Poverty and Priority Queueing

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Abstract

Pre-existing literature suggests that relative material scarcity – particularly wealth inequality – is a significant contributing factor in dictating how people behave. We characterize irrational decision-making across impoverished groups by examining the effects of inefficiency in time and effort allocation. We experimentally model time allocation in low SES groups by administering an artificial priority queue where agents must attend to tasks with differing levels of effort, urgency and value. Observations suggest that individuals from low SES groups prioritize urgent tasks while agents from high SES groups prioritize high value tasks.

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Chapter 1

Introduction

Poverty is a multi-dimensional problem, and behavioral scientists have focused on the effects of the environment on the decision-making process across socio-economic levels (Bertrand et al., 2004). Their underlying assumption is that humans share the same underlying biology and psychology, and that "poverty" causes significant changes in people's environments and, in turn, their decisions. For example, living in poverty often means having a limited set of options in life (from choosing what to have for dinner to which occupation to pursue), and it increases the number of demands in terms of time and mental resources (Banerjee & Duflo, 2012). This lack of control over choices leads to a chronic state of vigilance and stress (Chemin et al., 2013).

In this paper, we focus on the trade-offs between urgency and importance in day-to-day decisions. It is hypothesized that, in the mass of to-dos and responsibilities, those with limited resources have to leave specific tasks undone. Consequently, we argue that they may not have time to complete all tasks or the necessary money and, as a result, must decide what to prioritize in their lives. Although one could theoretically calculate the most optimal course of action, it is improbable that individuals would take this actuarial approach. Instead, we argue that they are more likely to use heuristics or intuition to decide what problem to address, where to spend money, and what to leave undone. Such heuristics, however, are prone to fail under particular circumstances.

We argue that, under the strain faced by the poor, a series of behaviors and physiological phenomena arise. Making "urgent versus important" trade-offs causes stress and anxiety levels to increase and shift attention towards specific features of a choice. We propose that an environment of poverty shifts the weight placed on the urgency of a task (e.g., estimating that urgent tasks will "come back to bite" much faster than others and estimating that nonurgent opportunities are unlikely to disappear or change). This urgency mindset may increase stress and anxiety levels, leading the poor to spend significant portions of their income

on tobacco, alcohol, and lotteries (Banerjee & Duflo, 2007; Blalock et al., 2007; Haisley et al., 2008; World Health Organization, 2021). Individuals in low socio-economic groups tend to save too little (Shurtleff, 2009) frequently borrow at exorbitant interest rates (Banerjee & Duflo, 2007; Skiba & Tobacman, 2008), and limit preventive healthcare services (Lusardi et al., 2010).

1.1 Poverty Traps

We argue that the poor are caught in an "urgency trap," where neglect of nonurgent tasks may cause an increase of urgency in the future. For example, not undergoing regular medical check-ups may increase susceptibility to unexpected illnesses.

This phenomenon is closely related to the theory of poverty traps. This framework defines a self-perpetuating phenomena that arise when an economy is caught within a cycle that suffers from persistent undevelopment. In this paper, we model poverty traps as an equilibrium which favors disutility over iterative cycles. To determine causal relationships between such outcomes and the behavior of low SES (type 1) agents, we examine cases of suboptimality that are distinct from high SES (type 2) agents. To assess self-reinforcing behavior intrinsic to poverty traps, we classify and compare the choice behavior of type 1 agents in regards to their time allocation.

1.1.1 Priority Queues, Urgency and Importance

Although some scientists have proposed a "Scarcity" view of poverty (Mullainathan & Shafir, 2014), their conclusions have not withstood the scrutiny of science, leaving the causes and mechanisms of these phenomena largely unexplained (O'Donnell et al., 2021). We seek a more rigorous understanding of how relative-poverty can be self-perpetuating through poor time allocation. We explain prioritization of day-to-day tasks as an attempt to balance two requirements: (1) maximize life satisfaction given one's limited resources, and (2) minimize the potentially harmful effects of leaving tasks undone change with time. We call the former requirement "importance" and the latter "urgency" (Bratterud et al., 2020).

The Eisenhower Matrix (see @app-eisenhower for details), a simple tool for determining optimal long-term decisions, is a simplification of how individuals determine their queue for attending to daily tasks. This framework uses dimensions of urgency (time scarcity) and importance (expected value maximization) as primary motivations for which tasks require completion. We intend to characterize the mapping between urgency U and importance I , namely $\{U, I\} \mapsto \mathbb{R}$. As discussed in Section 2.3, the literature speculates the influence of effort costs in decision-making - thereby suggesting Eisenhower Matrices should be modified to account for the added parameter.

Chapter 2

Theory

In this section, we present a novel decision-making model that underpins various real-life activities, from mundane daily choices to high-stakes strategic decisions. When individuals face multiple action options, they select the one that maximizes perceived value or utility. Our model integrates urgency, importance, and value, drawing on principles from decision theory, the Eisenhower matrix, and Markov Decision Processes (MDPs) (Puterman, 1994; Eisenhower, 1961).

2.1   Conceptual Framework

In our model, urgency refers to the time-sensitivity of a decision or the period until a choice is no longer viable. This concept captures the temporal aspect of decision-making, reflecting that opportunities for action often have a limited lifespan. For example, deciding to invest in a rapidly changing market or respond to a time-limited offer requires considering urgency. Importance is the value of a decision state, contingent on future states and transition probabilities. This concept captures the strategic aspect of decision-making, reflecting the reality that the consequences of a decision often depend on future events and conditions. For example, investing in education or training may be important because it affects future career opportunities and earning potential (Howard, 1960). Value is the present-discounted reward from choosing an action, incorporating the opportunity cost of a choice, which is the value of the best choice one must forego. This concept captures the economic aspect of decision-making, reflecting that resources such as time, money, and effort are limited and that choosing one action can often mean giving up the opportunity to choose another (Bellman, 1957). The optimal policy balances immediate rewards with future rewards, considering urgency, importance, and likelihood. It depends only on current, not past, states (Bellman, 1957).

2.1.1 Model Components

The model comprises several components inspired by the structure of MDPs, a mathematical framework for modeling decision-making in situations where outcomes are partly random and partly under the control of a decision-maker (Howard, 1960).

State Space: The current situation or context. Each state is associated with a set of possible actions. The state space captures the situational aspect of decision-making, reflecting that the available choices often depend on the current circumstances. For example, deciding to invest in a particular market depends on the current market conditions (Sutton & Barto, 2018).

Action Space: The available actions in a given state. Each action leads to a transition to a new state. The action space captures the behavioral aspect of decision-making, reflecting the reality that different actions can lead to different outcomes. For example, the decision to invest in a risky asset can lead to a high return or a significant loss (Daw et al., 2005).

Transition Probabilities: The likelihood of transitioning from one state to another, given a particular action. Transition probabilities capture the inherent uncertainty and randomness in real-world decision-making scenarios. For example, the decision to invest in a risky asset involves uncertainty about the future state of the market (Daw et al., 2005).

Rewards: The outcomes or results of a particular action from a given state. Rewards can be 1) immediate or delayed, and 2) positive (benefits) or negative (costs). The concept of rewards captures the motivational aspect of decision-making, reflecting that the desire to achieve positive outcomes and avoid negative ones can often drive decisions (Sutton & Barto, 2018).

Discount Factor: Reduces the value of future rewards to reflect that individuals value immediate rewards more highly than future ones. The discount factor encapsulates the decision maker's time preference or discount rate. For example, investing in a long-term project involves discounting the future benefits to reflect their present value (Bellman, 1957).

Policy: This strategy defines which action to take in each state. The policy can be deterministic (always choosing the same action in a given state) or stochastic (choosing among several actions with specific probabilities). The concept of policy captures the strategic aspect of decision-making, reflecting that decisions often involve a sequence of actions over time (Puterman, 1994).

2.1.2 Comparison to the Two-Step Task

The two-step task is a well-established paradigm in cognitive neuroscience used to assess two types of reinforcement learning: model-free and model-based learning. Model-free learning depends on the direct association between actions and their outcomes. In contrast, model-based learning involves planning and

decision-making through a mental model of the task structure (Daw et al., 2005). The proposed decision-making model can be related to the two-step task, providing a richer understanding of the dynamics involved in these types of learning. In the two-step task, participants make two sequential decisions that navigate them through two "stages" defined by different stimuli. The first-stage choices lead to one of two second stages with varying probabilities, and each second-stage choice is associated with some probability of receiving a reward. The goal of the subject is to maximize rewards in the second stage, which requires continuous learning and adaptation to the changing reward probabilities.

For example, consider the first stage with an initial state that includes two choices: "buying a phone" or "taking a course." The transition probabilities are defined by the likelihood of moving to the second stage, given the first-stage choice. For instance, choosing "taking a course" could lead more often to a state where one gets a promotion (State 2a), while "buying a phone" could lead more often to a state where one does not get promoted and keeps the same job (State 2b). In the second stage, the state spaces include another choice, such as "buying a car." In State 2a (getting a promotion), the decision maker could choose "buying a phone" or "buying a car," where the car would be brand new and fancy, reflecting the increased financial resources in this state. In State 2b (keeping the same job), the decision maker could choose "taking a course" or "buying a car," where the car would be cheap and used, reflecting the lower financial resources in this state. In this context, both stages have rewards associated with the actions that are not a result of the transition to future states. Specifically, buying a phone would lead to immediate subjective value (e.g., the thrill of having a new gadget), and so would education (e.g., the fulfillment of getting a diploma or gaining knowledge). The value of each action, however, is the sum of its associated reward and the value of all future states weighted by their respective transition probabilities. The policy in this context would be the strategy that defines which action to take in each state. For instance, the decision maker might adopt a policy of always choosing the action with the highest immediate reward or adopt a more complex strategy that considers each action's urgency, importance, and value. Key in this decision is also the discount factor, which reflects the decision maker's time preference or discount rate. For instance, the decision maker might value the immediate pleasure of buying a phone more highly than the potential future benefit of a promotion (Daw et al., 2005).
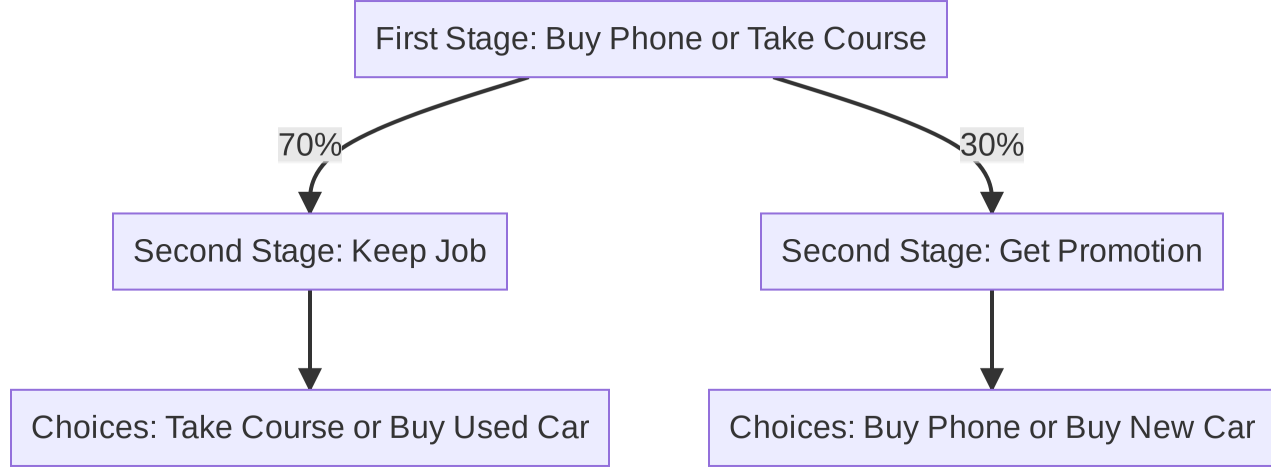
2.1.3 Priority Queuing

In our two-step task example, we observed how the unchosen task was "transferred" to the next state. This characteristic is a crucial feature of a priority queueing model, which we will delve into to enrich our understanding of decision-making dynamics further.

Priority queueing models often represent ordinal choices of tasks attended to based on some subjective value or utility function. These models are prevalent in various real-world scenarios, such as triaging bays, which treat queues as a function of urgency and order of arrival, and donor matching programs, which facilitate queues based on a point system that weights time, severity, and likelihood of survival.

Cobham and Barabasi have developed two critical priority queueing models. Cobham's model treats a queue as an infinite list of tasks with varying task arrival times and execution rates. On the other hand, the Barabasi model treats the queue as a finite size list with waiting times (τ_w). The mathematical expression for the waiting time distribution in the Barabasi model is as follows:

$$P(\tau_w) = \begin{cases} 1 - \frac{1-p^2}{4p} \ln \frac{1+p}{1-p}, \\ \frac{1-p^2}{4p(\tau_w-1)} [(\frac{1+p}{2})^{\tau_w-1} - (\frac{1-p}{2})^{\tau_w-1}], \end{cases}$$

Interestingly, as $p \rightarrow 0$, this distribution reduces to an inverse Poisson distribution. This expression is independent of the priority distribution, suggesting that the alignment of task priorities has no role in the time for these respective tasks to be executed.

Despite their powerful predictions, these existing models for priority queues have limitations in their applications. The literature is scarce about priority queuing

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in marginalized groups and how priority queuing is rationalizable. Some literature describes priority queues as a double-sided matching market with queues that depend on priorities and impatient customers (Castro et al., 2020). In this literature, customers of high value are matched prior to those of low value. Likewise, impatient customers can leave the queue if they are not matched immediately with a customer of their priority. This behavior is representative of many real-life cases but does not align with the behavior that the extended literature from Role Strain suggests about the decision-making choices of individuals from low SES. There is an apparent disconnect between how the average individual prioritizes tasks and how individuals from low SES do.

In our model, we aim to bridge this gap by integrating the principles of priority queueing into the decision-making process. By considering each task's urgency, importance, and value, we can create a more nuanced and realistic representation of how individuals allocate their time and resources. This approach allows us to capture the complexities of decision-making in a way that traditional models cannot, providing a more comprehensive understanding of the dynamics involved in model-free and model-based learning.

In the next sections, we will explore how this integration of priority queueing into our model can provide new insights into the decision-making process, particularly in the context of individuals from low SES.

2.2 Simulation

Priority queue models offer a tangible mechanism for capturing the choices and inter-event times that agents require when making decisions about daily tasks. Drawing on the existing literature surrounding poverty, we simulate an artificial priority queue using a priority function:

$$\text{Priority} = \alpha U + (1 - \alpha)I \qquad (2.1)$$

where U, I, α represent "urgency," "importance," and the urgency weight, respectively.

Our first step is to run a discrete-event simulation (DES) to uncover the relationship between α, the probability of survival, and burstiness measures. DES is a technique for modeling stochastic, dynamic, and discretely evolving systems, making it a powerful tool for understanding complex decision-making processes (Banks, J., Carson, J. S., Nelson, B. L., & Nicol, D. M. (2005). Discrete-Event System Simulation. Prentice Hall.). In this framework, we consider:

1. An individual who is capable of completing any job,
2. A ready supply of jobs with no prospect of any shortages,
3. Jobs are allocated a priority when they arrive in the queue according to Equation 2.1,
4. The time taken to complete a job is variable but independent of the task.

We define the completion time for the different activities as random draws from an exponential distribution with $\lambda = 5$. Similarly, the interarrival times for tasks are from an exponential distribution of $\lambda = 5$. Each incoming task receives $U, I \sim \text{Unif}(0, 1)$ and a priority according to Equation 2.1. Tasks are completed in the order of priority.

Importantly, each task contains a survival rate as a function of its importance. The higher the urgency, the more likely the task will fail (or die off). This feature internalizes the fact that urgent tasks may bring imminent negative consequences. A Weibull distribution with a monomial function gives the survival probability of a task:

$$\Pr(\text{survival}|\alpha = s(1 + U), \beta = 1) = 1 - e^{(-t/\alpha)^{\beta}}$$

where t is the wait time, and s is a scaling parameter (in the following simulations, calibrated to 100). As such, each task contains a survival probability, which is then accumulated throughout the task, such that the cumulative survival rate of later tasks are smaller than those of earlier ones.

By simulating this queue, we can graph a heatmap with the relationship of the weight of urgency on the priority function (α) and cumulative survival rate:
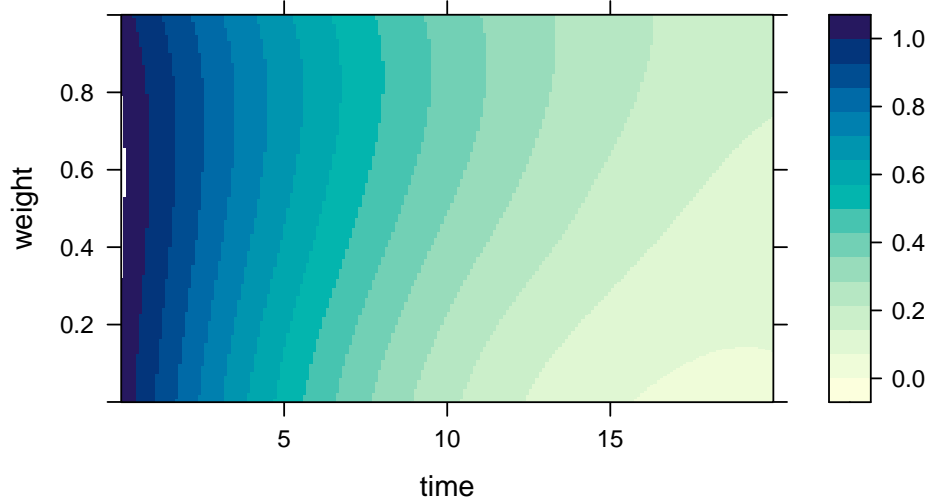
@img-simmer-simulation shows that those with higher urgency weights are more likely to survive longer in the queue. This finding suggests that the weight of urgency in the priority function plays a significant role in determining the survival probability of tasks in the queue. This finding underscores the importance of considering both urgency and importance when prioritizing tasks, particularly in contexts where survival rates are critical, such as in decision-making scenarios faced by individuals living in poverty.

2.3   Integrating Our Model with Poverty

Integrating our model with poverty is crucial in understanding its complex dynamics and effects on various aspects of life. Poverty is not just a state of financial deprivation but a multifaceted issue that affects health, education, and overall quality of life (Barrett et al., 2016). Our model aims to capture the combined effect of these complexities.

We integrate poverty by considering it a multidimensional variable that influences and is influenced by various factors: 1) Poverty can affect health outcomes by limiting access to healthcare services and nutritious food. In turn, poor health can exacerbate poverty by reducing a person's ability to work and earn income; 2) Social factors can be determinants of poverty. These include education, employment, and social support, which can significantly influence a person's likelihood of falling into poverty; 3) Poverty is not a fixed state but a condition that changes with time and circumstances. People can move in and out of poverty over time. Though past research has explored the dynamics of these three phenomena, we offer a novel integration of these physical, mental, social, and temporal determinants into our priority queueing model.

2.3.1   Temporal Discounting

Temporal discounting, as a behavioral economic concept, plays a pivotal role in our model, particularly in poverty. It refers to the well-established tendency to value immediate rewards at the expense of future outcomes (Frederick et al., 2002). This bias is often associated with lower wealth. It is more pronounced in populations with lower socioeconomic status (SES) (Ruggeri et al., 2022, The globalizability of temporal discounting. Nature Human Behaviour).

In our model, we incorporate temporal discounting as a critical factor influencing the decision-making process of individuals in poverty. The model allows for flexibility in the rate of temporal discounting, and individuals with lower SES are likely to have higher rates. In the context of poverty, temporal discounting can exacerbate financial difficulties. For instance, individuals facing financial strain may opt for immediate, smaller rewards instead of larger, delayed ones, potentially perpetuating a cycle of poverty (Haushofer & Fehr, 2014, On the psychology of poverty. Science).

To illustrate this, consider the decision-making process in our model. The decision-maker, who is in a state of poverty, is faced with two choices: "Work an extra shift" or "Attend a free community college class." The former offers an immediate reward, while the latter promises a future benefit. According to previous findings, some decision-makers in low SES are likely to choose the immediate reward due to the higher rate of temporal discounting. In many cases, the immediate need for financial resources outweighs the potential future benefits of attending a class. Our model captures this behavioral preference through a discount factor, denoted by γ.

However, this decision-making process is dynamic. It evolves as the decision-maker's circumstances change and as they gain more information about the potential future benefits of their actions. For instance, if the decision-maker learns that attending a class could significantly increase their future income, they might be more inclined to choose this option, even if it means forgoing the immediate reward of working an extra shift. This ability to foresee or predict future states is central to our model, and the following section will address it.

2.3.2 Foreseeing Future States

Individuals with lower SES often face uncertainty and instability, which can cloud the decision-making process, making it difficult to foresee the long-term consequences of their actions (Mullainathan & Shafir, 2013). This uncertainty is not merely a passive process but an active one. A study by Peters and Büchel (2010) found that the ability to vividly imagine future events can reduce temporal discounting.

Individuals likely learn to imagine future events in their social environments. Notably, community trust plays a significant role in this temporal discounting. Research by Farah and Hook (2017) suggests that SES significantly predicts high temporal discounting, particularly in environments characterized by low community trust (Farah & Hook, 2017, Trust and the poverty trap. Proceedings of the National Academy of Sciences). This finding implies that trust within a community can serve as a buffer against temporal discounting, encouraging individuals to make more beneficial decisions in the long term. Perhaps one channel through which this modulation occurs is learning from one's peers' experiences and expanding their set of imagined possible states, particularly for actions with small immediate rewards.

McIvor and Paton (2007) present an interesting example of social influences in future state prediction. Specifically, they look at preparedness for natural hazards and show that people are more likely to take precautions against earthquakes if they are part of a community that encourages safety measures and if they believe that taking action will have a positive impact on their safety. This finding suggests that the relationship between individuals and their community, including their trust in community institutions, can significantly influence their ability to visualize and predict future states (McIvor and Paton, 2007, Preparing for natural hazards: normative and attitudinal influences).

2.3.3 Transition Probabilities

Transition probabilities, which determine the likelihood of moving from one state to another, play a crucial role in our model. These probabilities influence individuals' choices based on their actions' potential outcomes, and correctly estimating them is essential to maximizing value.

In the context of decision-making strategies, psychologists have identified two

primary approaches: model-free and model-based strategies. Model-free strategies do not rely on transition probabilities but evaluate actions based solely on their reward history (Daw et al., 2005). On the other hand, model-based strategies rely on transition probabilities, using a cognitive model of potential actions and their consequences to make goal-directed choices (Daw et al., 2005). The balance between these two strategies can be fluid and contextually sensitive, with the reliance on a given strategy depending on the cognitive and affective demands placed on the individual (Otto, Gershman, et al., 2013, The curse of planning: dissecting multiple reinforcement-learning systems by taxing the central executive; Otto, Raio, Chiang, Phelps, & Daw, 2013, Working-memory capacity protects model-based learning from stress.).

Previous research has found that factors such as stress and education levels can affect the proportion of model-free and model-based strategies used in decision-making. Research suggests stress can also impact decision-making, leading to a greater reliance on model-free strategies (Schwabe & Wolf, 2013, tress and multiple memory systems: from 'thinking' to 'doing'). Furthermore, education levels can influence the ability to use model-based strategies, with higher education levels associated with greater use (Worthy et al., 2011, Heterogeneity of strategy use in the Iowa gambling task: A comparison of win-stay/lose-shift and reinforcement learning models).

2.3.4   Urgency

Our model is beneficial for analyzing the decisions of individuals in low-SES (Socioeconomic Status) environments. Here, we build on the two-stage decision-making model by incorporating urgency. In the first stage of our model, the decision-maker, an individual encounters two choices: "Work an extra shift" or "Attend a free community college class." The choice of "Work an extra shift" predominantly leads to a state where the individual has extra money (State 2a), while "Attend a free community college class" more frequently leads to a state where the individual gains new skills (State 2b). The urgency component is crucial in this stage. The opportunity to work an extra shift is fleeting, available only on the current day. If not seized, this opportunity will expire, and the potential for additional income will be lost. Conversely, the community college class, part of a recurring weekly course, presents a less urgent choice. The individual could attend the class the following week, but missing classes could lead to a cumulative knowledge gap, jeopardizing the overall benefit of the course. In the second stage, the state space expands to include another choice. In State 2a (having extra money), the individual could choose between "Buy groceries" or "Pay utility bills." In State 2b (gaining new skills), the individual could opt to "Apply for a better job" or "Start a small business." Urgency is also a pivotal factor in the second stage. The utility bill payment is due imminently, and failure to pay will discontinue essential services. On the other hand, buying groceries, while a recurring necessity, may not have the same urgency. However, a prolonged delay in this action could lead to health

and well-being implications, underscoring its medium-term urgency.
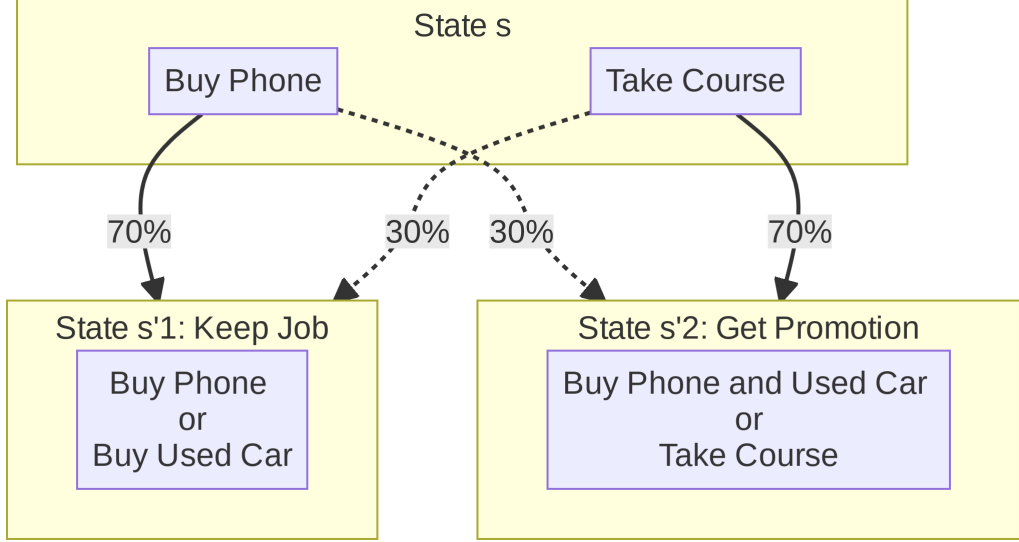
To illustrate the role of urgency in decision-making, we will use a mathematical representation of our model. We will consider a simplified version of the two-stage decision-making scenario described above, focusing on the first stage, where the decision-maker must choose between "Work an extra shift" or "Attend a free community college class."

Let us denote the state of the decision-maker by s and the set of available actions by $A(s) = \{$"Work an extra shift", "Attend a class"$\}$. The urgency of action $a \in A(s)$ is the time limit T_a, after which the action is no longer available.

The decision-maker's policy π determines the action to take in each state. The policy is a function of the current state and time, $\pi(s, t)$, and it changes over time as the urgency of the actions changes.

The value $V(s, t)$ of a state s at time t is the expected future reward when following policy π, discounted over time:

$$V(s,t) = \mathbb{E}_\pi \left[R(s_t, a_t) + \gamma \sum_{s' \in S} P(s'|s_t, a_t) V(s', t+1) \right],$$

where $R(s_t, a_t)$ is the immediate reward from taking action a_t in state s_t, $P(s'|s_t, a_t)$ is the transition probability from state s_t to state s' given action a_t, and $\gamma \in [0, 1]$ is the discount factor that determines the present value of future rewards.

The urgency of an action affects the value of a state by limiting the time available to take the action. As the deadline T_a approaches, the decision-maker's available time budget decreases, constraining the set of feasible actions.

Now, consider the case where "Work an extra shift" is an "immediate-reward task" with a high reward of $R_{\text{work}} = 100$ and a short deadline of $T_{\text{work}} = 1$ day. If the decision-maker does not work the extra shift within one day, they will miss the opportunity to earn additional income. However, this action does not significantly change the future state values, as working an extra shift does not lead to a permanent increase in income.

On the other hand, "Attend a class" is a "future-reward task" with a lower immediate reward of $R_{\text{class}} = 10$ and a longer deadline of $T_{\text{class}} = 7$ days. If the decision-maker does not attend the class within a week, they will miss the opportunity to gain new skills, which could lead to better job opportunities and higher future state values.

The optimal policy π^* balances the immediate rewards with the future rewards, considering the actions' urgency and potential future benefits. It is given by:

$$\pi^*(s, t) = \arg \max_{a \in A(s)} Q(s, a, t),$$

where $Q(s, a, t)$ is the action-value function that represents the expected future reward from taking action a in state s at time t:

$$Q(s, a, t) = R(s, a) + \gamma \sum_{s'} P(s'|s, a)V(s', t + 1),$$

where $P(s'|s, a)$ is the transition probability from state s to state s' given action a.

In this case, if the decision-maker follows the optimal policy, they will choose "Work an extra shift" on the first day due to its high immediate reward and urgency and then "Attend a class" on the subsequent days to maximize the potential future benefits. This example illustrates how the urgency of tasks and the distinction between immediate and future rewards can influence the optimal decision-making policy. By incorporating urgency into the decision-making model, we can capture the temporal dynamics of real-life decisions and provide a more accurate representation of the decision-making process.

2.3.5 Suboptimal Time Allocation

Inefficient time allocation of daily tasks is another factor that can contribute to the persistence of poverty. Individuals make a sequence of decisions and bargains to reduce the strain of their daily demands and roles in a process similar to an economic decision: Allocating limited resources such as energy, time, emotions, and goods in different ways (Goode, 1960). For individuals

from a higher SES, delegating these roles becomes far more manageable, and the bandwidth to tackle other tasks increases significantly. The converse is true, however: the poorer one is, the more uncontrolled demand for time and money.

A recent study by Jachimowicz et al. (2022) provides a compelling illustration of this phenomenon. The authors found that financial scarcity is associated with greater distress intensity in everyday life. They propose that financial resources allow individuals to reduce the distressing impact of everyday hassles, increasing one's life satisfaction. This research suggests that financial scarcity shrinks the sense that one can use economic resources to reduce the adverse impact of daily hassles. While money may not necessarily buy happiness, it reduces the intensity of stressors experienced in daily life—and thereby increases life satisfaction.

In the context of our model, suboptimal time allocation can exacerbate the effects of poverty, leading to a cycle of immediate-reward task selection and persistent financial scarcity. The immediate reward of completing a task and reducing the day's demands can outweigh the potential future benefits of tasks that require more time and effort. This feature is particularly true for individuals facing financial scarcity who may not have the luxury of investing time in tasks with delayed rewards.

The ability to delegate tasks significantly alleviates this burden. Delegation allows individuals to offload tasks to others, freeing up their time and mental resources. This advantage is especially beneficial for urgent tasks, which can consume a disproportionate amount of time and attention. However, the ability to delegate is often a privilege reserved for those with sufficient financial resources. For individuals facing financial scarcity, the cost of delegation may be prohibitive.

By incorporating these dynamics into our model, we can better understand the decision-making processes of individuals in different socioeconomic circumstances.

2.3.6   Role Strain

Introduced by sociologist William Goode in 1960, the concept of role strain motivates our theoretical framework. Goode proposed that individuals, faced with an impossibility of satisfying all role demands, engage in role decisions and bargains to modulate these demands. This process necessitates allocating limited resources such as time, emotions, and goods across various role obligations. The ultimate goal is to minimize perceived role strain, defined as the cognitive and emotional exertion involved in fulfilling duties (Goode, 1960).

Role strain is particularly salient among individuals experiencing poverty, who often grapple with an elevated effort dimension or the subjective value ascribed to task completion. Morris and Coley's 2004 study on role strain correlates among mothers revealed many factors that amplify "strain" in this demographic, many of which are income-related (Morris & Coley, 2004). A separate study

on family caregivers of adult cancer patients in Kenya further exemplifies this phenomenon. The researchers discovered that these caregivers, typically under financial strain, experienced significant role strain due to the simultaneous management of multiple responsibilities (Mugenda et al., 2020). These findings underscore the disproportionate burden of role strain borne by those in poverty, who must navigate a labyrinth of tasks and roles with scarce resources.

Adding tasks to already demanding circumstances intensifies role strain, while providing social support to assist with tasks can mitigate it (Lewis, 1989 https://www.jstor.org/stable/2784697). A proposed cause of poverty traps is the tendency of impoverished individuals to overcommit to high-urgency tasks, thereby neglecting or under-committing to high-effort or high-importance tasks.

Goode's theory differentiates between role conflict, where two roles present mutually exclusive demands, and role overload, where an individual lacks the resources to meet the demands of multiple roles. The latter is particularly pertinent to our research objectives. Role overload arises when an individual is tasked with fulfilling multiple roles concurrently and struggles to meet these roles' demands. For instance, a full-time student may concurrently struggle to care for young children (Nickerson, C. (2023) https://www.simplypsychology.org/what-is-role-strain-in-sociology.html).

Our model seeks to elucidate how task overload influences decision-making processes and outcomes, contributing to our understanding of poverty dynamics.

2.3.7 Scarcity

The intricate interplay between poverty and cognitive function is critical to socioeconomic studies. Individuals from lower socioeconomic strata often grapple with a dearth of resources, significantly influencing their behavioral patterns and cognitive abilities. This observation has sparked investigations into the so-called "scarcity mindset," a psychological state hypothesized to precipitate three primary cognitive effects: attentional drift, pronounced trade-off thinking, and diminished mental bandwidth (de Bruijn & Antonides, 2022). These cognitive shifts, in turn, can elucidate common behavioral characteristics observed among those of low socioeconomic standing, including overborrowing, more consistent consumption decisions, and increased time discounting and risk aversion (de Bruijn & Antonides, 2022).

For instance, experiments designed to induce a scarcity mindset by deliberately limiting resources revealed that participants demonstrated heightened focus on tasks due to the limited opportunities for success (Shah et al., 2012; Shah et al., 2019). While this increased focus improved efficiency and accuracy in task completion, it also increased borrowing and elevated stress levels, making tasks increasingly taxing and requiring more attention. However, other studies suggest that further evidence is required to substantiate these conclusions (de Bruijn & Antonides, 2022).

Moreover, the assertion that poverty reduces mental bandwidth and increases time discounting and risk aversion requires further empirical support (O'Donnell et al., 2021). Current studies only partially align with empirical data and need more precision for a comprehensive understanding (de Bruijn & Antonides, 2022). Notably, a replication study by Shah et al. (2019) examined how different forms of scarcity affect attention and borrowing behavior, finding no evidence that scarcity on one task leads to cognitive fatigue on subsequent tasks, thereby contradicting the results from Shah et al. (2012).

In a more recent study, Madsen et al. (2022) conducted a field experiment using Danish unemployed social assistance recipients to test the psychological consequences of scarcity. The researchers randomly assigned survey recipients to three groups: (a) those surveyed before receiving social assistance benefits, (b) those surveyed after receiving them, and (c) those surveyed in the middle of the month. Interestingly, they found no impact of the scarcity manipulation (those surveyed before payment) on the mindsets of social welfare recipients. However, they did find that subjective scarcity, or "the feeling of having too little," correlated positively with an increased focus on problem-solving but negatively with psychological well-being, mastery, and job search self-efficacy.

The relationship between poverty and cognitive function is complex and multi-faceted. While scarcity can lead to heightened focus and efficiency in task completion, it also induces a scarcity mindset that can lead to suboptimal decisions and behaviors. Our theory builds on this literature and suggests that people must balance their current and future expenses when they have limited budgets and uncertain incomes. This strain can be challenging and requires attention, executive control, and working memory, leaving fewer cognitive resources for other less urgent tasks. As such, we seek to understand the mechanisms underlying these effects and how they may perpetuate poverty.

2.4   Affective States

The present study proposes that the behavioral deviations observed in individuals living in poverty, specifically the overweighting of urgency, are mediated by affective states such as stress and anxiety. This proposition is rooted in the understanding that stress and anxiety can significantly influence decision-making processes. For instance, a meta-analysis by Starcke and Brand (2016) found that stress generally increases risk-taking.

Indeed, individuals of low socioeconomic status (SES) often report feeling overwhelmed, which can exacerbate stress and anxiety. A study by Williams (2018) on populations of color, who often experience low SES, found that race-related stressors can significantly affect mental health, leading to higher levels of psychological distress. Similarly, a study by Heers and Lipps (2022) found that almost one fifth of parents reported feeling overwhelmed by homeschooling obligations during the Covid-19 pandemic, with women, mid-aged and lower-educated indi-

viduals, as well as those with young children and a lower income, being particularly affected. This feeling of being overwhelmed did not cause changes in life satisfaction, stress, and negative affect, but it did lead to a decrease in positive affect.

The intricate relationship between poverty and mental health has been the subject of extensive research, with numerous studies suggesting a bidirectional link between the two. Poverty can exacerbate mental health issues due to the stress and strain of living in financial hardship. In contrast, mental health issues can lead to poverty due to reduced productivity and employment opportunities (Lund et al., 2010). Ridley et al. (2020) further corroborated this relationship, highlighting the detrimental impact of mental illness on economic outcomes.

As mentioned, the stress and tension arising from role strain are central to our hypothesis. Morris and Coley (2004) identified several factors that increase role strain among mothers, including low income, lack of social support, low education, lack of health insurance, and reliance on government welfare.

Similarly, Stack and Meredith (2018) found that single parents are at high risk of financial hardship, leading to poor mental health and low psychological well-being. Single parents often experience higher levels of chronic stress, loneliness, and depression, despite making extensive efforts to meet their financial obligations.

Thus, our proposed model suggests two channels through which role strain may increase the urgency bias. The first channel posits that the subjective experience of strain, which can be exacerbated by factors such as low income, lack of social support, and reliance on government welfare, can lead to an urgency bias in decision-making. The second channel suggests that the stress and anxiety resulting from role strain can also lead to an urgency bias.
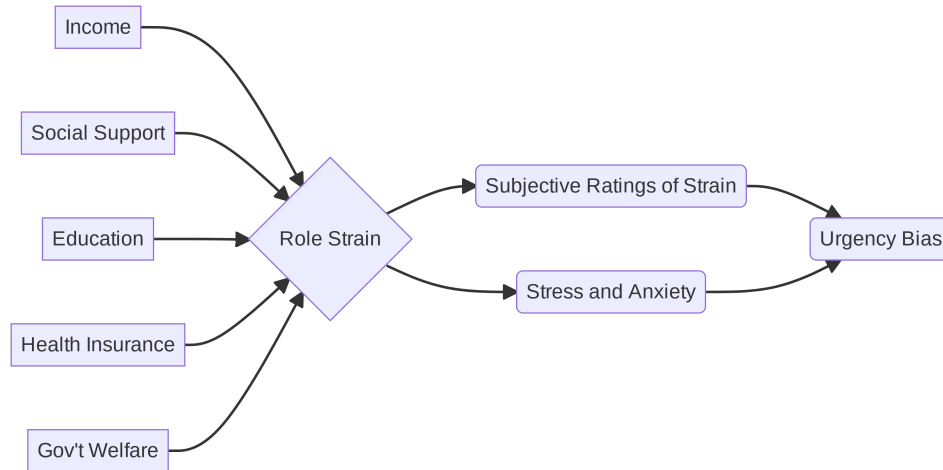
2.5   Research Questions

1. How do urgency and importance shape task selection, and what are the underlying cognitive processes that drive these effects?

2. To what extent does Socioeconomic Status influence task prioritization, and what is the mediating role of role strain in this process?

3. What are the key affective mechanisms that contribute to suboptimal time allocation, and how do they interact with cognitive and environmental factors?

Chapter 3

Pilot Experiment

3.1 Methodology

Our experimental design simulates the environment of an ice cream parlor using an interactive online game. The game was developed in PsychoPy version 2023.1.3 and hosted on the Pavlovia platform. Participants played the role of ice cream parlor owners whose goal was to maximize profit by completing tasks with varying characteristics.

3.1.1 Structure

In the game interface, participants saw a queue of tasks representing ice cream orders on the sides of the screen. Each task varied according to three characteristics: effort, importance, and urgency. These characteristics corresponded to icons on each task image to aid the participants' decision-making process, as depicted in @img-choice.

1. Effort: We operationalized effort through the number of clicks required to complete an order. More complex orders required more elements on the ice cream, some of which were relatively difficult to discern (e.g., the different types of sprinkles). We deem tasks with more elements, or hard-to-discern elements, more effortful.

2. Importance (value): We equate importance with subjective value, represented by dollar signs on the image. A single dollar sign indicated low importance (yielding one point), while two dollar signs indicated high importance (yielding two points). The points were the participants' earnings, and each point was worth $0.05. The total earnings, a proxy for the participant's performance, were displayed at the top of the screen.

3. Urgency: We used clock icons on each image to convey the degree of urgency of a task. Two clock icons denoted a high-urgency order, while one clock icon
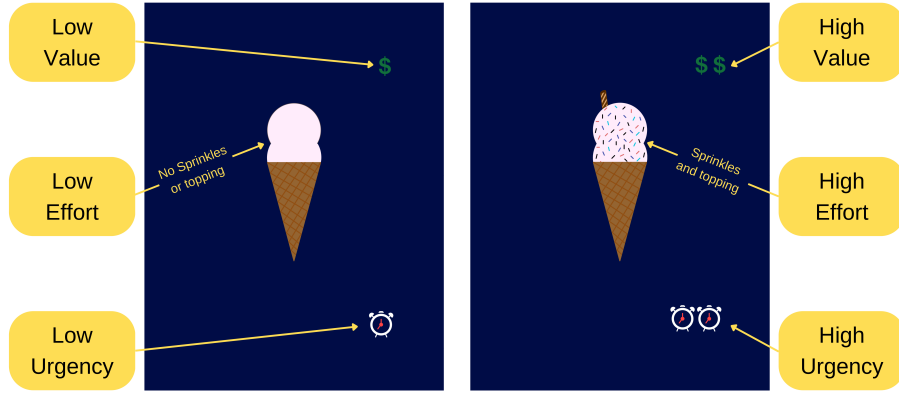
Figure 3.1: Example of two tasks with differing levels of Importance (Value), Effort, and Urgency.

represented a low-urgency order. High-urgency tasks lost value (dollar signs) if participants did not complete them in a given round (e.g., an urgent task worth 2 points would become an urgent task worth 1 point in the next round, and an urgent task worth 1 point would lose all of its value). If a high-urgency task lost all its value, it would disappear from the queue, and the participant was "punished" by having only one order in the queue for the following two rounds. Conversely, low-urgency tasks stayed in the queue until selected and completed.

In each round, participants saw the screen shown in @img-pilot-exp. They were instructed to select a task from the queue (left or right) and click on the matching ice cream icons in the center of the screen to complete it. If they made a mistake, they could use the trash can icon to discard the current order and start over. The game continued for a total of 20 orders. Participants were not restricted to a specific order of task completion; they could choose any task from the queue at any time. This open-choice design allowed us to observe and analyze the decision-making and prioritization strategies employed by the participants. Note that we incentivized players in the game by offering a prize of up to $1.00 , contingent on the total number of points players accumulated throughout the game.

3.1.2   Simulation

We devised a theoretical model for how we expect rational decision-making to manifest in our priority queuing experiment such that frequency of deviations from rationality can be monitored. To formalize the optimal, or rational, set of behavior for maximizing rewards over long-term exposure in a queue, we devel-

oped a closed-form model. We hypothesize that this decision-making process reduces to a simple subjective-value function, where every individual determines the priority or preference $\succeq_q$ by the subjective value utility representation. We thus developed a stochastic model, as follows:

$$V(s) = \max_a(r(s,a) + \gamma \sum_S P(s,a,s')V(s'))$$

$$S = \{HHU \times HHU, HHU \times HH0, LHU \times LHU, ...\}$$

$$r(a,s) = i_a - c_a$$

$$R = r(HHU, HHV \times HHU) = 1 - c_H, ...$$

$$V(s_{final}) = \max_a(r(s_{final}, a))$$

In **?@eq-model** the agent calculates the value of state $s' \in S$ (which is the next state, i.e., next period). i is the reward (in dollars) for completing a task, c_i is the effort cost (estimated in dollar unites), and $r(a,s)$ is the net payoff of completing action a at state s. P is the probability of transitioning from state s to another state (s'), given that our agents takes action a in state s. $V(s')$ is the value of that new state. We subsequently sum these results over all the possible future states. Note we use γ as our discount factor. In our normative model, we set the discounting factor to be 1, given the tasks are very close to each other in time. Note that this model only has two cost parameters $c = \{c_L, c_H\}$.

We build upon this by then generating an optimal protocol for identifying the best set of choices at any stage for maximizing long-term outcomes. Using dynamic programming, a recursive method of taking the outcomes of subgames and applying it to the entire scheme, we identify which tasks should be chosen at any given stage of the 2-task queue. Given this framework, we can graph the ratio of urgent choices at each given state, as a function of the cost parameter c_H and the discount factor (here $c_L = 0$ for all cases).

Figure 3.2 shows that the optimal percentage of urgent choices varies by around 0.10, with lower probabilities centered around low cost parameters and high discount factors.

3.2   Hypotheses

We hypothesize that many participants may rush their decisions due to the induced scarcity, which could lead to stress and potentially affect their performance. To gather data on participants' socioeconomic status and anxiety levels, we administered pre- and post-experiment surveys.

While certain task scenarios in the game require minimal cognition (e.g., a high value, high urgency task will always be prioritized), other scenarios present more complex decisions. For instance, when presented with a high importance, low
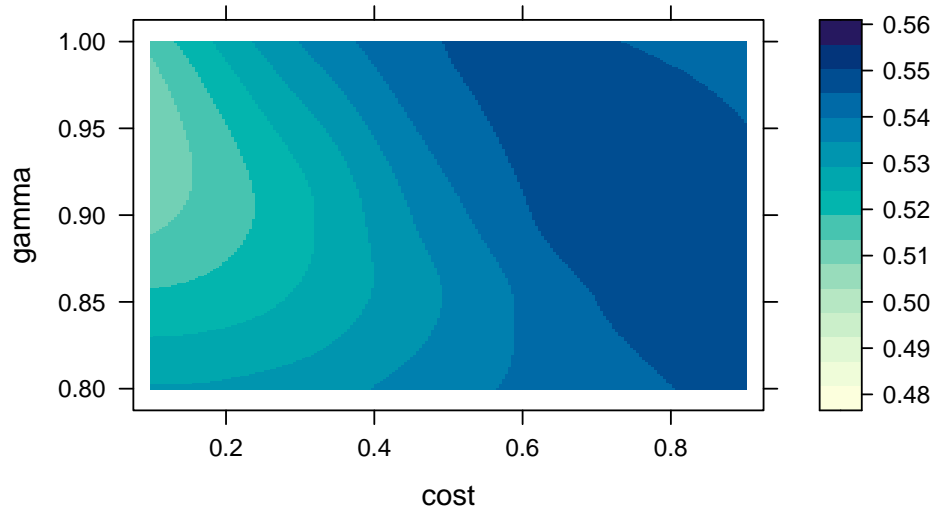
Figure 3.2: Percentage of Urgent Choices

urgency task and a high urgency, low importance task, the optimal course of action may not be immediately clear. We analyze the choices made by participants under these circumstances to gain insight into their prioritization strategies.

3.3 Data

We administered our experiment over both Mturk and Prolific. In our MTurk administration, we acquired N = 22 participants, and via Prolific, N = 53. Here, we treat these samples as independent replications.

3.3.1 Demographics

For both Mturk and Prolific, we distinguish high-low income and high-low anxiety by a median split. The high income mean is about 70k, while the low income mean is around 30k ($p < 0.001$). Likewise, the high anxiety mean score is 56.29, while low anxiety mean score is 37.17 ($p < 0.001$).

MTurk N=22 x 20 trials	Mean	Median	Min	Max
Age	34.53	33	19	50
Income		$40,000 to $49,999	Less than $10,000	$90,000 to $99,999
Education		Bachelor's degree	High school graduate	Master's degree

MTurk N=22 x 20 trials	Mean	Median	Min	Max
STAI	44.21	47	20	67

Table 3.2: The two samples display similar demographics

Prolific N=53 x 20 trials	Mean	Median	Min	Max
Age	30.13	28	18	75
Income		$40,000 to $49,999	Less than $10,000	$90,000 to $99,999
Education		Bachelor's degree	High school graduate	Master's degree
STAI	45.04	45	20	68

3.3.2 Measures of Poverty

Although income-based measures have long been the standard for assessing poverty, studies have since determined that purchasing power and standard of living are not accurately measured by such a metric (CITE). Rather, relative deprivation and state-trait anxiety measures are often more accurate empirical measurements of an individual's socioeconomic status (SES).

3.3.2.1 Self-Reported Income

Though the simplest measure to collect, self-reported incomes has a number of limitations. Participants may have the incentive not to divulge their true income levels. This bias can occur in both directions depending on the context and demand effects (e.g., a participant may want to appear richer or poorer than they actually are). Further, because exact income, when combined with other demographic measures, could potentially be used to identify participants, it is customary to elicit income brackets (vs. absolute income levels). This limitation may also reduce power and granularity in the our analysis.

3.3.2.2 ZIP code Measures

To supplement the self-reported income data and account for any potential measurement errors, we employed additional economic indicators based on participants' ZIP codes. The Internet Protocol (IP) addresses collected automatically by Qualtrics were used to determine the ZIP code of each participant's location. From these ZIP codes, we extracted relevant economic data, including

median income and poverty measures, which provided a broader context for each participant's socioeconomic status.

The poverty measures in our analysis come from the American Community Survey (ACS) conducted by the U.S. Census Bureau. The ACS determines poverty status based on a set of income thresholds that vary by family size and composition. It provides a comprehensive and nuanced understanding of poverty by incorporating the complexity of family structures and income levels into its poverty thresholds.

The median income data we used is also sourced from the ACS. This data reflects the median income distribution across all households and families within each ZIP code, including those with no income. As a result, it provides a robust measure of the overall economic status of the communities in which our participants reside.

For a more detailed understanding of these measures, please refer to the ACS Subject Definitions document available at this link.

3.3.2.3 ¶Composite Measure (PCA)

Given that poverty is a multidimensional variable, we attempt to capture it through a series of questions (see @questionnaires for details). We created several questions about physical, mental, and monetary deprivation. We then summarized these results in a PCA. We use only the top two components, as per the Scree plot:

Scree plot
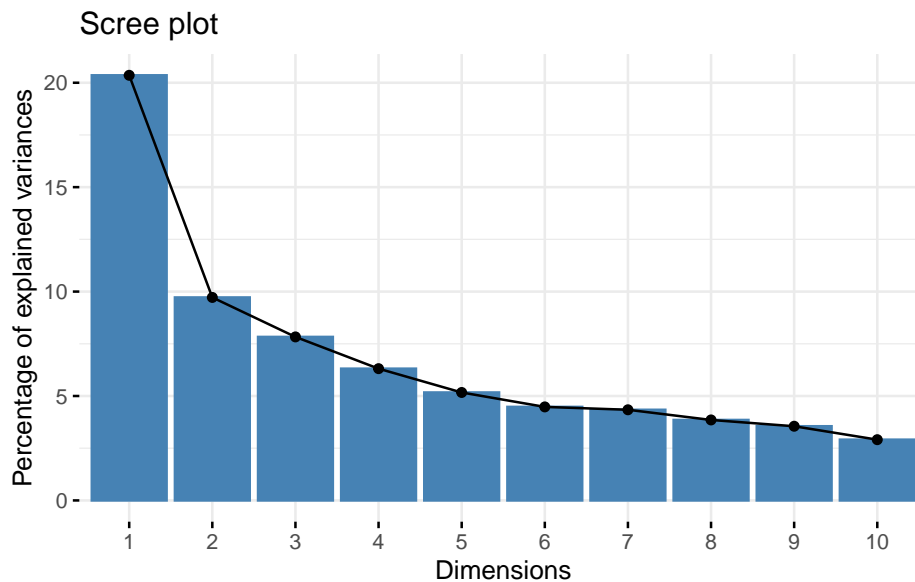
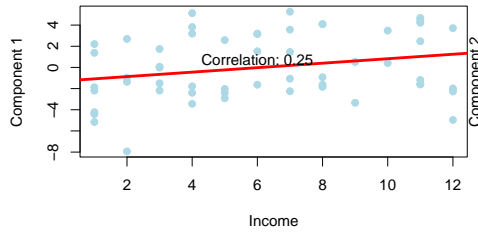### 3.3.2.3.1 "Dimension 1" top 5 contributors:
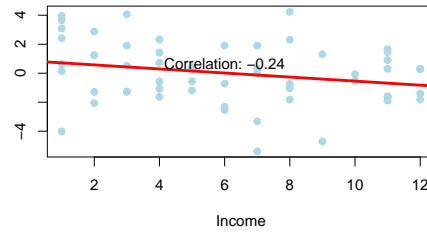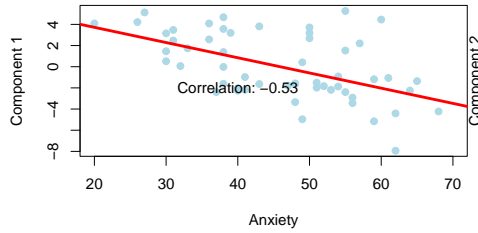
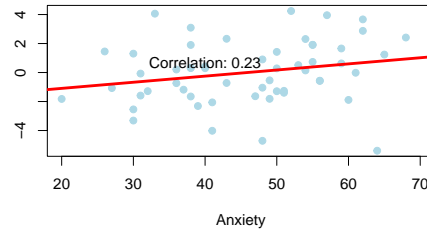Figure 3.3: Plot

Figure 3.4: Plot

Figure 3.5: Plot

Figure 3.6: Plot

(Higher dimension values = higher "depression")

1. How would you rate your mental health over the past 4 weeks? (1-5)
2. Please select Yes or No for each of the following questions (YES = 1, NO = 2).
    a. I am happy about achieving something good in the last 4 weeks.
    b. Depressed and unhappy.
3. Over the past 2 weeks, how often have you felt down, depressed, or hopeless?
4. Over the past 2 weeks, how often have you felt little interest or pleasure in doing things?

3.3.2.3.2 "Dimension 2" top 5 contributors:

(Higher dim. values = higher "concern for mental health")

1. How important are the following:
    a. How you feel about yourself
    b. Your mental state of being
    c. Your physical state of being
2. How important are the following aspects of your life?
    a. I need to be mentally healthy
    b. Having a good house to stay in

Note: We included other deprivation questions related to physical/monetary deprivation. However, those questions did not yield sufficient variance.

3.4 Results

The dataset from our experiment comprised multiple choice variables (Important, Hard, and Urgent tasks) and participant demographic information (STAI score, income level, and platform). We used this dataset to conduct a regression analysis to examine how participants' choice behavior influenced their total points accumulated in the task.

3.4.1 Task Performance

We compiled data on each participant's selection and non-selection of each type of task (Important, Hard, and Urgent), then computed the frequency with which each participant picked a particular task type when given an option. Table 3.3 indicates that the decision to complete Important tasks significantly affected the total points a participant amassed (Estimate = 16.098, p < .001). Specifically, a ten percentage point rise in the ratio of selected Important tasks (two points, as opposed to one point) resulted in an increase of 1.6 points in the overall score. However, the percentage of times a participant chose Hard or Urgent tasks did not significantly explain the total points accumulated (Estimate = -7.563, p = .371 for Hard tasks; Estimate = 6.539, p = .142 for Urgent tasks).

We also included demographic variables and participant characteristics (STAI score, income level, and platform) as control variables in the regression model, but none showed a significant relationship with total points.

The model accounted for approximately 20.24% of the variance in total points (Adjusted R-squared = 0.132), with an overall significant model fit ($F(6,68)$ = 2.877, p < .05).

3.4.2 Trade-off Decisions

When we compare an individual's choice of "challenging" tasks: decisions between high urgency - low importance or low importance - high urgency tasks, we observe that high anxiety and low income individuals more often choose high urgency tasks over high value tasks, which corroborates the current non-quantitative literature as can be observed in the plots below.

Accuracy in trade-off decisions as a function of income and anxiety

Multiple regression models to test the same hypotheses with different measures of income.

Percent of urgent choices (vs. important) as a function of income and anxiety.

3.4.3 General Urgency Bias

Individuals in the low income groups and in the high anxiety groups chose urgent tasks more often than important tasks. This result is not consistent for high

Table 3.3: Regression analysis of total points on participants' choice behavior and demographic variables. The predictors include the percentage of choices where Important, Hard, and Urgent tasks were chosen, participants' STAI score, income level (High vs. Low), and the platform on which the experiment was conducted (Prolific vs. Mturk).

	Dependent variable:	
	Total Points	
	(1)	(2)
Percentage of Important task chosen	16.098***	15.685***
	(4.501)	(4.481)
Percentage of Hard task chosen	−7.563	−2.389
	(8.406)	(8.140)
Percentage of Urgent task chosen	6.539	5.963
	(4.397)	(4.398)
STAI Score	0.006	
	(0.069)	
Low Income	1.083	
	(1.113)	
Platform: Prolific (vs. Mturk)	0.866	
	(1.786)	
Constant	20.543***	21.485***
	(4.166)	(2.073)
Observations	75	76
R^2	0.202	0.170
Adjusted R^2	0.132	0.136
Residual Std. Error	6.692 (df = 68)	6.748 (df = 72)
F Statistic	2.877* (df = 6; 68)	4.922** (df = 3; 72)

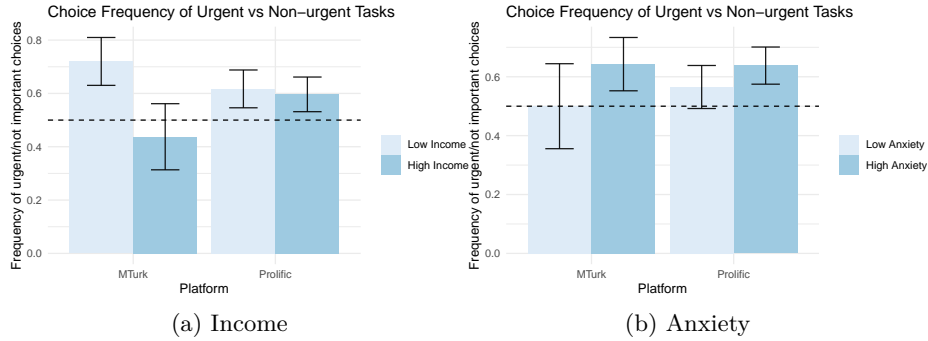| *Note:*	*p<0.05; **p<0.01; ***p<0.001

Figure 3.7: Choice proportions by income and anxiety

income or low anxiety groups. Future graphs in this document will show that the difference-in-difference is not as clear.

1.
2. Multiple regression models to test the same hypotheses with different measures of income.

It seems that when controlling for Dim 1 and 2, some effects become significant. Multicollinearity might be a problem, although correlations between STAI and PCA components are not higher than 0.6 (see correlation plots above). These results might be a result of a separation between State and Trait Anxiety. Although we only included the State questions of STAI, state and trait scores are likely correlated. PCA dimensions 1 and 2 may control for this confounding effect.

We review the Key Results from the first pages: urgent choices do seem to be above 50% for key groups, but the differences-in-differences across income and anxiety levels are not significant.

Again, people might not mind leaving the High Importance task undone. This is what some friends have called the "insurance ice cream." That is, if I leave this High Importance task in my queue, I can use it when I get a task that is High Effort but Low Urgency.

3.4.4   Reaction Time

3.4.5   Accuracy

We also obtain a comparison of the choices participants make and the optimal, or rational, protocol we generated. This is done by estimating a hierarchical Bayesian model...
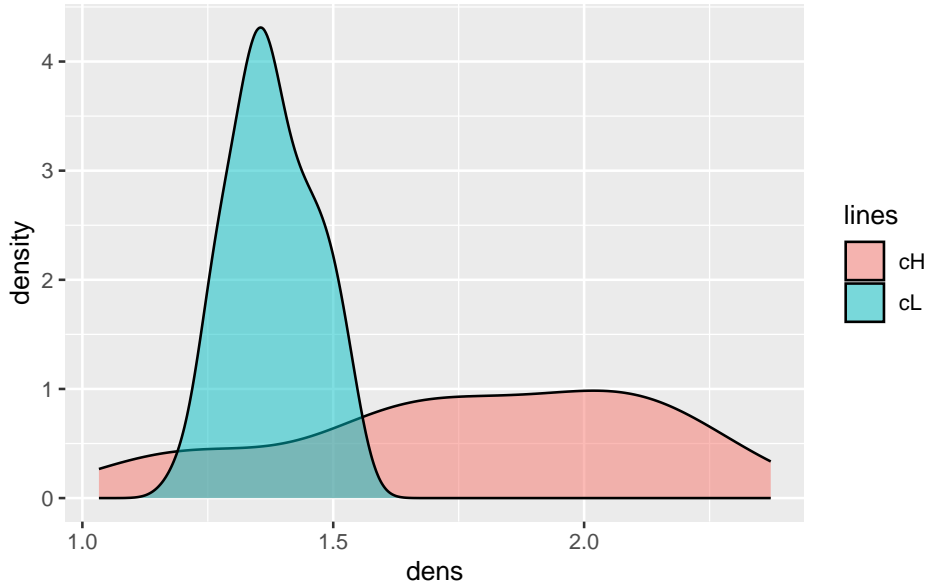
Figure 3.8: Histogram of Estimated Costs per Participant

This score is calculated by first estimating the cost parameters for each participant and then using them with backwards induction to discover the optimal choice at each presented state.

Figure 3.9 highlights how participants typically make optimal decisions (when given 'challenging' tasks) with a probability in between 0.5 and 0.6. This is generally what we expect to observe.

3.4.5.1 Accuracy, Anxiety, and Income

1. Accuracy in trade-off decisions as a function of income and anxiety

Finally, we compare for each participant, how many of their choices are identical to a model that observed the full horizon for the Markov decision process. Each participant is a dot, y axis is the percentage of correct choices in the experiment while x axis is the STAI (anxiety measure). Generally the results are very similar to figure 1.5.

It appears that Accuracy does not vary across income and anxiety levels with these measures. Some possibilities of this fact might include that, since time discounting here is virtually 0, leaving the important task behind will not affect participants as much (depending, of course, of the estimated cost parameters).

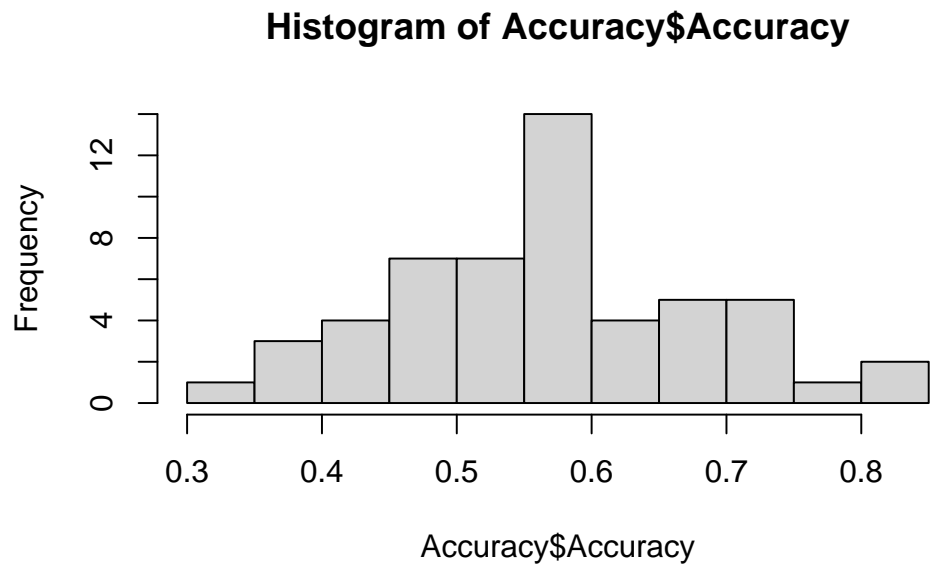#### 3.4.5.2 General Linear Models of Accuracy

Histogram of Accuracy$Accuracy

Figure 3.9: Histogram of Accuracy Proportions
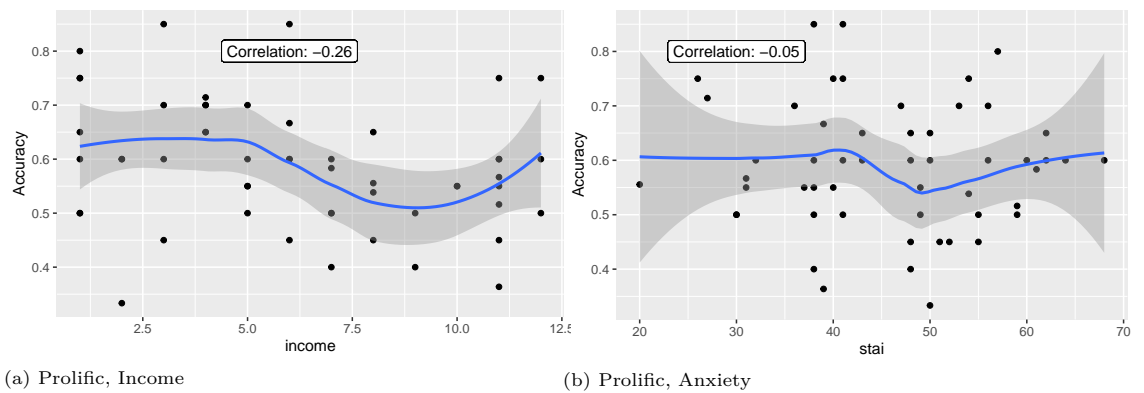

(a) Prolific, Income

(b) Prolific, Anxiety

Figure 3.10: Participant Accuracy by Income and Anxiety

Chapter 4

Experiment 1

4.1 Methodology

Experiment 1 was developed in PsychoPy version 2023.1.3 and hosted on the Pavlovia platform.

4.1.1 Structure

In line with the pilot study, the game interface for Experiment 1 presented participants with a queue of tasks, each varying in effort, importance, and urgency. As previously depicted in @img-choice, we visually represented these characteristics with corresponding icons on each task image.

1. Effort: As in the pilot study, we operationalized effort through the number of clicks required to complete an order, with more complex orders demanding more effort.

2. Importance (value): The representation of importance remained consistent with the pilot study, with dollar signs indicating the subjective value of a task. However, with each point now worth $0.05, participants now earn up to $4.00 based on their total points.

3. Urgency: The urgency of tasks was conveyed similarly to the pilot study, with clock icons indicating the degree of urgency. However, low-urgency tasks now remained in the queue for four rounds before being replaced, and, unlike high-urgency tasks, there was no penalty if low-urgency tasks disappeared after four rounds.

In each round, participants saw the screen shown in @img-exp. They were instructed to select a task from the queue (left or right) and click on the matching ice cream icons in the center of the screen to complete it. The game continued for 40 orders, doubling the length of the pilot study to provide a more robust

measure of participant behavior. As in the pilot study, participants were not restricted to a specific order of task completion, allowing for an open-choice design that facilitated the observation and analysis of decision-making and prioritization strategies. The potential earnings increased to a maximum of $4.00, contingent on the total number of points accumulated throughout the game, to further incentivize participation.

Experiment 1 introduced a critical modification to the task queue logic, distinguishing it from the pilot study. As previously noted, specific task scenarios in the game posed more complex decision-making challenges, where the optimal course of action was not immediately apparent (e.g., choosing between a high-importance, low-urgency task, and a high-urgency, low-importance task). Due to the uniform task sampling employed in our pilot study, these "hard choices" were infrequently encountered.

Experiment 1 addressed this limitation by adjusting the task queue logic. Specifically, if the remaining task in the queue was of high importance and low urgency, there was a 50% chance that the subsequent task would be of high urgency and low importance, and vice versa. This element of randomness introduced an additional layer of unpredictability into the task queue, thereby enhancing the realism and complexity of the decision-making process for participants. This significant redesign from the pilot study increased the frequency of "hard choices," enabling us to delve deeper into analyzing participants' decision-making and prioritization strategies under these more challenging circumstances.

4.2 Hypotheses

4.3 Data

Our experiment was conducted on the Prolific platform. In total, we acquired data from N = 92 participants, each of whom completed the modified experimental paradigm and revised questionnaires designed to explore the relationships between financial status, anxiety, and decision-making under uncertainty.

4.3.1 Demographics

Our experiment involved participants with various income levels and anxiety scores. Table 4.1 summarizes the demographics of the participants. Regarding income, we observed a significant difference between high-income and low-income participants (p = 0.05). The mean income for the high-income group was approximately $146,012.57, while for the low-income group, it was around $17,571.42. This substantial income disparity within our sample reflects the economic diversity of the participants, ranging from those experiencing financial hardship to those with more substantial financial resources. For anxiety scores, as measured by the State-Trait Anxiety Inventory (STAI), we observed
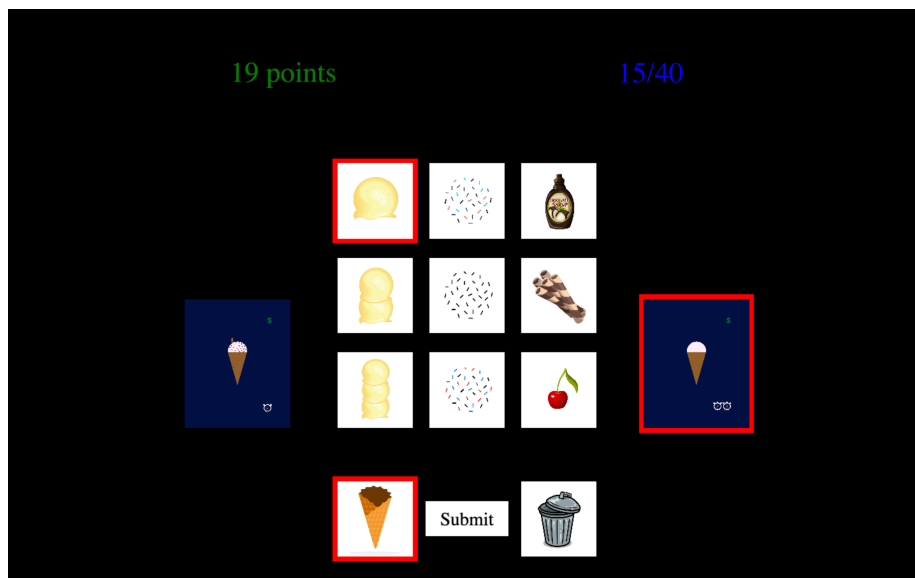
Figure 4.1: Game interface for Experiment 1. Participants have a queue, with a task on each side, and a series of icons they must press in order to complete a task. The clocks and dollar signs on a task represent the urgency and importance of the task, respectively. The top of the screen displays a points counter and a rounds counter.

stark differences between the high- and low-anxiety groups, both pre- and post-experiment. Before the experiment, the mean State Anxiety score for the high-anxiety group was 48.38, compared to 39.97 for the low-anxiety group (p < 0.001). Similar patterns were observed post-experiment, with a mean State Anxiety score of 48.81 for the high anxiety group and 38.23 for the low anxiety group (p < 0.001). The Trait Anxiety scores followed a similar pattern, with a mean of 48.65 for the high-anxiety group and 39.43 for the low-anxiety group (p < 0.001).

Table 4.1: Descriptive statistics for income and anxiety scores. Mean values are provided for high- and low-income groups and high- and low-anxiety groups. The p-values from t-tests comparing high and low groups are also included.

Group	Mean High	Mean Low	p-value
Income	$146,012.57$	$17,571.42$	5.307×10^{-2}
State Anxiety (pre-experiment)	48.38	39.97	2.488×10^{-27}
State Anxiety (post-experiment)	48.81	38.23	6.306×10^{-14}
Trait Anxiety	48.65	39.43	1.251×10^{-10}

4.3.2 Comprehensive Poverty Measures

To develop a more nuanced measure of poverty, we revisited our questionnaire to address variance issues (@pca-measure). We contemplated expanding our sample to include more lower-income individuals or introducing new questions to elicit more variance. Our current iteration of comprehensive measurements is available in @questionnaires.

We employed Factor Analysis, a statistical technique widely used to identify underlying relationships between measured variables. This method is particularly advantageous when dealing with scale compatibility issues, reducing many variables into fewer factors, and assisting in data interpretation, especially in large datasets.

Before proceeding with the Factor Analysis, we addressed the issue of missing data in our dataset, as it can significantly skew the results. We opted to use Multiple Imputation by Chained Equations (MICE), an approach that fills in missing values multiple times to create several complete datasets. The number of imputations was set to the overall percentage of missing cases in the dataset, ensuring a robust and comprehensive imputation strategy. We chose the Random Forest (rf) method for our imputations. Random Forest is a flexible, non-parametric method that can handle complex interactions and non-linear relationships between variables, making it suitable for datasets with complex structures and patterns, like ours.

Following this, we conducted a Factor Analysis on the complete datasets generated by the MICE procedure. This analysis aimed to uncover latent variables,

or factors, that explain the variability among observed, correlated variables. This method is particularly useful in understanding the structure of correlations among the variables. For this specific analysis, we selected a subset of the survey data, including responses to questions regarding household conditions, work conditions, and food deprivation. We performed the factor analysis using principal axis factoring, a method of extraction primarily used when the analysis aims to identify latent constructs underlying the variables. It is a commonly used extraction method for psychological and social data. We also employed an oblique rotation method to facilitate the interpretation of the factors. Such a method simplifies and clarifies the data structure and allows for the factors to be correlated, which is a more relaxed and often more realistic assumption. Lastly, we used a correlation-preserving scoring method (TenBerge), which provides unbiased estimates of the factor scores.

Figure 4.2 displays the scree plot, a graphical representation of the eigenvalues of factors or components in an exploratory factor analysis. It helps in determining the number of factors to retain in the analysis. The x-axis represents the number of factors, and the y-axis represents the eigenvalues. The point at which the slope of the curve is leveling off (the "elbow") indicates the number of factors to retain. Although the elbow is a standard guideline, the decision to choose the number of factors should also consider the interpretability of the factors and the theoretical understanding of the measured constructs. In our case, the elbow in the scree plot suggested that two factors might be sufficient. However, upon further analysis, we found that a three-factor model provided a more meaningful and comprehensive understanding of poverty.
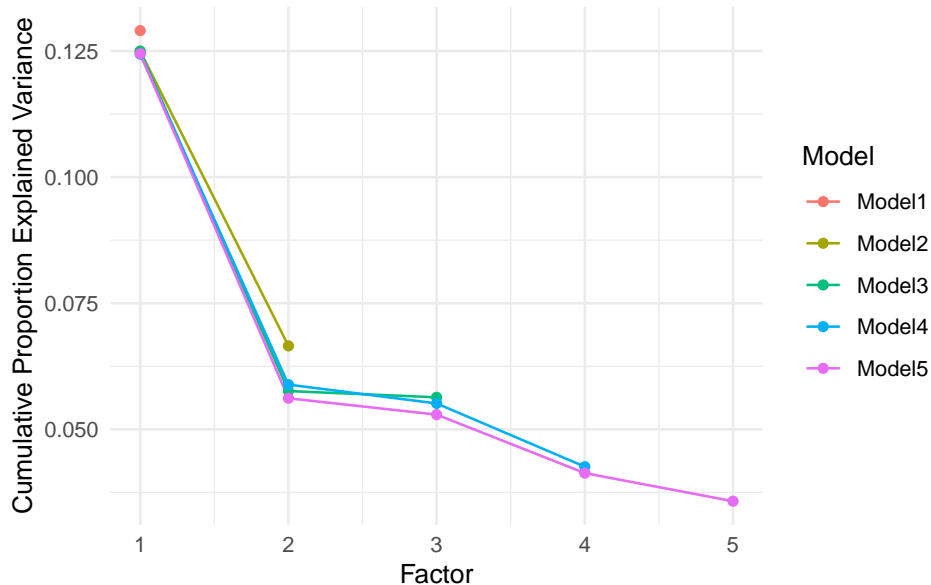

Figure 4.2: **?(caption)**

More specifically, the two-factor model included "Financial Hardship" and "Employment and Economic Status" factors, which, while simpler, did not capture the full complexity of our data. The four-factor model added two additional factors. The third factor was a "Housing Status" factor, and the fourth was the "physical condition of the home ."It included variables related to a leaking roof, broken windows, exposed electrical wires, and a malfunctioning stove or refrigerator. However, the four-factor model did not significantly improve model fit. After careful consideration and analysis, we have opted for the three-factor model as the most appropriate means of capturing the complexity of poverty in our data. This model balances complexity and interpretability, allowing for a comprehensive understanding of poverty's main dimensions while remaining concise and comprehensible. The three distinct factors that comprise this model—financial hardship, employment and economic status, and housing status—align with the multidimensional nature of poverty, which extends beyond mere income deprivation to encompass various other aspects of life.

Our three-factor model fits our data moderately well. The root mean square of residuals (RMSR), which measures the average residual correlation among variables, was 0.08, indicating a moderate fit. However, the Tucker-Lewis Index (TLI) was 0.475, below the desired threshold of 0.90, also suggesting only a moderate model fit. The root mean square error of approximation (RMSEA), which measures the discrepancy between the observed covariance matrix and the model covariance matrix per degree of freedom, was 0.073, with 90% confidence intervals between 0.069 and 0.08. This value suggests a reasonable error of approximation.

The derived factors, based on their highest loadings, represent the following constructs:

1. **Factor 1 (PA1)**: This factor had high loadings primarily on the 'Q48' series and 'Q50' questions, which indicate experiences of financial hardship and food insecurity within the past 12 months. We labeled Factor 1 as a "Financial Hardship" factor. This factor is moderately negatively correlated with Factor 3 (PA3).

2. **Factor 2 (PA2)**: The highest loadings on this factor were hours worked weekly and the participant's annual salary, suggesting that this factor might be related to the work and economic conditions of the respondents. There was a slight positive correlation between this factor and Factor 3 (PA3). Given the nature of the variables that load heavily on this factor, we interpreted it as an "Employment and Economic Status" factor.

3. **Factor 3 (PA3)**: This factor had the highest loadings on questions related to home ownership. Thus, we interpret Factor 3 as a "Housing Status" factor. This factor had a negative correlation with Factor 1 (PA1) and a slight positive correlation with Factor 2 (PA2).

The correlation of the factor scores with the factors for PA1, PA2, and PA3 were 0.99, 0.94, and 0.91, respectively, indicating high accuracy of the factor scores.

Similarly, the multiple R square of scores with factors for PA1, PA2, and PA3 were 0.98, 0.88, and 0.83, respectively, suggesting a strong relationship between the observed variables and the extracted factors. The minimum correlation of possible factor scores were 0.97, 0.77, and 0.67 for PA1, PA2, and PA3, respectively, further supporting the adequacy of the factor scores.

4.3.3 Zip Code Poverty Measures

Similar to our pilot study, we validated participants' income reports by analyzing economic data from their ZIP codes. We used the American Community Survey to obtain poverty and median income measures, allowing us to analyze the impact of geographic and community-level factors on individual experiences of poverty.
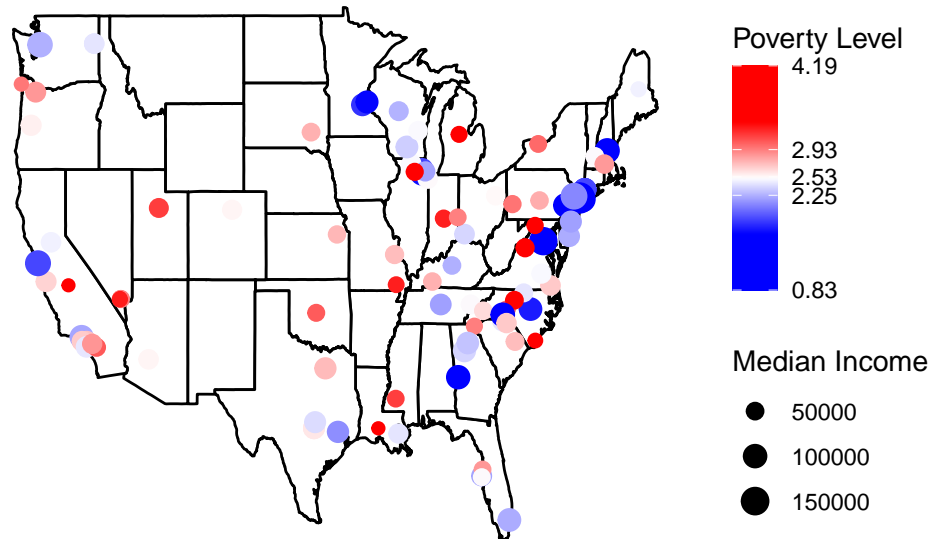

Figure 4.3: Income and Poverty Levels by ZIP Code

4.4 Results

4.4.1 Choice

4.4.2 Task Performance

We compiled data on each participant's selection and non-selection of each type of task (Important, Hard, and Urgent), then computed the frequency with which each participant picked a particular task type when given an option. Table 4.2 indicates that the decision to complete Important tasks significantly affected the total points a participant amassed (Estimate = 16.098, p < .001). Specifically, a ten percentage point rise in the ratio of selected Important tasks (two points,

as opposed to one point) resulted in an increase of 1.6 points in the overall score. However, the percentage of times a participant chose Hard or Urgent tasks did not significantly explain the total points accumulated (Estimate = -7.563, p = .371 for Hard tasks; Estimate = 6.539, p = .142 for Urgent tasks).

We also included demographic variables and participant characteristics (STAI score, income level, and platform) as control variables in the regression model, but none showed a significant relationship with total points.

The model accounted for approximately 20.24% of the variance in total points (Adjusted R-squared = 0.132), with an overall significant model fit ($F(6,68) = 2.877$, $p < .05$).

4.4.3   Trade-off Decisions

When we compare an individual's choice of "challenging" tasks: decisions between high urgency - low importance or low importance - high urgency tasks, we observe that high anxiety and low income individuals more often choose high urgency tasks over high value tasks, which corroborates the current non-quantitative literature as can be observed in the plots below.

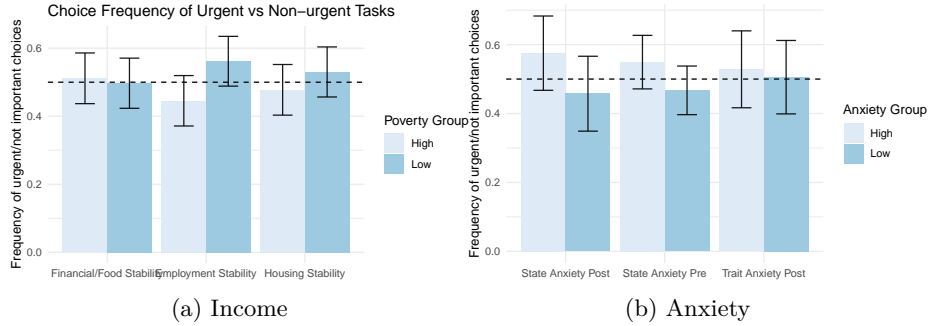(a) Income   (b) Anxiety

Figure 4.4: Choice proportions by income and anxiety

Accuracy in trade-off decisions as a function of income and anxiety

Multiple regression models to test the same hypotheses with different measures of income.

Percent of urgent choices (vs. important) as a function of income and anxiety.

4.4.4   General Urgency Bias

Individuals in the low income groups and in the high anxiety groups chose urgent tasks more often than important tasks. This result is not consistent for high income or low anxiety groups. Future graphs in this document will show that the difference-in-difference is not as clear.

1.

Table 4.2: Regression analysis of total points on participants' task choice behavior and personal characteristics. The predictors include the percentage of choices where Important, Hard, and Urgent tasks were chosen, participants' pre- and post-experiment STAI scores, and three poverty-related factors.

	Dependent variable:		
	Total Points		
	(1)	(2)	(3)
Important task chosen	32.191***	28.129***	31.797***
	(5.148)	(2.268)	(5.147)
Hard task chosen	−2.423	−0.881	−1.883
	(5.428)	(2.402)	(5.464)
Urgent task chosen	−22.116***	−1.127	−21.858***
	(5.403)	(2.969)	(5.439)
SAI (Pre)		−0.193*	
		(0.078)	
SAI (Post)		0.078	
		(0.074)	
TAI (Post)		0.059	
		(0.054)	
Factor 1			−0.057
			(0.515)
Factor 2			−0.648
			(0.475)
Factor 3			−0.518
			(0.484)
Constant	56.881***	51.921***	56.764***
	(4.286)	(2.940)	(4.305)
Observations	92	42	92
R^2	0.632	0.889	0.645
Adjusted R^2	0.619	0.870	0.620
Residual Std. Error	4.402 (df = 88)	1.483 (df = 35)	4.394 (df = 85)
F Statistic	50.287*** (df = 3; 88)	46.608*** (df = 6; 35)	25.776*** (df = 6; 85)	31.

Note: *p<0.05; **

2. Multiple regression models to test the same hypotheses with different measures of income.

It seems that when controlling for Dim 1 and 2, some effects become significant. Multicollinearity might be a problem, although correlations between STAI and PCA components are not higher than 0.6 (see correlation plots above). These results might be a result of a separation between State and Trait Anxiety. Although we only included the State questions of STAI, state and trait scores are likely correlated. PCA dimensions 1 and 2 may control for this confounding effect.

We review the Key Results from the first pages: urgent choices do seem to be above 50% for key groups, but the differences-in-differences across income and anxiety levels are not significant.

Again, people might not mind leaving the High Importance task undone. This is what some friends have called the "insurance ice cream." That is, if I leave this High Importance task in my queue, I can use it when I get a task that is High Effort but Low Urgency.

4.4.5 Reaction Time

4.4.6 Accuracy

We also obtain a comparison of the choices participants make and the optimal, or rational, protocol we generated. This is done by estimating a hierarchical Bayesian model...

This score is calculated by first estimating the cost parameters for each participant and then using them with backwards induction to discover the optimal choice at each presented state.

Figure 3.9 highlights how participants typically make optimal decisions (when given 'challenging' tasks) with a probability in between 0.5 and 0.6. This is generally what we expect to observe.

4.4.6.1 Accuracy, Anxiety, and Income

1. Accuracy in trade-off decisions as a function of income and anxiety

Finally, we compare for each participant, how many of their choices are identical to a model that observed the full horizon for the Markov decision process. Each participant is a dot, y axis is the percentage of correct choices in the experiment while x axis is the STAI (anxiety measure). Generally the results are very similar to figure 1.5.

Participant Accuracy by Income and Anxiety

Figure 4.5: **?(caption)**

It appears that Accuracy does not vary across income and anxiety levels with these measures. Some possibilities of this fact might include that, since time discounting here is virtually 0, leaving the important task behind will not affect participants as much (depending, of course, of the estimated cost parameters).

4.4.6.2   General Linear Models of Accuracy

4.4.7   Reaction Time

4.4.8   Accuracy

Chapter 5

Discussion

Our findings underscore the critical importance of prioritization strategies in task performance. Despite the intuitive appeal of tending to urgent matters, our data suggest that focusing on important tasks yielded superior performance outcomes.

5.0.1 Intergenerational Poverty

People likely learn how to estimate transition probabilities from parents and peers. If people in this support network are not themselves proficient in estimating, then the individual is left to their own devices. Further, affective states can be passed down generations (e.g., anxiety, stress, depression).

Chapter 6

Future Directions: Experiment 2

6.1 Methodology

6.1.1 Structure

1. A clock on the screen will display how long you have until that task, or the customer, decides to leave the line.

2. This will mean you can no longer make money for that task.

3. In the first round of this experiment, you will experience monetary "shocks." This means that at random times, some money might be taken from your total accumulated reward with no warning.

4. In the second round of this experiment, the rate at which orders arrive will be doubled at random times. However, there will be no monetary shocks.

5. Queue length is not fixed.

- Skin conductance, Cortisol, Eye tracking

6.1.1.1 §Probabilistic Choice

As seen in @accuracy-results,

Revisit the experiment to address the range of urgent choices. One possibility is to add an artificial discount factor. Another possibility is to explore non-deterministic choices (that is, urgency does not mean certain decay of value from one state to another, but a probable decay).

6.1.1.2   Flexible Queue Size

6.1.2   Simulation

6.1.3   Power Analysis

6.1.3.1   §Behavioral Measures

```
(Intercept)
  0.7685878
```

```
(Intercept)
  0.5509434
```

```
(Intercept)
  0.3838275
```

```
(Intercept)
  0.5942471
```

```
[1] 0.07260647
```

```
[1] 2.567568
```

6.1.3.2   ¶Physiological Measures

"Sartorial Symbols of Social Class Elicit Class-Consistent Behavioral and Physiological Responses: A Dyadic Approach" (Kraus et al 2014)

Goal of paper: Determine the psychological response among participants paired across socio-economic groups.

N = 128, 64 dyads (20 upper class, 20 lower class, 24 neutral condition)

DV = HRV (Heart Rate Variability) reactivity differences between high vs. low class

Prior = Upper-class = -0.69, se = 0.31; Lower-class = 0.04, se = 0.31

6.1.3.3   Perceived Effort

Stress has been suggested to increase perceived effort (e.g., the study will investigate whether it's more tiring to complete a task when stressed), leading low-income individuals to be less likely to take up welfare programs, regardless of eligibility (Bertrand et al., 2006; Hernanz et al., 2004).

In our model, cost can include a subjective component. Instead of counting it as simply the number of clicks, we can assume that the agent may dread or fantasize about action a. As such, someone who likes the task might not be bothered by doing it so the cost may be very close to zero (or negative). And vice versa for someone who hates it. Similarly, we can account for substituting *subjective* probability for objective probability. That is, people might distort the actual probability of future events.

6.2 Hypotheses

6.3 Population

In Los Angeles, 18% of residents worry every day or almost every day about paying their bills, and 23% worry about job loss (Baldassare et al., 2021). This constant mindset of worry likely affects the livelihood of these citizens. In a recent PPIC survey, about "one in five Californians report that they or someone in their household has cut back on food (21%), put off seeing a doctor or purchasing medicine to save money (18%), been unable to pay a monthly bill (17%), or had difficulty paying the rent or mortgage (17%) in the last 12 months" (Baldassare et al., 2021).

6.3.1 Online Sample

Pros and cons.

6.3.2 Homeless

M: Look Sera's studies

IRB: Justification

6.3.3 Other Low SES Cohorts

M: Proposal

Chapter 7

Conclusion

Chapter 8

References

Chapter 9

Appendix: Supplementary Models and Analyses

9.1 Burstiness and Memory in Discreet Event Simulation

Further, with interevent times, we can calculate the burstiness and memory as a function of urgency weights.
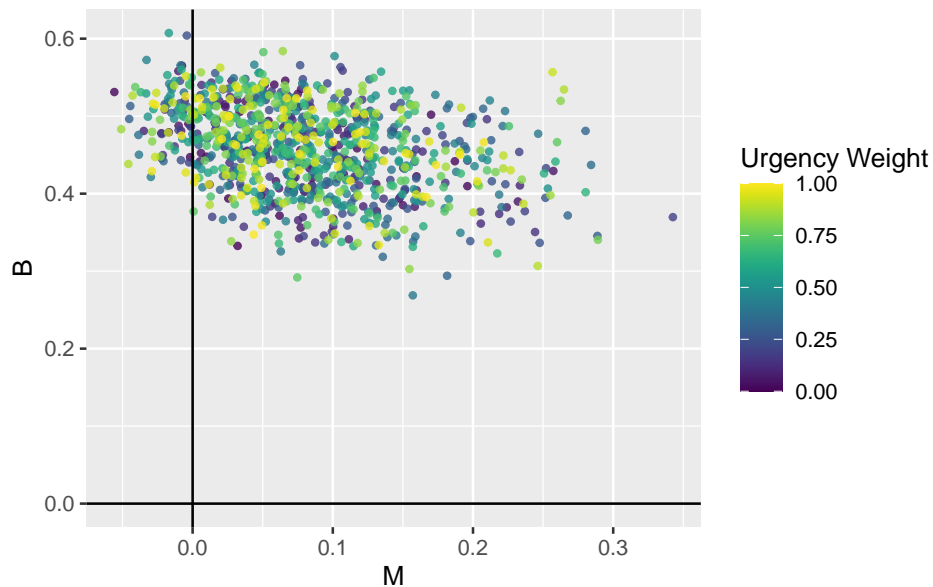

Figure 9.1: Burstiness by Urgency Weight

@simmer-burstiness shows that the surviving tasks are indeed around the area of bursty phenomena as reported in the literature. However, there does not seem to be a relationship between urgency weighting and burstiness.

9.2 Fantasy and Dread Model

$$V\left(s'\right) = r(a) - c(a) + \gamma \sum_s P\left(a, s', s''\right) V\left(s''\right)$$

$$\mathrm{SV}\left(\mathrm{s'}\right) = \mathrm{r(a)} - e\left(a \mid z_e\right) + \gamma \sum_s SP(\cdot) V\left(s'\right)$$

$$e\left(a \mid z_e\right) = z_e(c(e))$$
$$\mathrm{SP}\left(a, s', s'' \mid z_p\right) = z_p\left(P\left(a, s', s''\right)\right)$$

where z_e, z_p correspond to fantasy/dread and a sense of urgency, respectively. One possible

P() depends on whether unattended task "decays"

(a) Probability Weighting
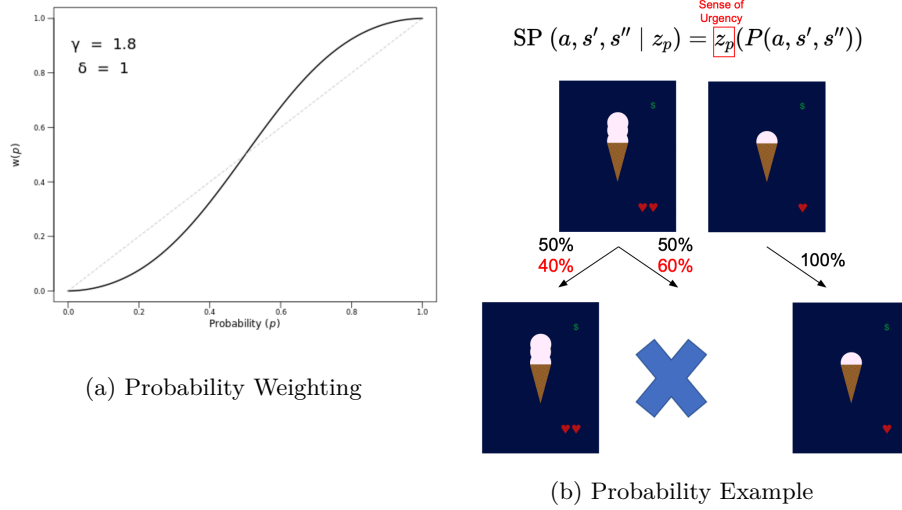
(b) Probability Example

Figure 9.2: Example of Subjective Probabilities

9.3 Priority Queuing Simulation

9.4 Dynamic Programming Simulation

In this analysis, we constructed a Markov Decision Process (MDP) model of the game, then used dynamic programming to solve the MDP and derive an optimal policy – the best course of action at each state. To derive a dynamic

programming strategy to optimally play the game, we must clearly define the state, action, and reward at each step in the game.

1. **State**: The state of the game at any given time can be represented by the current tasks in the queue, each of which is characterized by its effort, importance (value), and urgency. Additionally, the state should also include the round number because the available tasks and their urgency can change from round to round.

2. **Action**: An action in this game is the selection of a task from the queue.

3. **Reward**: The reward is the profit (points) gained from completing a task, which is determined by its value (importance).

With these definitions, we can formulate the optimal policy of the game using dynamic programming. The goal is to maximize the total profit over the game.

We denote the state at round i as s_i and an action at round i as a_i. The reward of taking action a_i at state s_i is denoted as $r(s_i, a_i)$. The state-transition function, which describes the new state after taking an action, is denoted as $T(s_i, a_i)$. Our aim is to find the policy π^* that maximizes the total reward:

$$\pi^* = \arg\max_{\pi} \sum_{i=1}^{40} r(s_i, \pi(s_i))$$

The Bellman equation for this game can be written as:

$$V(s) = \max_{a} \left(r(s, a) + V(T(s, a)) \right)$$

This equation states that the value of a state s is the maximum over all actions a of the immediate reward $r(s, a)$ plus the value of the state resulting from taking action a, $V(T(s, a))$.

The crux of this methodology revolves around the Value Iteration algorithm, which involves iteratively updating the value function (the expected cumulative reward from each state) until convergence. To find the optimal policy, we use backward induction; that is, we start at the end of the game and work backward, iteratively computing the value function for each state until we reach the start of the game. At each state, the optimal action is the one that maximizes the immediate reward plus the value of the next state.

Interestingly, after a sufficient number of iterations (over 100 trials), we observed a steady state in the value function, whereby the expected cumulative reward was nearly identical across all states. This convergence suggests that as we approach infinity, the long-term expected reward is almost the same, irrespective of the state under an optimal policy.

Notably, this does not imply that the policy for each state will be identical. However, as is common in many Markov Decision Processes, the task-based game has a level of inherent balance, where we have structured the potential outcomes of different actions to ensure a relatively even distribution of long-term rewards across various states.

Above all, these findings underline the complexity of decision-making processes and the intricate dynamics in this and other task-based games. In practice, the large number of possible states in this game (due to the different combinations of tasks and their characteristics) might make exact dynamic programming infeasible for humans. As such, approximation methods such as function approximation or reinforcement learning techniques are necessary.

9.5 Bayesian Model for Cost Estimation

9.5.1 Model

### 9.5.2 Model Data

### 9.5.3 Estimation

9.6 Factor Analysis for Experiment 1

?@fig-mice offers a visual representation of the imputation process. The intermingling of different imputation streams indicates a successful multiple imputation process, suggesting that the chains have converged. Additionally, we expect no visible trends in the later iterations, indicating that the imputations have reached a stable solution.
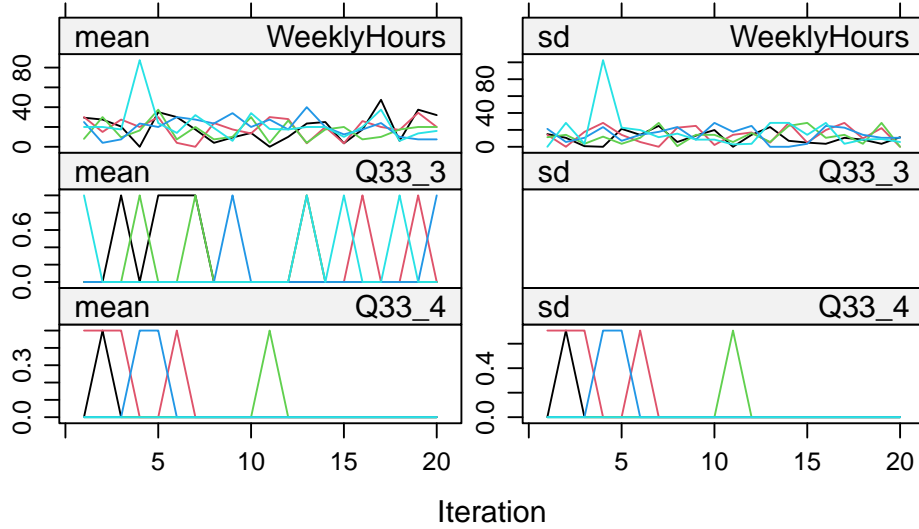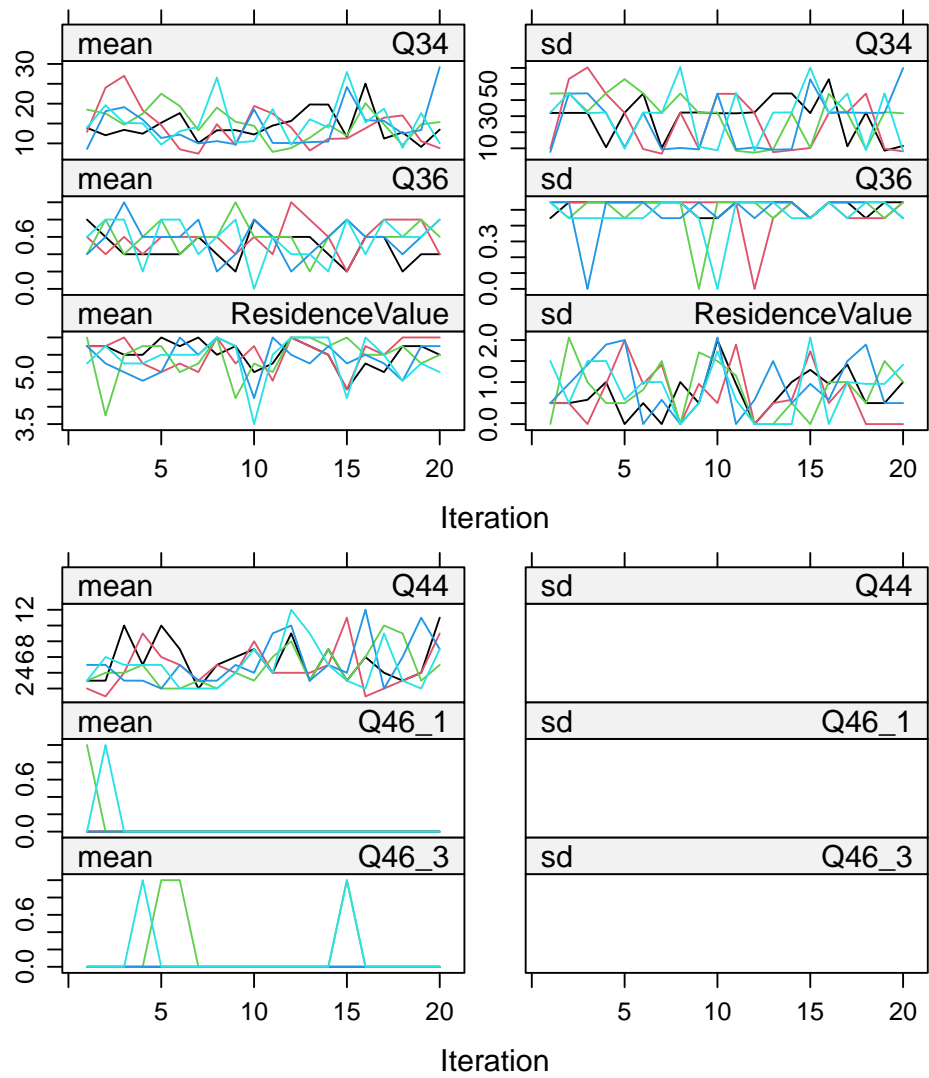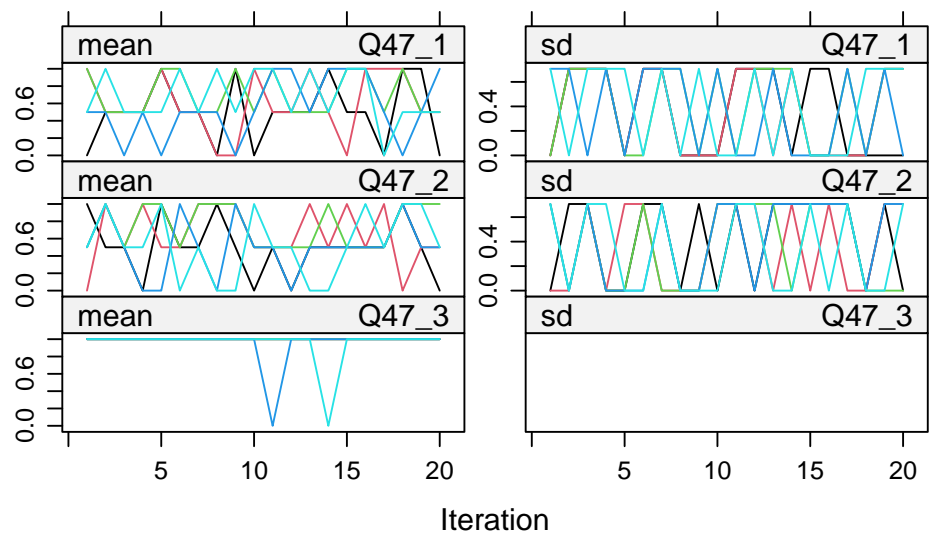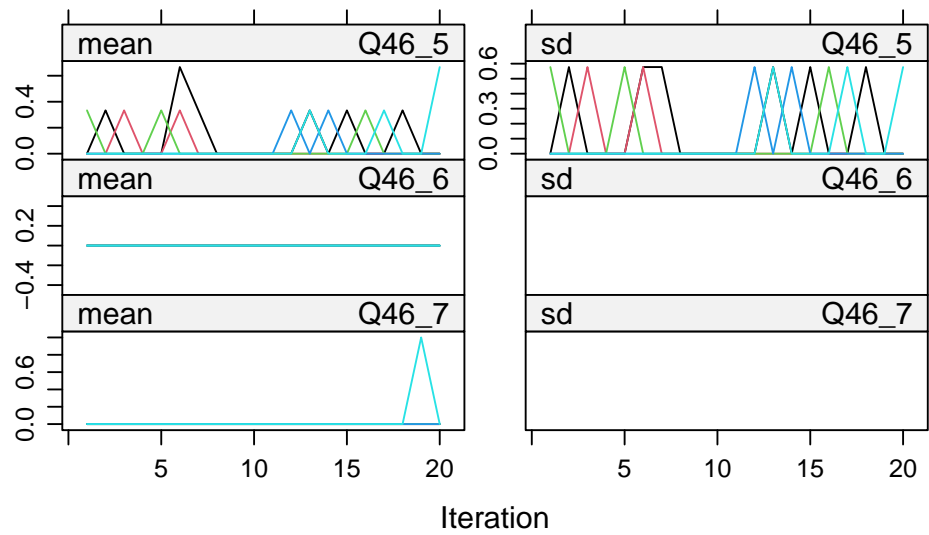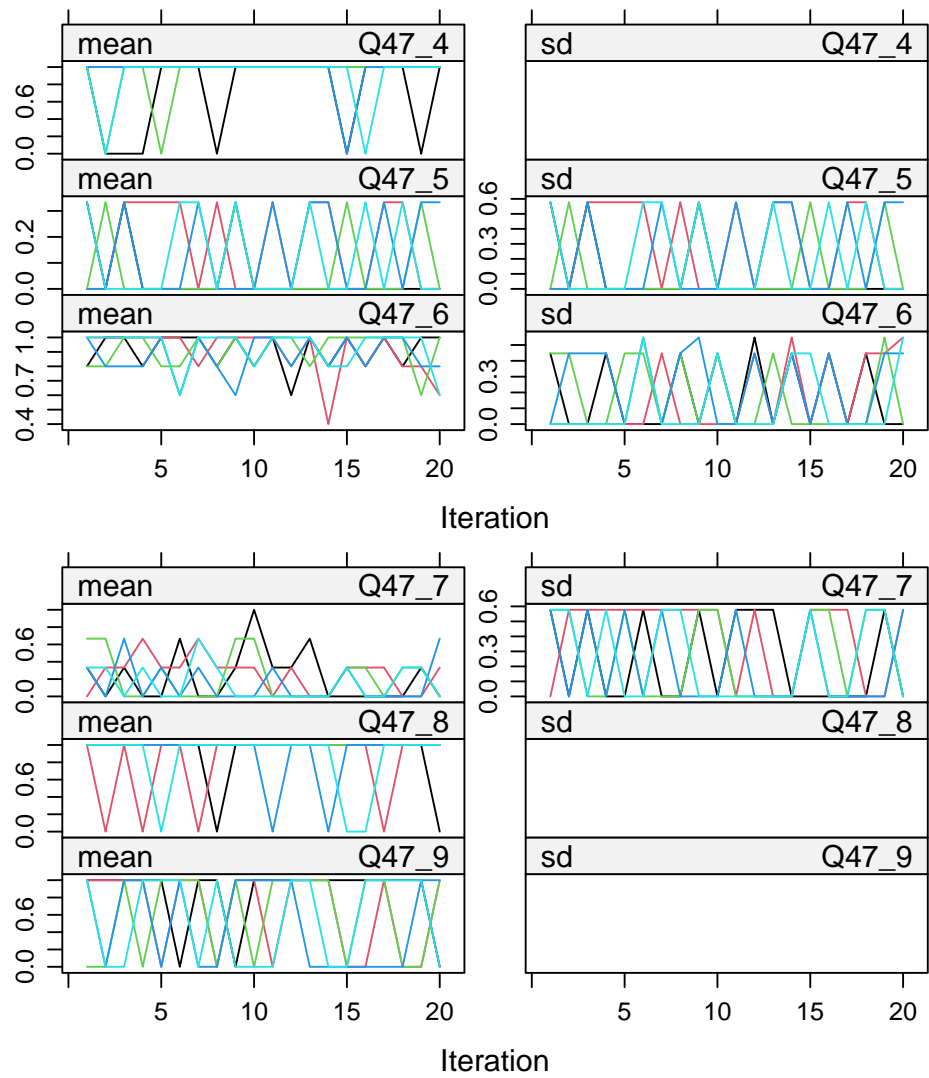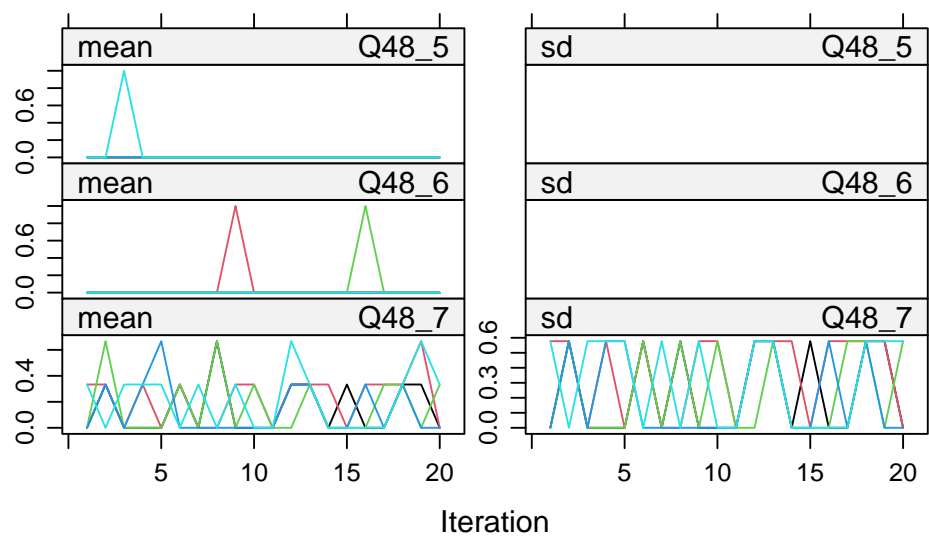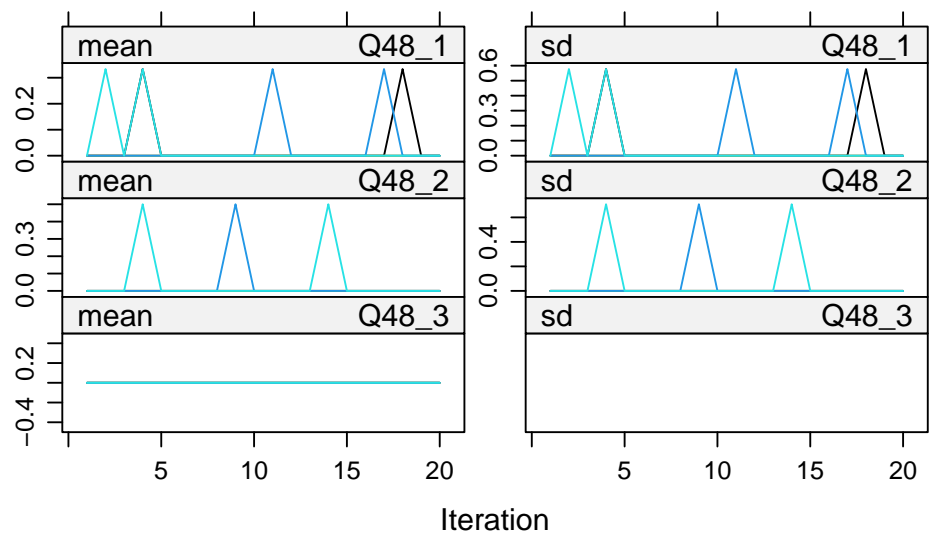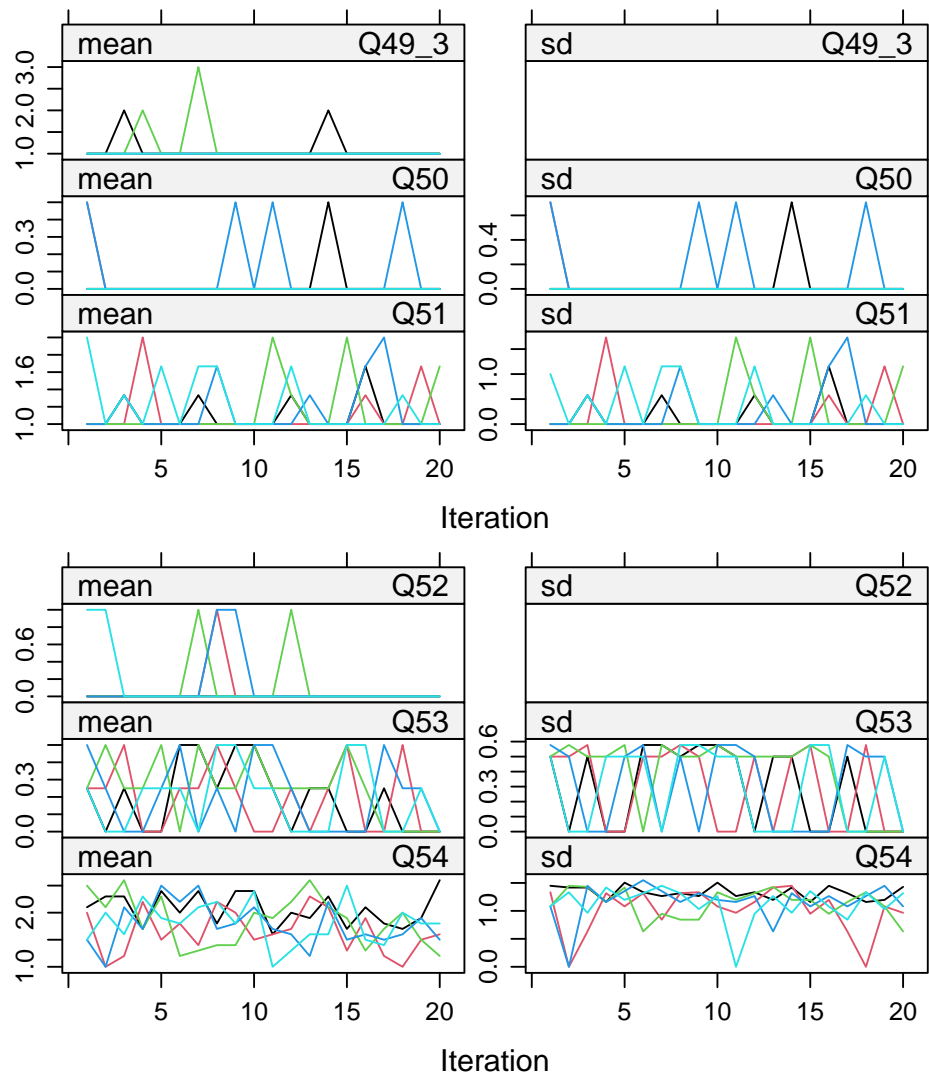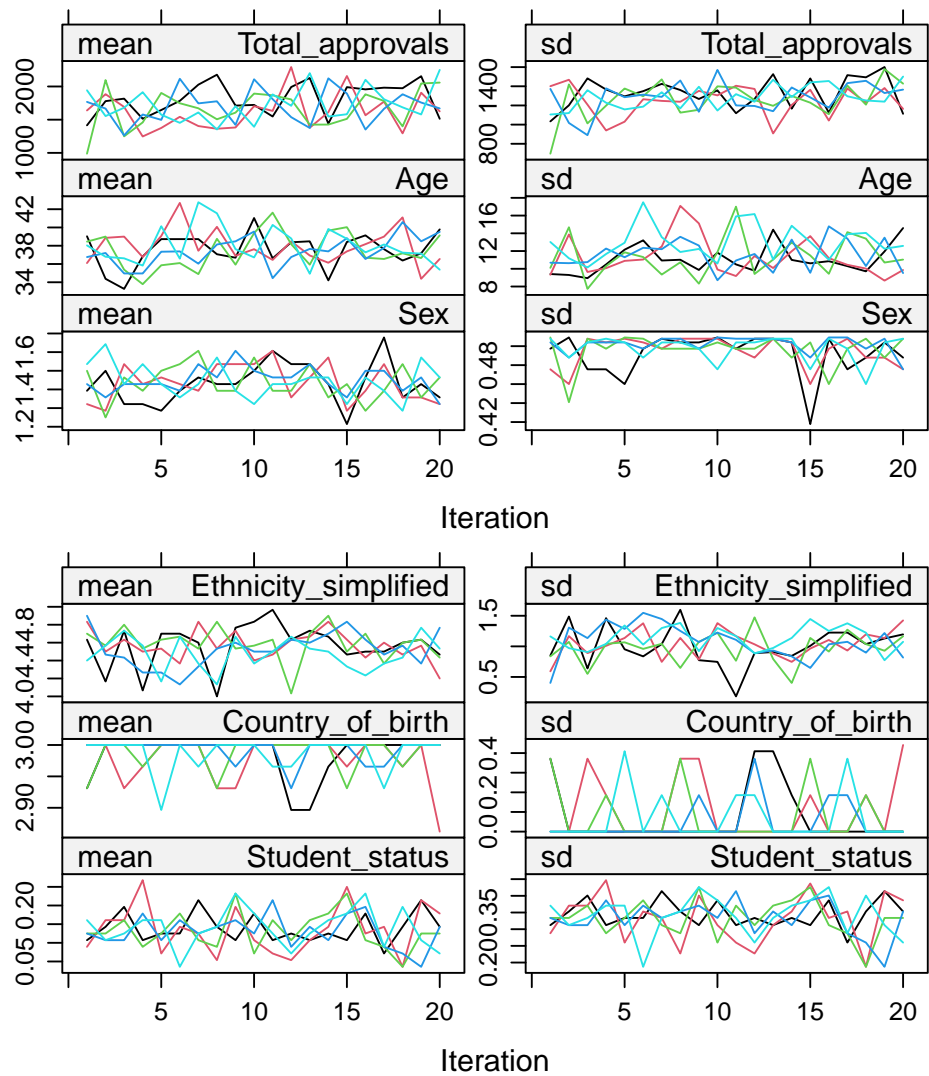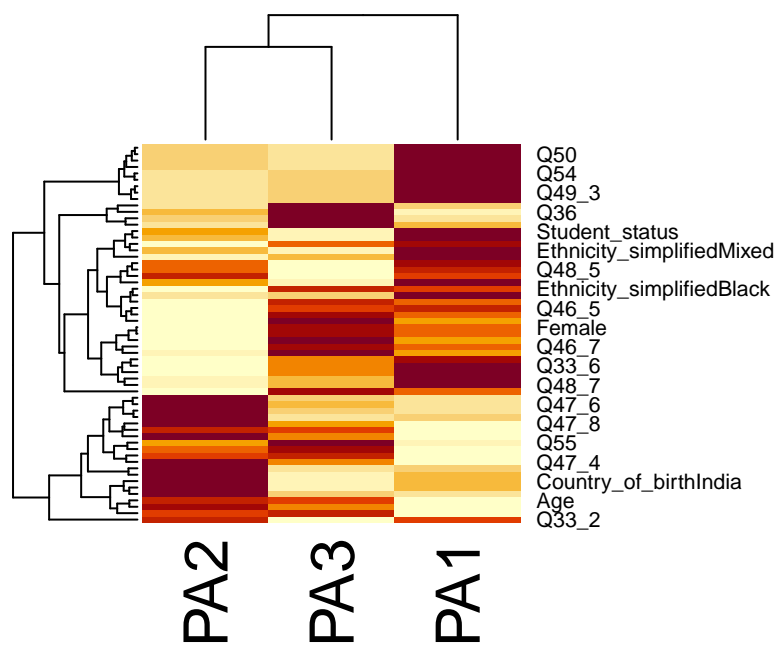
Next, we conducted Factor Analysis on the complete datasets generated by the MICE procedure. The output below shows the factor loadings, which represent the correlations between the observed variables and the factors. High absolute values indicate a strong relationship with the factor. Next, we will examine the factor loadings in a more interpretable format by creating a loading plot. **?@fig-exp1-loadings** displays the loadings of each variable on each factor, facilitating the interpretation of the factors. Variables with high loadings on the same factor are likely to be related to each other and represent the same underlying construct.

Q50
Q54
Q49_3
Q36
Student_status
Ethnicity_simplifiedMixed
Q48_5
Ethnicity_simplifiedBlack
Q46_5
Female
Q46_7
Q33_6
Q48_7
Q47_6
Q47_8
Q55
Q47_4
Country_of_birthIndia
Age
Q33_2

PA2
PA3
PA1

Chapter 10

Appendix: Images

10.1   The Eisenhower Matrix

"Who can define for us with accuracy the difference between the long and short term! Especially whenever our affairs seem to be in crisis, we are almost compelled to give our first attention to the urgent present rather than to the important future."

--- Dwight D. Eisenhower, 1961 address to the Century Association

10.2   Pilot Experiment Image

10.3   Priority Queuing

A list can contain an arbitrary number of tasks and the priority of each task is an integer drawn from some distribution. The tasks are set to arrive with the rate λ following a Poisson dynamics with exponential arrival time distribution and they are executed with rate μ by always choosing the one with the highest priority.
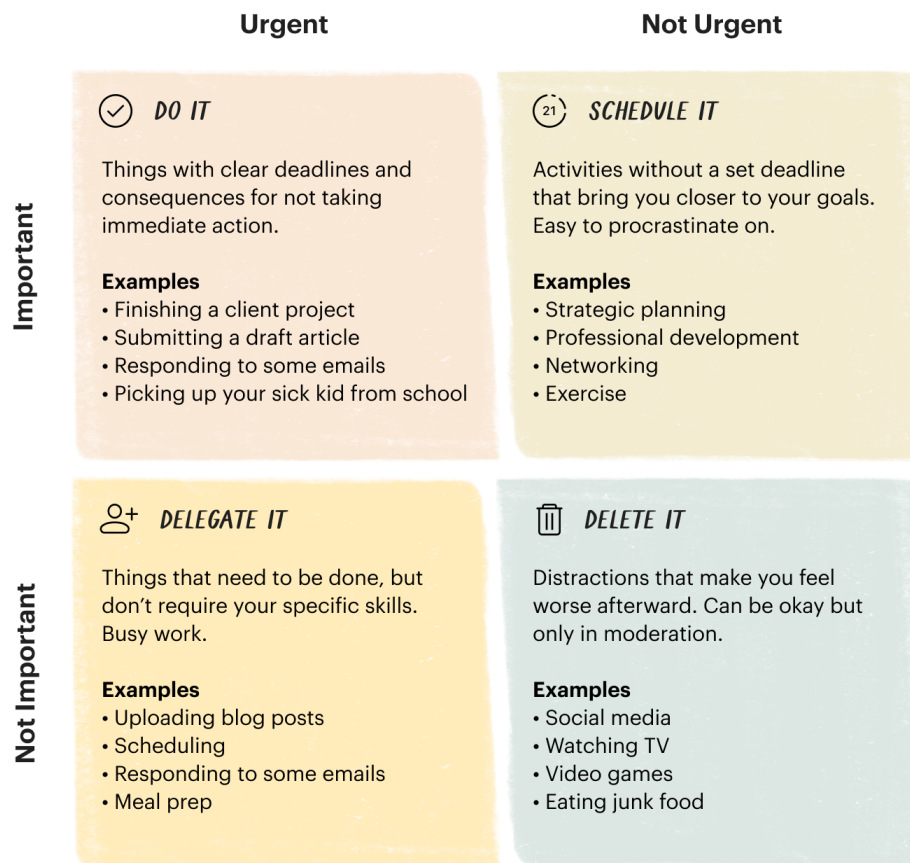
Urgent   **Not Urgent**

Important

DO IT

Things with clear deadlines and consequences for not taking immediate action.

Examples
• Finishing a client project
• Submitting a draft article
• Responding to some emails
• Picking up your sick kid from school

SCHEDULE IT

Activities without a set deadline that bring you closer to your goals. Easy to procrastinate on.

Examples
• Strategic planning
• Professional development
• Networking
• Exercise

Not Important

DELEGATE IT

Things that need to be done, but don't require your specific skills. Busy work.

Examples
• Uploading blog posts
• Scheduling
• Responding to some emails
• Meal prep

DELETE IT

Distractions that make you feel worse afterward. Can be okay but only in moderation.

Examples
• Social media
• Watching TV
• Video games
• Eating junk food

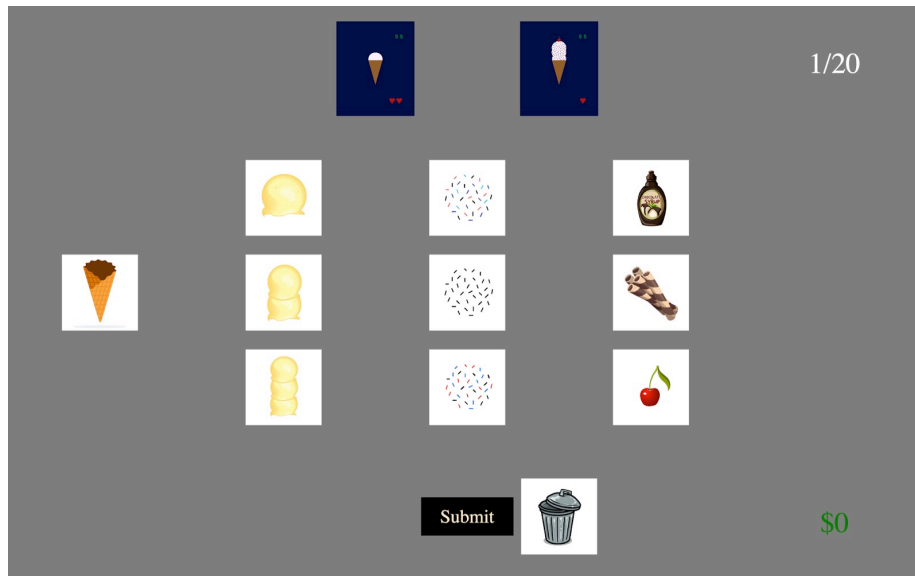Figure 10.1: Source: https://todoist.com/productivity-methods/eisenhower-matrix

Figure 10.2: Game interface for Pilot Experiment. Participants had a queue with two tasks on top of the screen and a series of icons they must press in order to complete a task. The clocks (hearts, in this version) and dollar signs on a task represent the urgency and importance of the task, respectively. The right side of the screen displays a rounds counter (top) and a points counter (bottom).
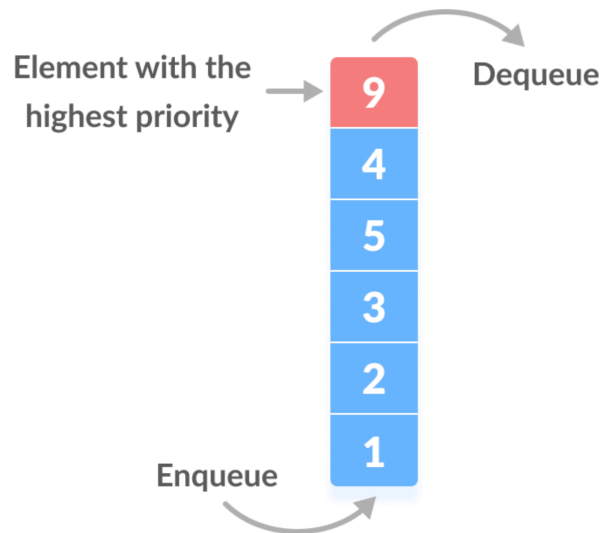

Figure 10.3: Sample Queue

Chapter 11

Appendix: Documentation

11.1 Questionnaires

11.2 IRB