritising the Experimental Goal Compared with the Current MGPM's Predictions as a Function of the Experimental Goal's Initial Deadline and the Experimental Goal's Initial Distance. Error bars represent the standard error for the observed data. The dark red line represents the mean of the model's predictions. The pink shaded area represents the 95% credible interval of the model's predictions.

**Computational modelling.** To determine whether the current MGPM could account for the data generated from Experiment 1, I performed a hierarchical Bayesian parameter estimation implemented using the *rstan* package, which provides an RStudio interface for the programming language *Stan* (Stan Development Team, 2020). Stan was used because it is particularly well suited for running complex, hierarchical Bayesian models. This analysis estimates the values of the model's *free parameters* (parameters that are estimated based on the observed data) that result in the best fit between the model and the data. Further, this was achieved by pooling these estimates both at the group level, by evaluating the best fitting parameters of the whole sample, and at the individual level, by estimating the best fitting parameters for each individual participant respectively (Chaudhuri, Mondal, & Yin, 2017). The current MGPM contains three free parameters that were estimated in this analysis: expectancy sensitivity ($\gamma$), discount rate ($\Gamma$), and threshold ($\theta$), all of which were assumed to vary at the participant level. Like in Ballard et al. (2018), I chose weakly informative priors that assume little prior knowledge about the true value of each parameter (see Appendix B). The parameter estimates that resulted in the best fit between the model and the observed data are presented in Table 3 (Figure 4 provides a visual representation of the model fit to aid interpretation).

Table 3

*Average of the subject-level parameter estimates for the current MGPM in Experiment 1*

| | | 95% Credible Interval | |
|---|---|---|---|
| Parameter | *M* | Lower Bound | Upper Bound |
| Expectancy sensitivity ($\gamma$) | 0.45 | 0.39 | 0.53 |
| Discount rate ($\Gamma$) | 9.26 | 6.68 | 12.12 |
| Threshold ($\theta$) | 0.57 | 0.50 | 0.66 |

*Note.* When estimating parameters, the 95% credible interval informs the distribution of parameter estimates that are most credible given the observed data, and unlike when evaluating statistical models, does not necessarily inform the credibility of an effect.

To assess the model's ability to account for the observed data, I visualised the model predictions and evaluated them against the observed data graphically as seen in Figure 4 (a similar approach was used in Ballard, Yeo, Loft, et al., 2016). This revealed that most of the observed data was within the 95% credible interval of the model's predictions. Although there was a greater difference between the model's predictions and the observed data in the Medium Distance and Long Distance conditions, the model still captured the qualitative tendency described in Hypothesis 3 for the negative effect of deadline to begin reversing in these conditions. Therefore, for the purposes of Experiment 1, it was reasonable to conclude the model was able to account for the data generated in this task. Having established that both the statistical effects and computational modelling from Ballard et al. (2018) generalised to the novel task used in this thesis, in Experiment 2, I examined how deliberation time influences this process.

## Experiment 2

### Method

The study protocol (i.e., model predictions, sample, exclusion criteria, study design, procedure, and analysis plan) for Experiment 2 was pre-registered at the Open Science Framework (see https://osf.io/jnhx4/)

**Participants.** One hundred and forty-one first-year undergraduate psychology students from the University of Queensland participated for course credit. In line with my pre-registered exclusion criteria, thirty-three participants were excluded because they did not finish the task, five were excluded due to technical issues that rendered incomplete data, and nine were excluded because they had a response rate of $< 80\%$, leaving a final sample of 94. Of those remaining, 41 identified as male and 53 as female, and were aged between 18 and 43 ($M = 19.84$, $SD = 3.53$). I used a larger sample for Experiment 2 compared to Experiment 1 because Experiment 2 involved comparing competing models rather than only evaluating model fit, so greater power was necessary. The appropriateness of the sample for distinguishing between each model was confirmed using a model recovery analysis, and a parameter recovery analysis confirmed that the sample size was sufficient to produce reliable parameter estimates for each model.

**Experimental design and procedure.** The task and procedure were the same as in Experiment 1, with the exception that 50 blocks were completed instead of 25, due to the extra deliberation time condition wherein people only had 1.5 seconds to deliberate over which goal to prioritise (called the *reduced* deliberation time condition). This was in addition to the *normal* deliberation time condition which was the same as in Experiment 1, where people had 4.5

seconds to deliberate. Deliberation time was manipulated between blocks rather than within blocks (i.e., for every decision within a whole goal-striving block, deliberation time was the same) and the presentation of these blocks was random. Experiment 2 took approximately 90 minutes to complete, not including breaks.

**Results**

As outlined in my pre-registration, and as in Experiment 1, all trials after the first deadline or goal was reached were removed, leaving a total of 37,559 trials subject to data analysis. These results are reported in two sections: a statistical analysis where I investigated how the main effects and interactions found in Experiment 1 varied as a function of deliberation time; and a computational modelling analysis, where I compared the Current MGPM against four variants of the MGPM which each make different assumptions about the effect of deliberation time on goal prioritisation, in order to identify which could best account for the observed data in this Experiment 2.

**Statistical analysis.** As in Experiment 1, I performed a Bayesian mixed effects logistic regression analysis using the *brms* package in RStudio using the default priors (Bürkner, 2017). The dependent variable was whether or not the experimental planet was prioritised (1 = yes, 0 = no). The fixed effects were standardised deadline, standardised starting distance, deliberation time (-1 = reduced deliberation time, 1 = normal deliberation time), and the associated two-way and three-way interactions. Participant was the only random effect. The results of the statistical analysis are shown in Table 4 and depicted in Figure 5 to aid interpretation.

As in Experiment 1 and consistent with Hypothesis 1, there was a credible main effect of deadline, such that there tended to be a higher proportion of choices prioritising the experimental goal when it had a nearer deadline. Consistent with Hypothesis 2, there was also a credible main

Table 4

*Effects from the Bayesian mixed effects logistic Regression analysis in Experiment 2*

| | | 95% Credible Interval | |
|---|---|---|---|
| Effect | Standardised Coefficient | Lower Bound | Upper Bound |
| Subject (random effect) | .26 | .22 | .30 |
| Deadline | -.44 | -.46 | -.42 |
| Starting distance | -.25 | -.27 | -.23 |
| Deliberation time | -.02 | -.04 | .0003 |
| Starting distance × deliberation time | -.01 | -.004 | .04 |
| Deadline × starting distance | .28 | .26 | .30 |
| Deadline × deliberation time | -.03 | -.05 | -.004 |
| Deadline × starting distance × | .03 | .01 | .05 |

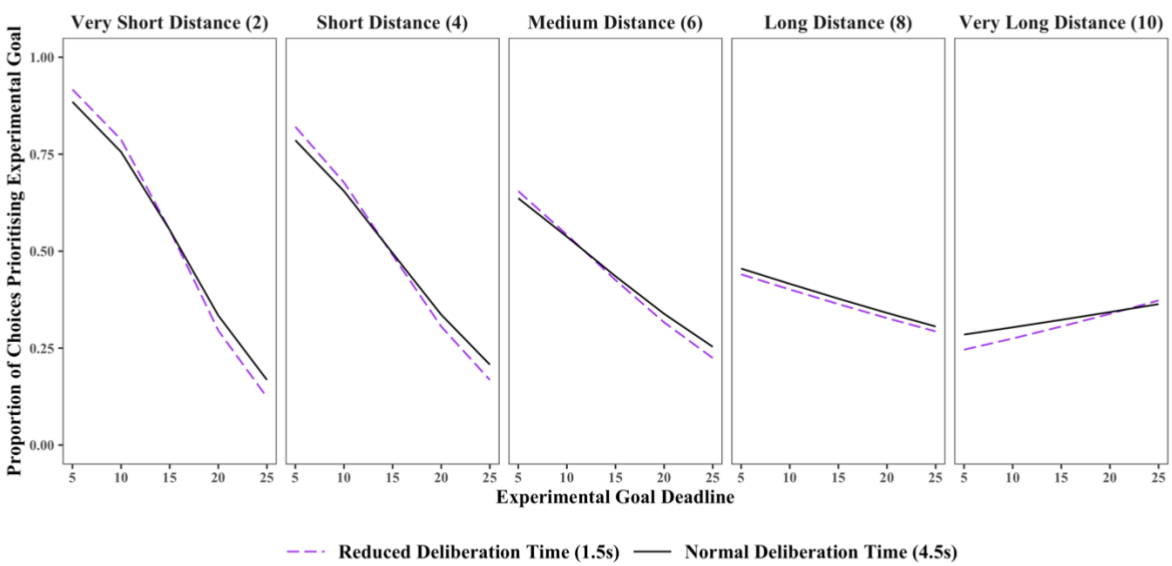


*Figure 5.* Proportion of Choices Prioritising the Experimental Goal as a Function of the Experimental Goal's Initial Deadline and Initial Distance as Predicted by the Bayesian Mixed Effects Logistic Regression. Different line types/colours represent different deliberation Time Condition.

effect of starting distance, such that there was a higher proportion of choices prioritising the experimental goal in the shorter starting distance conditions compared to in the longer starting distance conditions. The main effect of deliberation time was not credible, nor was the starting distance × deliberation time interaction. However, consistent with Hypothesis 3, there was a credible deadline × starting distance interaction (as found in Experiment 1). Lending support to the deadline heuristic variant of the MGPM, there was also a credible deadline × deliberation time interaction. Lending further support to the deadline heuristic variant, the deadline × starting distance × deliberation time interaction was also credible, such that in addition to the deadline × starting distance interaction (as identified in Experiment 1), people were more likely to prioritise the experimental goal when it had the nearest deadline in the reduced deliberation time condition. It should be noted however, that while the effects of deliberation time were statistically credible, they were quite weak in comparison to the effects of deadline and distance.

**Computational modelling.** The goal of this analysis was to determine which of the five models— the current MGPM, or the respective speed/accuracy trade-off, deadline heuristic, expectancy heuristic, or valence heuristic variants of the MGPM— provided the best account for the data. As in Experiment 1, I ran a hierarchical Bayesian parameter estimation implemented in Stan and RStudio. To compare the performance of models, I evaluated Watanabe-Akaike information criterion (WAIC), which is a measure of the estimated predictive error for a model (Watanabe, 2010). WAIC is regarded as a useful measure of comparison between models because in addition to considering how well the model predictions align with the observed data, it also considers model flexibility, to ensure that more parsimonious models are favoured over more complex models that have similar predictive power.  Lower WAIC values indicate a better trade-off between parsimony and predictability, so when comparing the performance of models, the model with the lowest WAIC is generally regarded to be the best performing model.

Like in Experiment 1, I chose uninformative priors (see Appendix B) because I had no prior beliefs about the distribution of parameters. Table 5 shows the WAIC values for each model. The deadline heuristic variant of the MGPM had the lowest WAIC, indicating that it was

Table 5

*WAIC values produced from the hierarchical Bayesian parameter estimation*

| MGPM Variant | WAIC | *SE* |
|---|---|---|
| Deadline heuristic | 34498.33 | 127.67 |
| Expectancy heuristic | 34665.39 | 125.84 |
| Valence heuristic | 34793.38 | 124.47 |
| Speed/accuracy trade-off | 34824.03 | 123.68 |
| Current | 34879.79 | 123.82 |

the best performing model. The next best model was the expectancy heuristic variant, followed by the valence heuristic variant, then the speed/accuracy trade-off variant and finally, the current MGPM. However, WAIC values were relatively similar across all models, with a difference in WAIC of only 381.46 between the worst performing model and the best performing model (as a comparison, Ballard et al., 2018 found a difference in WAIC of 9,554.93 between the best and worst performing model), indicating that there was only a small difference in the performance of each model. Parameter estimates for the best performing model, the deadline heuristic variant, are in Table 6, and this variant is plotted against the observed data in Figure 6 for interpretation.

Table 6

*Average subject-level parameter estimates for the deadline heuristic variant of the MGPM*

| | | 95% Credible Interval | |
|---|---|---|---|
| Parameter | *M* | Lower Bound | Upper Bound |
| Expectancy sensitivity normal ($\gamma_n$) | 0.66 | 0.18 | 1.49 |
| Discount factor (Γ) | 12.06 | 4.55 | 24.02 |
| Threshold (θ) | 0.76 | 0.46 | 1.22 |
| Expectancy sensitivity reduced ($\gamma_r$) | 0.38 | 0.19 | 0.65 |
| Valence sensitivity reduced ($\varphi_r$) | 0.46 | 0.46 | 0.84 |

*Note.* Valence sensitivity in the normal deliberation time condition ($\varphi_n$) is assumed to be 1 since this allows for valence to be calculated as normal in that condition (this was the same for all models where valence sensitivity was assumed to vary across deliberation time conditions, see Table 1).

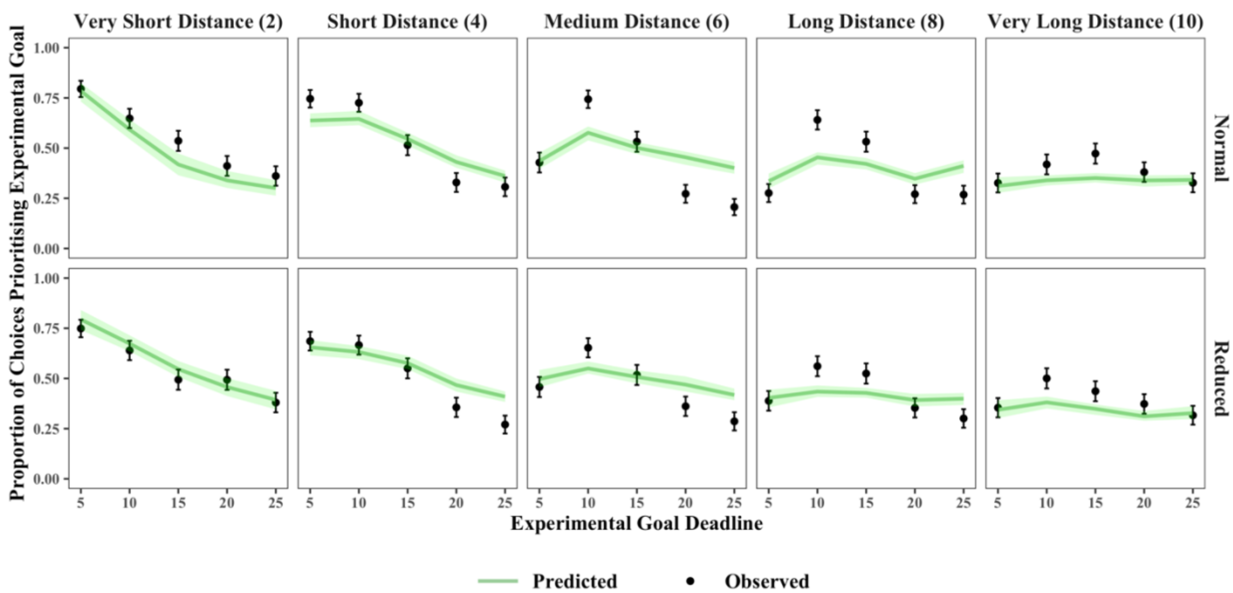


*Figure 6.* Observed Proportion of Choices Prioritising the Experimental Goal Compared with Predictions from the Deadline Heuristic Variant of the MGPM as a Function of the Experimental Goal's Initial Deadline and the Experimental Goal's Initial Distance. The top panel represents data and predictions from the normal deliberation time condition, the bottom panel represents data and predictions from the reduced deliberation time condition. Error bars represent the standard error of the observed data. The dark green lines represent the mean of the model's predictions. The green shaded area represents the 95% credible interval of the model's predictions.

## Discussion

The MGPM seeks to describe how people decide between competing goals. While the MGPM has been successful at describing this process in a variety of contexts, it assumes that these decisions do not change as a function of deliberation time. As described, this is a critical gap given that deliberation time cannot reasonably be ruled out as a factor involved in goal prioritisation decisions, as is acknowledged in the broader decision-making literature (Brown & Heathcote, 2008; Gigerenzer & Gaissmaier, 2011; Ratcliff & McKoon, 2007). This thesis therefore aimed to extend, and formally test the MGPM to include deliberation time.

Experiment 1 was a conceptual replication of Ballard et al. (2018) where distance from the goal and deadline were manipulated. As hypothesised and as was previously found in Ballard et al. (2018), participants tended to prioritise the goal with the nearest deadline, except when the discrepancy between distance and deadline was such that the goal would reasonably be perceived as unachievable. Furthermore, the current MGPM was able to provide an accurate account for this effect when its predictions were compared against the data, indicating that the model could generalise to the novel task used in this thesis. These results suggest Ballard et al. (2018) was successfully replicated, supporting the external validity of the current MGPM, and demonstrating that my novel experimental paradigm was sensitive enough to recreate Ballard et al.'s (2018) previously found effects of deadline and distance on goal prioritisation.

In Experiment 2, I investigated how these effects were influenced by deliberation time, in order to distinguish between two conflicting theoretical perspectives: speed/accuracy trade-offs and heuristics. Specifically, I developed four novel adaptions of the MGPM which integrated either a speed/accuracy trade-off, deadline heuristic, expectancy heuristic, or valence heuristic; to see if they could provide a better account for the observed data over and above the current

MGPM. Again, as in Experiment 1, participants tended to prioritise the goal with the nearest deadline unless distance was such that the goal would reasonably be perceived as too difficult to achieve. However, while this effect also emerged in the reduced deliberation time condition, there was a higher proportion of decisions prioritising the goal with the nearest deadline compared to when deliberation time was normal. When directly evaluating each model against the data, the deadline heuristic variant of the MGPM; which assumes people attend less to valences and expectancies and thus, proportionately more to deadlines when deliberation time is reduced—was best able to account for this effect compared to the current MGPM, and each of the other variants of the MGPM respectively.

**Theoretical Contributions**

These findings support existing multiple goal pursuit theory by demonstrating that deadlines, expectancies and valences were still integral for predicting goal prioritisation decisions, even when deliberation time was reduced (see Ballard et al., 2018; Ballard, Yeo, Neal, et al., 2016; Schmidt & Dolis, 2009; Vancouver, 2008; Vancouver et al., 2010). However, with less time to deliberate, the current study suggests that people attended less to expectancies (the likelihood of achieving a goal) and valences (the value of a goal) in favour of deadlines. I was able to extend the MGPM to account for this finding, by adjusting expectancy sensitivity and valence sensitivity such that they were constrained to be lower in the reduced deliberation time condition. This is in line with research into heuristic decision-making, which has found that people cope with time pressure by neglecting otherwise relevant information (Gigerenzer & Gaissmaier, 2011; Hafenbrädl et al., 2016; Todd & Gigerenzer, 2000).

This is an important finding in the context of broader decision-making theory, since I was able to distinguish between two conflicting theoretical explanations for the effect of deliberation time on decision-making. In particular, my results suggest that a heuristic approach provided a better explanation of participants' goal prioritisation choices over and above a speed/accuracy trade-off approach (e.g., Brown & Heathcote, 2008; Ratcliff & McKoon, 2007). Although the speed/accuracy trade-off variant of the MGPM improved predictions compared to the current MGPM, it did not perform better than any of the heuristic variants. Therefore, this suggests that integrating a speed/accuracy trade-off approach into the MGPM only minimally improved its predictive power and could not fully explain the effects of deliberation time on multiple goal pursuit in this study.

Instead, I found preliminary support that people relied on a "deadline heuristic" when deliberation time was reduced, which suggests deadline could be a particularly salient cue in multiple goal pursuit that participants attended to at the expense of valence and expectancy. This could be because deadlines offer important information about a goal but are computationally simple, and thus, are a useful cue when under time-pressure. Whereas evaluations of deadline only involve identifying the time available to achieve a goal, according to the MGPM, valences and expectancies are comprised of both the time available and the time required to achieve a goal; thus, requiring more mental computation than deadlines. Furthermore, since deadlines (through time available) contribute to evaluations of both expectancy and valence, one could potentially glean a partial estimation of valence and expectancy through deadline alone. This suggests that in addition to deadlines being easier to evaluate compared to expectancies and valence, people might regard deadlines to be highly informative.

My results are broadly consistent with Cognitive Load Theory, which would suggest that participants changed their decision-making strategy as a function of deliberation time because time pressure restricted their capacity to process information (Gigerenzer & Gaissmaier, 2011;

Paas et al., 2003). To further test the efficacy of this conclusion and inform a more comprehensive understanding of how cognitive resources influence the deliberation process, future research should investigate whether other types of cognitive load have a similar influence on goal prioritisation. For example, by concurrently manipulating working-memory during a multiple goal pursuit task (see Paas et al., 2003; Whitney, Rinehart, & Hinson, 2009). If people change their decision-making strategy as a function of deliberation time because their capacity to process information is reduced, other manipulations of cognitive load should elicit similar effects to those found in this study.

**Practical Application**

This thesis provided insight into how people might decide between multiple goals in contexts where deliberation time varies, which has important practical implications. In many applied settings, disproportionately attending to deadlines might not be an optimal decision-making strategy and could lead to serious errors in judgement. To illustrate this point, I will use the example of firefighting—a context where the time available to deliberate over competing goals fluctuates regularly and where the cost of errors is high. Imagine that a firefighting commander attending to a bush-fire must prioritise one of two areas of the fire: either area A, where the fire is spreading rapidly towards a small settlement; or area B, where the fire is spreading slowly towards a large city. Deadline is nearest for area A because the fire will reach area A first, but it would not necessarily be a wise decision to prioritise area A, given the greater potential cost associated with the loss of area B. Therefore, in this situation, reliance on a deadline heuristic would be problematic.

With the knowledge gleaned from this thesis, one could take measures that safeguard against the tendency to disproportionately prioritise the goal with the nearer deadline when deliberation time is reduced, to inform better goal prioritisation decisions. This could involve ensuring that valences and expectancies are presented in way that minimises computational strain, such that they are highly salient and easy to evaluate. The deadline heuristic variant of the MGPM could also be directly incorporated into broader applied systems to facilitate a better fit between automated models and human workers. Continuing with the firefighting example, fire behaviour models are often used when responding to bushfires, which integrate information such as topography, vegetation, wind, and other characteristics of the fire and its environment, in order to predict different aspects of fire behaviour (Beloglazov, Almashor, Abebe, Richter, & Steer, 2016; Jolly & Freeborn, 2017). The deadline heuristic variant of the MGPM could be directly incorporated into these models to identify when human operators are likely to be under-attending to critical information and adjust their output to ensure all relevant information is appropriately attended to.

**Additional Considerations**

One consideration is that our participants did not have any prior experience with the task, which might limit the generalisability of my findings in applied contexts where people have months or years of experience balancing multiple goals in that particular domain. This is an important consideration because heuristic decision-making is often highly context specific and driven by expertise. Indeed, experts in many domains use highly specialised heuristics which allow them to make fast, accurate judgements in conditions where novices perform poorly (Klein, 2015). For example, as a result of their expertise, medical practitioners have been found to use heuristics based on limited but specific patient information, which allow them to make highly accurate diagnostic decisions quickly (Marewski & Gigerenzer, 2012). To be clear, the results from the current study suggest people use a deadline heuristic in novel tasks; however, perhaps people do not prioritise deadlines on tasks they have experience in and, instead, the heuristics they use might be driven by their expertise within that specific domain. Therefore, it is important that future research investigates whether expertise influences the degree to which people disproportionately attend to deadlines, or whether more generally, the information that people attend to varies across applied multiple goal pursuit contexts.

Another consideration is that the deliberation time manipulation used in this thesis could have been too week to produce the full range of effects. Indeed, the difference in goal prioritisation between deliberation time conditions was very small in comparison to the effects of deadline and distance, which also meant that there was only a small difference in the predictive power of each model. This suggests that the overall magnitude of the effect of deliberation time on multiple goal pursuit could be very small and perhaps, might not bear much practical significance. However, this could also be because the task was relatively simple, so reducing deliberation time from 4.5 seconds to 1.5 seconds may not have substantially changed the task demands. To correct for this potential limitation, and to better understand the full magnitude of the effect of deliberation time on multiple goal pursuit, future research should attempt to induce a stronger manipulation of deliberation time. This could be achieved either by implementing a more complicated task such that the effects of time pressure are more noticeable, or by increasing the difference in deliberation time between conditions.

## Conclusion

In this thesis, I developed and tested a version of the MGPM that could explain how decisions to prioritise a goal are influenced by deliberation time. Specifically, I found that by integrating a heuristic approach which assumes people disproportionately attend to deadlines in response to time pressure, the MGPM could account for the observed tendency for people to be more likely to prioritise the goal with the nearest deadline when deliberation time was reduced compared to when deliberation time was normal. Therefore, this research offers novel insights into how people pursue multiple goals and has the potential to inform goal prioritisation decisions and mitigate errors in applied contexts that are characterised by fluctuating deliberation times.

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# Appendix A

*Current MGPM equations from Ballard et al. (2018)*

Valence:

$$V_k(t) = \max\left[k_{k1} \cdot d_k(t) + k_{k2} \cdot \frac{TR_k(t)}{TA_k(t)'}\ 0\right], \tag{1}$$

Where $V_k(t)$ is the valence for prioritising goal *k* at time *t,* $K_{k1}$ is a gain parameter that represents the importance of a goal's distance, $d_k(t)$ represents the distance from that goal, and $K_{k2}$ is a gain parameter that represents how important the time until a deadline is for that goal. $TR_k(t)$ is a variable that represents how much time an individual perceives is required to achieve the goal (i.e., *time required*), and is determined by distance to the goal and how much time one thinks it will take to reduce the goal's distance by one unit (i.e., expected lag, or α). $TA_k(t)$ is a variable that relates to how much time one thinks is available to achieve a goal before the deadline (i.e., *time available*), determined by the time until the goal's deadline.

Expectancy:

$$E_k(t) = \frac{1}{1 + exp[-\gamma \cdot (TA_k(t) - TR_k(t))]'} \tag{2}$$

Where $\gamma$ represents expectancy sensitivity, which is an individual's sensitivity to the discrepancy between time available and time required.

Expected Utility:

$$U_k(t) = \frac{V_k(t) \cdot E_k(t)}{1 + \Gamma TA_k(t)'} \tag{3}$$

Where $U_k(t)$ is the expected utility of prioritising goal $k$, and $\Gamma$ is the discount factor, which represents the degree to which an individual perceives a future deadline to be less motivating than a more immediate deadline.

# Appendix B

*Priors used for hierarchical Bayesian parameter estimations.*

Individual level parameters were gamma distributed so that they could only take on positive values. Group-level parameters were drawn from normal distributions that were constrained to only take on positive values. For group-level estimations, the means of the prior distributions were 0 and the standard deviations were 1.