Weighting waiting: A decision-theoretic taxonomy of procrastination and delay

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Abstract

Why do today, what you can fail to do tomorrow? Pacing, postponing, and ultimately procrastinating tasks are widespread pathologies to which many succumb. Previous research has recognised multiple types of delay, influenced by a myriad of psychological and situational factors. However, the main mechanistic explanation, which concerns temporal discounting of delayed rewards, only encompasses a subset. Here, we introduce a systematic taxonomy of delay and procrastination within a reinforcement learning framework in which these choices are samples from policies associated with decision-making tasks. The mechanisms driving delays are then closely tied to elements governing these policies, such as task structure and the (sub-)optimality of the solution strategy. Through a detailed analysis of real-world data on student engagement (Zhang & Ma, *Scientific Reports*, 2024), we illustrate how some of these diverse sources of delay can explain behavior. Our approach provides a theoretical foundation for understanding pacing and procrastination, enabling the integration of both established and novel mechanisms within a unified conceptual framework.

Keywords: procrastination, delay discounting, decision making, computational modeling, real-world data

"You may delay, but time will not."

\- Benjamin Franklin

1 Introduction

We frequently face the choice not only of what to do but also when to do it. In some cases, this choice is constrained by externally-imposed deadlines; in other cases, only internal factors come to bear. In general, we see very diverse patterns of engagement, either with or without deadlines, with some people acting at the first possible moment; and others at the last one, or even failing to complete on time or successively making and breaking commitments to act at later points. The more extreme cases are considered to be procrastination. Procrastination is widespread with some 80% of students and 20% of the general adult population affected (Steel, 2007). In fact, many lose money (O'Donoghue and Rabin, 2001), suffer negative consequences for their health (Sirois, 2007), and waste precious time due to delays. Most procrastinators want to do so less (O'Brien, 2002).

Myriad empirical studies have found a range of psychological and situational factors associated with procrastination. Some of these findings come from explicit measurements of delay in real-world tasks and experiments showing the influence of deadlines, reward timings, reward valence, and other components on the extent of procrastination (Bisin and Hyndman, 2020; Le Bouc and Pessiglione, 2022; Park et al., 2018; Reuben et al., 2015; Steel et al., 2018). Other studies employ questionnaires which query people about procrastination in the past, and find correlations with personality traits such as conscientiousness and neuroticism, and other psychological factors such as fear of failure, low self-esteem, achievement motivation, and clinical conditions such as depression and anxiety (Flett et al., 1995; Johnson and Bloom, 1995; Rozental and Carlbring, 2014; Schouwenburg and Lay, 1995). Studies have also asked procrastinators to report what they believe are their reasons for their behaviour (Grunschel et al., 2013).

These empirical studies have led to various attempts to classify types of procrastination. However, most mechanistic explanations for procrastination (and indeed some recent large-scale empirical data; Zhang and Ma, 2024) hinge on the concept of temporal discounting, the subjective devaluation of future reward with delay, relative to immediate effort. Such theories and models typically treat procrastination as the natural outcome of preference reversals engendered by non-exponential discount functions and associated with problems of self-control (Ainslie and Haslam, 1992; Laibson, 1997; Loewenstein and Elster, 1992). Perhaps most comprehensively, Steel (2010)'s temporal motivation theory (TMT) treats discounting as its main causal component, and integrates the various correlates found from empirical studies into a common scheme.

However, TMT does not cover all types of delay. We introduce a theoretical framework based on principles from decision-making and reinforcement learning (RL) that can offer a systematic categorization of the multifarious patterns of working over extended periods of time, and ultimately also procrastination. This categorization goes beyond temporal discounting. We interpret working patterns as trajectories of choices sampled from systematic ways of behaving ('policies') that are the solutions to suitable Markov decision problems (MDPs). This perspective provides a structured way of examining potentially optimal, approximately optimal, and frankly sub-optimal, routes to normative and problematic delays.

In the rest of the paper, we begin with a brief review of the empirical findings on, and theoretical approaches to, procrastination. Then, we introduce the MDP framework and discuss how working patterns and procrastination may be operationalised. Next, we propose a taxonomy of types and mechanisms of effective and ineffective working patterns based on the decision and policy structure. We integrate the many complementary understandings and routes to procrastination into the framework. Finally, we model data from a real-world task (Zhang and Ma, 2024) to illustrate the utility of the taxonomy in categorising and characterising diverse sources of engagement and delay.

2 Review of procrastination research

Perhaps the most common understanding of procrastination is that it is 'a voluntary delay of an intended course of action despite expecting to be worse off for the delay' (Steel, 2007). We focus our analysis on the first part of this definition, for both theoretical and empirical reasons. Theoretically, it has been noted that there can be strategic reasons to delay an action in order to improve performance (Chu and Choi, 2005). Equally, as we will see, there can be a competition between multiple internal 'selves' (Ainslie and Haslam, 1992), some of which expect to benefit, rather than suffer, from the delay, and so snooker the other selves by volunteering to wait. Empirically, quantitative data from large-scale studies such as Zhang and Ma (2024) and other task-based measures provide ample evidence about voluntary delays in the initiation and completion of tasks, but not about the evolving subjective expectations about the consequences of those delays or whether the delays were even deleterious at all. However, such delays are often referred to in the original studies as procrastination.

By contrast, questionnaire-based assessments of people's views and recollections about past and perhaps likely future behavior make more direct contact with expectations about the consequences of delay, and have been tied to affective and personality characteristics. These predominate in parts of the literature.

To square this descriptive circle, we model voluntary delay using data where delay was not necessarily deleterious. However, theoretically, we consider the extremities of problematic delay to constitute procrastination (which can also be accounted for by our models).

2.1 Empirical findings and interpretations

Task-based Measures Task-based measures of procrastination typically record the extent of delay in completing a task at hand. Based on the structure of the task, this could be the completion time relative to the earliest possible such time (Bisin and Hyndman, 2020; Reuben et al., 2015); or, for a task with multiple intermediate states, it could be the cumulative number of units of work completed by each relevant time step (Steel et al., 2018) or the mean completion time of each of the units (Zhang and Ma, 2024). Sometimes, studies rely on self-reports of completion to estimate delay (Ferrari and Scher, 2000; Kachgal et al., 2001). In more controlled tasks, one might measure the percentage of choices to delay instead of working earlier (Le Bouc and Pessiglione, 2022; Zentall et al., 2020). Such quantities often correlate negatively with task outcomes such as bad grades or missing deadlines (Park et al., 2018; Steel et al., 2018).

These measurements have been carried out in a variety of different conditions, from real life behavior and field studies to controlled laboratory experiments. Educational environments where students are required to complete assignments and coursework are commonly examined in procrastination research. Some studies directly measure the timing of completion or submission of these requirements (Bisin and Hyndman, 2020; Burger et al., 2009; Steel et al., 2018; Zhang and Ma, 2024), and the increasing use of online learning management platforms allows for more detailed data collection (Goda et al., 2015; Horton, 2021; Park et al., 2018; Sabnis et al., 2022). Procrastination is also investigated in other contexts, such as filling out forms (Le Bouc and Pessiglione, 2022), redeeming vouchers and checks (Reuben et al., 2015; Shu and Gneezy, 2010), and engaging in savings plans and other financial behaviors (Gamst-Klaussen et al., 2019). Controlled laboratory experiments often constrain choices to applying effort or doing a specific task immediately or at some delay for precisely measured rewards (Le Bouc and Pessiglione, 2022). Among the few animal experiments, Zentall et al. (2018)'s research explores how pigeons delay pecking for food rewards.

These studies have revealed characteristics of the environment and the context in which individuals find themselves that help predict delays. For example, tasks that are aversive in some way, such as being too effortful, anxiety-inducing or boring commonly lead to postponement (Ferrari and Scher, 2000; Kachgal et al., 2001). On the other hand, tasks that are considered interesting and those that require a greater variety of skills are less subject to procrastination (Ackerman and

Gross, 2005).

The timing of the rewards and punishments associated with the task exerts a particular influence over delays. This often occurs when benefits are temporally distant from the time of action. Examples include receiving grades for an assignment only at the end of the semester, a doctor's visit where the prevention of future harm is the only goal, or saving up for retirement where the fruits of prudence can only be enjoyed several years or even decades later (Rozental and Carlbring, 2014). However, people also procrastinate when rewards are available immediately on completing an action. For instance, people delay cashing a check for immediate money rewards they themselves chose over larger delayed rewards (Reuben et al., 2015); they put off redeeming gift vouchers at the risk of forgetting and expiry (Shu and Gneezy, 2010), and delay doing effortful actions for immediate rewarding outcomes (Le Bouc and Pessiglione, 2022). Zhang et al. (2023) showed that offering rewards immediately on completion, rather than at a deadline, encourages people to start and complete work earlier in a reading assignment task. However, even in their experiment, changing reward timing does not eliminate all procrastination. Furthermore, while most of these situations only consider tasks where there are rewards to be gained, real life presents many cases in which it is necessary to work to avoid a negative outcome, for example working to avoid failing an exam or losing money.

In accordance with this emphasis on timing, procrastination has long been viewed as a quintessential example of the sort of temporal inconsistency that is frequently studied in behavioral economics (Akerlof, 1991; O'Donoghue and Rabin, 2001). This starts from the definition of temporal discounting as the subjective diminishment of value with delay. Discounting the value of all options according to a exponential function of the delay with a single time constant or discount factor preserves a consistent preference between different options in time. This means that if the optimal decision at time t_1 is to perform an action at time $t_2 > t_1$, then, all else being equal, it remains optimal at time t_2 to perform that action. However, given the sum of multiple different exponential discount factors or a discounting function that is not exponential, there can be preference reversals, such that the optimal decision once the time is t_2 may be not to carry out the action after all (Ainslie and Haslam, 1992; Laibson, 1997; Loewenstein and Elster, 1992). In the context of procrastination, present-biased preferences for immediate gratification can cause one repeatedly to defer applying the effort that had previously been planned (O'Donoghue and Rabin, 2001). Related routes to such defections include discounting effort more steeply than reward, and hence underestimating how effortful the task will be in the future (Akerlof, 1991; Le Bouc and Pessiglione, 2022), or discounting reward from leisure more steeply than reward from work (Fischer, 1999). This literature is also concerned with whether or not a person with such inconsistent preferences is aware of them (naive or sophisticated) and how they solve the resultant self-control problem if they are indeed aware. A few studies have indeed found a correlation between discounting (preference for small, sooner rewards over larger, delayed rewards) and extent of procrastination on task (Reuben et al., 2015; Zhang and Ma, 2024).

Although there are ample examples in everyday life in which people procrastinate even in the absence of a deadline, including going to the gym or scheduling an appointment with the dentist, there does appear to be a special role for deadlines. Indeed, people often postpone tasks until they immediately loom, be it students rushing at the last minute to submit an assignment, researchers submitting to a conference, or employees filing taxes. The length and structure of the deadlines substantially influence the nature of procrastination. Knowles et al. (2017) show that people are quicker to fill in a survey if they are given one week or no deadline, as opposed to a whole month. Ariely and Wertenbroch (2002) found that students self-impose deadlines as a pre-commitment mechanism which improves their performance, although they are not as effective as externally placed, evenly-spaced deadlines. However, other studies showed that students complete requirements at a lower rate if there are self-imposed deadlines or externally specified intermediate deadlines for work (Bisin and Hyndman, 2020; Burger et al., 2009).

Deadline-based tasks have also been studied in animals. For instance, in temporal avoidance tasks, subjects have to perform an effortful action (e.g. jumping over a barrier) to avoid an aversive outcome (e.g. receiving a shock) within some limited time. Animals quickly learn to act to avoid shocks, but at least in some cases, delay their responses until close to the outcome (Hineline and Herrnstein, 1970). Zentall (2021) suggested that the anticipation of the aversive event intensifies over time, accompanied by increasing anxiety. Completing the task acts as a negative reinforcer by eliminating the anticipated aversive event, and thus, the longer the delay, the greater the relief, which reinforces procrastination. Zentall (2021) proposed that a similar mechanism might be at play in humans working (and procrastinating) towards an anxiety-inducing deadline or other such negative outcomes, although this remains to be tested. Experiments in pigeons have also shown that the animals prefer to defer an effortful action (e.g. pecking many times) for a positive reinforcer (e.g. food reward) (Zentall et al., 2020). One explanation could be the 'delay reduction theory' where stimuli and actions closer to a reward (such as the delayed pecks) are reinforced (Fantino et al., 1993; Zentall et al., 2020)

There are mixed findings about the relationship between procrastination and cognitive load, with the latter being manipulated by changing the cognitive demands of the tasks. Students who had to complete a harder versus easier Stroop task prior to a main study-based assignment completed less work initially, but slightly more frequently ended up finishing their main assignment (Burger et al., 2009). Ferrari (2001) found that procrastinators (identified by questionnaire responses) had lower accuracy on a task with higher cognitive load.

Some studies not only measure the the final time of finishing or submission of the task but also the course of work leading up to finishing (Gevers et al., 2006; Horton, 2021; Konradt et al., 2021; Steel et al., 2018; Zhang and Ma, 2024). This has allowed the shapes of work, also called 'pacing styles' (Gevers et al., 2006) to be characterised. In some cases, there are a variety of ways in which students distribute their efforts in time: 'early', 'deadline ', 'steady', 'U-shaped' and 'inverted-U-shaped' actions (Gevers and Claessens, 2008; Konradt et al., 2021). Others find that students complete most work towards the deadline (Horton, 2021; Steel et al., 2018).

Questionnaire Measures By far the most popular method of measurement involves self-reported scales and questionnaires. In contrast to task-based measures that estimate the extent of delay directly from individuals performing specific tasks, questionnaires rely on individuals recalling how they typically behave in similar situations. Although questionnaires introduce subjectivity and lack the specificity of task-based structures, they are more time and resource efficient, can be more robust by generalizing across multiple tasks, and can potentially assess subjective feelings about any delays.

Some established scales include the Procrastination Assessment Scale-Students (Solomon and Rothblum, 1984), the General Procrastination Scale (GPS) (Lay, 1986), Adult Inventory of Procrastination (AIP) (McCown et al., 1989), Decisional Procrastination Scale (DPS) (Mann et al., 1997), Irrational Procrastination Scale (IPS) (Steel, 2002), Pure Procrastination Scale (PPS) (Steel, 2010), etc. Items on these scales attempt to capture various aspects of procrastination behaviour including the difficulty to meet deadlines, rushing towards deadlines, delaying beyond what is intended, perceiving delays as unnecessary or unreasonable, feeling time has been wasted, and undesirable effects on performance or efficiency due to delay. There are also diary studies which collect periodic logs over time, gathering information about students' intentions, plans, achievements, and strategy use (Bäulke et al., 2021; Ferrari and Scher, 2000; Grund and Fries, 2018).

One validation of these measures is the generally negative association between the extent of delay or procrastination scores estimated from scales, and performance/outcomes on a wide range of tasks and real-life situations, including: missing deadlines (Schraw et al., 2007), lower grades and exam scores for students (Ferrari and Scher, 2000; Steel et al., 2018), worse health outcomes (Sirois, 2007), worse savings and financial outcomes (Gamst-Klaussen et al., 2019).

Personality correlates and cognitive and motivational factors Given the observation that procrastination has trait-like stability across time and contexts (Steel, 2007), there have been attempts to associate it with other trait measures of individual differences. In turn, these have been used to generate what are at least partial typologies for procrastination (Klingsieck, 2013; Yan and Zhang, 2022) .

The big-five personality framework has been particularly important in these attempts to find predictive factors (Digman, 2003). (Lack of) Conscientiousness and neuroticism are the most reliable correlates of procrastination. In particular, there is a negative correlation between facets of conscientiousness such as responsibility, self-regulation and self-control, organisation, discipline, achievement motivation and industriousness (Johnson and Bloom, 1995; Lee et al., 2006; Schouwenburg and Lay, 1995). Procrastination is a bit more weakly correlated with facets of neuroticism such as self-consciousness, low self-esteem, and impulsiveness; the latter being most strongly correlated among these factors Johnson and Bloom (1995); Schouwenburg and Lay (1995). By contrast, other big five personality traits (openness to experience, agreeableness, extraversion) are typically not associated with procrastination (Steel, 2007).

Over time, studies focused on the relationship between more specific motivational, cognitive and emotional factors and procrastination. Intrinsic motivation and need for achievement are especially anti-correlated with procrastination Grund and Fries (2018); Klingsieck (2013); Rozental and Carlbring (2014). Abilities and beliefs such as self-regulation, self-control and self-efficacy are also negatively related, while irrational beliefs such as fear of failure, perfectionism and self-handicapping are positively related (Lay et al., 1992; Pychyl and Flett, 2012; Solomon and Rothblum, 1984). Emotional factors include the preference for short-term mood repair and maladaptive coping strategies when faced with aversive tasks, where the resultant response is to avoid by delaying the task (Sirois and Pychyl, 2013; Sirois and Kitner, 2015). Finally, there are some positively correlated clinical factors such as depression, anxiety, rumination and ADHD (Constantin et al., 2018; Flett et al., 1995; Klingsieck, 2013). Note, though, the potential circularity stemming from the possibility that procrastination itself may influence an individual's mood, and increase the person's anxiety, stress, depression, and low self-esteem (Duru and Balkis, 2017; Ferrari, 1991; Rozental et al., 2022).

2.2 Integration

This brief review of research reveals that delaying is a complex phenomenon that occurs in tasks with a range of structures and characteristics and is associated with numerous personality, cognitive and motivational correlates. A pertinent question arises: do multiple mechanisms drive procrastination in different situations, or do these varied correlates stem from a single underlying cause?

Steel and König (2006) put forth the temporal motivation theory (TMT), which treats discounting as a common cause. According to TMT, motivation (which would reduce procrastination) is directly proportional to value and expectancy of reward and inversely with delay and discount rate.

Hence, procrastination is correlated with lack of self-efficacy since this signals low expectancy; it is correlated with motivational factors such as intrinsic motivation and need for achievement which indicate high value of task; and correlations with impulsivity are explained by the discount factor. In this framework, impulsivity then forms the common base for all procrastination, while neuroticism and extraversion affect how each type is manifested explaining other correlations (Schouwenburg, 2004).

While TMT has the advantage of being a common framework integrating different correlates, it runs the danger of overlooking other possible mechanisms that might be mediating the same correlations and other types of problematic delays that do not involve deferring on plans to work. Thus, an alternative tradition posits that procrastination may have multiple explanations, interpreting the various empirically found correlates as indicators of different underlying mechanisms. There have been many attempts to construct typologies based on these correlates. One of the earliest proposed classifications was between arousal, avoidant and decisional procrastinators (Ferrari, 1992; Ferrari and Emmons, 1994). These respectively refer to procrastination for thrills, fear of failure, and the tendency to defer making decisions (or indecision). However, the durability of this concept rather outstrips the supporting evidence (Steel, 2010). Other studies analysing questionnaire responses have found factors or clusters corresponding to anxiety and neuroticism, impulsivity and disorganisation, low-energy and depression among procrastinators (Lay, 1987; McCown et al., 1989). Some studies analyse the reasons provided for procrastination, which then forms the basis for classification. Most commonly, anxiety or fear of failure and task aversiveness are cited as reasons for procrastination (Grunschel et al., 2013; Solomon and Rothblum, 1984). However, the theoretical or mechanistic bases of these types are not clear.

Here, we aim to construct a common, theoretical framework that captures broad families of engagement in working, allowing types of procrastination to be characterized in a systematic manner. To this end, we base our taxonomy on formal treatments of decision-making over, and about, time.

3 Taxonomy

One of the most general ways to formalize decision making over time is to use the framework of Markov decision processes (MDP; Kaelbling et al., 1996; Sutton and Barto, 2018). These model sequential decisions with incomplete information, where a present choice can affect future rewards and possibilities for action. In Section 4.2, we provide a mathematical description of MDPs that we use to account in detail for the delaying behaviour of participants in the task we use for illustrative purposes. Here, we provide a qualitative description.

3.1 MDP

An MDP is defined by states, actions, transitions, immediate costs and rewards, and a notion of a long-run optimization objective. States characterize an individual's position in the underlying environment. This could include aspects of the tasks, the state of their completion and the time to a deadline. The individual chooses actions, such as working on a particular task; this then engenders transitions, which characterize the change in the state (for instance, getting closer to completion). Transitions can be stochastic, if, for instance, success at a task is not guaranteed. States, actions and transitions are associated with costs, for instance, of effort, and rewards, often provided by the experimenter or the environment. The individual then has the goal of optimizing their expected long run summed net utility (i.e., rewards minus costs), where, from the perspective of the current state, utility to be received in the future may be discounted, i.e., worth less than utility to be received soon.

This goal is realized by a policy, which is a systematic mapping from the state (or the individual's subjective belief about the state) to an action (i.e., how much to work on which task) or a probability distribution over actions. It is very hard to compute an optimal policy; many suboptimalities, including aspects of procrastination, arise from suboptimal policies and heuristics.

Individuals typically solve multiple tasks over a long period, and these can interact. For instance, by trying and failing at a current task, an individual might realize that they are incompetent, and so would likely also fail at future tasks – something associated with low utility. They might therefore employ a heuristic to deflect blame for failing.

3.2 Classes of delay

Under this MDP framework, the temporal pattern of working is the output of the policy in response to the observations or states, and in the light of the utilities. As we will see in section 4, details matter – for instance, Zhang and Ma (2024) pointed out that the convexity of the immediate cost of working as a function of effort helps determine whether it is better to work in minimal or maximal aliquots. However, the studies we described focus particularly on delays, which will be the focus of our taxonomy.

There can be systematic ways in which an agent might settle on a wrong behavior (policy) in terms of optimising the long run utility. This is particularly relevant for procrastination, since we are not concerned with just any decision to delay, but rather delays that lead to problematic consequences. One common type discussed in the context of procrastination arise from processes such as non-exponential discounting that lead to time-inconsistent preferences and thereby defections on initial intentions. However, there are other ways to choose suboptimally. For instance, computing a wrong solution to the decision problem at hand may result in delays with negative consequences. Here there is no defection, but the original intention is itself problematic. This can readily occur because of computational or resource limitations that necessitate approximation or the use of heuristics rather than the exact solution. Alternatively, an individual might incorrectly estimate different elements of the problem such as the amount of effort required to complete a task the degree of controllability of the environment; they may also suffer biases about their own ability.

Problematic behavior can also arise from optimising a poorly chosen objective. Examples include discounting delayed rewards too steeply or prioritising protection of self-esteem over successful completion of work. Finally, the individual may suffer gaps in their knowledge or be uncertain about various aspects of the task, which means they must find a solution ignoring such unknowns or defer engagement in the task until they have been clarified. This could inevitably lead to a delay not only in working but also in making a commitment to the time at which they will work. In both cases, the agent might be doing its best given the uncertainty or adopted utility function, but this might still lead to negative consequences.

We use the structures of commitment and compliance implied by this variety of optimal and sub-optimal policies to classify problematic delays. We identify four broad classes :

1. Deliberately delaying a task, leaving insufficient time to complete it satisfactorily before a deadline, or losing time.
2. Delaying acting to a later time in spite of intending to act earlier.
3. Not committing to a time of action and hence missing a deadline or losing time.
4. Initially abandoning a task, but then later doing it nonetheless.

Delays can come at the start, continuation or completion of a task. So for example, a job may be started promptly, but the subsequent work might be procrastinated. Furthermore, the delays can be rational or irrational at the time that they are chosen.

These choices can be visualised as a decision tree, as shown in Figure 1. The structures of the four types of delays are shown as schematic diagrams accompanying their respective branch of the tree.

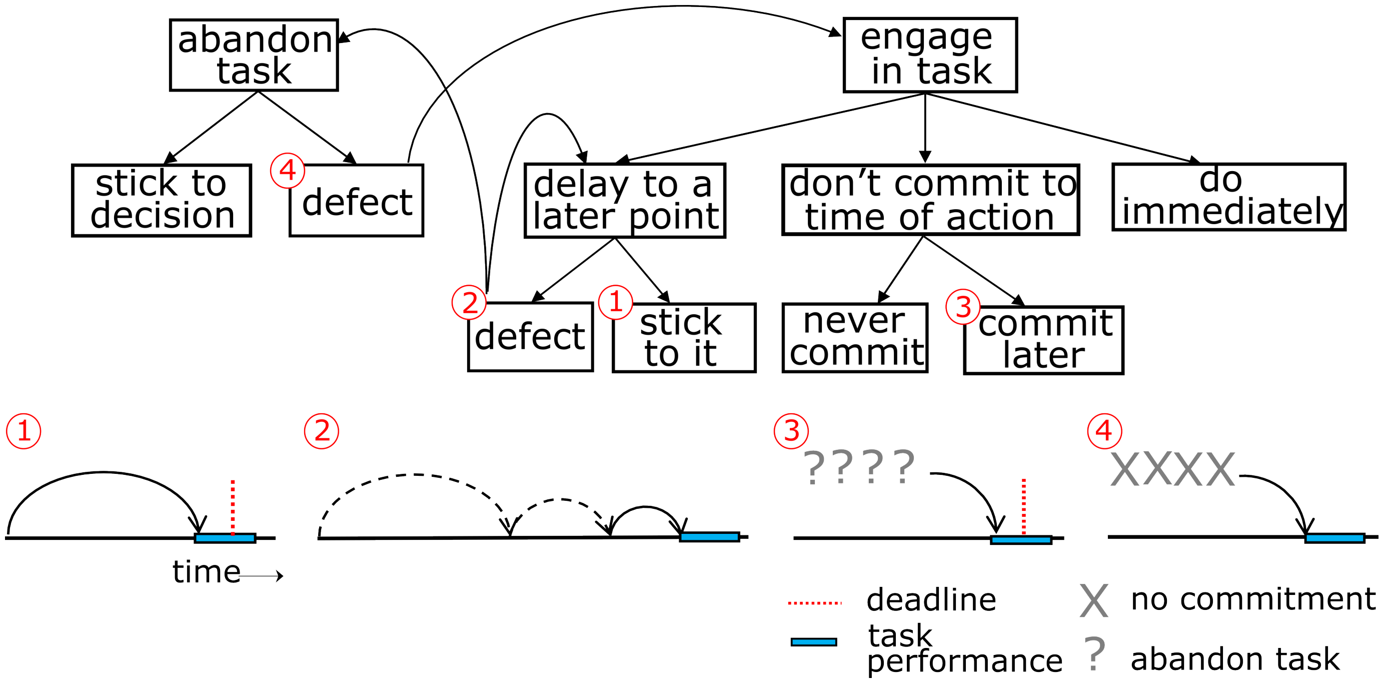

Figure 1: An illustration of the type of delays in the form of a tree that constitutes procrastination. Possible explanations for each branch point can aid our understanding of particular instances of procrastination. The numbers refer to Section 3.2.

3.3 Mechanisms

This classification naturally induces a taxonomy of explanations for ways that procrastination can emerge. For each branch of the decision tree, we can ask about possible reasons for its associated choice: Firstly, what persuades someone to engage in a task at all and not abandon it? Do they commit to a time of action or not? If they do not, what makes them do the job later? Why would someone commit to doing it too late? What are the mechanisms that drive defections on these plans? The possible reasons for each choice to delay can span optimal or sub-optimal policies. These explanations map onto the assortment of optimal and suboptimal policies we discussed.

For convenience, we use an asterisk to indicate the mechanisms that we are able to illustrate in Section 4 with a substantial real-world task from Zhang and Ma (2024).

Why engage?

Why is it worth engaging in a task and not abandoning it all together (even if at a delay)? One motivator is the potential reward (a good grade, better health, internal satisfaction) to be gained on completing the task successfully or to avoid a negative outcome on non-completion (bad grade, losing money, internal costs like feeling of failure). These positive and negative benefits then have to be weighed up against the anticipated efforts required, be they physical or cognitive energy, money or time required, including any **non-linearities** in the accrual of costs.

It is then the changing objective and subjective weightings of these various factors that can lead to delays and defection.

Why commit but late?

In the first type of delaying, an individual commits to a delay and adheres to it, but the planned delay is itself detrimental in terms of not leaving sufficient time to finish the task or losing potential reward, resources or time which cannot be recovered. This can happen because of miscalculations in the attempt to find a good plan or optimisation of an unfortunate objective. We discuss some possible explanations below, some derived from past explanations, others novel.

*Discounting: Discounting is the subjective reduction of value with delay. As we discussed in Section 2, even with time-consistent, exponential discounting, immediate rewards will be preferred over temporally distant ones - hence, working on a task with distant rewards (like an assignment that is graded after the deadline) is procrastinated in favor of immediate temptations.

*Bias about abilities: Critical to the choice to embark on a task late (e.g., because of discounting) is an accurate estimate of the time it will take to finish the task (and of the likelihood of finishing it in the first place). An overestimation of one's efficacy or belief that a task is easier than it is (amounting to an erroneous transition function), might result in a decision to start later than required, contributing to procrastination. This is related to the planning fallacy where past difficulties are ignored, leading to unrealistic goal setting (Rozental and Carlbring, 2014). Conversely, a belief in lower efficacy might lead one to start earlier to ensure better chances of finishing the task in time (and could thus be a component of a training strategy to counter untoward delays).

Ego protection: Self-handicapping has been found to be correlated with procrastination (Lay et al., 1992). As mentioned above, someone anticipating failure or under-performance at a task could plan to delay it long enough or engage in unrelated tasks in an act of self-handicapping, setting themselves up for failure. This allows them to deflect blame to the act of starting late rather than their inability, preserving an aspect of their own reputation in the process. This is a case where the utility function is skewed to managing emotions and self-esteem rather than performance on an important task.

Relief: Avoiding a negative outcome can itself be reinforcing, providing relief that a loss has been averted. When one has to perform a task to avoid a delayed negative response, as (Zentall, 2021) suggests, anxiety might intensify the closer one draws to the the aversive event and so too the relief obtained from averting it, driving delayed performance. Mapping this mechanism onto the MDP requires an heuristic, for instance associated with cognitive control (Lloyd and Dayan, 2019).

*Specific anticipation of a better future: Delays might result from the (correct or incorrect) belief that there will be a more opportune time in the future for more successfully or more efficiently completing the task. For example, people might anticipate improvements in their effectiveness as the deadline approaches incentivising delays (Ferrari, 1992). While this could still be the optimal decision in terms of utility, the delay might lead to subpar performance or a lack of completion because of insufficient time.

Avoiding information: People could be worried that a task will turn out to be more difficult than they thought (for example, in terms of effort required or their own skill level). Hence, they could delay starting a task to avoid finding information that would confirm their fears. Avoiding the task altogether might have serious consequences. The benefit of doubt is the possibility that a positive outcome can be gained, while resolving uncertainty eliminates this. In short, people might delay resolving uncertainty due to a pessimistic expectation.

Why defect?

The next question is why renege on an intended course of action, whether it is delaying in spite of intending to act earlier, or re-engaging despite initially abandoning the task. A classic explanation for such defections relies on inconsistent discount factors, but we also suggest two other reasons.

*Non-exponential discounting: As we discussed in Section 2, when the temporal discounting function is not a single exponential (including the sum of multiple exponential functions), there can be reversals in preferences between options in time (Ainslie and Haslam, 1992; Laibson, 1997; Loewenstein and Elster, 1992). For our purposes, this means that a decision to work on a task in the future can be defected upon closer to the time of working.

Unexpected changes in task environment: Unexpected changes in the task or some aspect of the environment can also drive defections on initial plans, which were made without awareness that these changes would occur. This can mean going back on the intention to act when the anticipated suitable conditions do not arrive or deciding to work due to unexpected improvements, despite initially deciding to abandon the task. Story et al. (2014) discuss evidence for preference-reversals that might occur due to changes in the environmental or motivational states that may not have been foreseen and not necessarily due to hyperbolic discounting. For example, people prefer to avoid invasive anesthesia many weeks ahead of an operation but their preferences reverse at the time of operation in a painful state in which the utility of anesthesia may be higher (Christensen-Szalanski, 1984).

Forgetting: Human memory is limited and fallible. Forgetting to perform an action one has planned in the past is yet another route to defections. One might remember to complete the action later on, effectively introducing a delay and hence procrastinating, or one might miss the opportunity to act altogether.

Why not commit?

Finally, people might not commit to a time of action in the first place and hence lose time. We propose that various types of uncertainty might play a role in this type of delay.

*Waiting for an uncertain opportune time: There might be uncertainty regarding when a more favourable circumstance or environment may arise. This can lead to a decision to put off doing a task now and wait for more suitable circumstances where performance would be better. For example, this might be due to uncertainty about whether one might be more motivated in the future, whether a problem might go away saving effort or whether a more interesting alternative might arise, manifesting in a non-commitment to act until better conditions are in sight. A potential danger with this is that the better future might never arrive or arrive too late (for a deadline), or the circumstances might actually get worse with time without action. In an MDP, this uncertainty could arise from probabilistic transitions between states.

The difference from ’Specific anticipation of a better future’ is one of subjective (un)certainty. There, the individual plans for, and so commits to, a particular better moment in the future. Here, the individual is unsure, and so fails to commit.

Waiting for information: When some aspects of the task are uncertain, it might make sense to collect more information before working, especially when a decision is irreversible. Some examples could be waiting to see if a medical problem can be mitigated without an expensive intervention, or delaying submitting a paper in the hope that it could be made better. This could lead to repetitive delaying until ‘enough’ information has been acquired. These mechanisms could correspond to the resolution of uncertainty about the state, transition or reward functions in a (partially observable) MDP.

4 Illustration

Although procrastination is very widespread, sources of large-scale evidence about task performance and abandonment that could be used to illustrate and interrogate the taxonomy are, unfortunately, not. Most of the data come from academic settings in which students have to complete various course components before deadlines, allowing exploration of mechanisms that involve deadlines only. Furthermore, the bulk of the students typically finish in time, again limiting the examination of the more extreme forms of delay and procrastination, and are not invited to report their subjective expectations about the costs or benefits of any of their delays.

Nevertheless, since the taxonomy describes forces shaping the allocation of work over time, we can use it to elucidate the patterns of working, even when they are successful. Thus we turn to what is, to our knowledge, the largest, open-source, dataset (Zhang and Ma, 2024) which reports the participation of students in mandatory psychological experiments over the course of a semester.

We use the taxonomy to construct six models that could explain reasons behind students' decisions to delay, and in general, to allocate work across the semester. These models pick out various of the mechanisms described in the taxonomy and span the different types of delay, from sticking to a wrong commitment, to defections and non-committing and a range of sub-optimal to optimal policies. While more detailed experiments and manipulations are required to tell apart the models, we show that all of them constitute plausible explanations of students' temporal choices.

4.1 Task and data

Zhang and Ma (2024) collected data from 194 bachelor students in a psychology course who had to participate in at least 7 hours of research experiments by the end of a 16 week semester to receive course credit. Each experiment lasted for 0.5, 1, 1.5 or 2 hours, so 0.5 hours defines a unit of work, with the students having to complete at least 14 units. Research participation above 14 units contributed $1/8^{th}$ of a grade point per unit up to a maximum of 8 extra units. The data for each student consist of the day of completion of each experiment, along with its length.

We noted that a consensus definition of procrastination requires delays have to have *expected negative consequences*. The only such consequence evident in the data would be a failure to complete the minimum requirement of 14 units; and this is seen in only three of the students. Many more students did not complete the 8 extra units for which they would receive limited extra credits; but we do not know whether they would consider this to be deleterious. However, as we shall see, examining the mechanisms governing students' distribution of work through the semester and their decisions to work later than earlier is instructive of their reasons for procrastination, where there are negative consequences for delay.

The original study, Zhang and Ma (2024) only included 93 students who completed exactly 7-7.5 hours, to avoid confounds in their metric of procrastination (which differs from the above). Their metric averaged the time taken to complete each unit of the task and hence they defined the extent of procrastination as the extent to which each unit was delayed relative to the start of the semester. After the course ended, students were asked to participate in an online delay discounting task. Although it was long suspected, their results are the first to report a positive correlation between the estimated discount rates and the extent of procrastination.

For our purposes, we only exclude students who dropped out and those who completed more than 22 units. This left us with 160 subjects. We first analysed students' patterns of work allocation and completion. We normalised the trajectories by the total number of credits completed, since students completed different numbers. Then, we performed k-means clustering with a Euclidean distance metric on the normalized trajectories. As expected, the within cluster sum of squares decreases with the number of clusters. Using the elbow method (see Supplementary Figure 8), we identified the 8 clusters shown in Figure 2 that capture a variety of patterns of work allocation in the task, possibly reflecting different strategies. In line with research on pacing styles (Gevers et al., 2006; Konradt et al., 2021), we found five broad styles of pattern: early completion (clusters 1, 2, 3); steady completion (clusters 4, 5); working at the beginning and end (cluster 6); performing the bulk of work at an intermediate point (cluster 7); and completion towards the deadline (cluster 8).

4.2 Models

We formalise the task mathematically using the framework of Markov Decision Processes (MDPs). We hypothesise six different models that might explain the various patterns of working which we also formalise using MDPs.

An MDP consists of the decision maker (agent) that can partially control the dynamics of environment through its actions and the environment in which the agent is situated in, consisting of the rewards (and their timing), task dynamics, and other characteristics of the task. Mathematically, an MDP is a 4-tuple comprising of: the set of states of the environment an agent might occupy ($\mathbf{S}$); the set of actions available in each state ($\mathbf{A}_{s_t}$); the transition probability of going to a state s_{t+1} on taking an action a_t in state s_t ($\mathbf{P}(s_{t+1}|s_t, a_t)$); and the reward function defining (positive or negative) utility obtained on taking action a_t in state s_t and transitioning to state s_{t+1} ($\mathbf{R}(s_t, a_t, s_{t+1})$).

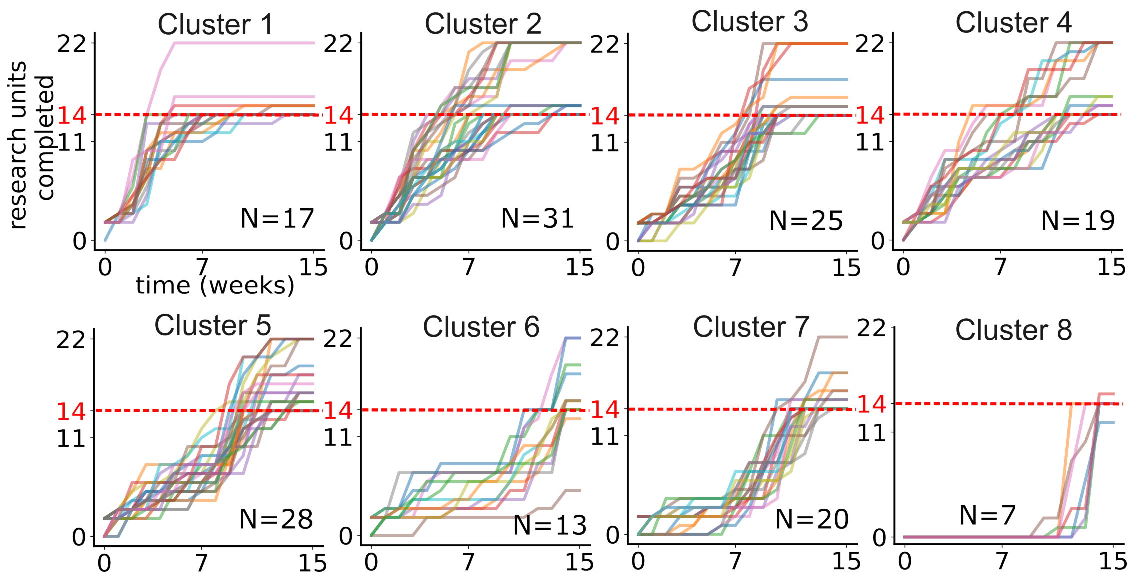

Figure 2: Eight clusters extracted using k-means represent various styles of work allocation by students in a real-world task (Zhang and Ma, 2024). The plots display the cumulative hours of work completed each week of the semester. The threshold of 14 units (7 hours) is marked in red.

In these formal terms, the specific task in (Zhang and Ma, 2024) is as follows:

1. Time horizon $\mathbf{T}$: 16 weeks ($0 \leq t \leq \mathbf{T} = 15$) to complete at least 14 units, and up to 22 units, of work.
2. States $\mathbf{S}$: ($\{0 \leq s_t \leq 22\} \times [0, T]$) indicating the number of units completed s_t and the week t.
3. Actions $\mathbf{A}_{s_t}$: ($0 \leq a_t \leq 22 - s_t$) number of units the agent completes in a week.
4. Transition probabilities $\mathbf{P}$: binomial success probability or efficacy ($\boldsymbol{\eta}$) governing the actual number of units completed (out of a_t units). This parameter essentially controls how many weeks it takes to complete a unit, in other words, the average rate of unit completion. This quantity is not directly apparent in the data – and so we use it to encompass factors such as uncertainty about how long other tasks take, and how effective a student is in organising their time. The Binomial transition probabilities are given by:

$$\mathbf{P}(s' \mid s, a) = \binom{a}{s' - s} \boldsymbol{\eta}^{s'-s} \, (1 - \boldsymbol{\eta})^{a-s'+s}$$

5. Reward function $\mathbf{R}$:

    i Effort costs: immediate cost, $\mathbf{R}_{\text{effort}}(a) = \mathbf{R}_{\text{effort}} \; a^{\mathbf{k}}$ for performing a units of work in a week, where $\mathbf{k}$ controls the concavity or convexity of the cost of effort, making it either easier or harder to execute multiple units (Zhang, 2024)

ii Reward for shirking: immediate reward, $\mathbf{R}_{\text{shirk}}(a) = 22 - a$ for every remaining unit of time used not to work but for an alternate task such as other university work, relaxing, chores, etc.

iii Reward for working: delayed or immediate reward, $\mathbf{R}_{\text{unit}}$ for every compulsory unit of work completed (delivered only if 14 units have been completed) and $\mathbf{R}_{\text{extra}}$ for every optional unit completed beyond 14 units

iv Reward for interest: $\mathbf{R}_{\text{interest}}$ in our final model ('no-commit') for completing rarely occurring, but interesting tasks. Please refer to Section 4.2.1 for more details.

Additionally, we have,

6. Policy function: given the task structure, we find a policy by optimising the corresponding objective using dynamic programming-based algorithms detailed in the methods Section 6. This gives rise to a so-called state-action value function $Q^*(s_t, t, a_t)$, which is the long-run discounted value of working a_t at state s_t on week t. We then consider a probabilistic policy given by the softmax function, with the inverse temperature, $\boldsymbol{\beta}$ controlling the degree of determinism:

$$\pi_t(a_t|s_t) = \frac{e^{\boldsymbol{\beta} Q_t^*(s_t,a_t)}}{\sum_b e^{\boldsymbol{\beta} Q_t^*(s_t,b)}}$$

7. Discount factor $\boldsymbol{\gamma}$: weights the rewards according to their delay, implying that sooner rewards and costs are valued more than delayed rewards in the resultant utility function.

4.2.1 Simulations

Noting that, as expected for a dataset of this sort, almost all participants hit the deadline, we sought to model potential causes of the varieties of ways that the students allocate effort over time. We propose the following six explanations for these patterns.

Before examining how well these models fit the data, we analyze their behavior and patterns through simulations under various conditions, exploring the effects of different parameters on performance. For each set of simulations, we plot the average time to cross the threshold of 14 units as a measure of delay and average rate of reaching 14 units or completion rate (averaged across 1000 runs). In addition, we show mean and sample trajectories of work (also averaged across 1000 runs) for some example parameters for each model. By default, we set the parameters as follows (unless mentioned otherwise): $\boldsymbol{\eta} = 0.8$, $\mathbf{R}_{\text{unit}} = 4$, $\mathbf{R}_{\text{extra}} = \frac{\mathbf{R}_{\text{unit}}}{4} = 0.5$, $\mathbf{R}_{\text{shirk}} = 0$, $\mathbf{R}_{\text{effort}} = -0.3$ and $\boldsymbol{\beta} = 5$. We selected values of rewards and efforts in a way that the net utility

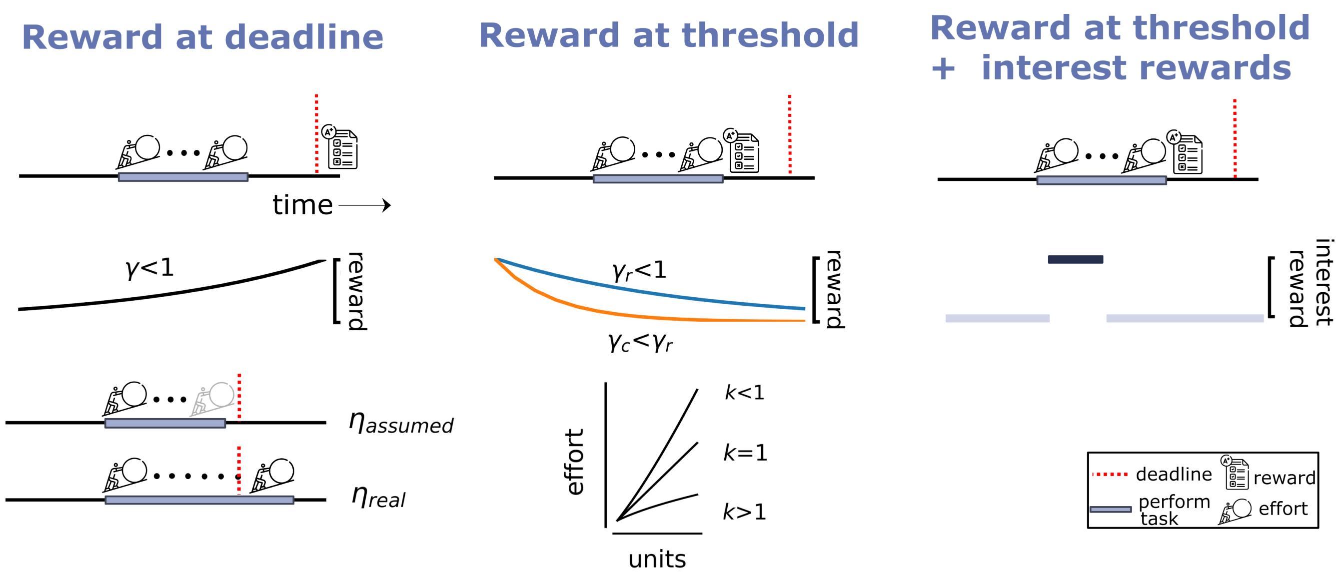

Figure 3: Illustration of model components and mechanisms. Students might perceive rewards for completing the requirements *at the deadline*, at the end of the semester. Alternatively, they might perceive rewards to come as soon as requirements are met, *at the threshold*. In addition, students might be waiting for uncertain and rare, interesting tasks to work on, which have extra *interest rewards* in our models. Discounting of delayed rewards ($\gamma < 1$), steeper discounting of efforts than rewards ($\gamma_c < \gamma_r$), mis-estimation of own efficacy ($\eta_{assumed} \neq \eta_{real}$), and non-linear scaling of efforts with amount of work ($k > 1$ or $k < 1$) are computational components of our models that influence extent of delay and patterns of engagement.

still makes it worthwhile to work, while preventing the effort from becoming overly inexpensive. This ensures the need to balance rewards and efforts, optimizing work distribution rather than promoting continuous work until task completion. We opted for a relatively high value of β to ensure that the trajectories are not overly noisy and accurately reflect the underlying policy, while still capturing the inherent variability in people's decisions.

4.2.2 Reward at deadline

In the first three set of explanations, the reward for completing a minimum of 14 units (or more) is assumed to come at the deadline at the end of the semester.

Temporal discounting of delayed rewards leads to delays in working; 'basic': In the first model, there is a common discount factor for positive and negative rewards. Firstly, in the absence of discounting ($\boldsymbol{\gamma} = 1$), rewards have the same value irrespective of delay. When $\eta < 1$, to ensure all units are completed in time, it is better to work first before shirking as long as the net value of working is higher than shirking, leading to early completion as demonstrated in the example trajectories in the lower panel of Figure 4B. When $\eta = 1$, it is equally good to work or shirk on each timestep. Further, the task is completed later as the efficacy ($\boldsymbol{\eta}$) decreases, shown in the lighter blue lines in Figure 4A. This occurs because, although the task is initiated promptly in all scenarios, lower efficacy results in more time being required to complete each unit of work.

In contrast, when $\boldsymbol{\gamma} < 1$, there is a temporal preference for putting off paying effort costs to secure a distant reward (which is discounted). Thus, delays become longer as $\boldsymbol{\gamma}$ decreases, and for low enough $\boldsymbol{\gamma}$, work is deferred to the latest possible time with completion rates dropping below 1 for lower efficacies (for example, for $\boldsymbol{\gamma} = 0.3, 0.6$ shown in the inset in Figure 4A). This leads to deadline-completion patterns as shown in the example trajectories in the upper panel of Figure 4B. Further, increasing the magnitude of effort costs of work leads to greater delays since delayed rewards no longer seem to justify the heightened effort, depicted in Figure 4C.

Notice that while there are delays in starting and hence completing the task at lower discount rates, delays lead to a drop in completion rates only in the extreme of cases, where efficacy is very low or costs of effort are very high. Hence, procrastination might be thought of as an extreme case of delay where there are negative consequences, with similar mechanisms explaining both. This is also true of the remaining mechanisms.

Gaps between real and assumed efficacy causes mis-estimation of delay; 'eff-gap': So far, we assumed agents calculate their best course of action based on perfect knowledge of their abilities. In the 'efficacy-gap' model, the agent has an estimate of its efficacy ($\boldsymbol{\eta}_{\text{assumed}}$) that may differ from the real efficacy ($\boldsymbol{\eta}_{\text{real}}$). When delayed rewards are discounted (here $\boldsymbol{\gamma} = 0.9$), it is optimal to start working earlier for lower efficacies to ensure there is enough time to finish the task. Hence, when the efficacy is underestimated ($\boldsymbol{\eta}_{\text{assumed}} < \boldsymbol{\eta}_{\text{real}}$), the task ends up being completed earlier than if the agent had correctly estimated $\boldsymbol{\eta}$, depicted in Figure 4D. This results in sigmoid-shape patterns, where the task ends up being completed at an intermediate time point as shown in the the example trajectories in Figure 4E. And conversely, overestimating efficacy ($\boldsymbol{\eta}_{\text{assumed}} > \boldsymbol{\eta}_{\text{real}}$) contributes to larger delays in work, even reducing completion rates for low $\boldsymbol{\eta}_{\text{real}}$ as seen in the inset.

Non-linear effort functions affect extent of delay; 'conv-conc': In the 'convex-concave' model, the effort function is no longer necessarily linear in the number of units worked. Every additional unit might be less effortful or alternatively, more effortful due to vigour costs (Niv et al., 2007). Zhang et al. (2023) operationalised this non-linearity as an exponent ($\mathbf{k}$) in the number of units of work. When $\mathbf{k} < 1$, indicating that the effort function is concave, there is an incentive to complete many units of work in a single week because it is more cost-effective per unit than distributing the work over multiple days. This improves completion times as shown in Figure 4F. $\mathbf{k} = 1$ is the case we considered before with linear costs. Finally, when the effort function is convex ($\mathbf{k} > 1$), it is better to spread work out, as doing many units in a single week is costly. This leads to flatter trajectories (Figure 4E; lower panel). Hence, it requires more time to finish as shown in Figure 4F.

4.2.3 Reward at threshold

In the previous three models, the rewards are obtained at the end of the semester. However, there is some ambiguity regarding reward timing, since some students might perceive rewards as arriving immediately upon completing the requirement, rather than at the end. We consider this possibility in the remaining models.

While immediate rewards eliminate delays due to discounting, convex effort functions lead to delays in working; 'imm-basic': In the 'imm-basic' model, all components remain the same, except that reward is provided as soon as the requirement is completed and immediately with the extra units as they are completed. When $\boldsymbol{\gamma} = 1$, the task is completed promptly as before, since present rewards are as valuable as delayed rewards. In contrast, with discounting $\boldsymbol{\gamma} < 1$, there is no delay in work since the rewards are immediate. There is even an opposite tendency to get the

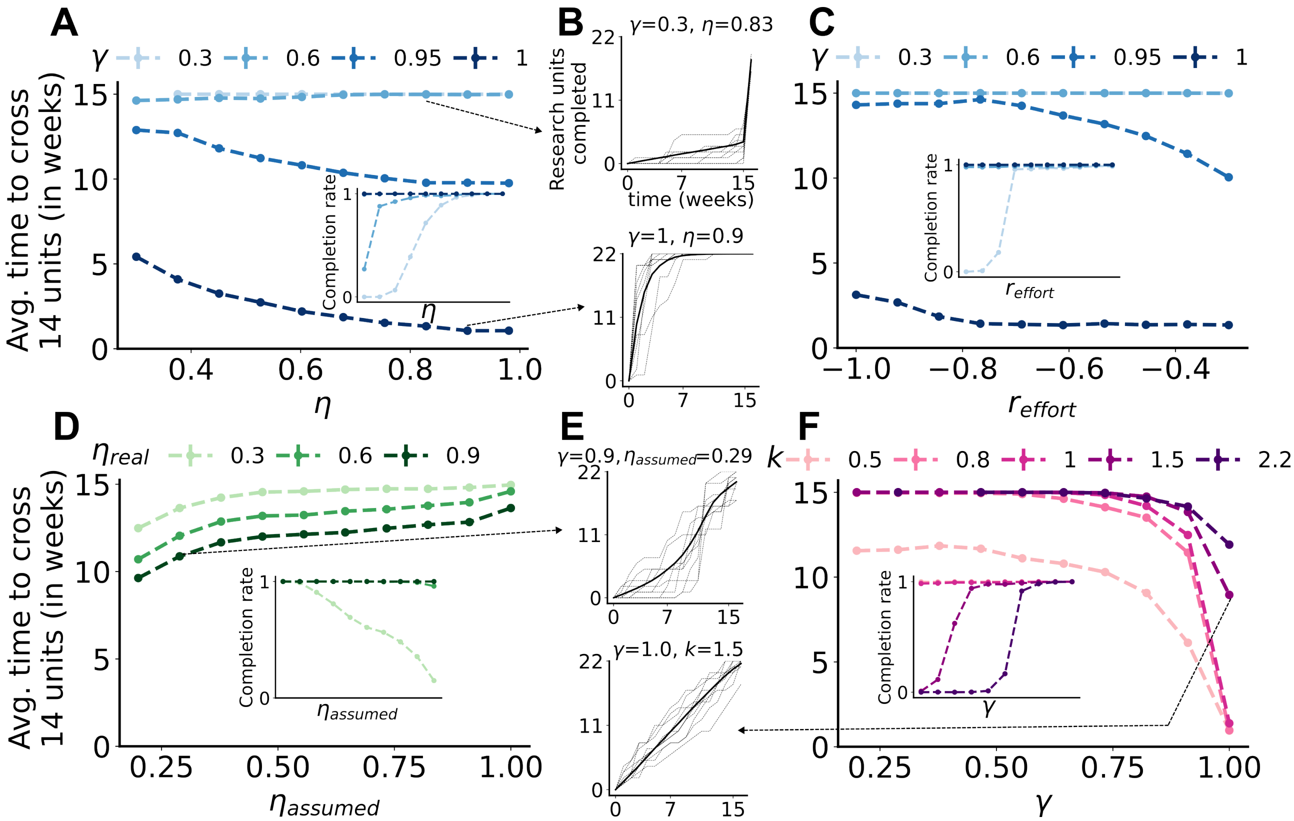

Figure 4: Simulations of models involving rewards that come at the task deadline. Main plots show average delay across parameters with average completion rates in the inset. Average trajectories are shown for some model configurations. A. Delays increase with extent of discounting (γ) and time taken to complete work increases with reducing efficacy. B. For low enough γ, work is delayed to the latest possible time while without discounting ($\gamma = 1$), there are no delays at all. C. Delays due to discounting increase with effort costs. D. Underestimating real efficacy ($\eta_{\text{assumed}} < \eta_{\text{real}}$) reduces delays while overestimating efficacy leads to delays and reduced completion rates. E. Sigmoidal trajectories from underestimating efficacy and flat trajectories from vigour costs. F. Non-linearity in effort function can reduce or increase delays. If effort function is concave in number of units, delays are reduced, while convex function encourages work to be spread out leading to delays.

rewards as soon as possible, further expediting work, depicted by the light pink line (when $\mathbf{k} = 1$) in Figure 5A.

We noted above that when the effort function is convex in the number of units of work done, work tends to be spread out over time. This spreading out of work also delays the compensation, making for an interaction between $\mathbf{k}$ and $\boldsymbol{\gamma}$: procrastination increases with steeper discounts, particularly for high convexity for example $\mathbf{k} = 2.2$, shown by the purple line in Figure 5A resulting in trajectories that curve upwards (Figure 5B).

Steeper discounting of efforts than rewards induces repeated delays due to temporal inconsistencies; 'diff-disc': In the 'diff-disc' model, effort is discounted more steeply than reward. This is a previously suggested explanation for procrastination (Akerlof, 1991; Le Bouc and Pessiglione, 2022; Shu and Gneezy, 2010). The presence of multiple discount factors leads to temporal inconsistencies, where the optimal action to take at a particular time step changes with the horizon. We show such a policy for $\boldsymbol{\gamma}_c = 0.5$ and $\boldsymbol{\gamma}_r = 0.9$ in Figure 5F: At $t = 0$ or horizon $= 15$, the best policy is to begin at $t = 2$, but by $t = 2$ or horizon $= 13$, it becomes rational to delay until $t = 4$ and so on. This effect disappears at high values of reward, so we set $\mathbf{R}_{\text{unit}} = 1$ and $\boldsymbol{\beta} = 10$. Hence, repeated delays dictate that one only starts at the end of the horizon. In other words, there is a persistent underestimation of how much effort one's future self will feel exerting to do the task. The defections are less pronounced with smaller disagreement between the two discount factors, and so too the extent of delays illustrated in Figure 5C.

Waiting for interesting tasks results in delays in the absence of discounting; 'no-commit': Some students reported verbally that they waited and signed up for studies they found interesting. Our final model 'no-commit' is inspired by this observation and consists of an 'interest reward' for completing rare, interesting experiments that come at unpredictable points in time, in addition to immediate rewards on completing the requirement. We introduce a probabilistic process to model this: there is a low-reward state (L) where rewards for completing work come at the 14 unit threshold as before, and a high-reward state where in addition, immediate 'interest' rewards $\mathbf{R}_{\text{interest}}$ are available for completing interesting work. The high-interest state (H) can also be interpreted as a high motivational state that might be rare for some students. Transitions between the two states are governed by probabilities $P(H|L) = 0.05$ and $P(L|H) = 0.95$, in other words, interesting tasks come up rarely and disappear quickly. We assume the students know ahead of time whether a task is interesting.

We assume that there is no interesting task to begin with. With $\boldsymbol{\gamma} = 1$, and uncertainty about when interesting tasks will appear, there is incentive to delay work and wait for them. The larger

$\mathbf{R}_{\text{interest}}$, the more an agent is willing to wait, as displayed in dark blue in Figure 5D. However, introducing delay discounting ($\gamma < 1$) effectively introduces 'impatience' and eliminates such delays because it becomes more appealing to take the smaller rewards available now rather than waiting for higher rewards that may or may not materialize in the future.

Procrastination types The structure of the resultant policies of each of the models corresponds to a variety of procrastination types that we laid out in our taxonomy (Section 3). Delays from models 'basic', 'eff-gap', 'conv-conc' and 'imm-basic' have the structure of committing and also complying to a time of action that might be insufficient. 'diff-disc' involves defections of initial plans of acting earlier and 'no-commit' involves delays from initially not committing to a time of action due to uncertainty in the timing of interesting tasks.

4.2.4 Model fits

Finally, we assess and compare how well each model fits the real trajectories. For model fitting, we find parameters of each model that maximise the log likelihood of the data. The model outputs include states (how much of the task has been completed by each week), actions (how many units the agent attempts to complete in each week) and in the final model, the 'interest state' (whether an interesting experiment is available in the current week). However, the only behavioral observations available from students were the number of units they had completed by each week, that is, the states (whose transitions are influenced by the efficacy η). The likelihood function was thus obtained by marginalising out the actions and in the final model, interest states from the joint likelihood probabilities. Mathematical details are in the methods Section 6.

The first column in Supplementary Table 2 shows the free parameters in each model that we fit to the data. We fix $\mathbf{R}_{\text{unit}} = 4$ and $\mathbf{R}_{\text{unit}} = 1$ for the different discounts case, since a common constant can simply be factored out of the rewards in the MDP. Fitting $\mathbf{R}_{\text{shirk}}$ as a free parameter revealed correlations between the fitted $\mathbf{R}_{\text{shirk}}$ and $\mathbf{R}_{\text{work}}$ (effort for work) and hence were non-recoverable together. Therefore, we fix $\mathbf{R}_{\text{shirk}} = 0$. Finally, since each student only has one trajectory of 16 data points, it is unreliable to fit the models student-wise. Instead, we fit models to each cluster consisting of multiple trajectories. The resultant models and parameters are generally recoverable. Please find plots for the recovery analyses in the Supplementary Figures 9, 10.

In general, our models are able to recapitulate the broad patterns in each cluster, as seen from agreement between trajectories from data and simulations from the fitted models shown in Figure 6. The fitted parameters for each cluster are listed in Supplementary Table 2. As a measure of goodness-of-fit, we calculate McFadden's pseudo-R^2 values (shown along with the plots) which

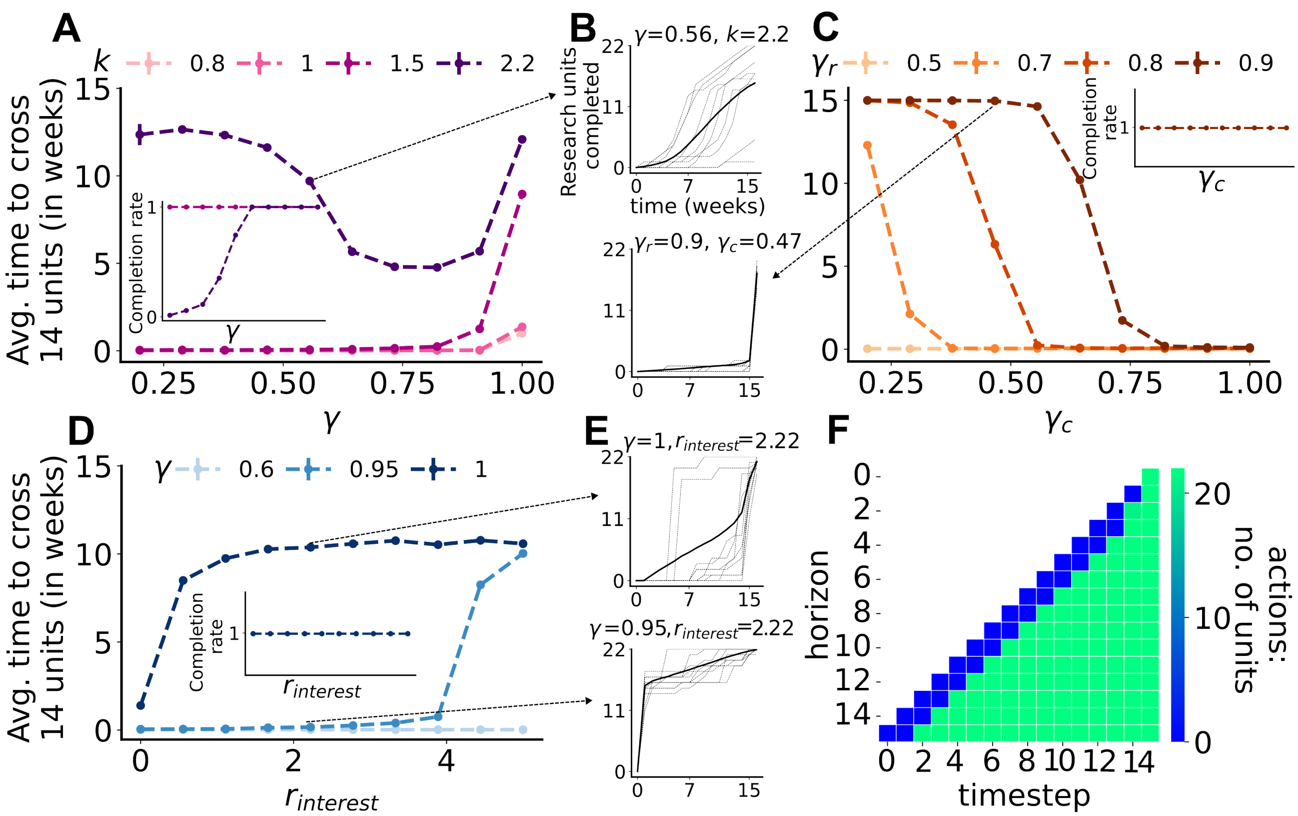

Figure 5: Simulations from models involving immediate rewards upon crossing the threshold requirement. A. With immediate rewards, delays are eliminated even with discounting. However, with convex effort functions, there are delays, leading to B. ramping up trajectories. C. Steeper discounting of efforts vs rewards leads to delays in working. F.These delays are due to repeated delays from time-inconsistent policy. D. Without discounting, it is optimal to wait for interesting tasks with uncertain timing. Higher the interest rewards, longer are the delays. Oppositely, steeper the discount rates, it is no longer appealing to wait for these distant, uncertain rewards. E. Trajectories showing delayed working with $\gamma = 1$ and immediate working with $\gamma = 0.95$ for the same interest reward, $r_{interest} = 2.22$.

	clusters							
models	1	2	3	4	5	6	7	8
basic	534.78	1253.96	999.15	856.56	1244.11	569.84	744.43	127.88
eff-gap	534.04	1255.96	989.35	854.86	1235.99	558.50	734.39	127.44
conv-conc	536.11	1252.82	1034.76	858.19	1241.67	557.12	731.12	130.97
imm-basic	543.38	1246.56	1032.95	851.93	1319.27	601.64	892.17	206.27
diff-disc	531.41	1296.67	994.67	851.28	1223.62	590.70	739.89	121.51
no-commit	528.61	1292.54	976.31	866.09	1237.93	611.67	743.86	138.02

Table 1: Akaike Information Criteria (AIC) for each cluster from each model fit

range between (0.27-0.77). The pseudo-R^2 values show how well the given model explains data in comparison to a random, null model. For reference, a value between 0.2-0.4 is typically considered a good fit (McFadden, 1977).

For model comparison, we computed the Akaike Information Criterion (AIC) which measures goodness-of-fit while penalising the number of parameters for parsimony and the model with the lowest AIC is selected. AIC values for each model fit from each cluster are in Table 1. Comparing them, it is apparent that for many clusters, multiple models fit the data similarly well. However, there are a few clusters in which some models can be excluded. For example, 'imm-basic' does much worse than other models for cluster 5, 7 and 8. This might be because the mechanism for delay in this model (interaction between $\mathbf{k}$ and $\boldsymbol{\gamma}$ described in the simulations Section 4.2.1) does not allow for the accelerated completion of units around a short interval of time found in these clusters. Further, the 'eff-gap' and 'conv-conc' models build on the basic model, and for some clusters they reduce to the basic model fits. For example, for cluster 1, all three models are in effect identical since $\mathbf{k} \approx 1$ for 'conv-conc' and $\boldsymbol{\eta}_{\text{assumed}} = \boldsymbol{\eta}_{\text{real}}$ for 'eff-gap'. Similarly, 'diff-disc' and 'no-commit' build on 'imm-basic' when $\mathbf{k} = 1$, and for cluster 0, they are nearly identical.

Finally, we show the dissimilarity matrices between fitted parameters for different clusters for each model type in Figure 7. Each cell in a matrix shows the normalised distance between parameters fitted for the given pair of clusters. Generally, parameters fitted to cluster 6 and for some, cluster 8 are farthest away from other clusters. This might be because these two clusters involve finishing a large number of units around the deadline.

5 Discussion

Whether to delay work, and how work on a task should ultimately be distributed across time, are choices with which we are ubiquitously confronted in daily life. Some of these choices can lead to procrastination, when there are negative consequences to delays. Here, we considered a

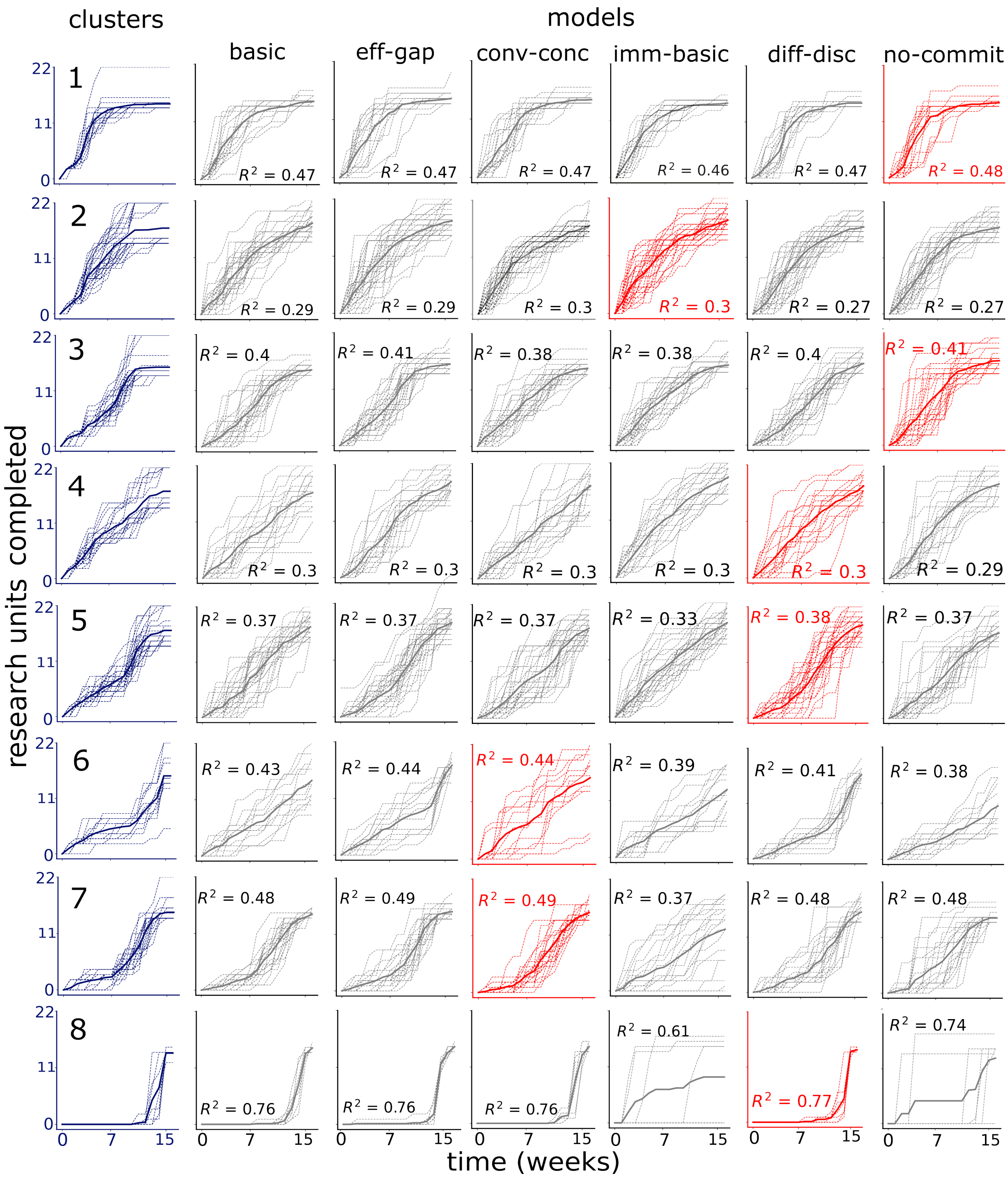

Figure 6: Comparison of trajectories from clusters and from simulations of corresponding fitted models. Most models fit the data reasonably well. Trajectories from data are in blue and trajectories from best fit models for each cluster are in red.

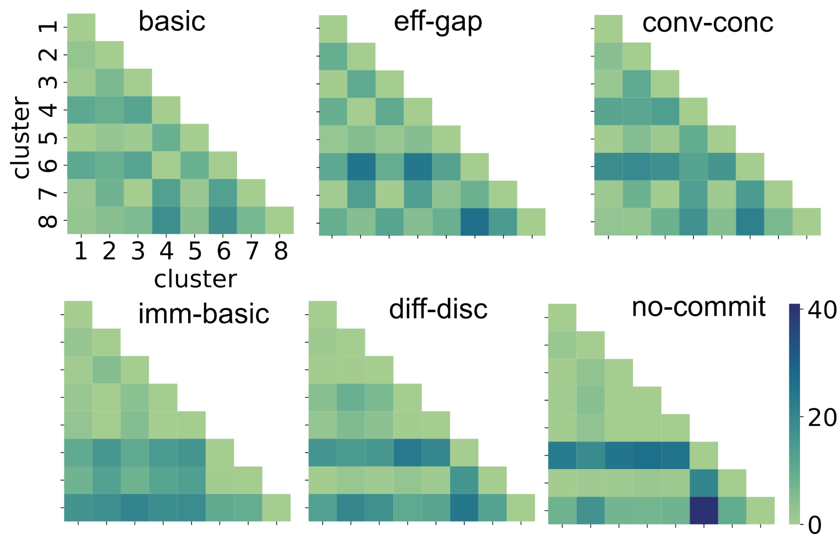

Figure 7: Dissimilarity matrices showing pairwise normalised distances between parameters fitted to clusters for each model

range of diverse routes to such choices, and constructed a systematic taxonomy of procrastination. We classified types based on the structure of the solutions of Markov decision processes (MDPs), namely the policies, which are the sequences of decisions to delay (or not). We identified four types of procrastination: intended delays with negative consequences, delays contrary to initial intentions to work, not committing to a time of action, and working later despite abandoning the task at first. We then examined the components of the decision making processes and hence, mechanisms that lead to these four types of procrastination. This also allowed us to incorporate previously suggested and novel explanations into this framework.

To illustrate parts of the taxonomy, we modelled data from a real-world task in which students were required to participate in a minimum number of hours of research (Zhang and Ma, 2024). Eight clusters captured a variety of students' patterns of engagement and delay on the task. We hypothesised six models corresponding to different procrastination mechanisms as possible explanations for these patterns: delay due to discounting of far away rewards, mis-estimation of efficacy in completing tasks, spreading work out due to non-linear scaling of effort with amount of work, interaction between non-linear efforts and discounting with immediate rewards, steeper discounting of efforts than rewards and delays due to waiting for interesting tasks with uncertain timing. The structure of the resultant policies from each model corresponded to three of the four types of procrastination we laid out in our taxonomy. Finally, fitting these models to the data revealed that they are able to reproduce broad patterns in each cluster, establishing the plausibility of multiple types of, and reasons for, procrastination.

5.1 Relation to other definitions and theories of procrastination

Our taxonomy classifies delays and hence, procrastination based on the structure of the sequence of decisions involved: sticking to a delayed time point of action, reneging on such an intention, acting later while initially not committing to a time of action or even intending not to work. Each of these types can have negative consequences, contributing to procrastination. Of these, only the second type involving defections has been traditionally defined as procrastination (Steel, 2007). On the other hand, extensive research in economics, neuroscience, cognitive science and computational psychiatry has elucidated a wider range of routes to sub-optimal behaviour. These include limited resources and the use of approximate solutions, skewed or abnormal utility functions, and mis-estimation of the problem (Huys et al., 2015a; Jolls et al., 1998).

We combined these insights to lay out ways other than defection that result in irrational or dysfunctional delays. Hence, for instance, sticking to delays that lead to harmful effects can also constitute procrastination. This type is similar in structure to the strategic delays that compose Chu and Choi (2005)'s active procrastination construct. However, in contrast, we only consider delays with negative consequences as procrastination.

Expanding the definition of procrastination and operationalising the types by the structure of delay also allowed us to spell out the different possible mechanisms underlying them. In our framework, the definitions are based on (possibly incorrectly) utility maximizing solutions of MDPs that express various task structures. While previous studies identify various correlates of procrastination, most mechanistic accounts largely rely on discounting of rewards with time to explain delays (Akerlof, 1991; Fischer, 1999, 2001; Le Bouc and Pessiglione, 2022; Steel and König, 2006). We list out many more mechanisms beyond discounting in Section 3, including rational or irrational decisions to deliberate and waiting to resolve uncertainty, which may cause people to miss deadlines or experience other adverse effects.

5.2 Psychological factors

There are some other proposed typologies of procrastination. Most of them classify types based on factors found from questionnaire responses on procrastination, reasons for it, and correlated personality and clinical scales. Fear of failure and anxiety, task aversiveness, depression, impulsivity and low self regulation, low motivation are some commonly found factors (and correspondingly, types of procrastinators) across different studies (Grunschel et al., 2013; Lay, 1987; McCown et al., 1989; Rebetez et al., 2015; Schouwenburg, 2004; Solomon and Rothblum, 1984). In our taxonomy, types are distinguished by a theoretical criterion (delay structure). The mechanisms are then also classified depending on which types of delays they explain. The various empirical factors may then be important components in different mechanisms. For example, fear of failure may coincide with explanations of ego protection and avoiding information (details in Section 3).

Past studies have correlated measures of procrastination in specific current (using behavior) or past tasks (using questionnaires) with cognitive, motivational and emotional factors and personality traits to find relevant variables for delays (Klingsieck, 2013; Rozental and Carlbring, 2014; Steel, 2007; Steel et al., 2018). Our models formalise cognitive processes that produce delays in specific types of tasks and hence can provide a natural interface between psychological factors and these behavioral measures of procrastination.

Impulsiveness is one major correlate of procrastination (Johnson and Bloom, 1995; Schouwenburg and Lay, 1995). This might relate to the extent of discounting of delayed rewards, prompting distractability from more readily rewarding tasks. Conversely, procrastinators seem to lack abilities such as self-regulation, self-control and discipline (Johnson and Bloom, 1995; Lee et al., 2006; Schouwenburg and Lay, 1995). These could be related to the ability to apply and enforce commitment devices and personal rules to prevent choice and temporal inconsistencies that result from mechanisms such as (Duckworth et al., 2018). We did not model these commitment mechanisms in this paper, although this would be an obvious task for future work.

Organisational skills might be related to long-term planning, effective time management and task prioritisation, coarsely captured by the efficacy parameter in our models: better organisation implies that a good proportion of planned tasks (e.g., for the next week) can be completed, hence higher efficacy. Mechanistically, the quality of such long-term plans depends on horizon and depth of decision tree considered, and the use of efficient heuristics to simplify complex planning problems such as pruning and chunking (Huys et al., 2012, 2015b).

Motivational factors such as achievement motivation, need for achievement and intrinsic motivation are most likely captured by the reward for task completion in our models. Need for achievement may be driven by extrinsic rewards such as grades and scores, or future academic and career goals (Rebetez et al., 2015). Intrinsic rewards might come from doing interesting tasks, learning something new, satisfaction from contributing to research and society, and feelings of accomplishment Murayama (2022). The amount of motivation controls how much effort one is willing to exert towards tasks which could constitute the facet of industriousness. Industriousness might also be related to how effort costs scale with the amount of work done per unit time and hence the capacity to exert a lot of effort.

In our models, efficacy determines the reliability with which an individual can complete the work planned for a week (factors in the transition function). The agent has its own estimate of this parameter (which could be different from the real efficacy). This mechanism captures, to an extent, another correlate of procrastination, self efficacy, which is one's belief in one's capacity to reach one's goals (Bandura, 1977). We also showed how overestimating efficacy could lead to, or exacerbate, procrastination. Low self beliefs might also underlie low self esteem. These factors can be considered a form of global metacognition (Seow et al., 2021).

Past research has found other beliefs considered to be 'irrational' that are correlated with procrastination such as perfectionism, self-handicapping, fear of failure among others (Pychyl and Flett, 2012). As we already discussed in Section 3, self-handicapping might come from skewed utility functions where protecting one's image becomes more important than completing an important task. Fear of failure and overly pessimistic expectations could motivate delay in starting a task to avoid information that confirms fears. All of these factors might mediate the link between anxiety and procrastination. Reinforcement provided by relief on avoiding a negative outcome by working might also exacerbate procrastination and provides yet another link with anxiety.

5.3 Links to effort/control allocation, temporal patterns of working, pre-crastination and other temporal decisions

As seen throughout the paper, in the process of modelling procrastination and delay, we also had to model the distribution of work in time. Indeed, while only three students in the dataset we modeled failed to complete the minimum requirements, the same mechanisms that we used to fit students' patterns of engagement can also serve as models of procrastination where there are negative consequences to delay. Studies considering the shape of work or 'pacing style' typically view cases in which completion is at the deadline ('deadline completion'; our clusters 6 and 8) as procrastination (Gevers et al., 2015; Konradt et al., 2021; Steel et al., 2018; Zhang et al., 2023). Our analyses suggest that not all deadline completion is necessarily procrastination and conversely, other patterns might also constitute procrastination.

In our models, the primary decision is whether to start work now or at a later time-point (i.e., to delay), and how much work to do (quantified as the number of units). In our models, the 'when' question is answered by the taxonomy of reasons we discussed, and the 'how-much' question is mainly governed by the non-linear effort function (Zhang and Ma, 2024). Convexity encourages spreading work out, while with linear and concave functions, it is best to attempt all units at once. Although our efficacy parameter controls how much work ends up being done, it does not directly affect the decision of how much to do. Other factors could modulate these decisions. For instance, Niyogi et al. (2014) model the decision of how much time to allocate to work vs. leisure in rats. The relative benefits of work and leisure along with the opportunity cost and the (sigmoidal) saturating value of leisure with time determine how long to work before engaging in leisure. Relatedly, Niv et al. (2005, 2007) and Dayan (2012) model the decisions about latency (delay) and vigour (speed) of actions for obtaining reward or avoiding punishments as a balance between the costs of acting too fast and the opportunity costs of acting too slow.

The decisions of when to engage in a task and how much effort to apply are also encountered at timescales other than those of days and weeks that we considered in the case of procrastination. The examples of controlling latency and vigour of actions for rewards in rats are already an example of smaller timescale decisions. When to engage and pay attention in time to perform sensory tasks is also determined by temporal expectation (Seibold et al., 2023). Anticipation of events based on temporal structure such as hazard rates, cues, and periodicities guide attention and action (Nobre and van Ede, 2018). Other studies investigate fluctuations in attention and the occurrence of lapses in tasks involving perceptual decisions, where animals apparently disengage from the task in bouts due to exploration or learning (Gupta et al., 2023; Pisupati et al., 2021).

Though the primary delay comes from putting off starting the task in our models, our general taxonomy suggests that it can also come from spending much time on finishing a promptly initiated task. One consideration here is the speed-accuracy trade-off, where it might make sense to spend more time on more uncertain decisions to improve accuracy (Wickelgren, 1977). In contrast, discerning the value of similarly valuable items might have little benefit, and less time should be spent on trying to make a correct choice (Oud et al., 2016). How much time should be allocated to a task also depends on the level of risk involved: for example, whether it is worth spending a lot of time on 'make-or-break' endeavors vs safe predictable alternatives (Analytis et al., 2019).

While we did not explicitly discuss it, pre-crastination is intimately related to the processes and mechanisms we examine in this paper. Pre-crastination is the mirror image of procrastination, involving working too hastily to one's own detriment. We could then picture a taxonomy of decisions underlying pre-crastination – working earlier than intended, sticking to a mis-calculated 'too-soon' latency and committing to a time of action too early. Rosenbaum et al. (2019) discuss some possible reasons for this tendency: desire for instant gratification, grabbing scarce resources, and reducing the cognitive demands required to remember what task to do when.

5.4 Model assumptions

To illustrate our taxonomy, we modelled data from a real-world task where students had to participate in a minimum number of hours of research for course credit. We proposed and fit six different models as explanations of students' patterns of engagement and delay in the task. We had to make some assumptions and simplifications while operationalising the models.

Firstly, we modeled the task and explanations of delay using MDPs for simplicity. These are a restricted form of Partially Observable Decision Processes (POMDPs) in which there is no uncertainty about the state (Kaelbling et al., 1998; Sutton and Barto, 2018). In a POMDP, not all components of the state may be known to the individual, for instance if the difficulty of a task or the individual's level of skill only become apparent when the task is attempted. In this case, the individual has access to observations that provide partial information about the state, and use probabilistic reasoning to calculate a subjective belief.

We assumed that the number of units of work students complete in each week is probabilistic due to uncertainty about available time for work, unknown tasks and students' effectiveness in organising their time, all of which control the average amount of time it takes to complete a unit. Further, we assumed that this probability is governed by a binomial distribution parameterised by efficacy. Others have used different stochastic processes to model completion times, for example Zhang et al. (2023) use a Poisson process to model how many units of a reading assignment a person expects to complete in the future. More detailed modelling of these micro-decisions (how to distribute the units planned for the week) could shed light on the most appropriate process to capture the completion probabilities.

Unfortunately, there was no information about how the availability of research experiments changed over the weeks, although, on average, there were more than enough tasks available per student (15 hours or 30 units per student). We assumed that there was no shortage of tasks each week and students could, in principle, finish as many hours as they wished each week (maximum is 11 hours). While we know that some students had variable interest in different experiments, we did not know which ones they were or when they came about. In one of our models, we assumed that there was a small, constant probability at which such interesting tasks come up and that they have additional 'interest' rewards on task completion. In addition, experiments lasted variable lengths of time, between 0.5-2 hours, but always as a multiple of 0.5 hours. We did not model this complexity but instead always allowed a choice of any multiple of 0.5 hours.

In our models, additional work above the threshold contributes $1/8^{th}$ of the reward from compulsory units. While we fixed this arbitrarily for simplicity, this could have been an additional free parameter capturing how much students in different clusters value completing additional units. Further, we do not make a distinction between extrinsic and intrinsic rewards for completion and simply have one reward term that might come immediately or at the end of the semester across the different models.

We fit the models to each cluster consisting of trajectories from different students, thereby constraining all students within a cluster to share the same parameter set. This might not necessarily be the case, but we could not fit models separately to each cluster, since one trajectory was not enough to recover parameters. Finally, many of our models produce heterogeneous patterns that might be grouped with different clusters. However, since we fit the models separately to each cluster, we are not able to account for the possibility of a single model explaining multiple clusters.

5.5 Future directions

We found that multiple models can explain the patterns of work observed in the research participation task. Targeted experimental manipulations in the future could help disambiguate these models. To address the ambiguity in reward schedules, rewards can be explicitly provided at specific times, as in Zhang et al. (2023). Offering immediate rewards removes delays associated with delay discounting, implicating other processes such as differential discounting of rewards and efforts or waiting for interesting tasks or better conditions. To test the latter mechanism, we could check if there is any reduction in delay when using a mix of boring and (rare) interesting tasks vs uniformly boring or interesting tasks. The tasks could be pre-rated to calibrate how interesting they are on average to students. In addition, mood and motivation states can be assessed continuously to survey if there are any correlations with when tasks are done. Finally, since differential discounts lead to delays at relatively low reward sizes, we could vary the size of immediate rewards to check if delays persist even at higher values, which would suggest the involvement of other mechanisms.

In addition to such controlled experiments, a promising area for future exploration comes from growing possibilities to track and record the detailed activity of students completing coursework and other requirements online. For instance, many universities now use online learning management systems where students access course material, submit assignments, begin and complete quizzes and homework, ask questions etc. This allows measurement not only of final completion times of each task but rather the entire course of working towards each task, making it possible to also model the fine-grained decisions involved in completing each requirement (Park et al., 2018; Sabnis et al., 2022). In a similar vein, online writing tools such as Google Docs grant access to the entire history of changes and edits made while writing an essay or a paper, making it possible to track the course of work (Horton, 2021).

A further appealing direction is to consider other mechanisms that dictate how people distribute their work towards the type of tasks we considered here. For instance, other causes that could drive defections on intentions to work include forgetting, unexpected changes in the environment (such as the appearance of other demands or work possibilities), or learning that a task is more effortful than anticipated. Reasons to work earlier instead of delaying a unit could include anticipating reduced free time towards the end of the semester, the mental burden of remembering to do unfinished tasks, or a preference for leisure after completing work rather than before.

As we noted before, people procrastinate in a variety of tasks with different structures and characteristics, where different factors and mechanisms might become important in explaining delays. We mainly considered tasks with deadlines. However, many real life situations in which people procrastinate, such as making medical appointments, exercising, and financial planning, do not have such time limits. Further, the tasks we considered here were not particularly hard for the students to complete, and even the amount of time needed was fixed. However, procrastination is often linked to tasks that are tough, such as challenging homework, preparing for an exam or writing a research paper, where it is not clear how long it will take to finish.

In addition, many tasks that are procrastinated involve averting negative outcomes, be it failing a test, or delivering a poor public talk. In these type of tasks, other mechanisms we considered in our taxonomy associated with relief, fear of failure, self-handicapping and other avoidant behavior may become very important. Apart from the uncertainty about the time it will take to finish the task or the probability of success, there are other sources of uncertainty that could modulate delay. These include lack of information about the environment, the task at hand, one's own abilities or uncertainty about the timing of events, such as when abilities will improve as a semester progresses. Future modeling and experimental studies could investigate in detail how delay and allocation of time are influenced by these forms of uncertainty. Finally, in our models, we did not consider adaptation and learning from experience while completing a task. For instance, there could be error-correction mechanisms that rectify incorrect estimates and wrong assumptions from experience. Further, people might adapt their strategies as they learn more about themselves and the task, for example, they may modify their delays if the task turns out to be harder or more time-consuming than expected.

5.6 Conclusion

In sum, we introduced a novel, systematic, taxonomy for procrastination and more broadly, delay. This is based on the structure of the choices involved. The various reasons for these choices then constitute possible mechanisms for procrastination. We provided some empirical evidence of the plausibility of multiple reasons for the patterns of engagement and delay of students towards course requirements over a semester. Finally, we discussed the relationship between previously identified psychological factors and the components of these computational models, the applicability of the taxonomy to broader forms of temporal decisions and directions for future computational and experimental research.

6 Methods

6.1 Optimising the returns

Single discount factor As we mentioned already, the conventional goal in an MDP is to find the optimal policy π_t^* that maximises the discounted or un-discounted sum of rewards over the time horizon:

$$V_t^*(s) = \max_{\{a_\tau \sim \pi_{\tau=t\ldots T}\}} \mathbb{E}\left[\sum\nolimits_{\tau=t}^{T} \boldsymbol{\gamma}^{\tau-t} \mathbf{R}(s_\tau, a_\tau, s_{\tau+1}) \,\middle|\, s_t = s\right] \tag{1}$$

In practice, this can be recursively solved by dynamic programming methods starting from the terminal values $V_T^*(s)$ (often $V_T^*(s) = 0, \forall s$). This is because the returns can be maximised by finding the action that maximises the sum of the immediate reward on taking the action and the subsequent expected returns from the future state, which can be written yet again as a similar sum. This is the Bellman equation (for $t < T$):

$$V_t^*(s) = \max_{a \sim \pi_t} \left\{ \sum_{s'} \mathbf{P}(s'|s,a) \left[\mathbf{R}(s,a,s') + \boldsymbol{\gamma} V_{t+1}^*(s') \right] \right\} \tag{2}$$

and leads to a state-action value function

$$Q_t^*(s,a) = \sum_{s'} \mathbf{P}(s'|s,a) \Big[\mathbf{R}(s,a,s') + \boldsymbol{\gamma} V_{t+1}^*(s') \Big] \tag{3}$$

where

$$V_t^*(s) = \max_a Q_t^*(s,a) \qquad \text{and} \qquad \pi_t^*(s) = \text{argmax}_a Q_t^*(s,a) \tag{4}$$

Different discount factors for negative and positive rewards One of our models employs two separate discount factors for negative and positive rewards ($\boldsymbol{\gamma}_c$ and $\boldsymbol{\gamma}_r$), instead of a common discount factor. We write the objective function as:

$$V_{t,t}^*(s) = \max_{\{a_\tau \sim \pi_{t,\tau=t\ldots T}\}} \mathbb{E}\left[\sum\nolimits_{\tau=t}^{T} \boldsymbol{\gamma}_r^{\tau-t}\, \mathbf{R}(s_\tau, a_\tau, s_{\tau+1}) + \boldsymbol{\gamma}_c^{\tau-t}\, \mathbf{C}(s_\tau, a_\tau, s_{\tau+1}) \,\middle|\, s_t = s\right] \tag{5}$$

where the different discount factors eliminate the recursive structure that we described previously because the discount factors can no longer be factored out at every expansion of the sum. Thus, the optimal policy at a single time t can depend on the time $\tilde{t} < t$ relative to which the optimization is referenced, so the various quantities become more complicated. The optimal value function at time t calculated from the perspective of time $\tilde{t}$ is then given by:

$$V^*_{\tilde{t},t}(s) = \max_{a\sim\pi_{\tilde{t},t}} \left\{ \sum_{s'} \mathbf{P}(s'|s,a) \Big[\boldsymbol{\gamma}_r^{t-\tilde{t}}\, \mathbf{R}(s,a,s') + \boldsymbol{\gamma}_c^{t-\tilde{t}}\, \mathbf{C}(s,a,s') + V^*_{\tilde{t},t+1}(s')) \Big] \right\} \tag{6}$$

resulting in the following state-action value function

$$Q^*_{\tilde{t},t}(s,a) = \sum_{s'} \mathbf{P}(s'|s,a) \Big[\boldsymbol{\gamma}_r^{t-\tilde{t}}\, \mathbf{R}(s,a,s') + \boldsymbol{\gamma}_c^{t-\tilde{t}}\, \mathbf{C}(s,a,s') + V^*_{\tilde{t},t+1}(s') \Big] \tag{7}$$

Notice that these functions depend on $\tilde{t}$, while for the case of a single discount factor, the value functions do not depend on the distance back in time for which the agent calculates it.

6.2 Parameter estimation

To estimate the parameters of each model from data, we maximise the likelihood of the data under the model which is the joint probability of the observed data ($\mathcal{D}$) as a function the model parameters (θ). In the current task, the observed data consists of the states of the MDP ($\mathcal{D} = (s_0, s_1, ..., s_T)$). The likelihood $\mathcal{L}$ can then be derived by marginalising out the actions of the MDP (which are not measured in the task). Due to the Markovian structure of the problem, probabilities are not dependent on the entire sequence of actions and states and can be factored out, hence making the likelihood calculation simple and tractable:

$$\begin{aligned} \mathcal{L} &= P(s_0, s_1, ..., s_T) \\ &= \sum_{a_0,...,a_T} P(s_0, a_0, s_1, a_1, ..., s_T) \\ &= \prod_{t=0}^{T-1} \Big[\sum_{a_t} P(s_{t+1}|s_t, a_t, \theta)\, \pi(a_t|s_t, t; \theta) \Big] \end{aligned} \tag{8}$$

For the final model, there are also 'interest states (i_t)' in addition to states and actions that also have to be marginalised out:

$$\begin{aligned} \mathcal{L} &= P(s_0, s_1, ..., s_T) \\ &= \sum_{a_0,...,a_T} \sum_{i_0,...i_T} P(s_0, a_0, is_0, s_1, a_1, i_1, ..., s_T, i_T) \\ &= \prod_{t=0}^{T-1} \Big[\sum_{i_{t+1}} \sum_{i_t} \sum_{a_t} P(i_{t+1}|i_t)\, P(s_{t+1}|s_t, a_t, \theta)\, \pi(a_t|s_t, t, i_t; \theta) \Big] \end{aligned} \tag{9}$$

We minimise the negative log likelihood function (equivalent to maximising the likelihood) to find the parameters θ that most probably explain the data. We use the L-BFGS-B algorithm implemented by `scipy.optimize` for minimisation.

6.3 Model fitting and comparison metrics

pseudo-R^2 To assess the quality of the model fit to data, we calculate McFadden's pseudo-R^2, as a measure of how well the fitted model explains data in comparison to a random, null model:

$$R^2 = 1 - \frac{\log \mathcal{L}_M}{\log \mathcal{L}_0} \tag{10}$$

where, $\mathcal{L}_M$ is the likelihood of the data under the fitted model and $\mathcal{L}_0$ is the likelihood under the null model. If $R^2 = 0$, this means the fitted model is no better than the null model at explaining the data, while $R^2 = 1$ implies that the fitted model is infinitely better at explaining the data. A value of $0.2 - 0.4$ is typically considered an excellent fit (McFadden, 1977). For the null model, we consider a similar MDP but with uniform probability of action selection and uniformly distributed efficacy (drawn for every trial).

AIC For each model fit, we use the Akaike Information Criterion (AIC) as a metric to compare the models. Since increasing the number of parameters improves model fit, AIC balances the goodness of fit (measured by $\mathcal{L}$) and the complexity of model (given by the number of parameters, k) to prevent overfitting:

$$AIC = 2k \, - \, 2 \log \mathcal{L} \tag{11}$$

The model with the lowest AIC is selected.

Dissimilarity matrix For each model type, we calculate the normalised distance between fitted parameters for each pair of clusters as a measure how dissimilar they are. We normalise the parameters by their variance across all the clusters:

$$d(i,j) = \sum_{k=0}^{M} \frac{(p_k^i - p_k^j)^2}{\mathrm{Var}(p_k^0, ..., p_k^7)} \tag{12}$$

where M is the number of parameters in the model (defining the dimensionality of the parameter vector), i and j are the pair of clusters between which the distance is being calculated and p_k^i is the

k-th parameter for cluster i.

7 Supplementary Information

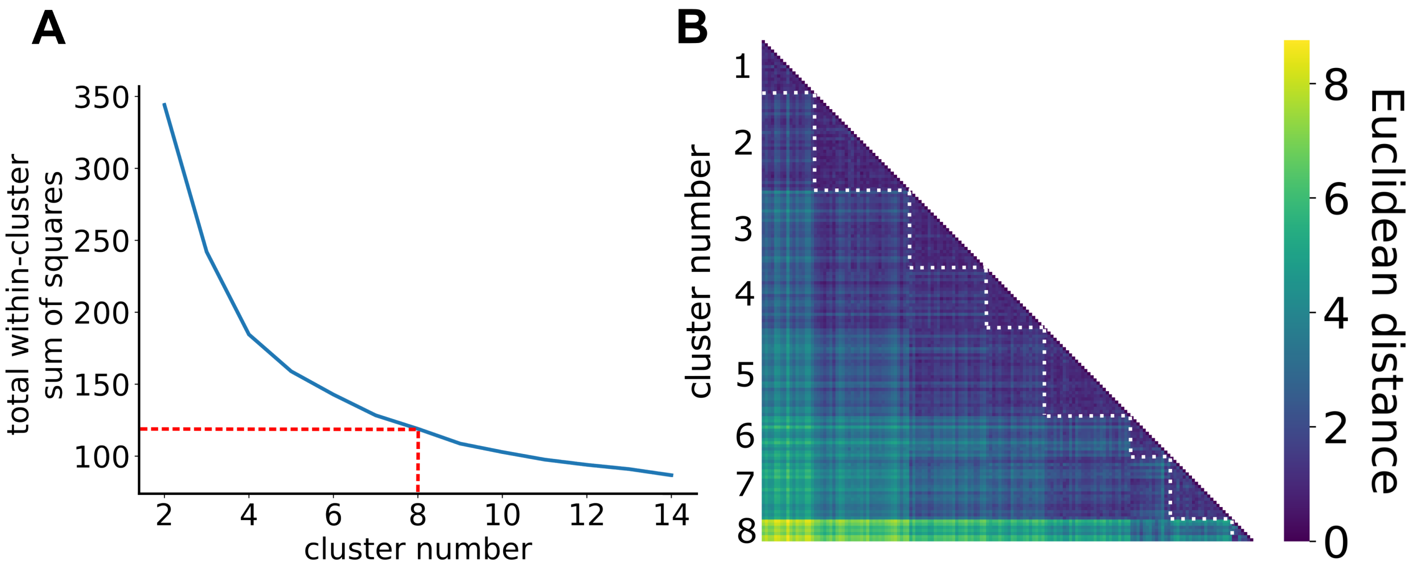

Figure 8: A. Elbow plot showing the total within-cluster sum of squares as a function of number of k-means clusters. We picked k$= 8$ marked in red in the plot. We obtain another clustering with $k = 8$ with a similar loss where cluster 8 is split into two clusters and we have two clusters capturing steady completion instead of three (here, clusters 3-5). We picked the current version because the clusters are more evenly split in the number of trajectories and overall shape. B. Distance matrix showing Euclidean distance between every pair of (160) trajectories, arranged according to cluster membership. Cluster boundaries are marked in white dashed lines. In general, trajectories are more similar to others within their cluster compared to other clusters.

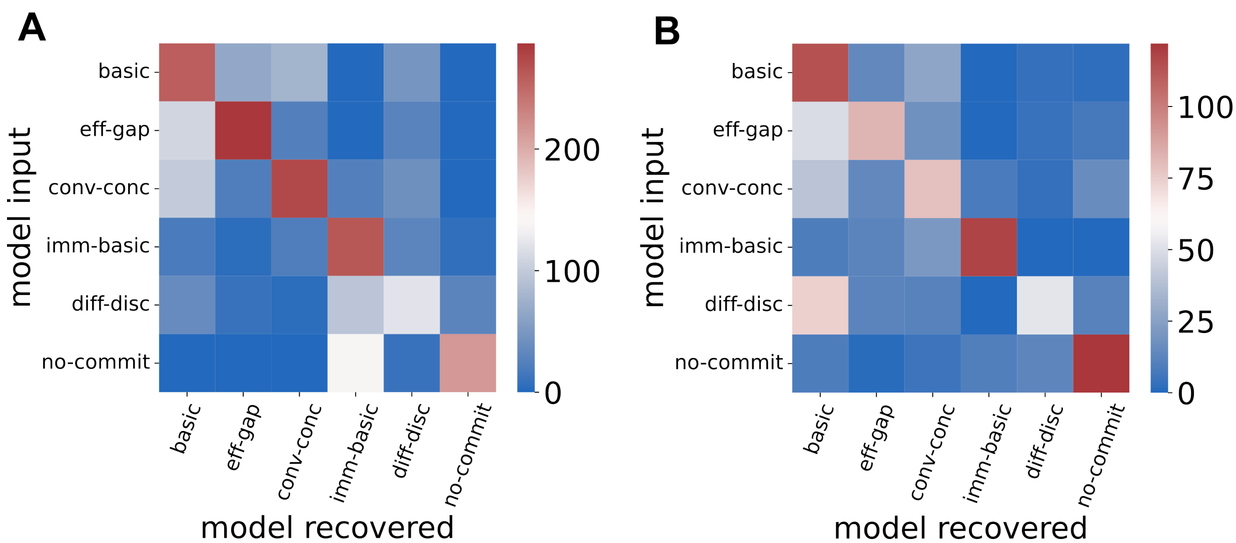

Figure 9: Model recovery. A. Count of the number of times the model fitting and comparison procedure identified each model from an input of trajectories (n= 15) of a particular model with randomly chosen parameters. B. Same as A, but for parameters fit to real data. In both A and B, the correct model has largely been identified with higher frequency than other models. The exception is 'diff-disc' model, especially for the fitted parameters.

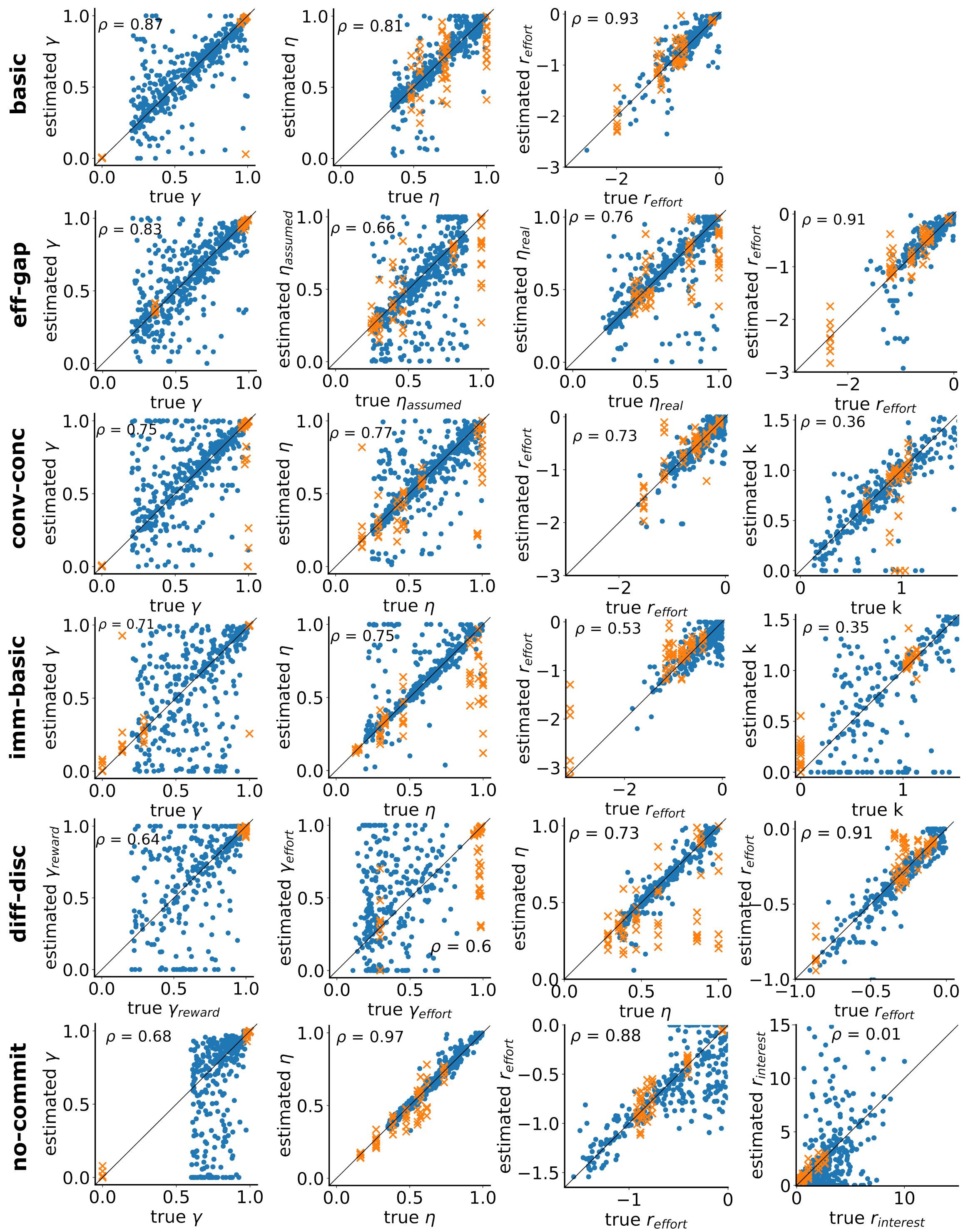

Figure 10: Parameter recovery. Plots show the parameter estimates from model fitting versus the input parameters along with the Pearson correlation between the two (ρ). Each row corresponds to parameters from each of the six models. Blue points show random parameters while orange crosses show parameters fitted to trajectories from real data. Discount factors ($\boldsymbol{\gamma}$) for imm-basic and no-commit show relatively poor recovery. This is because, when $\boldsymbol{\gamma} < 1$ in these models, it is best to complete work as soon as possible giving rise to similar trajectories. However, for these discount factors and other parameters such as k and $r_{interest}$, parameters fitted to real data (orange crosses) recover better than random parameters. $\eta \approx 1$, and $\gamma_c \approx 1$ show comparatively poor recovery for the fitted parameters.

		clusters							
models	free params	1	2	3	4	5	6	7	8
basic	$\boldsymbol{\gamma}$	0.99	0.99	0.99	0.00	0.98	0.00	0.97	0.95
	$\boldsymbol{\eta}$	0.69	1.00	0.54	1.00	0.73	1.00	0.48	0.71
	$\mathbf{R}_{\text{effort}}$	−1.13	−1.20	−0.74	−0.12	−0.85	−0.14	−0.68	−1.99
eff-gap	$\boldsymbol{\gamma}$	0.99	0.99	0.98	0.99	0.97	0.36	0.95	0.96
	$\boldsymbol{\eta}_{\text{assumed}}$	0.39	1.00	0.30	1.00	0.46	0.25	0.27	0.81
	$\boldsymbol{\eta}_{\text{real}}$	0.50	1.00	0.53	1.00	0.81	0.45	0.42	0.80
	$\mathbf{R}_{\text{effort}}$	−0.80	−1.20	−0.52	−1.15	−0.58	−0.10	−0.45	−2.33
conv-conc	$\boldsymbol{\gamma}$	0.99	0.99	0.99	0.00	0.98	0.00	0.97	0.95
	$\boldsymbol{\eta}$	0.42	1.00	0.18	1.00	0.46	1.00	0.29	0.58
	$\mathbf{R}_{\text{effort}}$	−0.79	−1.18	−0.35	−0.11	−0.55	−0.24	−0.52	−1.47
	k	0.99	1.01	0.93	1.07	0.97	0.66	0.88	0.97
imm-basic	$\boldsymbol{\gamma}$	1.00	1.00	1.00	1.00	1.00	0.00	0.28	0.14
	$\boldsymbol{\eta}$	0.45	0.97	0.30	0.91	1.00	0.15	0.13	0.33
	$\mathbf{R}_{\text{effort}}$	−0.83	−1.15	−0.40	−1.00	−1.09	−0.62	−0.72	−0.31
	k	1.03	1.04	1.13	1.06	1.05	0.00	0.00	0.00
diff-disc	$\boldsymbol{\gamma}_r$	1.00	1.00	1.00	1.00	1.00	0.97	1.00	0.97
	$\boldsymbol{\gamma}_c$	0.99	0.98	0.98	0.98	0.97	0.30	0.96	0.94
	$\boldsymbol{\eta}$	0.47	0.28	0.38	1.00	0.86	0.35	0.61	0.89
	$\mathbf{R}_{\text{effort}}$	−0.31	−0.12	−0.19	−0.34	−0.28	−0.09	−0.27	−0.86
no-commit	$\boldsymbol{\gamma}$	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.98
	$\boldsymbol{\eta}$	0.48	0.27	0.55	0.62	0.57	0.16	0.38	0.73
	$\mathbf{R}_{\text{effort}}$	−0.92	−0.41	−0.88	−0.82	−0.76	−0.05	−0.88	−2.63
	$\mathbf{R}_{\text{interest}}$	0.35	1.08	0.56	0.42	0.64	29.38	2.02	2.62

Table 2: Fitted parameters to each cluster for each model

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