Essays on the Consumer Journey of Goal Planning and Goal Pursuit

by

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Chapter 1

Overview

Goals and aspirations are key drivers of consumer preferences and decisions. The drive to constantly strive for better and maintain a positive outlook on life is crucial to consumer development and well-being. In this dissertation, I present two essays to explore two important components of this consumer journey: goal planning and goal-directed purchases.

In the first essay, co-authored with Joy Lu and titled "*A Little Bit of Each: Unpacking a Task into Detailed Subcategories Leads to More Ambitious Planning*," we focus on the process of goal planning. Having the right plan is crucial for consumers to effectively manage various tasks in their daily lives, and is essential to goal pursuit. Countless websites and online apps are designed to aid consumers in planning, and they often implement the popular strategy of breaking larger goals down into smaller subgoals to motivate users and make their plans appear more concrete and actionable. We investigate how unpacking a task into subcategories affects the magnitude of people's plans. Across

10 studies, we demonstrate that unpacking leads individuals to make more ambitious plans, and provide evidence of an underlying mechanism where unpacking makes a given task load seem less effortful. Notably, the more ambitious plans did not transfer to actual behavior, suggesting that unpacking may result in over-planning and goal failure if consumers commit to an overwhelming target during the planning phase. Beyond planning quantity, we also show that the unpacking effect extends to task preferences, shifting choice shares towards task options that are unpacked and, therefore, seem more attractive (*i.e.*, less effortful). Thus, our work highlights a potential downside of making goals more actionable via breaking them down, by demonstrating that some types of subcategorization may exacerbate the planning fallacy and lead to over-planning and suboptimal choices.

In the second essay, co-authored with Russell Golman and George Loewenstein, we introduce the concept of "*Aspirational Purchases*," a special type of purchase that is often made to prepare and facilitate the pursuit of goals and aspirations. We define aspirational purchases as purchases made for a future self that the consumer has yet to, but is aspiring to, become. We develop a formal model to demonstrate how people's aspirations, combined with optimism and motivated reasoning, can lead to suboptimal purchases. With four pre-registered studies, using both self-reported purchase intentions and real Amazon shopping history, we show that aspirational purchases are prevalent, driven by optimism, and likely to be under-used. Under-usage leads to a drop in satisfaction with aspirational products, although consumers believe they will use the products more in the future and are reluctant to part with them. These findings provide a novel demonstration of how aspirations can drive consumer purchases, with subsequent consequences for satisfaction and future purchase intentions.

Chapter 2

A Little Bit of Each: Unpacking a Task into Detailed Subcategories Leads to More Ambitious Planning

2.1 Introduction

Planning is an essential part of consumers' daily lives. The right plan helps people remember what to do, organize their lives, and gather the effort and self-control needed to work towards their goals (Bagozzi & Dholakia, 1999; Lynch et al., 2010; Townsend & Liu, 2012). Planning can transform daunting goals into actionable components, thereby encouraging goal pursuit and implementation (Dalton & Spiller, 2012; Gollwitzer, 1999; Townsend & Liu, 2012). It seems like there exists a website or online app to assist in planning every possible activity or goal, including fitness tracking, dieting, financial planning, work, and even sleep. Many of these apps will encourage users to break down a goal into smaller subgoals. For example, financial planning apps allow consumers to budget using spending categories. Project management apps often have dashboards that visually display progress towards goals broken down into more granular subgoals. These approaches are backed by a large body of research documenting the benefits of subgoals for goal pursuit (Amir & Ariely, 2008; Bagozzi & Dholakia, 1999; Jin et al., 2015; Newell & Simon, 1972).

Ensuring that a plan is neither too ambitious nor too conservative is crucial. The right plan (e.g., planning to practice guitar for an hour every day) can provide motivation and practical guidance to achieve the plan (Gollwitzer & Sheeran, 2006). On the other hand, a poorly set plan can lead to either stress and failure (e.g., planning to practice for 5 hours) or prevent one from fully realizing their potential (e.g., planning to practice for only 10 minutes). Importantly, prior work has documented the negative consequences of goal failure on affect and downstream behaviors (Brunstein & Gollwitzer, 1996; Höpfner & Keith, 2021; Soman & Cheema, 2004; Wang et al., 2016). A key driver of goal failure is the planning fallacy, where individuals systematically underestimate task completion time (Buehler et al., 1994; Buehler & Griffin, 2003; Kahneman & Tversky, 1979).

Our work aims to explore the tension between trying to make goals seem more actionable (e.g., via subgoals) and preventing the potential downside of individuals underestimating expected effort or time expenditure (e.g., planning fallacy), which may lead to overambitious goals and, ultimately, goal failure. Specifically, we focus on the context of task planning where a variable and measurable quantity of a task can be completed. For example, consider an individual whose New Year's resolution is to get more exercise and is attempting to make a concrete plan to achieve this goal. First, she might consider how many times she plans to visit the gym each week, estimating that she has the time and capacity for three visits in total. Alternatively, she may consider the different categories or types of workouts, and may plan to go to the gym twice for weights, three times for cardio, and once for group exercise class. We refer to the former approach as planning with the task in aggregated form, and the latter as planning with the task unpacked into subcategories or subtypes, which in our example has resulted in more ambitious exercise plans (i.e., six vs. three days per week).

In this article, we propose that unpacking tasks into detailed subcategories can lead to more ambitious plans. Furthermore, we show that this happens because unpacking makes a set of tasks seem less effortful, which leads people to plan to complete greater quantities of the task. Interestingly, this seems to run counter to prior work demonstrating that unpacking reduces the planning fallacy (Forsyth & Burt, 2008; Kruger & Evans, 2004). However, we also demonstrate that when plans are non-binding, the unpacking effect appears to only impact the planning stage and not task execution, which suggests that unpacking can actually lead consumers to over-plan and be more likely to fall short or risk goal failure. Additionally, we show that unpacking can make sets of tasks appear more attractive (i.e., easier), shifting consumer preferences and potentially resulting in suboptimal choices. Thus, while much of the research on consumer goals and the landscape of consumer planning apps and decision aids is focused on encouraging goal-setting and striving, as well as making goals appear more actionable to boost motivation, our work highlights a possible downside by investigating the effects of subcategory unpacking.

2.2 Conceptual Development

2.2.1 Subcategory Unpacking vs. Subgoals

A big plan or goal to complete a task can often be broken down into smaller components. The extant literature on goal pursuit has primarily focused on the effects of subgoals, which contribute towards an overarching end-goal and often occur sequentially. For example, the goal of growing a backyard vegetable garden might be broken down into the following subgoals: clean out the yard, buy seeds, water and fertilize plants throughout the season, and harvest. The goal of reducing sun damage can be achieved via the subgoals of wearing a sun hat and applying sunscreen (Fishbach et al., 2006), while completing a "stepping routine" workout can be broken down into smaller sections of the workout (Huang et al., 2017). These types of subgoals have been repeatedly shown to be beneficial for increasing motivation and commitment towards goal completion (Amir & Ariely, 2008; Bagozzi & Dholakia, 1999; Jin et al., 2015; Newell & Simon, 1972). In such settings, achieving a mere subgoal (e.g., one section of a workout) can reinforce to individuals that the overall goal is attainable and accessible, thereby boosting motivation in goal pursuit. Dividing goals into more granular subgoals (e.g., volunteering 200 hours a year vs. 4 hours a week) can also help boost goal progress via increased flexibility (Rai et al., 2022).

In the current research, we instead focus on a different way of breaking down goals, which we refer to as unpacking. Unpacking involves taking the individual quantifiable components of a larger plan or goal and presenting them as divided up into subcategories. For example, if an individual makes a plan to watch 10 documentary films in total, their plan may be unpacked into a plan to watch 5 nature documentaries and 5 true crime documentaries. Similarly, planning to reply to a set of emails can be broken down into replying to work emails and personal emails. Similar forms of subcategorization have been shown to reduce the rate of hedonic satiation by emphasizing the differentiating aspects of a stimulus or experience; for example, consumers satiate more slowly on jelly beans when they are labeled by their specific flavors (Redden, 2008). We aim to investigate the impact of subcategory unpacking on the planning or goal-setting process, specifically in terms of how big or ambitious consumers' plans are.

Importantly, our study of unpacking is distinct from the subgoal literature in several ways. Rather than treating an overarching goal as a set target that can be broken down into subgoals, we investigate the variable nature of goal-planning in terms of size or quantity. While it is not possible to complete "more" of a fixed goal or set of subgoals, we study situations where people can plan to complete more or fewer tasks during the goal-planning process (and similarly more or fewer tasks within unpacked subcategories), which allows us to quantify the degree of planning and how ambitious people's plans are. Additionally, the benefits of subgoals are often attributed to their "step-by-step" progression in motivating goal completion, while unpacked subcategories lack sequential ordering. In other words, the subcategory unpacking that we study is not necessarily applicable to all forms of goal planning. Some plans may be too small to be unpacked in a meaningful way (e.g., eating an apple), while others require sequential steps (e.g., growing a vegetable garden). Additionally, for many goals or tasks (e.g., taking out the trash every day) there are no quantifiable or ordinal ways to measure or adjust how "big" or "ambitious" the plan is (Garvey, 2012). In summary, in the current research, we focus on settings where consumers engage in planning to complete goals or tasks with the following properties: (1) they can be unpacked into subcategories, and (2) they can vary or be adjusted in terms of some measurable quantity.

2.2.2 The Role of Subadditivity in Task Planning

We argue that when planning for goals or general task planning, subcategory unpacking leads to more ambitious planning. For example, someone may make plans to play basketball recreationally for 1.5 hours. However, if they were to unpack basketball into multiple subcategories of activities, they may, for example, end up planning to practice 40 minutes of dribbling exercises, 40 minutes of shooting exercises, and 1 hour of scrimmaging with friends – resulting in a total of 2 hours and 20 minutes, a lot more compared to what they would have planned when considering "basketball" as a singular activity.

Our proposed effect of subcategory unpacking increasing the magnitude or quantity of a planned task is consistent with prior research demonstrating that unpacking can lead to subaddivity (i.e., the sum of component parts being greater than the total) when people are asked to make quantity estimates, including probability judgments and subjective ratings. For example, Tversky and Koehler (1994) found that when people were asked to estimate the likelihood of death resulting from natural causes, they gave a higher likelihood when "natural causes" were broken down into "heart disease, cancer, or some other natural cause." Similarly, Van Boven and Epley (2003) found that when people were asked to evaluate a lawsuit involving an oil refinery that polluted the environment and caused respiratory diseases in the surrounding communities, they rated greater suffering of the victims and gave harsher punishments to the refinery when "all varieties of respiratory diseases" was unpacked into "asthma, lung cancer, throat cancer and all other varieties of respiratory diseases." Unpacking has also been shown to result in higher frequency judgments in memory for personal events (Mulford & Dawes, 1999), more extreme evaluative judgments for consumer products (Seta et al. 2014), and greater quantity allocations across a variety domains such as retirement savings (Wong & Wong, 2014), donations (Sharps and Schroeder 2019), and spending predictions (Peetz et al., 2015). Interestingly, some research has documented the reverse effect (i.e., superaddivity), with unpacking leading to lower probability judgments when the unpacked events are atypical (Sloman et al. 2004), already highly accessible (Redden & Frederick, 2011), or unpleasant (Tsai & Zhao, 2011).

The classic mechanism for explaining subadditivity effects is Support Theory, which argues that people judge probability based on the perceived support of the focal event (Rottenstreich & Tversky, 1997; Tversky & Koehler, 1994). Unpacking an event reminds people of possibilities that may be overlooked when the event is presented in an aggregated form; the explicit mention of these possibilities makes them salient, which leads to higher perceived support of the event. Researchers have further applied Support Theory to explain subadditivity in other contexts, including more extreme evaluation of events with more detailed descriptions (Van Boven & Epley, 2003) and more positive affective and monetary attraction to multiple products when evaluated as a unit versus separately (Seta et al., 2014). Support Theory can also explain superadditivity effects. For example, unpacking an event into atypical examples yields weak support and lowers probability judgments (Sloman et al., 2004), while providing more details for an event can lead to processing disfluency (Redden & Frederick, 2011).

In this article, we aim to extend the effect of unpacking subadditivity to the domain of consumers making plans involving quantifiable goals, by demonstrating how the sum of subcategory plans can be greater than the plan for a single overarching category. Closest to our work is the study by Jia, Li, and Krishna (2020), who find when consumers are asked to set daily calorie budgets, they set lower budgets when they are asked to plan for breakfast, lunch, and dinner separately (i.e., meals unpacked) compared to when asked to plan for the entire day (i.e., meals aggregated), demonstrating a superadditive effect. They provide evidence of motivated reasoning as the underlying mechanism, with unpacking calorie budgets providing more opportunities to cut consumption among people who are strongly motivated. Note that in this setting, the more "ambitious" plans correspond to more restrictive or lower calorie quantities, in contrast to the goals and tasks we study, where more ambitious plans correspond to greater quantities of a task. We propose and investigate a new mechanism that is distinct from Support Theory and motivated reasoning, and is instead based on how unpacking modulates effort estimation.

2.2.3 Effort Estimation and the Planning Fallacy

We hypothesize that unpacking a task into subcategories makes the same plan or set of tasks seem less effortful, and thus leads people to make more ambitious plans. While estimates and perceptions of effort undoubtedly play an important role in how consumers start, engage with, and evaluate all kinds of goals and tasks, previous literature has documented their fallible and malleable nature. Most notably, people have been shown to exhibit the planning fallacy, where they systematically underestimate the time it will take to complete a task (Buehler et al., 1994; Buehler & Griffin, 2003; Kahneman & Tversky, 1979). One may plan to write a paper in one month, only to find herself still working on it a year later. Kahneman and Tversky (1979) argue that the planning fallacy arises because when making time estimates, people tend to overly focus on the details of completing a task (i.e., adopt an internal perspective), while ignoring how long similar tasks took them in the past (i.e., ignore the statistical and distributional external perspective). By neglecting the different ways in which things could go wrong and evidence that things have gone wrong in the past, they make overly optimistic estimates of completion time.

Naturally, it is useful for researchers to investigate strategies for reducing the planning fallacy and inducing individuals to make more accurate effort estimates. Interestingly, unpacking tasks has been shown to reduce the planning fallacy by leading people to come up with longer, and therefore more realistic, estimates of task completion time. Kruger and Evans (2004) found that asking participants to list the specific steps to complete a holistic task (e.g., unpacking meal preparation into different steps, unpacking formatting dictionary entries into adding boldface, punctuation, etc.) led to greater estimates of task completion time. However, unpacking had no effect on the actual completion time, so the increased time estimates reflected a reduction in the planning fallacy. Similarly, Forsyth and Burt (2008) found that unpacking also increases time allocation to future tasks, which they refer to as the segmentation effect. They argue that people are inclined to use rounded close approximations for their time allocation (e.g., 5 or 10-minute chunks), so errors across different subcategories or subtasks may add up to greater time estimates (or even overestimates).

In summary, prior work that studies the planning fallacy (Forsyth & Burt, 2008; Kruger & Evans, 2004) has found that unpacking tends to result in greater estimates of effort, specifically in terms of time. This seemingly contradicts our proposal that unpacking leads to more ambitious plans by decreasing perceived effort. To reconcile these opposing findings, note that the unpacking manipulations in this previous research involved breaking down a single holistic task into multiple subcomponents, which Kruger and Evans (2004) argue can increase perceptions of task complexity and magnitude, leading to a reduction in the planning fallacy. In support of this mechanism, they find that task complexity moderates their unpacking effect; specifically, while a complex condition with 4 types of formatting changes led to a reduction in the planning fallacy (i.e., longer time estimates), a simple condition with only 2 types of formatting changes had no effect (non-significant but directionally shorter time estimates).

In contrast, we study a form of unpacking that involves unpacking a task into smaller, more detailed subcategories, with individuals able to plan different quantities of the task or evaluate the effort involved in completing a set quantity. Unlike the subcomponents in Kruger and Evans (2004), subcategories are not separate components of the same holistic task and thus are not predicted to change perceived task complexity in the same way. Instead, we argue that subcategories will draw people's focus to how easy it would be to complete the smaller quantities of a task delineated within the subcategories, leading to lower perceptions of time and effort for a given set of tasks. This is more in line with the subgoal literature that suggests breaking down a big goal into "bite-sized" subgoals can make the task feel more doable and less challenging (Amir & Ariely, 2008; Bagozzi & Dholakia, 1999), as well as adding-up effects in choice bracketing where choices framed within narrow brackets seem inconsequential but are perceived to be more significant when broadly bracketed (e.g., Read, Loewenstein and Rabin 1991).

It is important to note that in Kruger and Evans (2004), the focus was on studying how unpacking mitigates the planning fallacy, but they did not find that unpacking had a significant impact on actual task completion time. Likewise, the unpacking effect we study applies to the planning stage rather than the task execution phase. Our proposed effort-based mechanism is based on how unpacking modulates perceptions of effort and

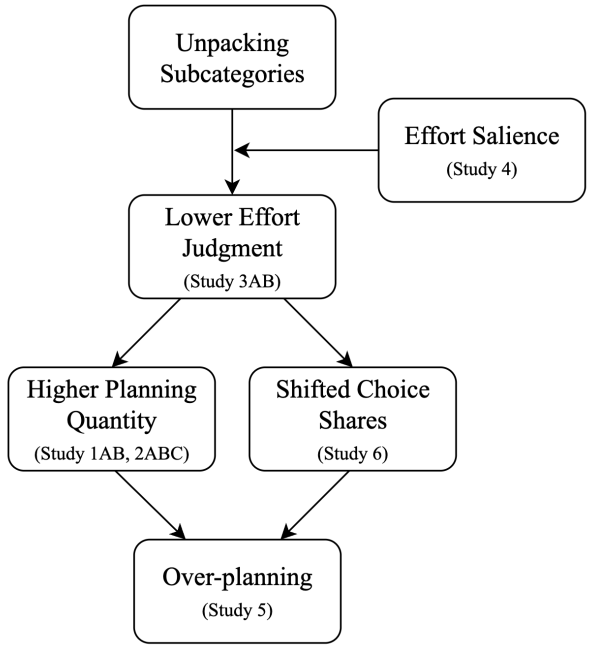


Figure 2.1: Conceptual Framework With Corresponding Studies

not experienced effort, so it is likely that unpacking creates a mismatch between what people expect the effort will be and the effort they actually need to exert when carrying out the plan. In other words, unpacking may increase the likelihood of consumers over-planning or setting goals that are too ambitious, which may lead to increased stress and frustration, or goal failure (Brunstein & Gollwitzer, 1996; Höpfner & Keith, 2021; Soman & Cheema, 2004; Wang et al., 2016)

2.2.4 Proposed Conceptual Framework

Across ten studies, we explore how breaking down a plan to complete a set of tasks via subcategory unpacking affects consumers' plans, effort judgments, and downstream behaviors. Materials for all studies, including stimuli and data, have been made available on ResearchBox at https://researchbox.org/1835&PEER_REVIEW_passcode=EYSRSZ.

Figure 2.1 illustrates our proposed conceptual framework. In Studies 1AB, we demonstrate our main effect: when a common task (e.g., learning vocabulary words, completing counting exercises) is unpacked into subcategories, people will make more ambitious plans in terms of the quantity of discrete tasks they wish to complete. In Studies 2ABC, we test the robustness of the subcategory unpacking effect across different tasks, planning paradigms, and participant samples. In Study 2C, we also find that while unpacking increases the quantity of planned tasks, it does not increase the corresponding effort perceptions for completing the tasks, which is suggestive of an underlying effort-based mechanism.

The following Studies 3AB further explore how unpacking modulates effort perceptions. Study 3A replicates the effort-based findings from Study 2C with a larger range of task quantities and statistical controls to account for variations in planned tasks across participants, while Study 3B demonstrates that unpacking decreases effort estimates when people are presented with fixed quantities of tasks. Study 4 offers a more direct test of the effort mechanism by showing that making effort salient moderates the unpacking effect.

In Study 5, we investigate the effects of unpacking on both the planning and task completion stages by giving participants the chance to complete tasks for bonus payment, with the results suggesting that unpacking increases over-planning rather than actual task completion. Finally, Study 6 demonstrates that unpacking can also impact consumer choices, with individuals shifting their preferences towards task set options that are presented in an unpacked format.

2.3 Study 1A: Unpacking Leads to More Ambitious Plans

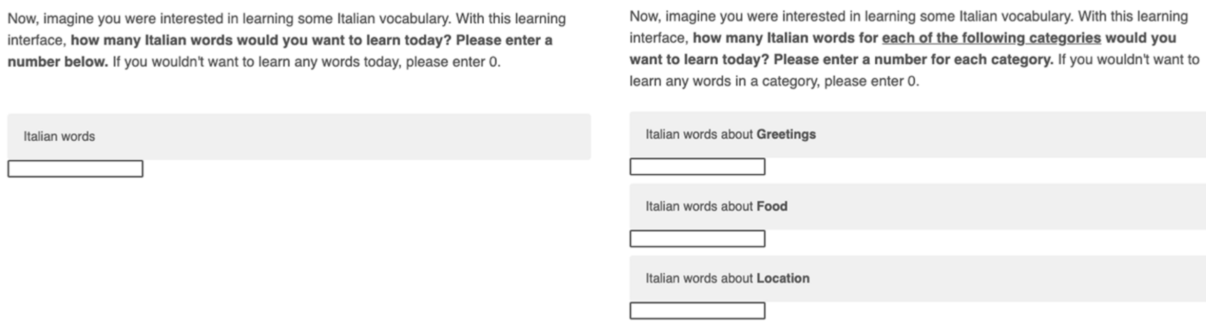
Study 1A offers an initial demonstration that unpacking a task into subcategories leads consumers to form more ambitious plans. We start off with a common activity, learning vocabulary words in a new language, and investigate how people's plans to learn new words are impacted by the words being unpacked into specific categories.

2.3.1 Method

We recruited 401 participants ($M_{\text{Age}} = 41$; 56% female) from the CloudResearch participant pool (formerly TurkPrime; Litman et al., 2017) on Amazon's Mechanical Turk (MTurk) platform. Participants were told a cover story that the researchers conducting the study were interested in testing the effectiveness of a language learning interface for learning Italian. They were then shown three screens with different phrases in English, paired with their Italian counterparts and a pronunciation guide (i.e., good afternoon and buon pomeriggio; chocolate and cioccolato; supermarket and il supermercato). Participants were then asked to consider how many Italian words they would want to learn that day using this language learning interface in two randomly assigned task representation conditions: aggregated vs. unpacked. As shown in Figure 2.2, in the aggregated condition, participants were asked to enter a single number to indicate the number of Italian words they would want to learn that day. In the unpacked condition, participants were asked to enter three numbers to indicate how many Italian words they would want to learn within each of the following categories separately: greetings, foods, and locations (note that these categories correspond to the three sample words/phrases they learned earlier in the study). Participants could enter any number they wanted with no maximum cap. Finally, participants answered some demographic questions regarding their current employment status, age, gender, and education level.

2.3.2 Results

We excluded 6 participants who did not enter valid responses for their plans to learn Italian words (i.e., non-numeric responses), as well as one participant who indicated that they would plan to study 825 words and represented a significant outlier (with the next highest response being 80 words), leaving 394 participants for the analysis. A one-way ANOVA revealed a significant main effect of task planning condition ($F(1, 392) = 26.02, p < 0.001, \eta^2 = 0.06$), with participants planning to study significantly more



(a) (b)

Figure 2.2: Task Planning Questions for Study 1A: (a) Aggregated vs. (b) Unpacked Conditions

words in the unpacked condition compared to the aggregated condition ($M_{\text{Aggregated}} = 4.52, SD = 4.47; M_{\text{Unpacked}} = 8.64, SD = 10.45; t(392) = 5.10, p < 0.001, \text{Cohen's}\, d = 0.51$). Note that we compared the number of planned words in the aggregated condition to the combined number of planned words across the three categories in the unpacked condition.

2.3.3 Discussion

Study 1A provides evidence that unpacking leads people to plan to complete more tasks, even if the activities being planned within the subcategories are effectively the same. It is also interesting to note that people planned more in the unpacked condition even though they were restricted to thinking about just three specific word categories (greetings, foods, and locations), while those in the aggregated condition were asked to indicate a total with no cues regarding specific categories (see Figure 2.2). One might expect participants in the aggregated (vs. unpacked) condition to feel less restricted in terms of the word categories and therefore plan more words, but instead we find the opposite effect.

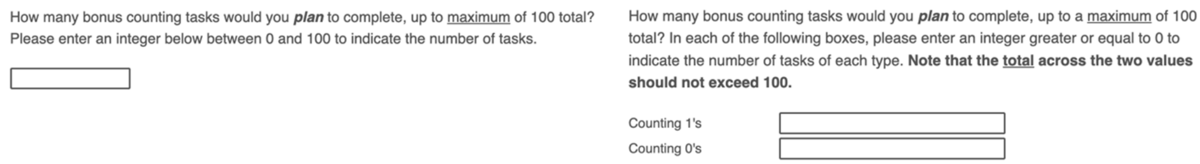
While the language-learning stimulus that we used in this study represents a realistic activity that consumers commonly engage in, one limitation is that the task was relatively open-ended and participants might have had different perceptions of what exactly they were planning for (i.e., what counts as truly "learning" a word?). Thus, to demonstrate that our findings generalize to other tasks, in Study 1B, we replicate our main unpacking effect with a new counting activity that allows for more concrete task planning.

2.4 Study 1B: Unpacking a Concrete Task Into Virtually Identical Subcategories

Study 1B was designed to test the unpacking effect using an activity that allowed participants to engage in more concrete task planning. Specifically, this study involved a simple counting activity that could be completed and tracked within an online survey, and thus participants could reasonably gauge the amount of time and effort it would take to complete their planned tasks. Additionally, the counting task allowed us to test whether our main unpacking effect holds when the subcategories are virtually indistinguishable, as discussed next.

2.4.1 Method

We recruited 401 Cloud Research participants on MTurk (M_{Age} = 42, 53% female). Participants were randomly assigned to either the aggregated or unpacked task planning condition. All participants were first asked to complete a short counting task in which they counted the number of 1's within an 8 by 8 matrix of 1's and 0's. In the aggregated condition, participants were asked to indicate how many tasks (counting either 1's or 0's) they would plan to complete for additional bonus payment ($0.20 per task), while participants in the unpacked condition were asked separately how many counting tasks they would want to complete in the "Counting 1's" category and the "Counting 0's" category separately, as seen in Figure 2.3. Notably, the counting categories presented to participants in this study were virtually identical and did not present any additional



(a) (b)

Figure 2.3: Task Planning Questions for Study 1B: (a) Aggregated vs. (b) Unpacked Conditions

information in the unpacked condition (relative to the aggregated condition), in contrast to Study 1A, where participants' plans in the unpacked condition may have been impacted by their preferences for specific Italian word categories or simply the presence of specific word category cues. Participants were instructed that the total number of planned tasks should not exceed 100. Finally, participants were asked to rate on 5-point Likert scales how difficult and stressful they found the counting task to be (e.g., 1 = Not at all difficult, 5 = Extremely difficult), as well as a series of demographic questions.

2.4.2 Results

We excluded 4 participants who did not follow the instructions and went over the 100-task maximum, leaving 397 participants for the analysis. Participants did not find the counting task to be particularly difficult or stressful, with one-sample t-tests revealing that average ratings were well below the midpoint of 3 on the 5-point Likert scales for both difficulty ($M = 1.72, SD = 0.83, t(396) = -30.69, p < 0.001$) and stressfulness ($M = 1.53, SD = 0.80, t(396) = -36.68, p < 0.001$). A one-way ANOVA revealed a significant effect of the task representation condition, with participants in the unpacked condition planning significantly more tasks compared to those in the control condition ($M_{\text{Aggregated}} = 55.32, SD = 42.12, M_{\text{Unpacked}} = 66.72, SD = 40.25, F(1, 395) = 7.60, p = 0.006, \eta^2 = 0.02, \text{Cohen's } d = 0.28$).

In summary, across Studies 1AB, which involve differing levels of concreteness in the tasks, we find that task representation matters such that unpacking a task into subcategories or subtypes leads consumers to make more ambitious plans into terms of the quantity of additional tasks they would like to complete. In the following Studies 2ABC, we replicate this main unpacking effect across a series of robustness checks, including unpacking unrelated tasks, displaying participants' summed total planned tasks in the unpacked condition, using a more effortful planning paradigm, and recruiting participants from a different population.

2.5 Study 2A: Unpacking Multiple Unrelated Tasks

In Study 2A, we demonstrate that our main unpacking effect holds even if the unpacked tasks are unrelated or independent. In the previous Studies 1AB, tasks were unpacked into either natural subcategories (e.g., vocabulary word categories) or indistinguishable subcategories (e.g., counting 1's vs. 0's or different-colored dots). In this study, the tasks that are unpacked are inherently separate tasks.

2.5.1 Method

We recruited 399 participants from the CloudResearch participant pool on MTurk (M_{Age} = 40; 54% female). All participants were asked to complete two different tasks: the counting 1's or 0's task used in previous studies, as well as a new task that involved rearranging 7 sentences to form a coherent paragraph (see Figure 2.4). Participants were again randomly assigned to either the aggregated or unpacked task representation condition. In the aggregated condition, participants were asked to indicate how many tasks of either type they would plan to complete if given the opportunity to earn $0.20 per task as bonus payment, and in the unpacked condition participants indicated the number of counting and sentence rearranging tasks separately. Participants were instructed that the total number of planned tasks should not exceed 100. Finally, participants were

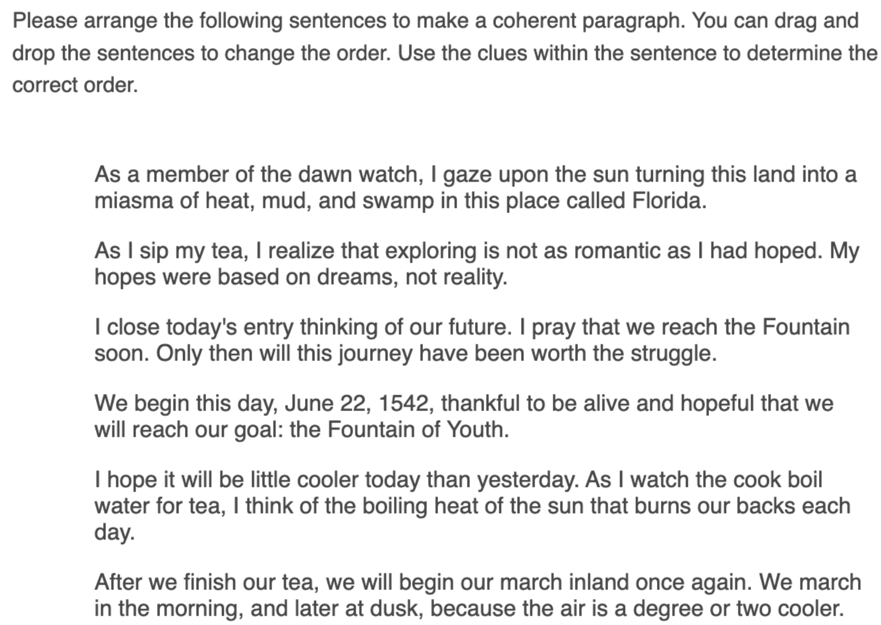


Figure 2.4: Sentence Rearranging Task Used in Study 2A

asked to rate on 5-point Likert scales how difficult and stressful they found the counting task to be (e.g., 1 = Not at all stressful, 5 = Extremely stressful), as well as a series of demographic questions.

2.5.2 Results

We excluded 10 participants who did not follow the instructions and went over the 100-task maximum, leaving 389 participants for analyses. We compared the number of planned tasks among participants in the aggregated condition to the sum of the planned counting and sentence rearranging tasks among participants in the unpacked condition. A one-way ANOVA revealed a significant main effect of task planning condition ($F(1, 387) = 16.30, p < 0.001, \eta^2 = 0.04$), where participants in the unpacked condition planned to do significantly more tasks compared to those in the aggregated condition ($M_{\text{Aggregated}} = 45.97, SD = 41.56; M_{\text{Unpacked}} = 62.86, SD = 40.87; t(387) = 4.04, p < .001$, Cohen's $d = 0.410$).

Similar to Studies 1AB, participants did not find the counting task to be difficult ($t(388) = 33.16, p < 0.001$) or stressful ($t(388) = 40.73, p < 0.001$), with the ratings significantly below the midpoint of 3 on the 5-point Likert scales. They also did not find the new sentence re-arranging task to be difficult ($t(388) = 6.18, p < 0.001$) or stressful ($t(388) = 20.06, p < 0.001$). However, the sentence rearranging task was rated as more difficult ($M_{\text{Counting}} = 1.59, SD = 0.84; M_{\text{Sentence}} = 2.67, SD = 1.05; paired - t(388) = 17.41, p < 0.001, \text{Cohen's } d = 0.88$) and more stressful ($M_{\text{Counting} = 1.44}, SD = 0.75; M_{\text{Sentence}} = 1.94, SD = 1.04; \text{paired-}t(388) = 9.10, p < 0.001, \text{Cohen's } d = 0.46$) compared to the counting task. Consistent with this, within the unpacked condition, participants planned to complete significantly more counting tasks on average than sentence rearranging tasks ($M_{\text{Counting}} = 45.44, SD = 37.04; M_{\text{Sentence}} = 17.42, SD = 23.40; \text{paired-}t(186) = 8.23, p < 0.001, \text{Cohen's } d = 0.60$). Participants in the aggregated condition gave a single number to indicate their total planned tasks, but it was not specified what proportion of the tasks would be counting or sentence rearranging tasks (i.e., they were simply told to imagine that they would be completing tasks "similar to the ones [they] just did"). This highlights an alternative driver of the unpacking effect that may arise in situations when consumers plan different tasks that are independent (or the task subcategories are more uneven in terms of the amount of effort required). The more ambitious plans when tasks are unpacked could be due to people planning to complete more of the easier task.

2.6 Study 2B: Displaying Total Planned Tasks Across Subcategories

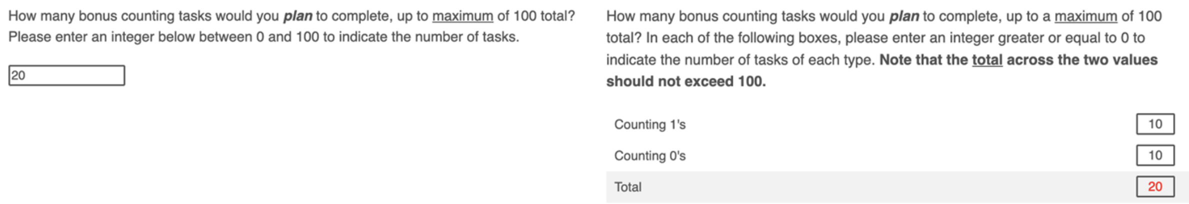
One potential issue with the design of Studies 1AB is that participants in the unpacked condition could have misunderstood the planning question and indicated how many counting tasks they would want to do if the task consisted of either counting 1's or counting 0's, rather than the total combined. To address this concern, In Study 2B, we displayed a total tally number in the unpacked condition.

2.6.1 Method

We recruited 401 participants from the CloudResearch participant pool on MTurk (M_{Age} = 41; 52% female), who were randomly assigned to either the aggregated or unpacked task representation condition. All participants first completed a short task involving counting the number of 1's within a matrix of 1's and 0's and were then asked how many additional tasks they would plan to complete (up to 100) for a $0.20 bonus per completed task. Participants in the aggregated condition gave a single number to indicate the total tasks, while those in the unpacked condition gave two numbers, one for the "Counting 1's" category and one for the "Counting 0's" category. This study was nearly identical to Study 1B, with the key difference being that in the unpacked condition, participants were additionally shown a tally box reflecting the "real-time" sum of the two values that they indicated. For example, as shown in Figure 2.5, if a participant in the unpacked condition entered 10 "Counting 1's" tasks and 10 "Counting 0's" tasks, then the number 20 would appear in the box next to "Total" to make it clear to participants that their response should indicate the number of total tasks they would want to complete across both categories. Finally, participants were asked to rate on 5-point Likert scales how difficult, stressful, and enjoyable they found the counting task to be, as well as a series of demographic questions.

2.6.2 Results

All participants in Study 2B stayed within the 100-task maximum, so we included all 401 participants in our analysis. Consistent with Study 1B, a one-way ANOVA revealed a significant main effect of task representation condition ($F(1, 399) = 20.35, p < 0.001, \eta^2 = 0.05$), with participants in the unpacked condition planning significantly



(a) (b)

Figure 2.5: Task Planning Questions for Study 2B: (a) Aggregated vs. (b) Unpacked Conditions

more tasks compared to those in the aggregate condition ($M_{\text{Aggregated}} = 52.70, SD = 43.81; M_{\text{Unpacked}} = 71.47, SD = 39.42, t(1,399) = 4.51, p < .001$, Cohen's $d = 0.45$).

2.7 Study 2C: Effortful Task Planning With Three Subcategories

Another potential concern with the study design used thus far is that it is trivial for participants to type in any number as their response to the task planning questions. To address this, in Study 2C, we implemented a more effortful paradigm for measuring task planning using a new counting task that could be unpacked into three identical subcategories.

2.7.1 Method

We recruited 141 undergraduates from the research pool of a large university ($M_{\text{Age}} = 20$; 58% female) who received course credit as compensation. All participants were first shown an image consisting of a mixture of 150 red, blue, and green dots, and asked to count the number of dots of a certain color, randomized across participants (see Figure 2.6). Participants were randomly assigned to either the aggregated or unpacked task representation condition, and asked to indicate how many additional counting tasks they would plan to do for $0.20 in bonus payment per task.

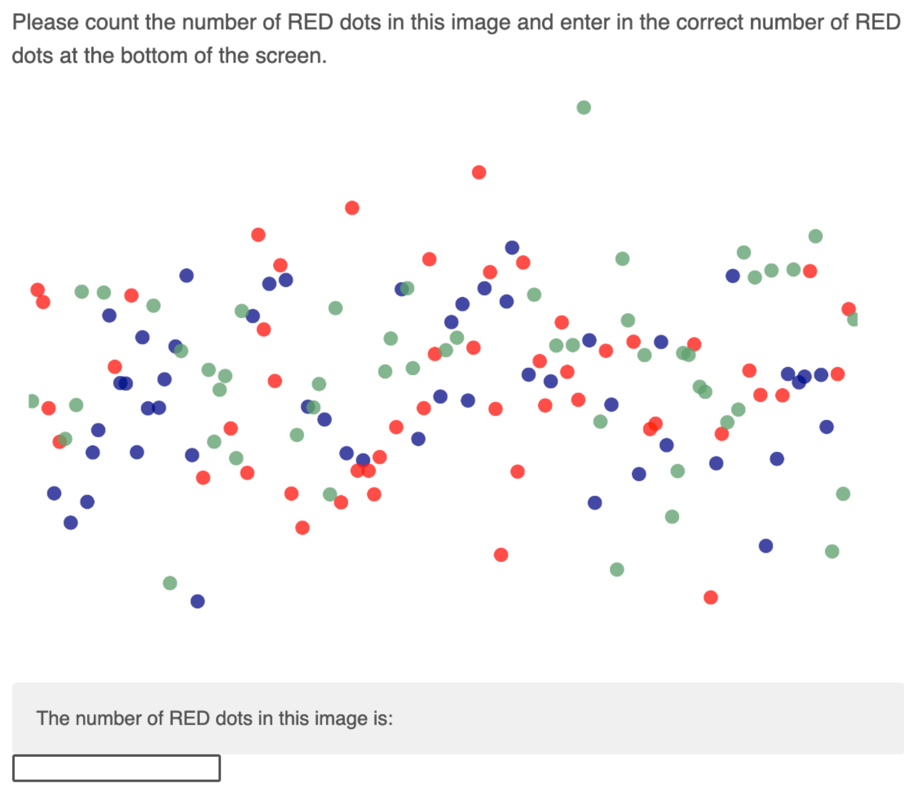
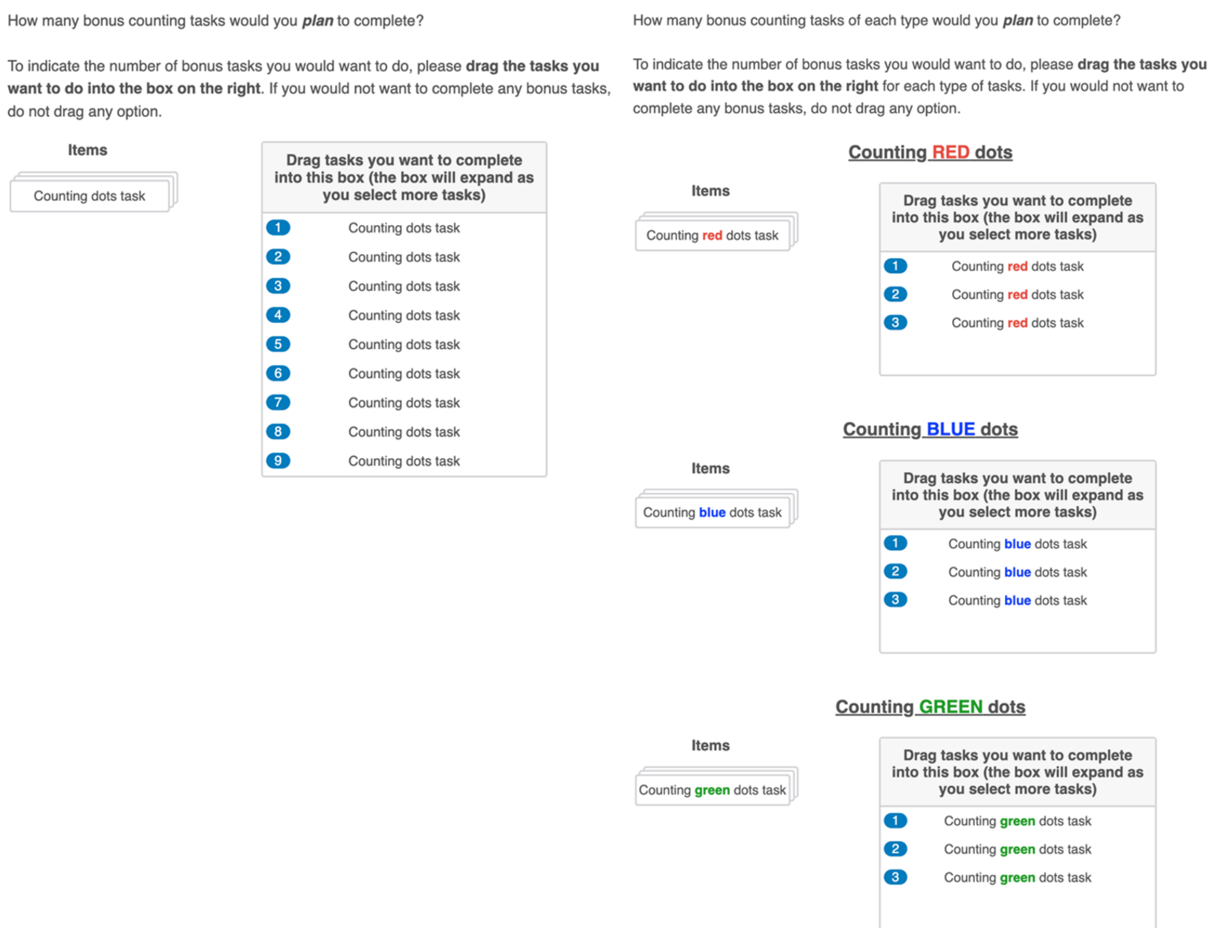


Figure 2.6: Dot-counting Task Used in Study 2C

To increase the effortfulness of answering the task planning question, participants were asked to drag-and-drop rectangles labeled with “counting dots task” into a larger box to indicate how many tasks they would plan to complete (see Figure 2.7). In the aggregated condition, participants were presented with 30 “generic” counting tasks, while in the unpacked condition, participants were presented with 3 sets of 10 rectangles labeled as red, blue, or green dot counting tasks that could be drag-and-dropped into 3 corresponding boxes.

After indicating their plans, participants were asked to estimate how long they thought it would take them to complete each individual task (in seconds) and all the tasks they had planned (in minutes). They were also asked to indicate on a 101-point slider scale how much effort it would take them to complete all the tasks they had planned, and how challenging it would be to complete all the tasks they had planned.



(a) (b)

Figure 2.7: Task Planning Questions for Study 2C: (a) Aggregated vs. (b) Unpacked Conditions

Finally, participants answered some demographic questions.

2.7.2 Results

Replicating the results from the previous studies, a one-way ANOVA revealed a significant main effect of task planning condition ($F(1, 139) = 5.64, p = 0.019, \eta^2 = 0.04$), with participants in the unpacked condition planning significantly more tasks compared to those in the aggregated condition ($M_{\text{Aggregated}} = 3.96, SD = 5.09; M_{\text{Unpacked}} = 6.57, SD = 7.66; t(1, 139) = 2.38, p = 0.019$, Cohen's $d = 0.40$).

Note that in this study, we also collected several measures of participants' effort perceptions regarding the task. Interestingly, even though participants in the unpacked condition planned significantly more tasks than those in the aggregated condition, we found no significant differences between conditions in terms of participants' ratings of how effortful ($F(1, 139) = 0.54, p = 0.464$) or challenging ($F(1, 139) = 0.15, p = 0.704$) completing their planned tasks would be, and also no significant differences in time estimates for completing a single task ($F(1, 139) = 1.61, p = 0.207$) or completing all planned tasks ($F(1, 139) = 0.99, p = 0.323$); note that time estimates were logged since the distributions of responses were highly right-skewed. In other words, even though participants in the unpacked condition planned to do more tasks, on average they did not perceive these greater quantities of tasks to be more effortful. We further explore the potential mechanism that unpacking leads to more ambitious plans by modulating perceived effort in Study 3A, which uses a higher task maximum and thus gives us a greater possible range of total tasks and effort ratings.

2.7.3 Discussion

In summary, across Studies 2ABC, we demonstrate the robustness of our main effect that unpacking a task into subcategories leads to more ambitious planning. Study 2A shows that the main unpacking effect holds even when the unpacked tasks are inherently independent (i.e., two unrelated tasks). In Study 2B, by presenting participants in the unpacked condition with a real-time total sum of their planned tasks across subcategories, we rule out the possibility that the unpacking effect is driven by a misunderstanding of study instructions (i.e., participants thinking that they were planning the tasks in each subcategory separately rather than considering the total). Finally, Study 2C involved an undergraduate student sample and a different counting task with three identical subcategories. The drag-and-drop paradigm used in this study increased the effort involved in task planning, demonstrating that our main effect is not an artifact of participants simply entering large meaningless numbers. In Study 2C, we also found that participants in the unpacked condition reported similar effort and time estimates on average as those in the aggregated condition, even though they planned to complete significantly more tasks. We further investigate the role of unpacking on effort perceptions in the following studies.

2.8 Study 3A: Initial Evidence That Unpacking Modulates Effort Perceptions

In the following set of studies, we test for evidence of our proposed mechanism that task unpacking leads to more ambitious plans by modulating perceived effort. In Study 3A, we replicate our main effect and further compare task effort ratings between the aggregated and unpacked task representation conditions among participants who planned a similar number of tasks. In Study 3B, we measure people's effort perceptions of fixed quantities of tasks and demonstrate that unpacking the tasks into subcategories leads to different ratings of effort and estimated completion time.

2.8.1 Method

This study's design, hypothesis, and analysis plan were pre-registered. We recruited 501 participants from the CloudResearch participant pool on MTurk (M_{Age} = 39; 61% female). Similar to Study 2C, all participants first completed a dot-counting task (see Figure 2.6), were randomly assigned into two task representation conditions, and then asked how many additional tasks they would want to complete if given the opportunity to earn a $0.20 bonus per task, responding with a single number (aggregated condition) or separate numbers for blue, red, and green dot-counting tasks (unpacked condition) up to a maximum of 100 tasks in total. Note that in the unpacked condition, the sum total across the three dot colors was displayed and updated in real-time to make it clear to participants that they were making plans across all three subcategories (similar to Study 2B). After indicating their plans, participants were asked to estimate how long they thought each task would take them (in seconds), and how long they thought it would take them to complete all the tasks they had planned (in minutes). They were also asked to indicate on a 101-point slider scale how much effort it would take them to complete all the tasks they had planned, and also how challenging it would be. Finally, participants answered some demographic questions.

2.8.2 Results for Main Unpacking Effect

We excluded 1 participant who did not follow the instructions and went over the 100-task maximum, leaving 500 participants for analysis. Consistent with our previous findings, a one-way ANOVA revealed a significant main effect of task planning condition ($F(1, 498) = 42.51, p < 0.001, \eta^2 = 0.08$), where participants in the unpacked condition planned significantly more tasks than those in the aggregated condition ($M_{\text{Aggregated}} = 35.32, SD = 40.50; M_{\text{Unpacked}} = 59.71, SD = 43.16; t(498) = 6.52, p < 0.001, \text{Cohen's}\, d = 0.58$). As pre-registered, these results also hold if we exclude the 28 participants who indicated that they would want to do 0 additional bonus tasks ($F(1, 470) = 43.51, p < 0.001, \eta^2 = 0.08$), with more tasks planned in the unpacked condition ($M_{\text{Aggregated}} = 37.68, SD = 40.76; M_{\text{Unpacked}} = 62.80, SD = 42.00; t(470) = 6.60, p < 0.001, \text{Cohen's}\, d = 0.61$) and the difference more pronounced since slightly more people in the aggregated condition opted for 0 bonus tasks.

As pre-registered, we analyzed whether participants' estimated effort and time to complete the tasks was related to the number of tasks they planned. Across all participants, there was a significant negative correlation between the total number of tasks they planned and their time estimates (in seconds) for completing a single counting task ($r = -0.19, t(498) = 4.31, p < 0.001$), indicating that those who found or estimated a single instance of the counting task to take longer subsequently planned to do fewer of them. There was also a significant positive correlation between total tasks planned and how effortful ($r = 0.17, t(498) = 3.88, p < 0.001$) and challenging ($r = 0.13, t(498) = 2.91, p = 0.004$) they rated their planned tasks (101-point scale), as well as their time estimates (in minutes) for completion ($r = 0.39, t(498) = 9.39, p < 0.001$); note that all time estimates were logged since the distribution of responses was highly right-skewed. These positive correlations indicate that, collapsing across experimental conditions, those who planned to do more tasks correctly estimated that it would take longer to complete them. For simplicity, in the remainder of the analysis, we focus on effort ratings as our main measure of effort, but we obtain similar results if we use logged time or the challenging rating.

2.8.3 Exploratory Analysis of Unpacking and Effort Perceptions

In this subsection, we further explore the data to understand the relationship between unpacking and perceived or estimated effort for completing a set of planned tasks. Note that this analysis was not pre-registered, but does provide some initial evidence of how unpacking may modulate effort perceptions. Given that participants in the unpacked condition planned significantly more tasks compared to those in the aggregated condition, we would expect them to have higher effort ratings for their planned tasks. However, we actually find there to be no significant difference in effort ratings between conditions ($M_{\text{Aggregated}} = 71.67, \text{SD} = 25.85; M_{\text{Unpacked}} = 73.48, SD = 23.13; t(498) = 0.82, p = 0.410, \text{Cohen's}\, d = 0.07$). The fact that average effort ratings were effectively the same between conditions (but total planned tasks were greater in the unpacked condition) suggests that those in the unpacked condition may perceive a given number of tasks to be less effortful compared to their counterparts in the aggregated condition.

Since participants in the aggregated vs. unpacked conditions planned different quantities of tasks on average, to make a more direct comparison of perceived effort (of the same task load) between conditions, we created a “normalized” effort rating for each

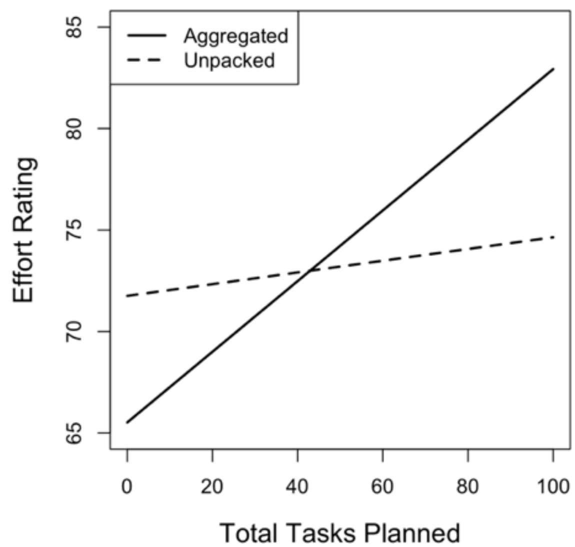


Figure 2.8: Comparison of Relationship Between Effort Ratings and Total Tasks Planned Across Aggregated vs. Unpacked Conditions in Study 3A

participant by dividing their original effort ratings by the total number of tasks they had planned. These normalized effort ratings essentially represent how effortful participants would find a single "unit" of the task. Note that we exclude the 28 participants who planned 0 tasks. A comparison of the normalized effort ratings reveals that participants in the unpacked condition indeed found each task unit to be less effortful compared to those in the aggregated condition ($M_{\text{Aggregated}} = 12.21, SD = 20.26; M_{\text{Unpacked}} = 5.31, SD = 10.10; t(470) = 4.66, p < 0.001,$ Cohen's $d = 0.43$).

To further investigate how unpacking changes effort perceptions, we estimate the following linear regression equation, where each participant i's effort ratings are modeled as a function of TotalTasks_i or the total tasks they planned, an indicator $\text{Unpacked}_i \in (0, 1)$ for whether they were in the unpacked (vs. aggregated) condition, and an interaction term.

$$\text{Effort}_i = \beta_0 + \beta_1 \text{TotalTasks}_i + \beta_2 \text{Unpacked}_i + \beta_3 (\text{TotalTasks}_i \times \text{Unpacked}_i) + \epsilon_i$$

The regression reveals there to be a significant positive effect of total tasks ($\beta_1 =$

$0.17, SE = 0.04, p < 0.001$), a marginally significant positive effect of being in the unpacked condition ($\beta_2 = 6.23, SE = 3.31, p = 0.060$), and a significant negative interaction ($\beta_3 = -0.15, SE = 0.05, p = 0.005$). To visualize this interaction, Figure 2.8 plots the regression lines for the relationship between effort rating and total tasks planned separately for the aggregated and unpacked conditions. Within the aggregated condition, when participants plan more tasks, they tend to give higher effort ratings, but within the unpacked condition, effort ratings are relatively insensitive to total tasks planned. This leads to effort ratings being significantly higher in the aggregated (vs. unpacked) condition when total tasks planned are above the median of 27.5, while effort ratings are similar at low values.

2.8.4 Discussion

In Study 3A, we again replicate the main unpacking effect, and also provide some initial correlational evidence that unpacking leads to more ambitious planning by modulating effort perceptions. Specifically, we find that even though unpacking increases the total number of bonus tasks planned, it does not increase the estimated effort for completing these plans, consistent with Study 2C. In fact, additional analyses reveal that participants' effort perceptions in the unpacked condition seem to be relatively insensitive to the total tasks planned. As an example, based on our data, 59 tasks presented in the unpacked format would seem equally effortful as 35 tasks presented in the aggregated format. To more directly test how unpacking affects effort perceptions, in Study 3B, we hold fixed the number of tasks presented to participants across aggregated and unpacked task representation conditions.

2.9 Study 3B: the Effect of Unpacking on Effort Perceptions for a Fixed Number of Tasks

In Study 3B, we present participants with a fixed sets of tasks to complete, and test whether presenting the tasks in an aggregated vs. unpacked format affects perceived effort.

2.9.1 Method

We recruited 399 participants from the CloudResearch participant pool on MTurk (M_{Age} = 43; 54% female). Participants were randomly assigned across a 3 (workload: low vs. medium vs. high, within-subject) × 2 (task representation: aggregated vs. unpacked, between-subject) mixed-effects design. For this study, we adapted the dictionary entry formatting task from Kruger and Evans (2004). Participants were asked to consider editing dictionary entries from "plain text" to a specific format, which would involve making changes such as boldfacing, italicizing, adding punctuation and specific characters, etc. Figure 2.9 depicts the example that all participants were presented with for the word "femur."

All participants were presented with three different hypothetical people with different workloads in terms of the number of dictionary entries they needed to format. Specifically, "Person A" had a low workload of 9 words to format, "Person B" had a medium workload of 15 words, and "Person C" had a high workload of 30 words. As shown in Figure 2.10, which depicts the workload for Person C, in the aggregated condition the total number of dictionary entries was displayed, while in the unpacked condition the dictionary entries were broken down into three equal sized subcategories: types of bones in the (1) arms and hands (2) legs and feet, and (3) torso. After viewing each of the three workloads, participants rated how effortful and challenging they thought completing the editing task would be on 101-point sliding scales, and how many

Example:

Before	After
femur ˈfiːmə noun plural femurs or femora ˈfɛmərə 1 the longest thickest bone of the human skeleton, articulating with the pelvis above and the knee below nontechnical name thighbone 2 the corresponding bone in other vertebrates origin of femur c18: from latin thigh	**femur** /ˈfiːmə/ *noun* plural **femurs** *or* **femora** (ˈfɛmərə) 1. the longest thickest bone of the human skeleton, articulating with the pelvis above and the knee below: Nontechnical name: **thighbone** 2. the corresponding bone in other vertebrates **Origin of femur** C18: from Latin: thigh

Figure 2.9: Dictionary Formatting Example Shown to Participants in Study 3B

Person C decides that she will format **30** dictionary entries.

(a)

Person C decides that she will format:
10 dictionary entries about **types of bones in the arms and hands,**
10 dictionary entries about **types of bones in the legs and feet,**
10 dictionary entries about **types of bones in the torso**.

(b)

Figure 2.10: Stimuli for Study 3B: (a) Aggregated vs. (b) Unpacked Conditions

minutes they estimated it would take to complete.

2.9.2 Results

Similar to Kruger and Evans (2004), we focus on estimated time in minutes as our main dependent variable (logged to deal with right-skewness). We conducted a 3 (workload: low vs. medium vs. high, within-subject) × 2 (task representation: aggregate vs. unpacked, between-subject) mixed ANOVA on the logged time estimates for the

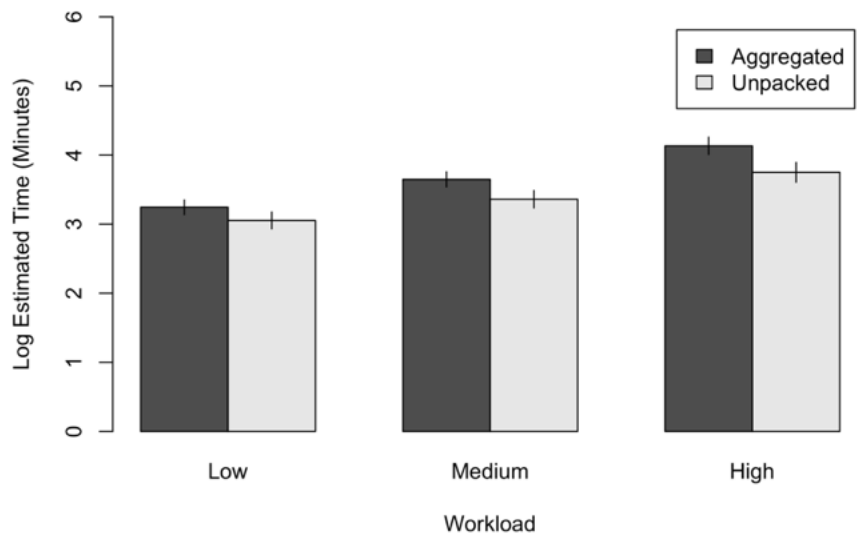


Figure 2.11: Comparison of Time Estimates Across Conditions in Study 3B, Plotting Means and 95% Confidence Intervals

different dictionary entry workloads. We found a significant main effect of workload ($F(1.47, 582.12) = 583.70, p < 0.001$), a significant main effect of task representation ($F(1, 397) = 11.70, p < 0.001$), and a significant interaction ($F(1.47, 582.12) = 8.48, p = 0.001$). In both the aggregated and unpacked conditions, estimated time to complete the tasks was higher for the medium and high workloads compared to the low workload. Importantly, as depicted in Figure 2.11, time estimates were significantly higher in the aggregated (vs. unpacked) condition for the low ($M_{\text{Aggregated}} = 3.24, SD = 0.77; M_{\text{Unpacked}} = 3.05, SD = 0.87; t(397) = 2.34, p = 0.06$), medium ($M_{\text{Aggregated}} = 3.65, SD = 0.79; M_{\text{Unpacked}} = 3.36, SD = 0.90; t(397) = 3.39, p = 0.002$), and high workloads ($M_{\text{Aggregated}} = 4.13, SD = 0.91; M_{\text{Unpacked}} = 3.75, SD = 1.03; t(397) = 3.94, p < 0.001$); note that p-values reported here have been adjusted for Bonferonni correction for multiple comparisons. The significant interaction between workload and task representation conditions can be interpreted as the unpacking effect being stronger for higher workloads.

2.9.3 Discussion

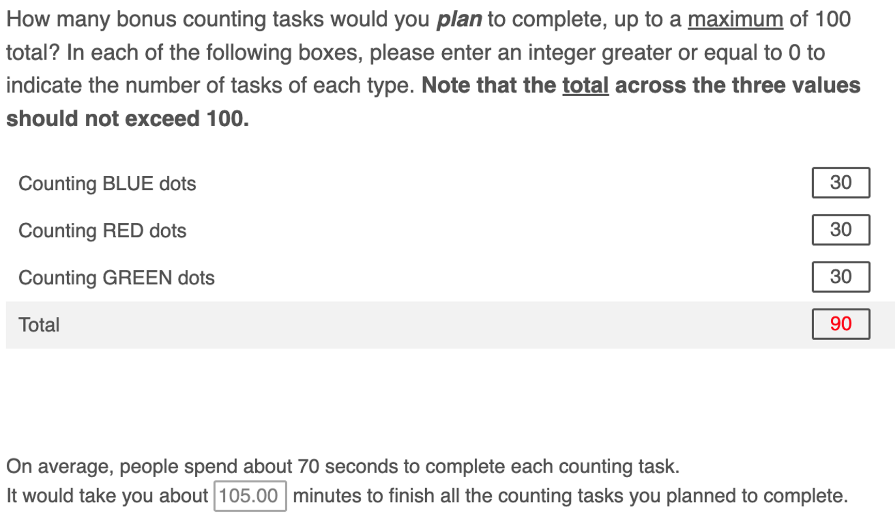
Study 3B shows that for a fixed quantity of tasks, merely unpacking the task into subcategories can make the overall workload seem less effortful. This result may explain the main unpacking effect found in the previous studies: when participants made plans to complete tasks, the unpacked subcategories made the tasks seem less effortful, leading to more ambitious plans. We replicate these findings with the goal of learning different workloads of Italian words unpacked into subcategories (see Appendix Study A). Next, we directly test the effort-based mechanism with a moderation study.

2.10 Study 4: Highlighting Effort Moderates the Unpacking Effect

Our previous Studies 3AB suggest that for a fixed number of tasks, unpacking decreases the perceived effort required for completion. To more directly test our proposed effort mechanism, in Study 4 we highlight the amount of effort it would take for participants to complete their planned tasks (i.e., by providing a concrete time estimate), which we predict will moderate the unpacking effect.

2.10.1 Method

We recruited 800 participants from the CloudResearch participant pool on MTurk (M_{Age} = 41; 53% female). Participants were randomly assigned to a condition within a 2 (task representation: aggregated vs. unpacked) × 2 (highlighting effort: no time estimate vs. time estimate) between-subjects design. Similar to Study 3A, participants were first shown a screen with a mixture of red, blue, and green dots and asked to count the dots of a particular color (randomized across participants). Participants were then asked how many additional tasks they would plan to complete if offered a $0.20 bonus payment per



How many bonus counting tasks would you ***plan*** to complete, up to a maximum of 100 total? In each of the following boxes, please enter an integer greater or equal to 0 to indicate the number of tasks of each type. **Note that the total across the three values should not exceed 100.**

Counting BLUE dots	30
Counting RED dots	30
Counting GREEN dots	30
Total	90

On average, people spend about 70 seconds to complete each counting task.
It would take you about 105.00 minutes to finish all the counting tasks you planned to complete.

Figure 2.12: Example of Stimulus Given to Participants in the Unpacked/Time Estimate Condition in Study 4

task up to a maximum of 100 tasks. Importantly, as shown in Figure 2.12, in the time estimate condition, participants were told that the average time to complete one counting task was 70 seconds (based on real data from participants in previous studies), and the number of minutes that it would take for them to complete the number of tasks they had typed into the response box (with the display updated in real-time). Participants in the no time estimate condition did not see this information (i.e., essentially replicating the conditions in Study 3A). After indicating their plan to complete more tasks, all participants reported time estimates for completing one task and all planned tasks, as well as how effortful and challenging they thought it would be to complete all planned tasks. Finally, they answered some demographic questions.

2.10.2 Results

Four participants gave responses that exceeded the 100-task maximum and were excluded, leaving 796 participants for the analysis. A 2 (task representation: aggregated vs. unpacked) × 2 (highlighting effort: time estimate vs. no time estimate) ANOVA on the number of planned tasks revealed a the significant main effect of task representation condition ($F(1,792) = 45.17, p < 0.001, \eta^2 = 0.05$), no main effect of highlighting effort ($F(1,792) = 1.87, p = 0.172, \eta^2 = 0.00$), and a significant interaction ($F(1,792) = 7.15, p = 0.008, \eta^2 = 0.01$).

Figure 2.13 plots the comparison of the number of planned tasks across conditions. On the left-hand side, we see that among participants in the no time estimate condition, we replicate our main effect where unpacking significantly increases task planning ($M_{\text{Aggregated}} = 37.99, SD = 41.54; M_{\text{Unpacked}} = 66.63, SD = 43.48; t(398) = 6.73, p < 0.001, \text{Cohen's}\, d = 0.67$). On the right-hand side, among participants in the time estimate condition, there is still a significant difference between the aggregated and unpacked conditions ($M_{\text{Aggregated}} = 41.94, SD = 43.41; M_{\text{Unpacked}} = 54.14, SD = 44.89; t(394) = 2.75, p = 0.006, \text{Cohen's}\, d = 0.28$), but the difference is much smaller. In particular, the moderating effect of highlighting effort on our main unpacking effect appears to be primarily driven by providing the time estimates to participants in the unpacked condition. While those in the aggregated condition planned the same number of tasks regardless of whether time estimates were provided ($M_{\text{TimeEstimate}-\text{NoTimeEstimate}} = 3.95, SD = 60.09; t(399) = 0.93, p = 0.353, \text{Cohen's}\, d = 0.09$), as illustrated by comparing the dark grey bars in Figure 2.13, those in the unpacked condition significantly reduced their planned tasks when provided with time estimates ($M_{\text{TimeEstimate}-\text{NoTimeEstimate}} = -12.49, SD = 62.49; t(393) = 2.81, p = 0.005, \text{Cohen's}\, d = 0.28$), as illustrated by comparing the light grey bars.

2.10.3 Discussion

This study demonstrates that highlighting effort can moderate the unpacking effect. By providing a concrete estimate of task completion time, we can correct the distorted effort estimation among participants in the unpacked condition, whereas those in the aggregated condition are not affected by this manipulation. This finding provides further support for perceived effort being a key mechanism for the unpacking effect.

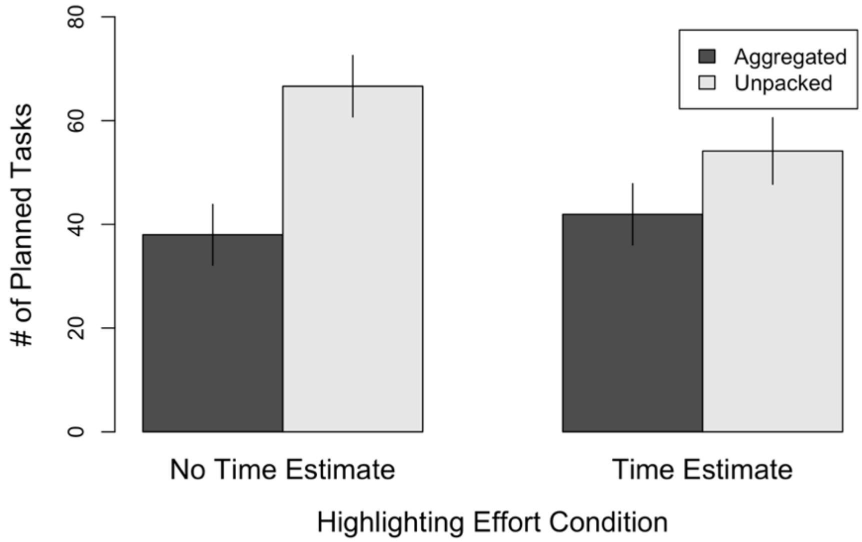


Figure 2.13: Comparison of Average Planned Tasks Across Task Representation (Aggregated vs. Unpacked) and Highlighting Effort (No Time Estimate vs. Time Estimate) Conditions in Study 4, With 95% Standard Error Bars

2.11 Study 5: Evidence That Unpacking Leads to Over-planning

Thus far, our studies have focused on the planning stage of task completion, with the consistent finding that simply altering the presentation of a task into unpacked (vs. aggregated) form can lead to more ambitious plans. A critical follow-up question is whether these more ambitious plans further result in greater task completion, or instead reflect greater over-planning whereby individuals are more likely to fall short of their planned completion goals. In Study 5, we investigate the downstream consequences of the unpacking effect by giving participants the opportunity to actually complete tasks for bonus payments following the planning stage. Importantly, the plans that participants made were non-binding and they could quit at any point, which allows us to measure the degree to which participants under/over-planned.

2.11.1 Method

This study's design, hypothesis, and analysis plan were pre-registered. We recruited 202 participants from the CloudResearch participant pool on MTurk (M_{Age} = 40; 50% female). We used the same task as Studies 2C and 3A, where participants counted red, blue, or green dots from a mixture of 150 dots (see Figure 2.6). After participants had tried out the task, they were asked to indicate how many additional tasks they would plan to complete for $0.10 in bonus payment each. Again, participants were randomly assigned to either the aggregated vs. unpacked task representation conditions, in which they entered a single number or separate numbers for blue, red, and green dot-counting tasks, respectively. Participants were told that the maximum number of bonus tasks was 30. They then estimated how long it would take to complete a single task (in seconds) and all tasks they had planned (in minutes), and also indicated on 101-point slider scales how effortful and challenging it would be to complete the planned set of tasks.

In this study, after making their plans, participants were then given the opportunity to complete up to 30 tasks for a maximum possible bonus payment of $3. Note that participants were presented with pictures of dots in sequence, and for each picture, they were randomly asked to count either the red, blue, or green dots, and could only move on to the next picture once they had entered the correct answer. After each completed task, they were presented with a tally of how many dot-counting tasks they had completed so far. Participants could quit at any time by selecting the "I want to end the study" option, and they received their final bonus payments based on the number of tasks they completed. Thus, since we were interested in measuring variation in task completion, the number of tasks participants had indicated during the planning stage was non-binding, so participants could complete as few or as many tasks as they wanted. This design allowed us to determine whether the effects of unpacking during the planning stage persisted in the task completion stage, or impacted the degree to which participants under or over-planned. Finally, participants answered some demographic questions.

Note that there were three key differences between the planning stage of this study and Study 3A: the maximum cap of 100 dot-counting tasks was lowered to 30 tasks, the bonus payment of \$0.20 per task was lowered to \$0.10, and the target sample size was reduced from 250 to 100 participants per condition. These changes allowed us to feasibly implement the actual bonus payments provided in Study 5, and also demonstrate the robustness of our main unpacking effect. Before collecting data for Study 5, to ensure that our main unpacking effect during the planning stage would replicate with these changes, we conducted an alternative version of Study 5 with only the planning stage of the study (see Appendix Study B).

2.11.2 Results

We excluded one participant who indicated they wanted to do more than 30 tasks despite the instructed maximum, leaving 201 participants for analysis. We first compare the number of planned tasks across conditions. As pre-registered, a one-way ANOVA revealed a significant main effect of task planning condition ($F(1, 199) = 8.75, p = 0.003, \eta^2 = 0.04$), with participants in the unpacked condition planning significantly more tasks compared to those in the aggregated condition ($M_{\text{Aggregated}} = 15.67, SD = 12.70; M_{\text{Unpacked}} = 12.82, SD = 12.00; t(199) = 2.96, p = 0.003, d = 0.42$). This significant difference held if we exclude the 27 participants who indicated that they planned to complete 0 bonus tasks ($F(1, 172) = 12.70, p < 0.001, \eta^2 = 0.07; M_{\text{Aggregated}} = 18.16, SD = 11.90; M_{\text{Unpacked}} = 23.98, SD = 9.47; t(172) = 3.56, p < 0.001, d = 0.54$).

As pre-registered, we investigated the relationship between the number of tasks participants had planned and the time/effort estimates. Although we again found a negative correlation between estimated time (in seconds, logged) to complete a single counting task and total tasks planned ($r = -0.07, t(199) = 0.930, p = 0.353$), this correlation was not statistically significant, possibly due to the smaller variation in total tasks with the 30-task maximum. Consistent with Study 3A, we again found significant positive corre-

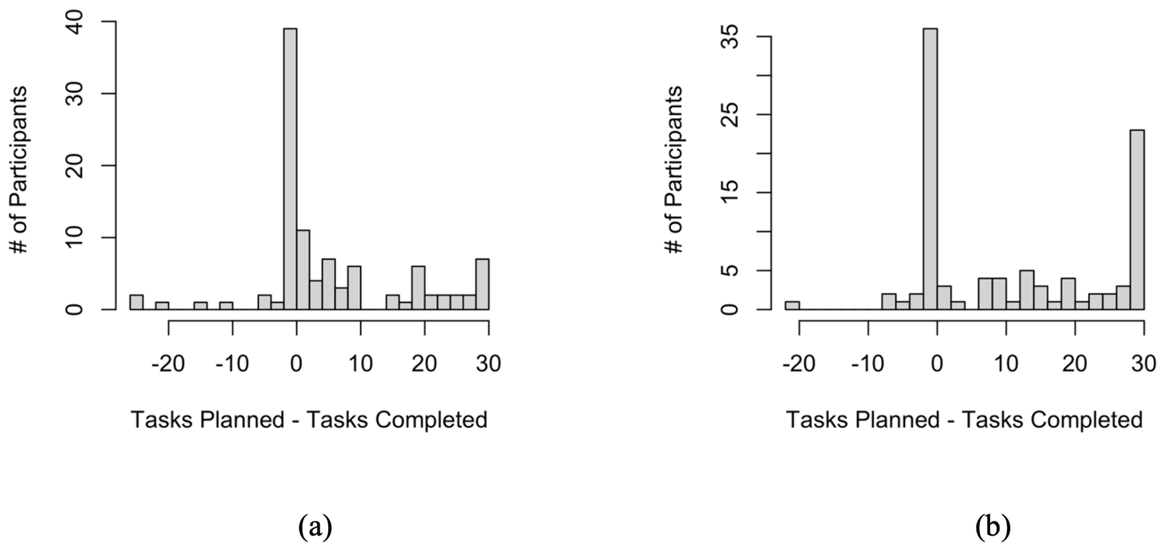


Figure 2.14: Degree of Over-planning in Study 5, as Measured by Subtracting the Number of Tasks Completed From the Number of Tasks Planned in the (a) Aggregated and (b) Unpacked Conditions

lations between total tasks planned and how effortful ($r = 0.38, t(199) = 5.87, p < 0.001$) and challenging ($r = 0.23, t(199) = 3.39, p < 0.001$) participants rated their planned tasks (101-point scale), as well as their logged time estimates (in minutes) for completion ($r = 0.41, t(199) = 6.42, p < 0.001$). To summarize, participants who planned more tasks accurately expected to take longer to complete the full set of planned tasks.

Also consistent with Study 3A, there was no difference in effort ratings between conditions ($M_{\text{Aggregated}} = 76.09, SD = 26.95; M_{\text{Unpacked}} = 77.74, SD = 22.64; t(196) = 0.47, p = 0.640$, Cohen's $d = 0.07$), despite participants in the unpacked condition planning to do more tasks on average compared to those in the aggregated condition. Excluding the 27 participants who planned to complete 0 tasks, a comparison of normalized effort ratings (i.e., computed by dividing participants' effort ratings by their total planned tasks) again showed that participants in the unpacked condition appeared to rate each task unit to be less effortful compared to those in the aggregated condition ($M_{\text{Aggregated}} = 12.97, SD = 20.96; M_{\text{Unpacked}} = 6.91, SD = 14.55; t(172) = 2.21, p = 0.028$, Cohen's $d = 0.34$).

Finally, we look at the downstream consequences of the task representation conditions; in other words, does making more ambitious plans in the unpacked (vs. aggregated) condition subsequently lead to more completed tasks? A one-way ANOVA revealed no main effect ($F(1, 199) = 0.05, p = 0.823, \eta^2 = 0.00$), with no difference in total completed tasks between conditions ($M_{\text{Aggregated}} = 9.67, SD = 12.37; M_{\text{Unpacked}} = 9.29, SD = 11.29; t(199) = 0.22, p = 0.823, d = 0.03$). We interpret this result as unpacking leading to more over-planning (rather than greater task completion). Figure 2.14 plots the degree of over-planning within each condition, computed by subtracting the number of tasks completed from the number of tasks planned. The greater over-planning among participants in the unpacked condition seems to be driven by a greater number of participants who indicated they planned to complete 30 total tasks, but ended up completing 0 (i.e., over-planned by 30).

2.11.3 Discussion

In summary, Study 5 demonstrates that our main unpacking effect holds in an incentive-compatible planning setting. Interestingly, we found that while participants in the unpacked condition planned to complete more tasks, they did not actually follow through with these more ambitious plans. This is consistent with our proposed mechanism that unpacking leads to lower perceived effort for the same set of tasks. Specifically, the results of our studies suggest that it may be the case that task unpacking leads participants to plan to complete more tasks, anticipating the effort required to be lower, but when the experienced effort (i.e., from actually attempting to complete the tasks) is higher than anticipated, they end up abandoning their plans. We can imagine that if the plans were binding like most real-life plans are, the more ambitious plans among those in the unpacked condition could potentially lead to stress, frustration, and failures in goal completion. Note that one concern in Study 5 was that asking participants the time and effort estimates right after the planning stage may have influenced their subsequent task completion decisions; thus, in Appendix Study C we replicate our results from Study 5 without the effort questions.

2.12 Study 6: The Effect of Unpacking on Choice

Thus far, we have focused on how unpacking affects consumer behavior in terms of planned quantities of tasks, with evidence that unpacking leads to more ambitious plans by decreasing the perceived effort required for task completion. In Study 6, we explore how unpacking may affect choice. Specifically, if consumers are faced with a choice between two different sets of tasks, our proposed framework predicts that unpacking one of the tasks should result in a shift in preference or choice share toward the unpacked task because unpacking makes the task set seem less effortful.

2.12.1 Method

We recruited 301 participants from the CloudResearch participant pool on MTurk (M_{Age} = 42; 61% female). Participants were introduced to two tasks, the dot-counting task used in previous studies and a new message encrypting task, which involved participants using an encryption code table to encrypt a message (i.e., "meet tomorrow at coffee shop"). The order in which participants completed the two trial tasks was counterbalanced. Participants were then asked to imagine that they were given an opportunity to complete an additional set of tasks for a total of $3 in bonus payment. Participants were randomly assigned to either the aggregated or unpacked dot-counting condition. In the aggregated condition, they made a choice between 30 dot-counting tasks versus 30 message encrypting tasks. In the unpacked condition, they made a choice between 10 red, 10 blue, and 10 green dot-counting tasks, versus 30 message encrypting tasks. We also measured the strength of preference for the option they chose on a 101-point slider scale, with 0 indicating indifference between the two options, and 100 being strong preference for the chosen option. Finally, they answered a few demographic questions.

2.12.2 Results

Interestingly, while the encrypting task on average took longer for participants to complete ($M_{\text{Dot-counting}} = 100.61\text{seconds}, SD = 94.64; M_{\text{Encrypting}} = 122.29, SD = 116.11;$ $t(300) = 2.580, p = 0.010$), overall the majority of participants across conditions preferred the encrypting task (79.1%). To test our hypothesis that unpacking the dot-counting task would shift preference towards it, we conducted a logistic regression with the task choice (dot-counting vs. encrypting) as the dependent variable and the aggregated vs. unpacked dot-counting condition as the independent variable. We found a significant effect of unpacking on choice ($z = 2.021, p = 0.043, AIC = 308.66$) such that a higher percentage of participants chose the dot-counting task in the unpacked condition (25.7%) compared to the aggregated condition (16.1%).

Since we also asked participants to indicate how strongly they preferred their chosen option, we can examine whether unpacking the dot-counting task shifted preferences on a continuous scale as well. We first recoded the preference measure from the 101-point scale to a scale from -100 to 100 by multiplying the preference scores of those who chose the encrypting task by negative 1. Thus, this recoded preference measure represents the degree of preference for the encrypting task vs. the dot-counting task that is also consistent with participants' indicated choice. We found a marginally significant unpacking effect such that participants in the unpacked dot-counting condition exhibited a stronger preference for the dot-counting task ($M_{\text{Aggregated}} = -56.49, SD = 60.47; M_{\text{Unpacked}} = -42.76, SD = 68.05; F(1, 299) = 3.421, p = 0.065$).

2.12.3 Discussion

Study 6 demonstrates that the effects of unpacking are not limited to the quantity of people's planned tasks, but may also impact the choices that consumers make regarding their future plans. By simply presenting a task in unpacked form, we were able to shift people's preferences from 16% to 26% in a binary choice—a 62.5% increase. These choices can have dramatic consequences since they are usually binding and can influence various short and long-term outcomes. This result also suggests the possibility of a different pathway from unpacking to over-planning, where consumers' preferences are shifted towards larger or more difficult tasks when they are presented in unpacked format, which may lead to suboptimal choices.

2.13 General Discussion

Planning plays an important role across a variety of consumer contexts, including setting goals and deciding how to spend work or leisure time, and can be subject to subtle (and sometimes seemingly arbitrary) influences that shift people towards smaller or larger workloads. We document a novel unpacking effect, where breaking down a task into detailed subtypes leads people to set more ambitious plans by making the task set seem less effortful. Additionally, consistent with Kruger and Evans (2004), our studies show that unpacking only seems to affect the planning stage of consumer decision-making but does not increase the actual amount of tasks completed (i.e., when the plans are non-binding). Thus, by making tasks seem easier, unpacking can lead to over-planning behavior. We also demonstrate that unpacking can impact consumer choices by increasing the attractiveness of unpacked task options.

Our study makes important theoretical contributions to the literature on goal pursuit, subadditivity, and planning. While most prior research on goals has focused on breaking down a single overarching goal into more granular subgoals, our subcategory unpacking effect instead applies to settings where individuals can vary or adjust the quantity of tasks they wish to complete during the planning stage. We also build upon prior work that demonstrates how unpacking leads to subadditivity in probability judgments by extending these effects to a different domain (i.e., goal-setting) and proposing a new pathway by which unpacking modulates effort perceptions. Importantly, our finding that unpacking decreases the estimated time it will take to complete a fixed set of tasks runs counter to prior findings that unpacking mitigates the planning fallacy by increasing effort judgments (Forsyth & Burt, 2008; Kruger & Evans, 2004). Study 3B offers a demonstration of this effect, where we adapted the dictionary entry formatting task from Kruger and Evans (2004). To explain the opposing findings, we recognize that the unpacking we study involves unpacking a task into subcategories (e.g., formatting dictionary entries for different categories of bone types) rather than unpacking a single holistic task into subcomponents (e.g., adding punctuation, italicization, etc.).

We next highlight three potential areas for future research that build upon our findings. First, the planning in our studies always consisted of varying amounts of a discrete task (e.g., learning vocabulary words, formatting dictionary entries, etc.). It would be interesting to explore other types of plans that can be unpacked into subcategories, but where the contents of the subcategories consist of continuous amounts (e.g., spending budgets, time allocation), or fully listing out distinct tasks (i.e., without reference to numbers), which would test the importance or necessity of smaller numbers being displayed for producing unpacking effect (e.g., studying 15 Italian words per day vs. studying 5 words in each of 3 categories).

Second, while we allowed the participants' plans to be non-binding in our incentive-compatible implementation (Study 5) in order to investigate the degree to which people over-planned, another area for further study would be to measure other downstream consequences of binding and non-binding plans. For example, being committed to overly ambitious binding plans may be a source of stress and lower people's motivation to complete additional goals, while overly ambitious non-binding plans may be more likely to result in goal failure.

Finally, the focus of our studies was on relatively productive or utilitarian activities, so the assumption was that greater effort or time expenditure was undesirable. This is especially relevant when studying consumer choices between tasks (Study 6), where unpacking increased preferences for sets of tasks by decreasing expected effort. Presumably, participants in our studies wanted to minimize effort expenditure. Thus, it would be interesting to investigate the effects of unpacking within contexts where consumers are instead interested in maximizing enjoyment (e.g., leisure or hedonic activities) or where more effort or time expenditure is preferred. For example, to make customers feel like they are getting their money's worth for a package of 30 exercise classes, a gym might consider emphasizing the overall number of classes rather than breaking down the classes into subcategories (e.g., 10 weightlifting classes, 10 zumba classes, 10 yoga classes). However, note that the reverse might be true for beginner gym-goers who are more interested in feasibility.

Our findings suggest that consumers should use caution when setting plans where the tasks or goals may be unpacked, contrary to the common belief that breaking goals down into subgoals is almost always helpful in goal pursuit (Bagozzi & Dholakia, 1999; Rai et al., 2022). While implementing subcategory unpacking with planning tools such as smartphone apps, websites, or simple to-do lists is easy in itself and can make tasks and goals seem easier and more doable as well, there are pros and cons. Unpacking can nudge people towards completing more ambitious goals if they are reasonable and the plans are binding in some way (i.e., include rewards or negative consequences). However, the findings from our studies uncover the potential downsides of unpacking, where more ambitious plans are not executed and therefore result in over-planning (especially when they are not binding), or the lower perceived effort levels lead consumers to choose less preferred options.

2.14 References

Amir, O., & Ariely, D. (2008). Resting on Laurels: The Effects of Discrete Progress Markers as Subgoals on Task Performance and Preferences. Journal of Experimental Psychology: Learning, Memory and Cognition, 34(5), 1158–1171.

Bagozzi, R. P., & Dholakia, U. (1999). Goal Setting and Goal Striving in Consumer Behavior. Journal of Marketing, 63(4_suppl1), 19–32.

Brunstein, J. C., & Gollwitzer, P. M. (1996). Effects of failure on subsequent performance: The importance of self-defining goals. Journal of Personality and Social Psychology, 70(2), 395–407.

Buehler, R., & Griffin, D. (2003). Planning, personality, and prediction: The role of future focus in optimistic time predictions. Organizational Behavior and Human Decision Processes, 92(1–2), 80–90.

Buehler, R., Griffin, D., & Ross, M. (1994). Exploring the "Planning Fallacy": Why People Underestimate Their Task Completion Times. *Journal of Personality and Social Psychology*, *67*(3), 366–381.

Dalton, A. N., & Spiller, S. A. (2012). Too much of a good thing: The benefits of implementation intentions depend on the number of goals. Journal of Consumer Research, 39(3), 600–614.

Fishbach, A., Dhar, R., & Zhang, Y. (2006). Subgoals as substitutes or complements: The role of goal accessibility. Journal of Personality and Social Psychology, 91(2), 232–242.

Forsyth, D. K., & Burt, C. D. B. (2008). Allocating time to future tasks: The effect of task segmentation on planning fallacy bias. Memory and Cognition, 36(4), 791–798.

Garvey, A. M. (2012). How Consumer Goal Characteristics Determine the Influence of Goal Progress on Goal Perseverance. The Pennsylvania State University.

Gollwitzer, P. M. (1999). Implementation intentions: Strong effects of simple plans. American Psychologist, 54(7), 493–503.

Gollwitzer, P. M., & Sheeran, P. (2006). Implementation intentions and goal achievement: A meta-analysis of effects and processes. In M. P. Zanna (Ed.), Advances in experimental social psychology, Vol. 38, pp. 69–119). Elsevier Academic Press.

Höpfner, J., & Keith, N. (2021). Goal Missed, Self Hit: Goal-Setting, Goal-Failure, and Their Affective, Motivational, and Behavioral Consequences. Frontiers in Psychology, 12.

Huang, S. chi, Jin, L., & Zhang, Y. (2017). Step by step: Sub-goals as a source of motivation. Organizational Behavior and Human Decision Processes, 141, 1–15.

Jin, L., Xu, Q., & Zhang, Y. (2015). Climbing the wrong ladder: The mismatch between consumers' preference for subgoal sequences and actual goal performance. Journal of Marketing Research, 52(5), 616–628.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. Econometrica, 47(2), 263–292.

Kruger, J., & Evans, M. (2004). If you don't want to be late, enumerate: Unpacking reduces the planning fallacy. Journal of Experimental Social Psychology, 40(5), 586–598.

Litman, L., Robinson, J., & Abberbock, T. (2017). TurkPrime.com: A versatile crowdsourcing data acquisition platform for the behavioral sciences. Behavior Research Methods, 49(2), 433–442.

Lynch, J. G., Netemeyer, R. G., Spiller, S. A., & Zammit, A. (2010). A generalizable scale of propensity to plan: The long and the short of planning for time and for money. Journal of Consumer Research, 37(1), 108–128.

Mulford, M., & Dawes, R. M. (1999). Subadditivity in Memory for Personal Events. Psychological Science, 10(1), 47–51.

Newell, A., & Simon, H. A. (1972). Human problem solving. Englewood Cliffs, NJ: Prentice-Hall.

Peetz, J., Buehler, R., Koehler, D. J., & Moher, E. (2015). Bigger Not Better: Unpacking Future Expenses Inflates Spending Predictions. Basic and Applied Social Psychology, 37(1), 19–30.

Rai, A., Sharif, M. A., Chang, E. H., Milkman, K. L., & Duckworth, A. L. (2022). A Field Experiment on Subgoal Framing to Boost Volunteering: The Trade-Off Between Goal Granularity and Flexibility. Journal of Applied Psychology.

Redden, J. P. (2008). Reducing satiation: The role of categorization level. Journal of Consumer Research, 34(5), 624–634.

Redden, J. P., & Frederick, S. (2011). Unpacking Unpacking: Greater Detail Can Reduce Perceived Likelihood. Journal of Experimental Psychology: General, 140(2), 159–167.

Rottenstreich, Y., & Tversky, A. (1997). Unpacking, repacking, and anchoring: Advances in support theory. Psychological Review, 104(2), 406–415.

Seta, J. J., Seta, C. E., Mccormick, M., & Gallagher, A. H. (2014). Monetary and affective judgments of consumer goods: Modes of evaluation matter. American Journal of Psychology, 127(3), 351–365.

Sharps, D. L., & Schroeder, J. (2019). The Preference for Distributed Helping. Journal of Personality and Social Psychology.

Sloman, S., Wisniewski, E., Rottenstreich, Y., Hadjichristidis, C., & Fox, C. R. (2004). Typical versus atypical unpacking and superadditive probability judgment. Journal of Experimental Psychology: Learning Memory and Cognition, 30(3), 573–582.

Soman, D., & Cheema, A. (2004). When Goals Are Counterproductive: The Effects of Violation of a Behavioral Goal on Subsequent Performance. Journal of Consumer Research, 31(1), 52–62.

Townsend, C., & Liu, W. (2012). Is planning good for you? The differential impact of planning on self-regulation. Journal of Consumer Research, 39(4), 688–703.

Tsai, C. I., & Zhao, M. (2011). Predicting consumption time: The role of event valence and unpacking. Journal of Consumer Research, 38(3), 459–473.

Tversky, A., & Koehler, D. J. (1994). Support Theory: A Nonextensional Representation of Subjective Probability. Psychological Review, 101(4), 547–567.

Van Boven, L., & Epley, N. (2003). The unpacking effect in evaluative judgments: When the whole is less than the sum of its parts. Journal of Experimental Social Psychology, 39(3), 263–269.

Wang, Y., Lewis, M., Cryder, C., & Sprigg, J. (2016). Enduring effects of goal achievement and failure within customer loyalty programs: A large-scale field experiment. Marketing Science, 35(4), 565–575.

Wong, R. S., & Wong, W. H. (2014). Subadditivity in Resource Allocation: An Experimental Study of the Hong Kong Mandatory Retirement Protection Scheme. International Journal of Business and Economics, 13(2), 93–113.

Chapter 3

Aspirational Purchases

I went down to the lower section of Sergels torg, to the music and film shop, where I bought three DVDs and five CDs, next up to Akademi bookshop, where I found a dissertation on Swedenborg published by Atlantis, which I bought along with a couple of journals. I wouldn't get round to reading much of this, which did not prevent me from feeling good, however.

— Karl Ove Knausgaard, A Man In Love: My Struggle Book 2

3.1 Introduction

Consumers are driven by all kinds of dreams and aspirations, which motivate them to work hard to become the kind of person they want to be, and to secure the kind of life that they aspire to live (Bagozzi & Dholakia, 1999; Elliott & Dweck, 1988). Aspirations can provide people with a sense of purpose and serve as a source of meaning (Karlsson et al., 2004). And aspirations, too, can drive people to make certain purchases. These purchases may not be appropriate for their present self just yet, but are consistent with the consumer's aspirational future image of themselves – the person they want to be instead of the person they are now. We use the term "aspirational purchases" to designate purchases made for a future self that the consumer has yet to become. For example, a person may watch a skillful guitarist perform, and aspire to learn how to play the guitar. They buy a fancy guitar, hoping to both use it to learn how to play and then to play it, and possibly even perform in front of others once they have mastered the skill.

We identify two overlapping, broad categories of aspirational purchases: (1) those that are required to gain an aspired-to skill (e.g., the guitar, or skates for a non-skater), and (2) products that are useful only if a desired circumstance arises (e.g., a cocktail dress for someone who aspires to be invited to cocktail parties, or champagne glasses for someone who aspires to become a consummate host). We label these skill-based aspirational purchases and opportunity-based aspirational purchases, respectively. These categories are often overlapping, because acquiring a skill is sometimes a necessary condition for – i.e., provides the opportunity for – using the product. The guitar, for example, fits into both categories: Acquiring a guitar is necessary to learn how to play it (making it a skill-based aspirational purchase), and owning the guitar will be beneficial only if one learns how to play it (making it an opportunity-based aspirational purchase). There are, of course, "pure" cases of both categories – e.g., for the first category, a product that can only be used to learn a skill (e.g., language tapes), and for the second category, a product that does not aid in skill-acquisition (e.g., the cocktail dress).

If aspirational products were purchased and used as intended, they might not be so interesting. However, we propose that, due to both cognitive and motivational biases, consumers often have unrealistic hopes of realizing their aspirations, and hence of using aspirational purchases. For purchases required to acquire a new skill, people may overestimate their own likelihood of investing the time and effort, and possibly underestimate the difficulty required, to develop the skill. Overconfidence about skill learning is consistent with a large literature documenting the "planning fallacy" (Buehler et al., 1994; Kahneman, Tversky, et al., 1977) – people's tendency to overestimate their own likelihood of completing tasks in a timely fashion. People can also overestimate the likelihood that desired occasions for using the purchase will arise. The idea that aspirational products are more likely than other categories of products to be purchased in error is one of the key predictions we test in the studies reported in this paper.

Most theoretical accounts of aspirations (e.g., Genicot and Ray, 2020; Stutzer, 2004) assume that adopting an aspiration lowers immediate well-being, by highlighting a discrepancy between one's current and desired situation. However, aspirational purchases are likely to have an immediate positive impact on subjective well-being. For both types of aspirational products, purchasing the product may be a necessary first step toward achieving the aspiration – e.g., to playing the guitar or becoming a fashionable attendant of swank parties, and may, as a result, be seen as moving the consumer closer to achieving their aspirations. For this reason, aspirational purchases often bring immediate satisfaction – the satisfaction of taking the first step toward a valued goal.

Moreover, even if aspirational products are not used as much as intended or expected, this does not mean that such purchases are necessarily mistakes. Aspirational purchases may confer value beyond being used – such as keeping one's dreams and hopes alive. However, much like lottery tickets that enable players to "buy a dream" (as marketing often pitches) of affluence, while simultaneously undermining the likelihood of achieving it, it is likely that under-used aspirational purchases will ultimately leave the consumer in a worse position than they would have been had they not made the purchase.

The notion of aspirational purchases is closely related to, but different from, several existing strands in the marketing literature. Perhaps most prominently, Sirgy, 1982 in a review of "self-concept in consumer behavior," proposes that consumers carry with them not only a notion of their actual, current self, but also a conception of an "ideal self" – a self who they would ideally aspire to be. Sirgy then proposes that people make buying decisions in part based on whether a purchase is congruent with their ideal self. Sirgy's notion of congruence between the ideal self and the attributes of a product is somewhat different from, as well as less precisely defined than, our idea that people have selves they aspire to become, and purchase goods either to help them become or to satisfy the preferences of the aspired-to self. We emphasize not only the alignment and congruency between aspired-to selves and products, but also the drive to pursue and achieve the aspiration, and the confidence that the successful pursuit will justify the purchase.

Another closely connected literature in marketing examines branding strategies and "brand personalities," which are often promoted with marketing campaigns and celebrity endorsements. This stream of research highlights the importance of crafting a brand image that aligns with consumers' ideal self image. Such purchases, and the marketing strategies associated with them, also seem to be motivated by consumers' desire to choose a brand that aligns with one's ideal self. Again, similar to the congruency literature, aspirational purchases are different in that these branding strategies are mostly concerned with the simple alignment with the ideal self image, and do not take into account that people are actively planning for the ideal self that they believe they aspire to become. These studies are also mostly limited to broad and abstract characteristics and personality traits (such as "beautiful," "adventurous," and "innovative"), whereas our account is more concrete and realistic (e.g. become a guitar player, become a fashionable party-goer).

A third related and fairly large literature in marketing, and also in economics, examines purchases of "Veblen goods" that people make to signal desired attributes to themselves or other people. "Conspicuous Consumption," a term coined by Veblen, 1899, refers to the purchase or consumption of luxury goods for the purpose of gaining status. In our conception of aspirational purchases, in contrast, people are not attempting to signal anything to themselves or others; they actually expect, or at least hope, to become the person they desire to be, and purchase goods to satisfy that person. Veblen goods are of special interest to economists because purchasing behavior can contradict the usual "law of demand" according to which the demand for a good declines with its price; in contrast, we would expect aspirational goods to satisfy the usual laws of consumer demand.

Although closely related to each of these concepts, our notion of aspirational consumption is different from those that have been previously proposed in the literature. Rather than purchasing something because of the image that the purchase conveys to self or other, our idea is that people purchase goods for a version of themselves that they intend, and expect, to become. Many of the predictions we test arise from the fact that these intentions and expectations are often unrealistic.

In what follows, Section 3.2 reviews relevant literature in psychology and marketing dealing with why aspirational products are likely to exist, and why people are likely to purchase them based on over-optimistic expectations of their likelihood of being used. Based on this literature, Section 3.3 presents a model that shows how people's aspirations, combined with optimism and motivated reasoning, can lead to suboptimal purchases, as well as underusage of the product. Section 3.3 then lays out the hypotheses we set out to test. Sections 4-7 present four studies that test these predictions. Study 1 confirms that aspirational purchases are common and prevalent, and identifies the crucial role of optimism, showing that optimistic people made more aspirational purchases. Study 2 is an experimental study in which some participants are primed to think about the self they aspired to be. As predicted, they are more inclined to make aspirational purchases. Study 3 begins our demonstration that aspirational products are more likely to be under-used, providing evidence that these purchases may be suboptimal. Study 4 examines actual purchase histories and provides further evidence that aspirational products are more under-used, and can lead to lower satisfaction; nevertheless, people still believe they will start to use their aspirational products more and do not want to get rid of them despite their underuse. Section 3.8 concludes.

3.2 Relevant Literature

3.2.1 Self-concept: actual and ideal selves, and self-congruence

As noted, the literature most closely related to aspirational purchases deals with self-concept and how it affects purchasing (Malhotra, 1988; Sirgy, 1982). This literature proposes that there are two key components of self-concept, the actual self, referring to how a person perceives themselves, and the ideal self, referring to how a person would like to perceive themselves (Higgins, 1987). Research has found that, in general, congruity between consumers' self-concept and a product is a crucial predictor of purchase intentions and preferences. This literature predicts that not only actual self, but also ideal self, influences purchasing and consumption (Sirgy, 1985).

In one of the few studies testing this idea, which helps to illustrate the importance of self-congruence with regard to both actual and ideal self, Sirgy, 1985 had participants report their preferences and hypothetical purchase intentions for four products: two magazines (Playgirl and Glamor) and two automobiles (an MGB and a VW Rabbit). Next, participants rated the four products on thirty attributes such as "extroverted," "sexy," and "conservative." Finally, participants evaluated themselves on the same 30 attributes on two dimensions, both (1) how they actually saw themselves and (2) how they would *ideally* like to see themselves. Supporting the idea that both dimensions of self-evaluation influence purchases, congruity between products and both actual and ideal self-ratings significantly predicted purchase intentions. The effect is additive in that it is not merely the overlapping attributes driving the effect; both aspects of congruity contribute to the purchase intention.

Additionally, people tend to favor brands that fit with their ideal self-image, showing more loyalty (Sop & Kozak, 2019) and forming more emotional attachments with these brands (Malär et al., 2011). This promotes the use of aspirational branding, especially for luxury brands (Truong et al., 2010). Advertising materials (Hong & Zinkhan, 1995) and celebrity endorsers (Choi & Rifon, 2012) that fit with consumers' ideal self-image are also shown to be more effective. In another example, research on tourism often sees travel destinations as their own brand with certain brand personalities. Thus, for example, Usakli and Baloglu, 2011 identified vibrancy, sophistication, competence, contemporary, and sincerity to be the brand personality of the city of Las Vegas. They then showed that tourists with higher actual congruity and ideal congruity with these personality traits have higher behavioral intentions to travel to Las Vegas.

Research on identity-based consumption provides a closely related perspective on consumption and self-concept, where self-identity is emphasized instead of self-image (Chen et al., 2024; Oyserman, 2009). This research suggests that people choose purchase options that are congruent with their identity, and a sought-after identity can also drive purchases, similarly to an ideal self (Reed II et al., 2012). For example, those wanting to achieve a "strong and healthy" identity would tend to select products and services linked to this ideal identity, such as a green smoothie. The role self-identity plays in consumption is also supported by evidence of consumers' preference for vanity clothing sizes which are made bigger to enable consumers to fit into smaller sizes (Hoegg et al., 2014). For the targeted consumers, being thin and fitting into a smaller size is very much in line with their ideal self-identity, and thus the vanity-sized products will seem particularly desirable, compared to buying standard-sized clothes where they must accept that they are of a larger size.

However, this stream of research usually stops at product or brand preferences and purchase intentions, and seldom explores how the products are subsequently used and consumed. A key focus of our paper is to investigate this downstream usage, especially for products that are only compatible with a consumer's ideal self-image, and not their actual self-image. If the purchased product does not fit into the consumer's current life, they might be used less than initially intended.

Previous work also focuses more on more abstract self-concepts (e.g., extroversion) and less on specific and concrete consumption areas that are aspirational (e.g., becoming a photographer). We usually cannot identify whether a person attains an abstract aspiration like becoming more extroverted, but we can identify whether a person attains specific aspirations, like gaining expertise in photography, which introduces the potential to measure the success of the purchase. Our examination of aspirational purchases focuses on specific aspirations rather than a general preference for products that align with an ideal self-image. Aspirational products, according to our narrow definition, are useful – and only useful – in the aspirational ideal state that people intend to achieve but have not yet reached. Our examination is, therefore, more nuanced and consequential, as it taps into a specific behavioral pattern in the pursuit of an aspiration.

3.2.2 Self-discrepancies

Having the image of an ideal self often naturally leads to more specific and actionable aspirations, and the drive and desire to achieve them. These aspirations can take various shapes or forms, such as daily goals, short- and long-term milestones, New Year's resolutions, and lasting life ambitions. Research has found that people hold aspirations in a wide range of domains, such as health, personal growth, relationships, community, wealth, fame, and image (Kasser & Ryan, 1996; Sheldon & Kasser, 1998; Williams et al., 2000). The pursuit and achievement of these aspirations is a key aspect of the process of personal development (Deci & Ryan, 2008; Sheldon et al., 2004). Research also suggests that having clear and meaningful aspirations is linked to psychological maturity and general well-being across the life span (Deci & Ryan, 2000; Sheldon & Kasser, 2001), while the absence of aspirations can be associated with negative outcomes such as lower self-esteem, lower life satisfaction, and depression (Grahek et al., 2019).

Adopting the proposal of Genicot and Ray (2020) and the Oxford English Dictionary (1989), we define an aspiration as a hope and ambition to achieve a desirable circumstance. This definition emphasizes three things. First, an aspiration paints a desirable image that is better than one's present circumstance, typically an image that aligns with one's personal goals and ideals. Second, the ambition to achieve it signals the intention to engage in striving and goal-directed behaviors. Finally, the hope to achieve the aspiration evokes the emotional state of desire, and implies a sense of possibility and optimism toward achieving the goal.

In addition to classifying aspirations according to what specific domain they apply to – e.g., health aspirations versus career aspirations, the literature on aspirations has also distinguished between intrinsic aspirations (e.g., personal growth) that satisfy individual psychological needs, and extrinsic aspirations (e.g., image) that depend on the reaction of others (Kasser & Ryan, 1996). Intrinsic aspirations are pursued because they are inherently rewarding and aligned with one's values, interests, or passions, whereas extrinsic aspirations are are usually motivated by external rewards or recognition, often driven by societal expectations or the desire for approval from others. Some research suggests that having more intrinsic goals and aspirations, as opposed to extrinsic aspirations, is associated with better outcomes in health, well-being, and performance (Deci

& Ryan, 2008).

Aspirations can sometimes highlight gaps or incongruities between how one wants to be and how one currently is, or "self-discrepancies" (Higgins, 1987). Mandel et al. (2017), in a review of the use of consumer behavior as a means to regulate self-discrepancies, summarized several distinct strategies that consumers can use to deal with them. They can directly resolve the discrepancy by improving in the domain (Kim & Gal, 2014), or signal symbolic mastery without directly improving in the domain (Rucker & Galinsky, 2008). For example, one can display their diploma in a visible spot when they feel insecure about their intelligence. Alternatively, they can choose to avoid the source of self-discrepancy: dissociate with it, avoid thinking about it, or focus on other aspects of self-identity.

Aspirational purchases mainly fit into the first of these strategies. Skill-based aspirational purchases are a necessary first step toward diminishing the discrepancy. And opportunity-based aspirational purchases provide useful inputs into making opportunities fulfilling, should they arise. Such purchases do not, however, necessarily lead to actual improvement. If a consumer aspires to be a better writer and buys an expensive ergonomic keyboard, the purchase itself does not reduce the self-discrepancy; her chance of becoming a good writer did not change, at least until she starts using it to practice her writing. Yet, even if these further steps are not taken, she may still feel like the purchase moved her closer to her vision and reduced her self-discrepancy. For example, since the ergonomic keyboard can not really show its worth until she starts actually typing, such an attempt to address self-discrepancy may leave her with no improvement in writing and a regretful purchase.

3.2.3 Conspicuous Consumption

Having an aspiration can sometimes drive one to paint a desirable image for oneself, as image and wealth are common extrinsic aspirations people have (Kasser & Ryan, 1993). As a result, conspicuous consumption of luxury products and status symbols is common among those who aspire to gain respect and admiration from others (Truong et al., 2010). People often attempt to signal status to others by using the same products used by wealthy consumers of a higher social class (Gupta & Srivastav, 2016; Srivastava et al., 2020). Conspicuous consumption has been shown to be related to feelings of pride, desire for more elite status, and social signaling goals, such as the need for uniqueness and belonging (Kumar et al., 2022).

Our discussion of aspirational purchases is distinct from conspicuous purchases, although some products can fit in both categories (*e.g.*, a fancy premium guitar). Conspicuous consumption is inherently social – people engage in these purchases as a social signal to people around them and to maintain a desirable social image. Aspirational purchases are different in that they are not, primarily, a show or a signal for other people, but are instead based on one's own belief that it is likely that one can achieve one's aspirations. Aspirational purchases are more about a self view than a social view. For this reason, aspirational purchases can happen for both private and public goods, whereas conspicuous consumption is mostly public, where others can see it (Kumar et al., 2022). Additionally, unlike conspicuous purchases, simply owning the product is not enough for aspirational purchases to serve their purpose. People would still need to use the product, or at least to expect to do so in the future, to justify the purchase.

3.2.4 Motivated Reasoning and Optimism

We argue that many aspirational purchases happen because of motivated reasoning about the prospect of achieving one's aspirations. Previous literature has shown that a strong directional goal can bias memory search and affect which beliefs and rules are accessed and applied in the reasoning process, leading to goal-oriented motivated reasoning and people believing what they want to believe (Epley & Gilovich, 2016; Kunda, 1990). Even though their reasoning is biased, they are still able to maintain an "illusion of objectivity" because they believe their reasoning is justified (Sharot & Sunstein, 2020). This can result in biased beliefs in a wide range of domains, such as political views (Redlawsk et al., 2010), childcare (Bastardi et al., 2011), and climate change (Druckman & McGrath, 2019), even in the presence of objective facts or scientific evidence.

When consumers have a desirable picture of achieving an aspiration, motivated reasoning can make them overly optimistic about the chance of achieving it. For aspirational purchases, people may be overestimating the probability that they can achieve their aspirations through biased memory queries and belief construction, driven by the goal of achieving their aspirations. They may believe that acquiring the skill required to achieve the aspiration would be easy and fun for skill-based aspirational products (because they remember seeing a 10-minute easy guitar tutorial on YouTube); or that the special occasion that they have been hoping for will happen quite often for opportunity-based aspirational products (because they remember the cold days when they imagined that they can wear that cool leather jacket all the time).

Additionally, exaggerated optimism towards achieving the aspirational state is also consistent with research on the optimism bias and wishful thinking, where people tend to hold a generally optimistic view about their life, and overestimate the likelihood of positive events happening (Sharot, 2011), sometimes without a clear reasoning process as in motivated reasoning. Research on the planning fallacy also shows that people tend to underestimate the magnitude of tasks and how long they will take, which can be particularly relevant for learning a skill to achieve skill-based aspirations (Buehler et al., 1994; Kahneman, Tversky, et al., 1977). These strands of research all point to strong, but often unjustified, optimism towards achieving aspirations and using aspirational products.

Because people are so focused on their aspirations and what it would be like to achieve them, they can forget about their current circumstances and how hard it will be to achieve their aspirations given their current situation. Therefore, people will often hold the false belief that they will be using the aspirational product very often, which justifies the purchase. If people believe that they will be playing the guitar a couple of times a week instead of twice a year, they are more likely to make the purchase and also to spend more money on a nicer guitar. They may recognize that other people often give up their aspirations and consider buying used gear or second-hand items to reduce the cost of such purchases, but they retain a biased view of their own propensity to use these products.

3.2.5 Underusage

One of the consequences of such optimism is underusing (or even not using at all) the aspirational products that have been purchased. Underuse can happen when an item is bought for a specific purpose and is not used as promptly as anticipated; it can be pushed to the back of the cupboard and forgotten (Wansink et al., 2000). It can also occur when not using an item makes it feel special, and people become less likely to use it in ordinary situations and instead save it for a more special occasion (Rifkin & Berger, 2021). Abstaining from consumption of desirable products is associated with missing and liking these products when alternative substitute products are not available for consumption, but decreased desire for the absent products when substitution is possible (Dai & Fishbach, 2014).

We focus on the gap between the intention for buying the product and the actual circumstance of consumption. We extend the literature on underusage by providing a new explanation of why underusage may occur: People make aspirational purchases that they do not follow through with. The fact that aspirational purchases are made for one's ideal self and not their current circumstances makes it especially likely that aspirational purchases are not suitable for people's current lives. People may be too busy to use the item, have other external constraints that they have overlooked, or simply lose the motivation that they once had. But when focused on the aspiration and driven by motivated reasoning that there will be plenty of opportunities to use them, motivation feels very strong, the real life seems far, and the constraints seem negligible.

Interestingly, people often fail to recognize these situations where they often (repeatedly) make aspirational purchases that end up being under-used. Motivated reasoning can also happen after the purchase, as people try to justify their purchase and reduce regret. People may rationalize their own underusage of aspirational products. For example, consumers might tell themselves that they bought expensive camping gear thinking that they would go camping, but it is only for a couple of months that they are especially busy and cannot make time for it, and eventually, they will go camping more frequently. As a result, they might choose to keep the aspirational product even after underusing the product rather than choosing to resell it or get rid of it, based on the hope and belief that they will use it more in the future.

Based on this literature, we believe that people will purchase aspirational products with the hope of using them a significant amount, but often end up underusing them. This is partially driven by the strong goal to achieve the aspiration, leading to motivated reasoning and over-optimistic views. Next, we outline a theoretical model that illustrates the conditions for making aspirational purchases and the role of optimism, and state our hypotheses.

3.3 Theoretical Model

We propose a simple model to help us understand when and why people make aspirational purchases, as well as the role of optimism and motivated reasoning in driving under-usage. Let x be the individual's current set of owned goods, and x^a the current set with the addition of an aspirational good. c^a is the cost of obtaining the aspirational good — *i.e.,* its price. The individual's current level of wealth is w, s is the individual's current state, and s^a is the aspired state in which the aspirational good is useful. This could include, for example, learning to ride a unicycle or a musical instrument, finding friends to enjoy one's patio with, and finding the time to read Swedenborg.

Assume that $u(x^a, w - c^a, s^a) > u(x, w, s) > u(x^a, w - c^a, s)$—*i.e.,* that the best state (better than the status quo) is to possess and use the good, and that the worst state is to purchase the good but not be in a position to use it. Assume that the actual probability of achieving s^a is p^a, but it is perceived as $\hat{p}^a$ at the time of purchase.

The individual will purchase the good if

$$u(x, w, s) < \hat{p}^a u(x^a, w - c^a, s^a) + (1 - \hat{p}^a) u(x^a, w - c^a, s) \tag{3.1}$$

We consider two classes of aspirational purchases, opportunity-based and skill-based aspirational purchases. They are similar in that the aspirational products are useful only if the desirable circumstance s^a is achieved, but differ in how to achieve s^a. In opportunity-based aspirational purchases, s^a arise due to some uncontrollable exogenous factor outside of the decision maker's control; in skill-based aspirational purchases, the decision maker can put in some investment of time and effort to increase their chances of achieving s^a. Note that if the aspirational good is a skill-based aspirational good, then $u(x, w, s^a)$ is not possible because one must own the aspirational good to achieve the altered state.

3.3.1 Opportunity-based aspirational purchases - exogenous factor determines s^a

In the first class of situation, which directly maps onto Equation 3.1, there is some exogenous factor that determines s^a, outside of the decision maker's control. This would be true, for example, of purchasing a cocktail dress that is only useful if one is invited to a fancy party. The person can decide whether or not to purchase the dress, but (by assumption) cannot control whether they'll get invited to a party.

In this situation, an optimistic person may overestimate p^a, thinking the ideal circumstance, such as being invited to a party, will be more likely to arise than it actually is: $\hat{p}^a > p^a$. This bias could reflect motivated reasoning; wanting to be invited to the party might lead the person to try to find reasons to expect that an invitation is forthcoming.

Suppose an individual's maximum willingness to pay for the aspirational good is $\hat{c}^{a*}$ under the overestimate of p^a, when Equation 3.1 takes equality, and the individual is indifferent between purchasing and not purchasing. c^{a*} is the unbiased valuation of the aspirational good without the overestimation. We have:

$$\hat{p}^a = \frac{u(x, w, s) - u(x^a, w - \hat{c}^{a*}, s)}{u(x^a, w - \hat{c}^{a*}, s^a) - u(x^a, w - \hat{c}^{a*}, s)} \tag{3.2}$$

We make the assumption that holding the consumption bundle fixed, utility for the state is additively separable from utility for wealth. In other words, $u(x, w, s') - u(x, w, s)$ does not depend on w:

$$u(x, w, s') - u(x, w, s) = u(x, w - \hat{c}^{a*}, s') - u(x, w - \hat{c}^{a*}, s) \tag{3.3}$$

Then we can simplify Equation 3.2 to

$$\hat{p}^a = \frac{u(x, w, s) - u(x^a, w - \hat{c}^{a*}, s)}{u(x, w, s^a) - u(x, w, s)} \tag{3.4}$$

Then we can prove Theorem 1 (proof in the Appendix):

Theorem 1. *Willingness to pay increases when the probability of attaining the ideal state is overestimated.*

3.3.2 Skill-based aspirational purchases - Investment determines s^a

In the second class of situations, getting into the aspired state involves some cost – typically an investment of effort, but also, potentially, of time or money. For this second class of situations, we can specify that I is the investment the individual makes to attempt to shift from s to s^a. Let $c(I)$ be the cost of that investment, converted to dollar equivalents, although it might involve time or effort, in addition to money. The investment I is continuous, and p^a increases with I. We will now discuss two potential forecasting errors, for $c(I)$ and $p^a(I)$, which are perceived as $\hat{c}(I)$ and $\hat{p}^a(I)$.

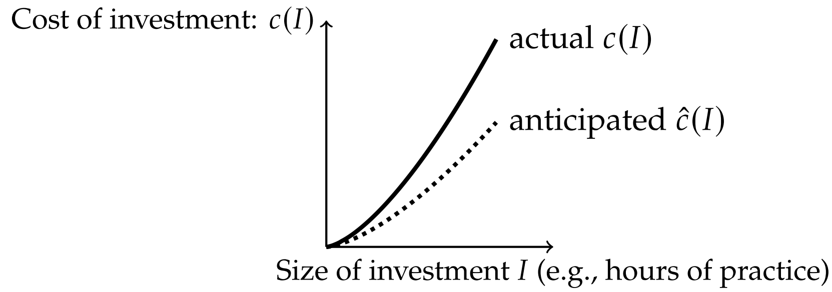


Figure 3.1: Underestimating the cost of investment.

In this situation, the assumed utility inequalities are modified to: $u(x^a, w - c^a - c(I), s^a) > u(x, w, s) > u(x^a, w - c^a - c(I), s)$, and the condition for making the purchase is:

$$u(x, w, s) < \hat{p}^a(I)u(x^a, w - c^a - \hat{c}(I), s^a) + (1 - \hat{p}^a(I))u(x^a, w - c^a - \hat{c}(I), s) \tag{3.5}$$

Our interpretation is that motivated reasoning may make a person overly optimistic about achieving their ideal state. This optimism can take the form of biased judgments about either the cost of investment, or the return on investment.

3.3.2.1 Underestimating the cost of investment

The cost of investment $c(I)$ reflects how much effort or "pain" one will experience while making a certain amount of investment, for example, the investment of time when practicing guitar for an hour every day to become a skilled guitar player. We assume $c(I)$ is convex, that the pain from investing is sensitizing. When the practice actually starts, one may realize that guitar practice is more boring and frustrating than they anticipated, as illustrated in Figure 3.1. That is, they underestimated the cost of investment: $\hat{c}(I) < c(I)$.

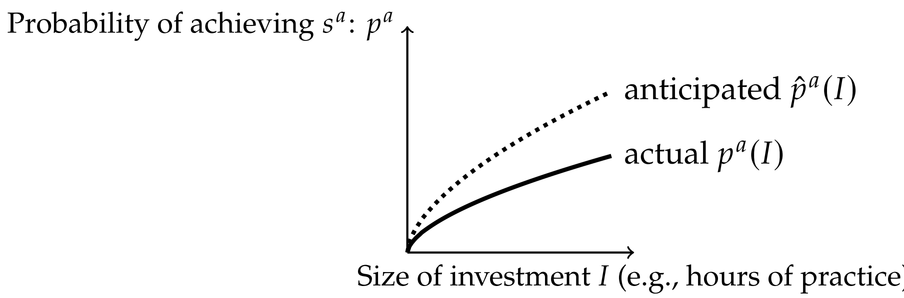


Figure 3.2: Overestimating the return on investment.

3.3.2.2 Overestimating the return on investment

One may also mispredict the return on investment. As one puts in investment I to increase their chance $p^a(I)$ of getting to the ideal state s^a, they may overestimate how much impact each unit of I can have on p^a. We assume $p^a(I)$ is concave, that the investment to increase p^a has diminishing returns. For example, one may anticipate that to have a good chance of becoming a skilled guitar player, they would need to put in 100 hours of practice, but once they buy the guitar and get started, they may realize they have very little chance of becoming good with only 100 hours of practice; they actually need a lot more. That is, they overestimated the return on investment: $\hat{p}^a(I) > p^a(I)$, as shown in Figure 3.2.

3.3.2.3 Implications of optimism

Mispredictions of both the cost of investment and the return on investment can result in the potential consumer anticipating they will be making an unrealistic investment to achieve s^a once they purchase the product. If someone believes that practicing guitar is easy and it doesn't require that many hours of practice to become good, they are likely to buy the guitar and anticipate that they will put in some practice and become a great guitar player. When deciding whether to make the purchase, they anticipate making the investment I that maximizes

$$\hat{p}^a(I)u(x^a, w - c^a - \hat{c}(I), s^a) + (1 - \hat{p}^a(I))u(x^a, w - c^a - \hat{c}(I), s). \tag{3.6}$$

However, after they make the purchase and their mispredictions are corrected by experiencing the reality of the situation, they now face the decision of how much investment to actually put in with accurate perceptions of the cost and return.

They would actually put in investment I that maximizes

$$p^a(I)u(x^a, w - c^a - c(I), s^a) + (1 - p^a(I))u(x^a, w - c^a - c(I), s). \tag{3.7}$$

We can prove:

Theorem 2. *People overestimate how much investment they will make when they are overly optimistic about the cost and return on investment.*

From this, we can then examine how this misjudgment affects purchase conditions. We prove:

Theorem 3. *Willingness to pay increases when people are overly optimistic about the cost and return on investment.*

Our model predicts that for both types of aspirational products, people will have a higher willingness to pay when they are optimistic about achieving their aspirations. Therefore, optimistic people may make aspirational purchases that a rational decision-maker would not. And since they are overconfident about achieving the ideal state, they will overestimate how much they will use the product, which means the product will be under-used after the purchase.

3.3.3 Hypotheses

Based on the literature and the model developed here, we state the following hypotheses.

With the important role that aspirations play in consumers' lives, we expect aspirational purchases to be prevalent, especially for optimistic people. Greater optimism will amplify the overestimation of the conditions under which opportunity-based products can be used, and the misprediction for both the cost and return on investment for skill-based products, resulting in more aspirational purchases.

Hypothesis 1. *Optimistic individuals make more aspirational purchases.*

We also consider factors that can encourage people to make, or discourage people from making, aspirational purchases. Our model assumes the aspirational state is more desirable than the status quo. Exactly how desirable the aspirational state can depend on how much people care about their aspiration, which can sometimes fluctuate. The more desirable the aspirational state is, the more likely it is that the condition in Equation 3.1 for purchasing the product will be met. We then have Hypothesis 2.

Hypothesis 2. *When a person cares more about their aspiration, they are more inclined to make an aspirational purchase.*

However, as we have pointed out in our model, such optimism about achieving one's aspirations is often unrealistic, which can lead people to realize, after the purchase, that they do not have enough opportunities to use the product (for opportunity-based aspirational products) and/or have overestimated their investment to build the skill (for skill-based aspirational products). Both of these mechanisms result in people using the product less than they expected or intended to. Therefore, we have Hypothesis 3.

Hypothesis 3. *Aspirational products are more likely to be under-used.*

Finally, we consider the change in satisfaction after aspirational purchases. We expect consumers to have more regret and dissatisfaction towards products that they bought but did not use as much as initially planned. Therefore, as a consequence of the underuse of aspirational products, we expect to see a drop in satisfaction for aspirational products as compared to non-aspirational products. Additionally, since the aspirational products represent not just a purchase but also a hope to achieve the aspiration, we hypothesize that underusing aspirational products will hurt even more as it dampens their dreams.

Hypothesis 4. *Compared to non-aspirational purchases, consumer satisfaction for aspirational purchases drops further after having experienced the products, especially when they are under-used.*

Now, we present 4 studies to test these hypotheses.

3.4 Study 1: Optimism and the Prevalence of Aspirational Purchases

The main goal of Study 1 is to establish that aspirational purchases are, in fact, common, and that they are more common for people who are optimistic. Survey respondents identified their last 5 purchases on Amazon.com, and coded them according to the degree to which they were aspirational. We also include a measure of trait optimism to explore the role of optimism and motivated reasoning.

3.4.1 Method

3.4.1.1 Screening

We recruited 503 participants from the Prolific participant pool for screening. Participants were asked a single screening question "How often do you shop on Amazon?"

which they answered on a scale from "I don't use Amazon" to "Several times a week." The 375 participants who answered "several times a month" or a higher frequency were sent a link to continue with the study. We preregistered anticipating around 250 participants to pass screening and complete the study, but ended up with a higher completion rate than anticipated, and recruited 299 participant.

3.4.1.2 Procedure

Respondents were asked to pull up their Amazon shopping history and report their latest 5 purchases above $20. This predetermined cut-off threshold was chosen to avoid small consumable purchases like food items. They were asked to provide the name and price of each item. On the next screen, they rated how aspirational each of the 5 products was. Specifically, they were given the following definition: "An aspirational item is one that you purchase to pursue an aspiration or to prepare for a special occasion that might or might not happen." They then answered on a 0 to 4 Likert scale to what extent each of their 5 purchases was an aspirational purchase (0 = Not at all; 4 = Extremely). For each item that they indicated to be at least a little aspirational (rating $\geqslant 1$), they were given a text box to write out their aspiration or special occasion for that purchase. We then used the two-item Optimism–Pessimism Short Scale–2 (SOP2) to measure the disposition of trait optimism (Nießen et al., 2022). Finally, they answered demographic questions regarding their current employment status, age, gender, and education level.

3.4.2 Results

A total of 1,495 purchases were reported by 299 participants ($M_{Age} = 40.4$; 55.2% female). Of these, 13 items did not have a valid numerical price (e.g., empty or had product name instead, by mistake), and 95 items were under $20 despite our instruction. These items were excluded from our analysis. The distribution of the aspiration rating of the

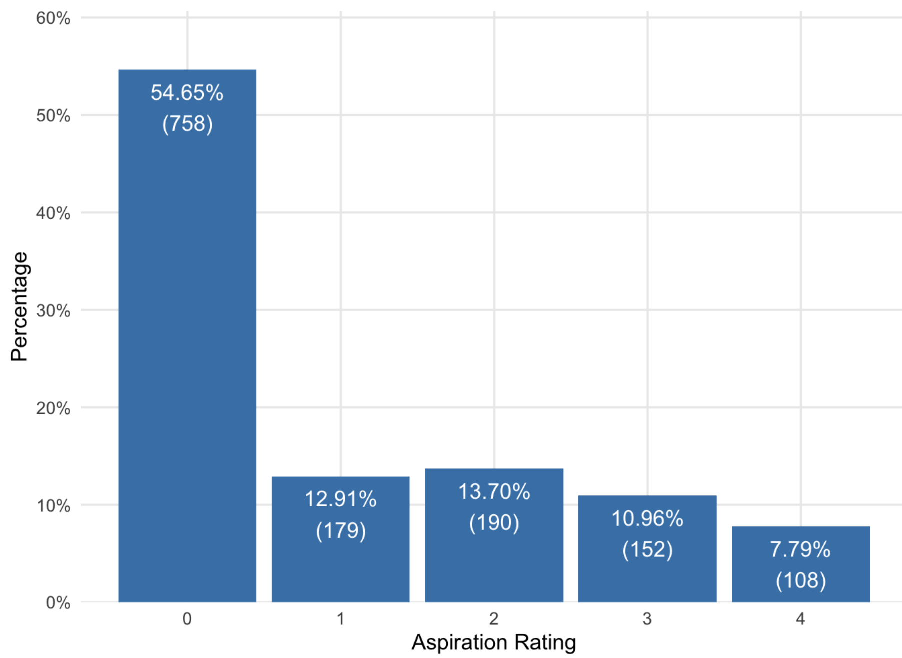


Figure 3.3: Distribution of aspirational rating among Amazon purchases.

remaining 1,387 valid purchases is shown in Figure 3.3. The majority of purchases are non-aspirational. But 19% of the purchases have an aspiration rating of 3 or 4 – i.e., are coded as either "very aspirational" or "extremely aspirational." Looking only at these, most recent, five purchases, 40.1% of the participants coded at least one of them as "very aspirational" or "extremely aspirational."

Participants reported purchases ranging from \$20 to \$2500 ($M_{Price} = 55.71, SD = 105.63, Median = 31.95$). Comparing the prices for products of various aspirational ratings, linear regressions showed that aspirational products are more expensive, for both logged prices ($b = 0.10, F(1, 1385) = 60.45, p < 0.001, R^2 = 0.04$) and raw prices ($b = 12.63, F(1, 1385) = 37.05, p < 0.001, R^2 = 0.03$). Figure 3.4 shows the average price of products at different aspiration rating levels. Adding up the prices of the five most recent purchases they reported on, 29.5% of spending was on products rated as

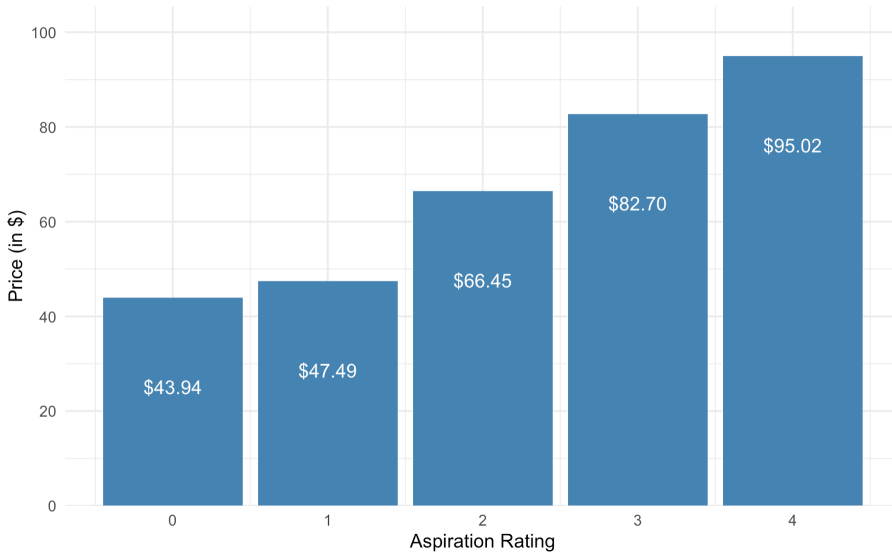


Figure 3.4: Average price for products of different aspirations

very aspirational or extremely aspirational, emphasizing the economic significance of aspirational purchases.

To examine the effect of individual traits, we averaged the aspirational ratings for each person's valid purchases. We calculate optimism tendency with the SOP2 scale by reverse coding the pessimism item and then average with the optimism item, as specified in Nießen et al., 2022. Consistent with Hypothesis 1, purchases made by optimistic people are more aspirational ($b = 0.104, F(1, 292) = 6.958, p = 0.009, R^2 = 0.02$, see Figure 3.5). As can also be seen in the figure, separating the optimism and the pessimism items reveals that the effect is entirely driven by the optimism item ($b = 0.180, F(1, 292) = 21.980, p < 0.001, R^2 = 0.07$), whereas the pessimism item has no effect ($F(1, 292) = 0.358, p = 0.550$). We observe similar results if we use the percentage of aspirational purchases (i.e., those with a 3 or 4 aspirational rating) instead of the average aspirational rating of the 5 purchases. Optimistic people are more likely to make aspirational purchases ($b = 0.031, F(1, 292) = 8.150, p = 0.005, R^2 = 0.03$). The effect is

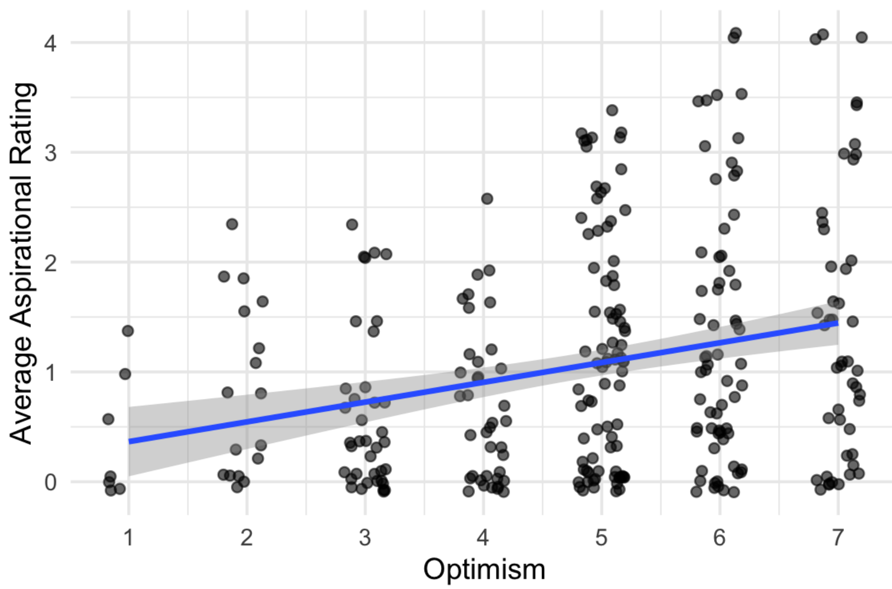


Figure 3.5: Average aspirational rating of purchases for individuals with different levels of optimism

again stronger when we only use the optimism item ($b = 0.049, F(1, 292) = 21.599, p < 0.001, R^2 = 0.07$); the pessimism item has no effect ($F(1, 292) = 0.988, p = 0.321$).

Looking at other demographics, a linear regression revealed that younger people made more aspirational purchases ($b = -0.014, F(1, 292) = 9.04, p = 0.003, R^2 = 0.03$). A one-way ANOVA showed that employment status also has a marginally significant effect on how aspirational people's purchases are , $F(4, 289) = 2.09, p = 0.082$). People who are employed full-time made more aspirational purchases. Gender, income, and education level have no significant effect on aspirational purchases.

Further looking into the products, we asked Llama3 (AI@Meta, 2024), a large language model by Meta, to categorize the products and the aspiration write-ups into categories. We found that the most aspirational categories are books, travel, and hobby. After coding people's self-reported aspirations into either skill-based or opportunity-based aspirational purchases, we found that the most aspirational categories for skill-

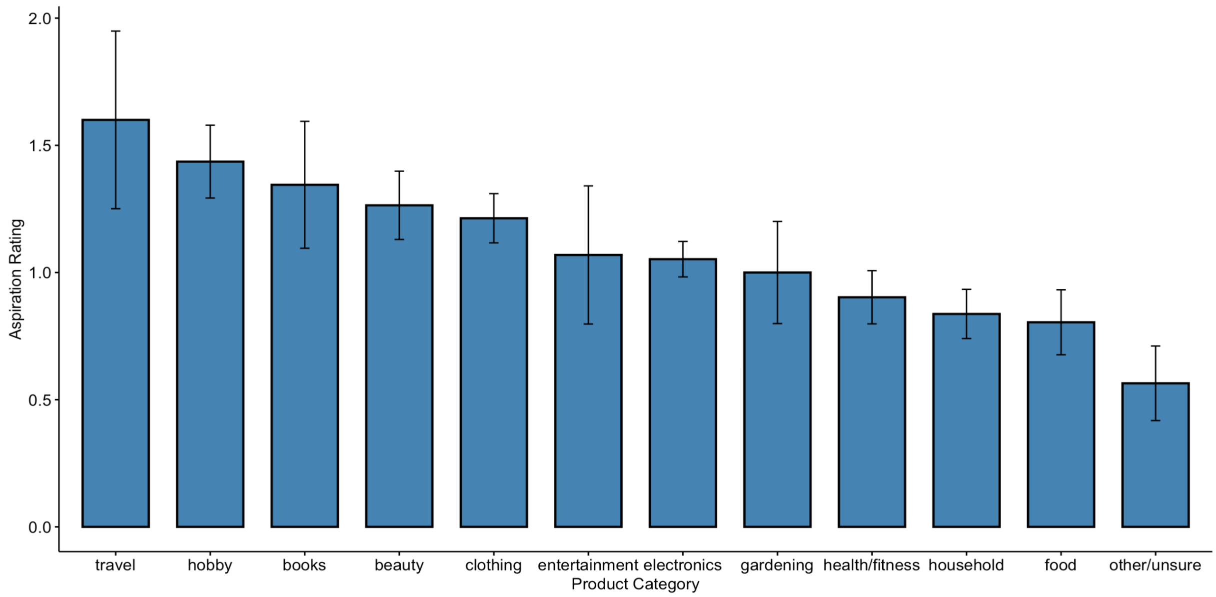


Figure 3.6: Aspirational rating of products of different categories, error bars are standard errors.

based aspirational purchases are books, hobby, gardening, and health/fitness, and the most aspirational categories for opportunity-based aspirational purchases are beauty, clothing, and entertainment.

3.4.3 Discussion

These results document the prevalence of aspirational purchases in people's daily lives, and provide evidence that optimism drives these purchases. Younger people may have more aspirations and less limitations to pursue whatever aspiration they want. Perhaps, being full-time employed provides a sense of security and certainty for people to feel grounded and ready to pursue an aspiration. Interestingly, however, there is no effect of income or educational level on aspirational purchases.

3.5 Study 2: Priming the Ideal Self

In Study 2, we are interested in what can potentially drive people to make aspirational purchases and specifically in the role of people's conceptions of the 'ideal self'. Since aspirational purchases represent a desire and expectation to achieve an aspirational ideal state, we hypothesized that increasing the salience of this ideal state should make people more inclined to make an aspirational purchase. Study 2 uses a priming paradigm that highlights the ideal self to make the aspirational state more salient and attractive, and examines the impact on participants' tendency to make an aspirational purchase.

3.5.1 Method

We recruited 601 participants (M_{Age} = 41.2; 53.4% female) from the Prolific participant pool. They were randomly assigned to two between-subject conditions, ideal priming vs. control. In the ideal priming condition, participants (N = 285) read the following prompt: "What would be your ideal self: the type of person you hope, wish, or aspire to be. Someone amazing, but who you can actually imagine being/becoming. What attributes, characteristics, and capabilities would/will you have?" Then on the next screen, they were asked to describe their ideal self in 3-5 sentences. This is similar to the ideal self priming procedure used in previous literature (e.g., Sela and Shiv, 2009), but with small modifications to fit our purpose. Those in the control condition (N = 316) were not primed with anything.

On the next screen, all participants were asked to report 3 purchases they were currently considering. For each one, they reported how aspirational the purchase would be (on a 5-point Likert scale of 0 = Not at all to 4 = Extremely), the likelihood of purchase in the next year (on a 5-point Likert scale of 1 = Not likely to 5 = Definitely), and the price of the item. For products that they indicated to be aspirational, they were also

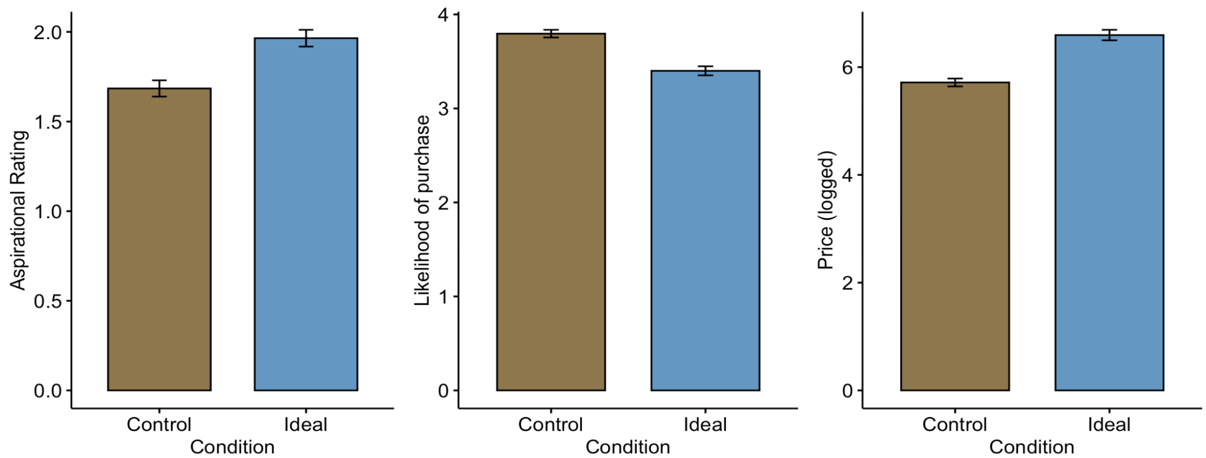


Figure 3.7: Aspirational ratings, likelihood of purchase, and price (logged) for the proposed purchases of the two conditions, error bars are standard errors.

asked to write out their aspiration. Finally, they answered an attention check question and reported demographics.

3.5.2 Results

All participants passed the attention check and were included in the analysis. In a mixed regression with a random intercept for each person, we found that purchases proposed in the ideal self condition have higher aspirational ratings than those in control ($b = 0.280, t(599) = 3.268, p = 0.001$).

Purchases reported in the ideal condition were also less likely to be purchased in the next year ($b = -0.395, t(599) = -4.895, p < 0.001$), and were more expensive (logged price: $b = 0.880, t(599) = 5.226, p < 0.001$; n.s. with non-logged price).

3.5.3 Discussion

Study 2 provides direct causal evidence that thinking about one's ideal self can lead to aspirational purchases. Consistent with Hypothesis 2, directly priming people to think about their ideal selves led them to spontaneously came up with more aspirational purchases. This directly confirms the important role of idealistic thinking in forming aspirational purchase intentions. We also observed that these proposed purchases are less likely to be realized in the next year, which suggests that aspirational purchases may sometimes be recognized as less realistic or less necessary.

3.6 Study 3: Underusage of Aspirational Products

In Study 3, we explore how aspirational products are used, and examine Hypothesis 3 to see whether aspirational products are more under-used. We generated a list of aspirational and control products, and explored people's use patterns to see whether aspirational products are more likely to be under-used, as well as the reason for such under-use.

3.6.1 Method

3.6.1.1 Pretest

We identified a set of 18 products that we hypothesized are aspirational and a set of 12 products that we hypothesized are not aspirational. In a pretest, we recruited 150 participants to rate these 30 products on how aspirational they are. Each participant gave aspirational ratings to 6 products randomly selected from the larger set on a scale of 1 = Not at all aspirational to 5 = Extremely aspirational, so we gathered around 30 data points for each product. From our original set, we narrowed down to 16 aspirational

Product	Aspirational Rating	Label	Product	Aspirational Rating	Label
Guitar	4.30	Aspirational	**Bread maker**	2.89	Aspirational
Pull-up bar	3.89	Aspirational	**Champaign glasses**	2.88	Aspirational
Cocktail dress	3.88	Aspirational	**Leather jacket**	2.72	Aspirational
Skis/snowboard	3.85	Aspirational	**Air fryer**	2.63	Control
Camera	3.81	Aspirational	**Power bank / portable charger**	2.55	Control
Painting supplies	3.75	Aspirational	**Mop**	2.53	Control
Dumbbells	3.56	Aspirational	**Umbrella**	2.38	Control
Blank journal (for diary)	3.34	Aspirational	**Post-it notes**	2.24	Control
Classical literature books	3.25	Aspirational	**Can opener**	2.15	Control
Camping gear	3.23	Aspirational	**Flashlight**	2.10	Control
Knitting supplies	3.19	Aspirational	**Lip balm**	2.07	Control
Gardening tools	3.08	Aspirational	**Stapler**	1.93	Control
Ice skates	2.91	Aspirational	**Fanny pack**	1.79	Control

Table 3.1: Products used in Study 2

products (e.g., dumbbells) that have high aspirational ratings and 10 control products (e.g., can opener) that have low aspirational ratings, as seen in Table 3.1.

3.6.1.2 Procedure

We recruited 498 participants (M_{Age} = 43.0; 47.0% female) from the Prolific participants pool for Study 2. They reported whether they had purchased the 26 products determined by the pretest. For products they had purchased, they rated whether they have used these products less than they expected (-1), as much as they expected (0), or more than

Tag	Reason
Motivation	Loss of motivation and interest
Opportunity	Didn't have the opportunity/circumstance to use the product
Time	Didn't have enough time
Habit	Change of habit
Alternatives	Had better alternatives
Constraints	Real-life constraints
Skills	Failed to gain the skills required to use the product
Difficult	The product is harder to use than expected
Bored	Used it and got bored
Other	Other - please specify

Table 3.2: Reasons for Underusing a Product Presented in the List

they expected (1). They then answer why they did not use the product as much as expected for their most and second-most under-used product in both an open-ended text box and a drop-down list of 9 possible reasons (shown in Table 3.2). Finally, they answered an attention check question and reported demographics.

3.6.2 Results

All participants passed the attention check and were included in the analysis. We are interested to find out whether aspirational products are more likely to be under-used. We had a total of 7660 usage ratings (-1 to 1) by 498 participants rating what they have purchased among the list of 26 products, which we used as the dependent variable. The label of aspirational vs. control was the independent variable, and we added random intercepts for each person and each product. Consistent with our hypothesis, a mixed-effect regression showed that aspirational products are indeed more likely to be used less than expected than control ($b = -0.327, t(23.61) = -4.810, p < 0.001$).

We ran a similar analysis at the product level, where each row is a product, and we averaged the usage ratings across all participants. We found again that aspirational products tend to be more under-used ($b = -0.305, F(1,24) = 22.03, p < 0.001, R^2 = 0.48$). The effect persists if we use the continuous measure of how aspirational each product is, as gathered from the pretest shown in Table 3.1 ($b = -0.161, F(1,24) = 8.768, p = 0.007, R^2 = 0.27$).

At the product level, we included the percentage of people who have purchased each product as a proxy of popularity. We found that more popular products (that are more widely owned) are also more likely to be used more than expected ($b = 0.638, F(1,24) = 22.98, p < 0.001, R^2 = 0.49$), and aspirational products also tend to be less popular ($b = 0.285, F(1,24) = 12.69, p = 0.002, R^2 = 0.35$). Importantly, the effect of aspirational products on usage frequency remains significant after accounting for the effect of popularity (Aspiration: $b = 0.190, t = 2.66, p = 0.014$; Popularity: $b = 0.408, t = 2.78, p = 0.011$), and the model has better explanatory power ($F(2,23) = 17.94, R^2 = 0.61$).

Comparing with the 61.5% base rate of aspirational products (16 out of 26), 73.1% of the most under-used products and 75.0% of the second most under-used products are aspirational products, showing that aspirational products are more likely to be dramatically under-used. We summarize the common reasons for underusing aspirational and control products in Figure 3.10, with the y-axis showing the percentage of each reason being selected for under-using, within the aspirational or control category. The top reasons for not using aspirational products are loss of motivation and not having enough time, whereas the top reasons for not using control products are not having the opportunity to use them and having better alternatives. The most disproportionally used reasons for aspirational products as compared to control products are loss of motivation, not having enough time, and failing to gain the skills required to use the product. This fits nicely with our intuition that the under-use of aspirational products is typically related to a loss of interest or feeling discouraged in the pursuit of

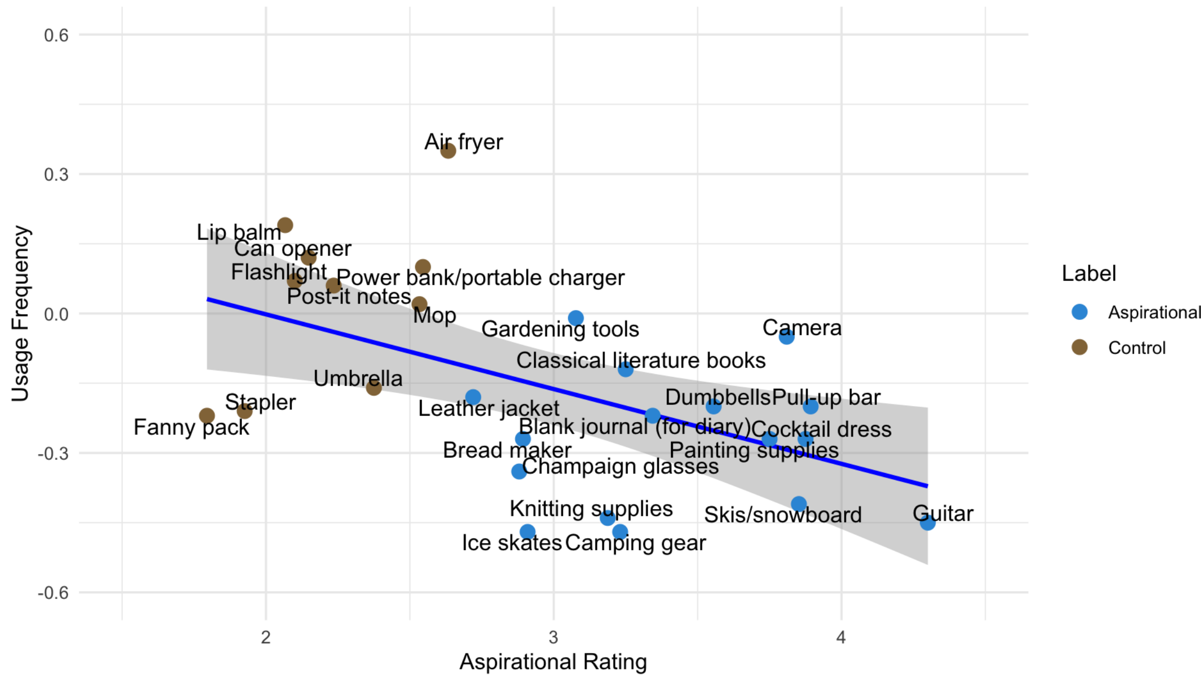


Figure 3.8: Frequency of Usage for Products of Various Aspirational Ratings

the aspiration, and non-aspirational products are subject to more neutral and realistic concerns. Chi-square tests showed that there were significant differences between the distribution of reasons given for aspirational and control products, both with the "other" group included ($\chi^2(9, N = 1521) = 180.45, p < 0.001$) or without the "other" group ($\chi^2(8, N = 1461) = 172.84, p < 0.001$).

3.6.3 Discussion

This study provides initial evidence for Hypothesis 3 that aspirational purchases are indeed more likely to be under-used, which is consistent with the idea that these products are bought for their ideal self and ideal circumstances, instead of their current self and circumstances, and that people are optimistically overestimating the chance that these circumstances will arise. Furthermore, analyzing the reasons they give for not using the

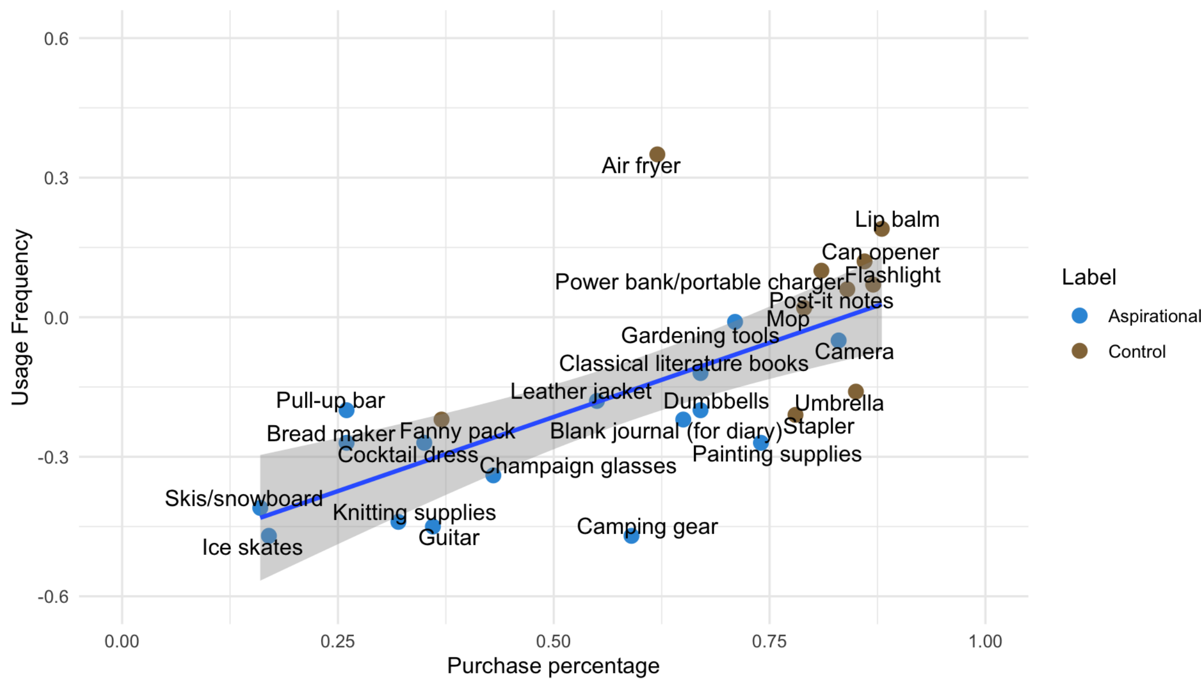


Figure 3.9: Frequency of Usage for Products of Different Popularity

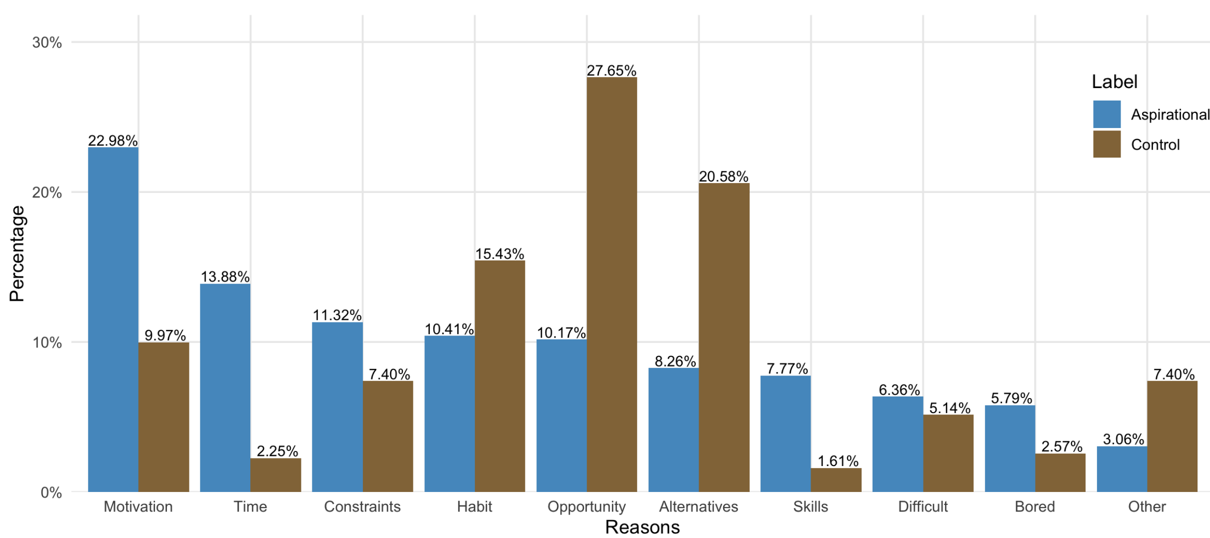


Figure 3.10: Reasons for Underusing Aspirational and Control Products. Bars indicate the percentage share of each reason within the aspirational or control product category.

product as much as they expected, the top cause of underusing aspirational products is waning motivation, perhaps as optimism meets reality, whereas reasons for underusing control products are much more neutral and objective.

3.7 Study 4: Experience with Aspirational Products

In Study 4, we seek to gain a deeper view of how aspirational products are used on an individual level. We are interested in further confirming any underuage effect of aspirational products beyond a given set of products. We ask Amazon shoppers to identify an aspirational purchase from over a year ago, and ask about their experiences of using the product, with a non-aspirational product as control. We also explore the future intentions participants might have with their products, given their current (under)usage.

3.7.1 Method

3.7.1.1 Screening

We planned to recruit 800 participants for Study 4 on the Prolific platform. In a screening survey, we screened for participants who have had a personal Amazon account for longer than 2 years, and used Amazon frequently in 2023 (a few times a month or more). Those who met these criteria were then invited to participate in Study 4. We preregistered to start with screening 1000 participants and add additional participants in increments of 100, until we reach 800 participants. We ended up screening 1700 participants, with 934 participants meeting the criteria and invited to the study. Eight hundred and twenty four of these (M_{Age} = 37.5 excluding 1 invalid age entry; 49.0% female) completed the study. Two participants submitted their responses twice, we kept the later entries.

3.7.1.2 Procedure

In early 2025 we asked participants to pull up their Amazon shopping history of 2023. They were given the definition of aspirational purchase and were asked to go through the list and find an aspirational purchase that they made for themselves in 2023. They were asked to provide the name, price, date of purchase, and aspirational rating (5-point Likert scale from 0 = not at all aspirational to 4 = extremely aspirational) for the purchase. Then, they were asked to find a non-aspirational purchase of a similar price, and also provide the name, price, date of purchase, and aspirational rating for the purchase.

For the two products they identified, they then answered a few questions for each, with the order of the 2 products randomized. We measured satisfaction at the time of purchase, and their satisfaction at the time of completing the survey, looking back at the decision to purchase, both on a 7-point Likert scale from -3 = very negative to 3 = very positive.

We measure the tendency to underuse in two ways. First, we compute a difference between their reported actual use of the product and their expected use when they purchased it. They were directly asked how often they expected to use the product when they purchased it, with slider options: more than once a day, about once a day, a few times a week, a few times a month, a few times a year, never. The answers were coded from 0 = never to 5 = more than once a day. They then reported how often they actually used the product after they purchased it, with the same slider options and default set to their previous answer. The difference between the two sliders is our first measure of whether they used the product more or less than they expected to. Second, we directly asked them whether they used the product more or less than initially intended, in terms of frequency. They answered on a 5-point Likert scale from -2 = a lot less than intended to 2 = a lot more than intended to.

Additionally, we measured whether they thought they would use the product more in 2025 than they previously had, on a 5-point Likert scale from 1 = definitely not to 5 = definitely yes. We also asked their intention to keep the product rather than selling it or giving it away – on a 5-point Likert scale from 1 = definitely not keeping it to 5 = definitely keeping it. We also asked for a description of the aspiration or special occasion for purchasing the aspirational product, and measured the trait optimism of the individual as in Study 1. To exclude products purchased for others, such as gifts, for both the aspirational and non-aspirational product, we asked whether the purchase was bought for someone else or for themselves. Finally, participants provided their demographic information.

3.7.2 Results

3.7.2.1 Exclusion

All our exclusion criteria are prespecified and preregistered. Out of the 824 participants, 5 failed the attention check and were excluded. The remaining 819 participants reported 1638 purchases. We asked for purchases in 2023 to ensure they had enough experience using the product. If they could not find any, they were instructed to look for one in the year of 2024, and we accepted purchases close to this time frame. Specifically, we preregistered excluding purchases that happened on or after July 1st, 2024 or before Jan 1st, 2022. We found that 127 purchases out of 1638 had invalid dates. Additionally, 7 products had names such as "nothing" or "none," and were coded as invalid products. Finally, 163 purchases were indicated to be gifts or were purchased for someone else. Excluding these entries leaves us with our data set of 1359 valid purchases.

Despite requesting that participants find a non-aspirational product of a similar price to their aspirational product, we still found that aspirational products cost significantly more than non-aspirational products ($F(1, 1327) = 6.533, p = 0.011$), consistent with our finding in Study 1 that aspirational products tend to be more expensive. Controlling for price does not change our findings.

3.7.2.2 Underusage

As planned, we compare expected use frequency and actual use frequency to see whether aspirational products are more under-used. We ran a linear mixed model of reported use frequency on a dummy variable for expected (as opposed to actual) frequency of usage and a second dummy variable indicating whether the purchase was aspirational (as compared with non-aspirational) We also included an interaction term of the IVs, and a random intercept for each person.

As shown in Figure 3.11, we found a significant main effect of aspiration, indicating that aspirational products have a lower expected use frequency ($b = -0.28, t(2037.5) = -4.600, p < 0.001$). There is no significant main effect of expected vs. actual use for the control product ($b = -0.09, t(1946.9) = -1.623, p = 0.105$). Importantly, we found a significant interaction effect between expected vs. actual use frequency and whether the product is aspirational ($b = -0.25, t(1946.94) = -2.986, p = 0.003$). Compared to control products, aspirational products are more likely to be used less than expected.

We also compared aspirational products and control products on the continuous Likert measure of to what extent the product is used as much as intended. A paired t-test found that aspirational products are more likely to be used less than intended than control products ($M_{aspirational} = 0.043, M_{control} = 0.182, t(597) = -2.423, p = 0.016$). A paired Wilcoxon signed rank test showed the same result ($V = 36950, p = 0.009$).

3.7.2.3 Satisfaction

We were also interested in whether underusing aspirational and non-aspirational products would have different consequences on satisfaction. Change in satisfaction is computed as current satisfaction - previous satisfaction. We ran a regression of change in

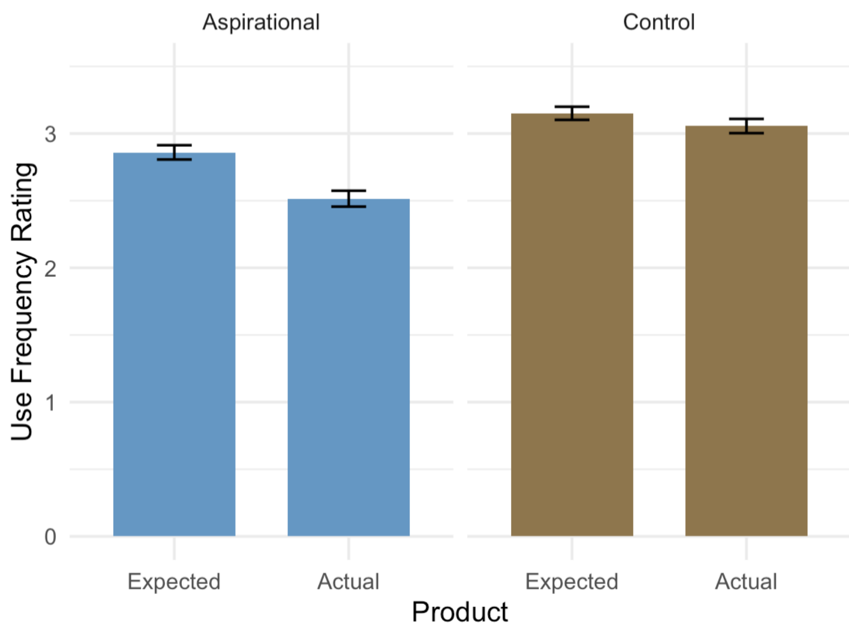


Figure 3.11: Aspirational products tend to be used less than expected. Error bars are standard errors.

satisfaction on relative use frequency and whether the purchase was aspirational, and included a random intercept for each person.

Results revealed two significant main effects: Aspirational products and products that are used less than intended tend to see a greater drop in satisfaction (aspirational: $b = -0.46, t(734.0) = -8.466, p < 0.001$; use frequency: $b = -0.24, t(1352.4) = 5.834, p < 0.001$). Crucially, we also found a significant interaction between the two IVs ($b = 0.145, t(1315.0) = 2.836, p = 0.005$). As visually shown in Figure 3.12, aspirational products suffered a greater drop in satisfaction if they ended up being under-used. Underusing aspirational products can lead to greater disappointment, perhaps because in many cases, the under-usage indicates that the aspiration was not achieved.

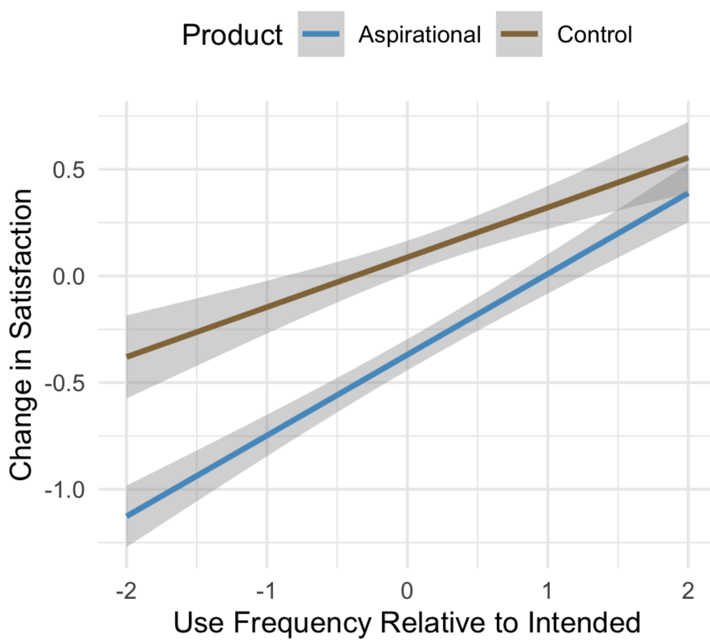


Figure 3.12: Underusing aspirational products leads to greater disappointment.

3.7.2.4 Future intentions

Next, we were interested in whether people would still have hopes of using aspirational products more in the future. A regression showed that people tend to believe that they will use their aspirational products more in 2025, more so than non-aspirational products ($b = 0.165, t(705.8) = 2.527, p = 0.012$). This result is still true after controlling for the use frequency relative to their intentions ($b = 0.233, t(703.9) = 4.055, p < 0.001$).

Finally, examining whether the respondent planned to keep the product as compared to giving it away or selling it, we found a main effect of use frequency relative to intended, such that they are more likely to get rid of their under-used products ($b = 0.282, t(1354.9) = 10.177, p < 0.001$). However, among the under-used products (use frequency relative to intended < 0), they are more likely to keep (rather than get rid of) the product if it is aspirational ($b = 0.533, t(239.8) = 3.650, p < 0.001$).

3.7.3 Discussion

Study 4 provides further insight into how aspirational products are used and enjoyed. Replicating the main finding of Study 3, Study 4 also finds that aspirational products are more likely than non-aspirational products to be under-used. This under-usage leads to a greater drop in satisfaction for aspirational than for non-aspirational products. Despite the disappointment, however, people are still hopeful about the future and believe they will start to use their aspirational products more, and are less likely to sell them or throw them away than under-used non-aspirational products.

These results also support our view that people are initially overly optimistic about how much they will use these products, but end up using them less in reality. This underuse, along with the observed drop in satisfaction, suggests that these purchases are often experienced as mistakes. These results are less consistent with an alternative view that people enjoy thinking about the prospect of achieving their aspirations or keeping the dream alive, even without making real progress. If that were the case, we would expect people to remain satisfied with their aspirational products even when they are not using them, yet our findings do not support this.

3.8 General Discussion

In this paper we introduced the concept of aspirational purchases, and, in four studies, identify the key patterns for purchasing and using aspirational products. Study 1 shows that aspirational purchases make up a substantial proportion of people's purchases and spending, especially for optimistic people. The connection to optimism confirms Hypothesis 1 and suggests that consumers may hold an over-optimistic view when making aspirational purchases. Study 2 tests the idea that making aspirations salient can lead to spontaneous aspirational purchases. We employ a simple priming paradigm to increase the salience of participants' ideal self and, therefore, their aspirations. This priming results in a greater proportion of aspirational purchases among participants' current purchase intentions, supporting Hypothesis 2. Study 3 compares the expected and actual usage frequency of 26 pretested aspirational and control products, among consumers who had purchased them. We find evidence that aspirational products are more likely to be under-used, supporting Hypothesis 3 and suggesting that aspirational purchases may be suboptimal. Finally, Study 4 utilizes actual purchase history data and compares a wider range of aspirational and control products. The results further confirm that aspirational products tend to be more under-used and, importantly, can lead to lower satisfaction, supporting Hypothesis 4. Despite this, a majority of people believe they will use their aspirational products more in the future than they did in the past, which may help to explain their reluctance to part with (e.g., sell) them.

Together, our studies paint an intriguing and paradoxical picture for aspirational purchases. People make these purchases because of a general optimism towards their future and their prospect of achieving an ideal version of themselves. For skill-based aspirational purchases, optimism leads people to underestimate the cost, and to overestimate the time and effort they are likely to put in, to achieve the skill required to use the product. For opportunity-based aspirational purchases, optimism leads people to overestimate their likelihood of experiencing the state in which the good will be used. Although the resultant under-usage leads to disappointment, it does not seem to squelch optimism; despite using the good less than intended or expected, in the past, people remain optimistic about their likelihood of using it in the future. As a result, they often hold onto the product despite having already experienced a reality that did not live up to their expectations.

Our results provide insights about practitioner behaviors and offer marketing implications. Marketers looking to promote sales of aspirational products often focus on making the aspirational state more attractive, beyond just emphasizing the product itself. For example, rather than just promoting the high-quality material used to manufacture a guitar, it is often more effective to focus on depicting a vivid and appealing aspirational scenario – perhaps playing a song at a wedding and getting cheers from friends and family. Additionally, our model and analysis suggest that another way to increase the attractiveness of aspirational products is to emphasize (or even misrepresent) the ease and feasibility of achieving the aspirational state. For opportunity-based aspirational products, this could mean persuading the consumer that the aspirational occasion will occur frequently. For skill-based aspirational products, this could mean reframing the effort required to gain the skill to make it sound less effortful, or choosing to depict an aspirational state that is easier to achieve. For instance, the guitar seller could offer courses that teach easy chords for popular songs, which could be learned in just a few hours.

On the other hand, our results also provide practical implications for consumers. Consumers should be cautious of the danger of underuse and clutter that can result from aspirational purchases. We found evidence that aspirational products are more likely to be under-used, and people are reluctant to get rid of them even after their underuse. These products can accumulate, leading to clutter and even hoarding, and potentially cause regret, stress, guilt, and anxiety. We would advise consumers to err on the side of being under-confident about achieving their aspirations. When making an aspirational purchase, they should have a clear and realistic estimate of how they plan to use the aspirational product, and how the product fits into their *current* lifestyle and routine. While dreaming about an ideal aspirational state can be exciting, it is important to recognize that such dreams can be just that, distorting consumers' evaluation of how likely they are to achieve that state and how useful the aspirational product will truly be.

3.9 References

AI@Meta. (2024). Llama 3 model card. https://github.com/meta-llama/llama3/blob/main/MODEL_CARD.md

Bagozzi, R. P., & Dholakia, U. (1999). Goal setting and goal striving in consumer behavior. *Journal of Marketing*, *63*, 19–32. https://doi.org/10.1177/00222429990634s104

Bastardi, A., Uhlmann, E. L., & Ross, L. (2011). Wishful thinking: Belief, desire, and the motivated evaluation of scientific evidence. *Psychological Science*, *22*(6), 731.

Buehler, R., Griffin, D., & Ross, M. (1994). Exploring the" planning fallacy": Why people underestimate their task completion times. *Journal of Personality and Social Psychology*, *67*(3), 366.

Chen, S. Y., Urminsky, O., & Yu, J. (2024). We do what we are: Representation of the self-concept and identity-based choice. *Journal of Consumer Research*, *51*(2), 298–320.

Choi, S. M., & Rifon, N. J. (2012). It is a match: The impact of congruence between celebrity image and consumer ideal self on endorsement effectiveness. *Psychology & Marketing*, *29*(9), 639–650.

Dai, X., & Fishbach, A. (2014). How nonconsumption shapes desire. *Journal of Consumer Research*, *41*, 936–952. https://doi.org/10.1086/678302

Deci, E. L., & Ryan, R. M. (2000). The" what" and" why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, *11*(4), 227–268.

Deci, E. L., & Ryan, R. M. (2008). Self-determination theory: A macrotheory of human motivation, development, and health. *Canadian Psychology/Psychologie Canadienne*, *49*(3), 182.

Druckman, J. N., & McGrath, M. C. (2019). The evidence for motivated reasoning in climate change preference formation. *Nature Climate Change*, *9*(2), 111–119.

Elliott, E. S., & Dweck, C. S. (1988). Goals: An approach to motivation and achievement. *Journal of Personality and Social Psychology*, *54*(1), 5.

Epley, N., & Gilovich, T. (2016). The mechanics of motivated reasoning. *Journal of Economic Perspectives*, *30*(3), 133–140.

Genicot, G., & Ray, D. (2020). Aspirations and economic behavior. *Annual Review of Economics*, *12*(1), 715–746.

Grahek, I., Shenhav, A., Musslick, S., Krebs, R. M., & Koster, E. H. (2019). Motivation and cognitive control in depression. *Neuroscience & Biobehavioral Reviews*, *102*, 371–381.

Gupta, S., & Srivastav, P. (2016). An exploratory investigation of aspirational consumption at the bottom of the pyramid. *Journal of International Consumer Marketing*, *28*, 2–15. https://doi.org/10.1080/08961530.2015.1055873

Higgins, E. T. (1987). Self-discrepancy: A theory relating self and affect. *Psychological Review*, *94*(3), 319.

Hoegg, J., Scott, M. L., Morales, A. C., & Dahl, D. W. (2014). The flip side of vanity sizing: How consumers respond to and compensate for larger than expected clothing sizes. *Journal of Consumer Psychology*, *24*(1), 70–78.

Hong, J. W., & Zinkhan, G. M. (1995). Self-concept and advertising effectiveness: The influence of congruency, conspicuousness, and response mode. *Psychology & Marketing*, *12*(1), 53–77.

Kahneman, D., Tversky, A., et al. (1977). *Intuituve prediction: Biases and corrective procedures*. Decision Research, Perceptronics.

Karlsson, N., Loewenstein, G., McCafferty, J., et al. (2004). The economics of meaning. *Nordic Journal of Political Economy*, *30*(1), 61–75.

Kasser, T., & Ryan, R. M. (1993). A dark side of the american dream: Correlates of financial success as a central life aspiration. *Journal of Personality and Social Psychology*, *65*(2), 410.

Kasser, T., & Ryan, R. M. (1996). Further examining the american dream: Differential correlates of intrinsic and extrinsic goals. *Personality and Social Psychology Bulletin*, *22*(3), 280–287.

Kim, S., & Gal, D. (2014). From compensatory consumption to adaptive consumption: The role of self-acceptance in resolving self-deficits. *Journal of Consumer Research*, *41*, 526–542. https://doi.org/10.1086/676681

Kumar, B., Bagozzi, R. P., Manrai, A. K., & Manrai, L. A. (2022). Conspicuous consumption: A meta-analytic review of its antecedents, consequences, and moderators. *Journal of Retailing*, *98*, 471–485. https://doi.org/10.1016/j.jretai.2021.10.003

Kunda, Z. (1990). The case for motivated reasoning. *Psychological Bulletin*, *108*(3), 480.

Malär, L., Krohmer, H., Hoyer, W. D., & Nyffenegger, B. (2011). Emotional brand attachment and brand personality: The relative importance of the actual and the ideal self. *Journal of Marketing*, *75*(4), 35–52.

Malhotra, N. K. (1988). Self concept and product choice: An integrated perspective. *Journal of Economic Psychology*, *9*(1), 1–28.

Mandel, N., Rucker, D. D., Levav, J., & Galinsky, A. D. (2017). The compensatory consumer behavior model: How self-discrepancies drive consumer behavior. *Journal of Consumer Psychology*, *27*(1), 133–146.

Nießen, D., Groskurth, K., Kemper, C. J., Rammstedt, B., & Lechner, C. M. (2022). The optimism–pessimism short scale–2 (sop2): A comprehensive validation of the english-language adaptation. *Measurement Instruments for the Social Sciences*, *4*(1), 1.

Oxford University Press. (1989). *The oxford english dictionary* (2nd).

Oyserman, D. (2009). Identity-based motivation and consumer behavior. *Journal of Consumer Psychology*, *19*(3), 276–279.

Redlawsk, D. P., Civettini, A. J., & Emmerson, K. M. (2010). The affective tipping point: Do motivated reasoners ever "get it"? *Political Psychology*, *31*(4), 563–593.

Reed II, A., Forehand, M. R., Puntoni, S., & Warlop, L. (2012). Identity-based consumer behavior. *International Journal of Research in Marketing*, *29*(4), 310–321.

Rifkin, J. R., & Berger, J. (2021). How nonconsumption can turn ordinary items into perceived treasures. *Journal of the Association for Consumer Research*, *6*, 351–361. https://doi.org/10.1086/714363

Rucker, D. D., & Galinsky, A. D. (2008). Desire to acquire: Powerlessness and compensatory consumption. *Journal of Consumer Research*, *35*, 257–267. https://doi.org/10.1086/588569

Sela, A., & Shiv, B. (2009). Unraveling priming: When does the same prime activate a goal versus a trait? *Journal of Consumer Research*, *36*(3), 418–433.

Sharot, T. (2011). The optimism bias. *Current Biology*, *21*(23), R941–R945.

Sharot, T., & Sunstein, C. R. (2020). How people decide what they want to know. *Nature Human Behaviour*, *4*(1), 14–19.

Sheldon, K. M., & Kasser, T. (1998). Pursuing personal goals: Skills enable progress, but not all progress is beneficial. *Personality and Social Psychology Bulletin*, *24*(12), 1319–1331.

Sheldon, K. M., & Kasser, T. (2001). Getting older, getting better? personal strivings and psychological maturity across the life span. *Developmental Psychology*, *37*(4), 491.

Sheldon, K. M., Ryan, R. M., Deci, E. L., & Kasser, T. (2004). The independent effects of goal contents and motives on well-being: It's both what you pursue and why you pursue it. *Personality and Social Psychology Bulletin*, *30*(4), 475–486.

Sirgy, M. J. (1982). Self-concept in consumer behavior: A critical review. *Journal of Consumer Research*, *9*(3), 287–300.

Sirgy, M. J. (1985). Using self-congruity and ideal congruity to predict purchase motivation. *Journal of Business Research*, *13*(3), 195–206.

Sop, S. A., & Kozak, N. (2019). Effects of brand personality, self-congruity and functional congruity on hotel brand loyalty. *Journal of Hospitality Marketing & Management*, *28*(8), 926–956.

Srivastava, A., Mukherjee, S., & Jebarajakirthy, C. (2020). Aspirational consumption at the bottom of pyramid: A review of literature and future research directions. *Journal of Business Research*, *110*, 246–259. https://doi.org/10.1016/j.jbusres.2019.12.045

Stutzer, A. (2004). The role of income aspirations in individual happiness. *Journal of Economic Behavior & Organization*, *54*(1), 89–109.

Truong, Y., McColl, R., & Kitchen, P. J. (2010). Uncovering the relationships between aspirations and luxury brand preference. *Journal of Product & Brand Management*, *19*(5), 346–355.

Usakli, A., & Baloglu, S. (2011). Brand personality of tourist destinations: An application of self-congruity theory. *Tourism Management*, *32*(1), 114–127.

Veblen, T. B. (1899). *The theory of the leisure class: An economic study of institutions*. The Macmillan Company.

Wansink, B., Brasel, S. A., & Amjad, S. (2000). The mystery of the cabinet castaway: Why we buy products we never use. *Journal of Family and Consumer Sciences*, *92*, 104–107.

Williams, G. C., Hedberg, V. A., Cox, E. M., & Deci, E. L. (2000). Extrinsic life goals and health-risk behaviors in adolescents. *Journal of Applied Social Psychology*, *30*(8), 1756–1771.

APPENDICES

Appendix A

A Little Bit of Each: Unpacking a Task into Detailed Subcategories Leads to More Ambitious Planning - Additional Studies

A.1 Appendix Study A

In this study, we replicated our results from Study 3B using a similar design, but with participants considering learning Italian words (like in Study 1A) instead of formatting dictionary entries. Again, we show that holding the number of tasks fixed, merely unpacking the tasks into subcategories can make them seem less effortful.

A.1.1 Method

We recruited 200 participants from the CloudResearch participant pool on MTurk (M_{Age} = 40; 52% female). Note that we excluded one participant who entered an invalid age, most likely a phone number. Like Study 3B, we used a 3 (workload: low vs. medium vs. high) by 2 (task representation: aggregate vs. unpacked) mixed design with workload as a within-subjects factor and task representation as a between-subjects factor. All participants were first shown the language learning interface and asked to learn the Italian words for "good afternoon", "chocolate," and "supermarket" (like in Study 1A). Participants were then presented with 3 different schedules for how three hypothetical students might learn additional Italian words. Participants were told that "Person A" had a low workload of 9 words per day, "Person B" had a medium workload of 15 words per day, and "Person C" had a high workload of 30 words per day. As shown in Figure A1, which depicts the workload for Person C, in the aggregated condition the total number of words was displayed (as a single number), while in the unpacked condition the number of words was unpacked into three subcategories (i.e., greetings, food, and locations). After viewing each of the three schedules, participants rated how effortful and challenging they thought learning the words each day would be on 101-point sliding scales, and how much time in minutes each person would spend learning Italian words each day.

A.1.2 Results

We conducted a 3 (workload: low vs. medium vs. high, within-subject) × 2 (task representation: aggregate vs. unpacked, between-subject) mixed ANOVA on the logged time estimates for the different learning schedules. We found a significant main effect of workload ($F(1.45, 286.84) = 361.85, p < 0.001$), a significant main effect of task representation ($F(1, 198) = 6.72, p = 0.010$), and a significant interaction ($F(1.45, 286.84) =$

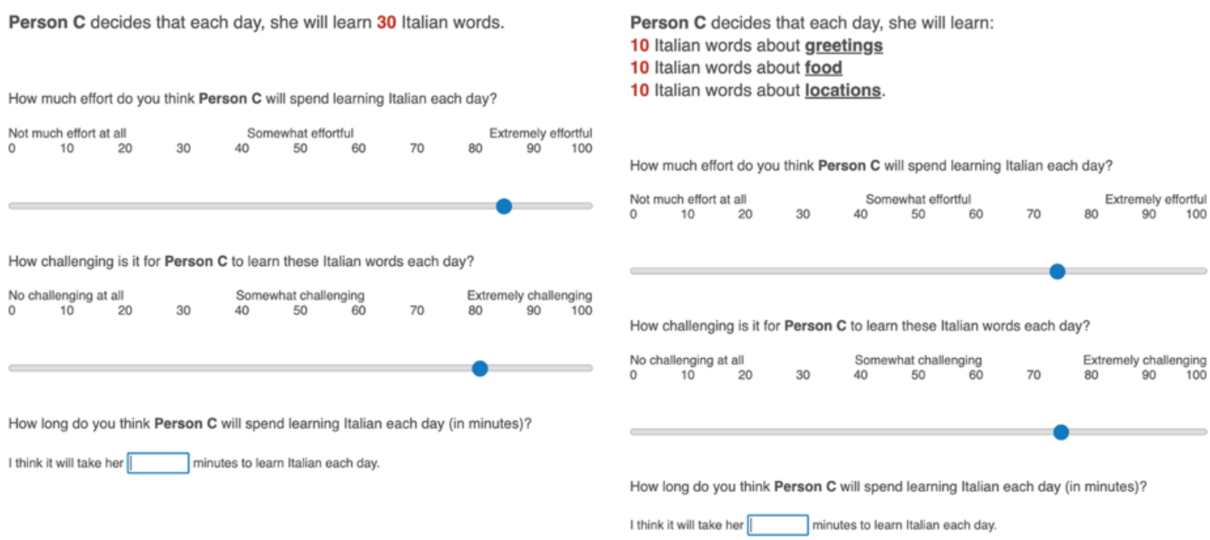


Figure A.1: Stimuli for Appendix Study A: (a) Aggregated vs. (b) Unpacked Conditions

$7.83, p = 0.002$). Estimated time to complete the tasks was higher for the medium and high workloads compared to the low workload. As shown in Figure A.1, time estimates were not significantly different between the aggregated and unpacked conditions for the low workload condition ($M_{\text{Aggregated}} = 3.41, SD = 0.78; M_{\text{Unpacked}} = 3.27, SD = 0.84; t(198) = 1.23, p = 0.219$), but were significantly higher in the aggregated condition in the medium ($M_{\text{Aggregated}} = 3.87, SD = 0.80; M_{\text{Unpacked}} = 3.58, SD = 0.82; t(198) = 2.54, p = 0.036$) and high ($M_{\text{Aggregated}} = 4.43, SD = 0.75; M_{\text{Unpacked}} = 4.03, SD = 0.84; t(198) = 3.57, p = 0.001$) workload conditions; note that p-values reported here have been adjusted using Bonferonni correction for multiple comparisons. Again, the significant interaction between workload and task representation conditions can be interpreted as the unpacking effect being stronger for higher workloads.

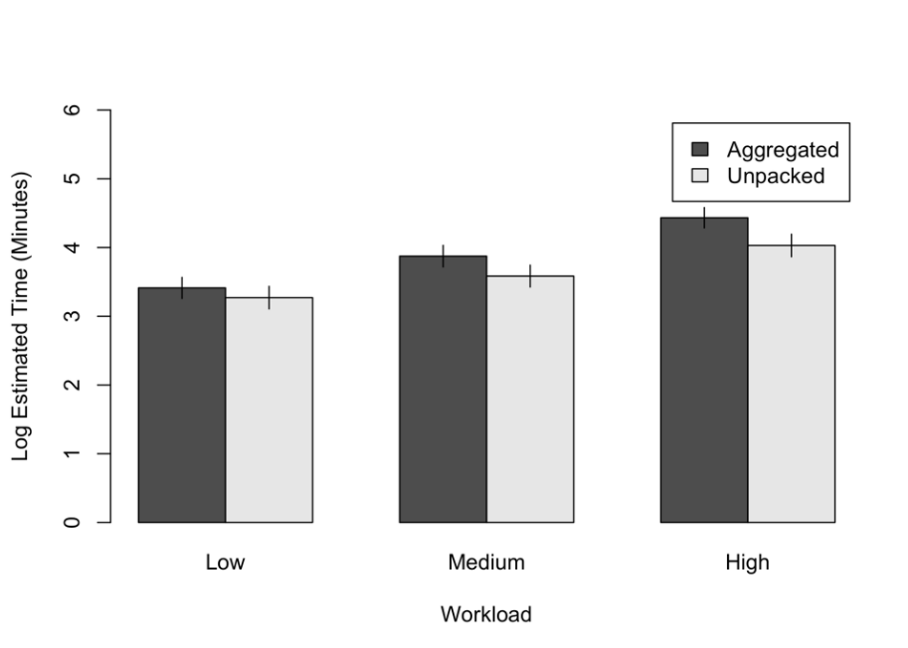


Figure A.2: Comparison of Time Estimates Across Conditions in Appendix Study A, Plotting Means and 95% Confidence Intervals

A.2 Appendix Study B

The purpose of this study was to “pre-test” the design of Study 5 from the main paper, which essentially replicates Study 3A, with three key differences: the maximum cap of 100 dot-counting tasks was lowered to 30 tasks, the bonus payment of $0.20 per task was lowered to $0.10, and the target sample size was reduced from 250 participants per condition to 100 participants per condition. These changes allowed us to feasibly implement the actual bonus payments provided in Study 5, and also demonstrate the robustness of our main unpacking effect.

A.2.1 Method

We recruited 200 participants from the CloudResearch participant pool on MTurk (M_{Age} = 39; 42% female). All participants first completed a dot-counting task (see Figure 2.6) and were then asked how many additional tasks they would want to complete for a $0.10 bonus per task, responding with a single number (aggregated condition) or separate numbers for blue, red, and green dot-counting tasks (unpacked condition), up to a maximum of 30 tasks in total. They then estimated how long it would take to complete a single task (in seconds) and all tasks they had planned (in minutes), indicated on 101-point slider scales how effortful and challenging it would be to complete the planned set of tasks, and answered some demographic questions.

A.2.2 Results

We excluded 2 participants who did not follow the instructions and went over the 30-task maximum, leaving 198 participants for analysis. Consistent with our results from Study 3A, a one-way ANOVA revealed a significant main effect of task planning condition ($F(1, 196) = 15.58, p < 0.001, \eta^2 = 0.07$), with participants in the unpacked condition planning significantly more tasks than those the aggregated condition ($M_{\text{Aggregated}} = 11.66, SD = 12.65; M_{\text{Unpacked}} = 18.1, SD = 13.17; t(195) = 3.94, p < 0.001, \text{Cohen's}\, d = 0.56$). These results were robust to excluding the 56 participants who planned to do 0 additional bonus tasks ($F(1, 140) = 21.62, p < 0.001, \eta^2 = 0.14; M_{\text{Aggregated}} = 17.07, SD = 11.91; M_{\text{Unpacked}} = 25.12, SD = 8.53; t(140) = 4.65, p < 0.001, \text{Cohen's}\, d = 0.78$).

Also consistent with Study 3A, collapsing across task representation conditions, we found that total tasks planned and logged time estimates (in seconds) for completing a single counting task were negatively correlated ($r = -0.26, t(196) = 3.81, p < 0.001$). There were again significant positive correlations between total tasks planned and how effortful ($r = 0.48, t(196) = 7.75, p < 0.001$) and challenging ($r = 0.36, t(196) = 5.40, p <$

0.001) participants rated their planned tasks (101-point scale), as well as their logged time estimates (in minutes) for completion ($r = 0.42, t(196) = 6.49, p < 0.001$). In other words, participants with higher time estimates for a single task planned to do fewer of them, and those who planned more tasks accurately expected to take longer to complete the full set of planned tasks.

Consistent with Study 3A, interestingly, there was no difference in effort ratings between conditions ($M_{\text{Aggregated}} = 66.51, SD = 35.57; M_{\text{Unpacked}} = 67.59, SD = 32.70$; $t(196) = 0.22, p = 0.825$, Cohen's $d = 0.03$), despite participants in the unpacked condition planning to do more tasks on average compared to those in the aggregated condition. Excluding the 56 participants who planned 0 task, a comparison of normalized effort ratings (i.e., computed by dividing participants' effort ratings by their total planned tasks) shows that participants in the unpacked condition appear to rate each task unit to be less effortful compared to those in the aggregated condition ($M_{\text{Aggregated}} = 10.44, SD = 13.17; M_{\text{Unpacked}} = 4.48, SD = 5.24; t(140) = 6.58, p < 0.001$, Cohen's $d = 0.60$).

A.3 Appendix Study C

This study replicates Study 5 from the main paper without the effort questions that followed the planning part of the survey, in order to address concerns that the effort estimates may influence participants' subsequent task completion decisions.

A.3.1 Method

We recruited 200 participants from the CloudResearch participant pool on MTurk ($M_{\text{Age}} = 41$; 50% female). We used the dot-counting task, where participants counted red, blue, or green dots from a mixture of 150 dots. After participants had tried out the task, they were given the chance to complete additional tasks for $0.10 per task completion. Before they started, they were asked to make a plan of how many counting tasks they would like to complete in two randomly assigned task representation conditions: aggregated vs. unpacked. Participants in the aggregated condition were directly asked how many dot-counting tasks they would plan to complete, while those in the unpacked condition were asked to separately indicate how many blue, red, and green dot-counting tasks they would plan to complete. Similar to Study 5, the planned number of tasks participants indicated was not binding, and they could complete more tasks than they had planned or quit early and receive what they had earned so far. Participants could plan and complete a maximum of 30 dot-counting tasks in total.

After making their plans, participants then moved on to the actual task completion portion of the study. Note that unlike in Study 5, they did not complete the effort questions (e.g., time estimates, effort estimates, etc.). Participants were presented with up to 30 pictures of mixtures of dots and randomly asked to count red, blue, or green dots, and could only move on to the next picture once they had entered the correct answer. They could quit at any time by selecting the "I want to end the study" option, and they received their final bonus payments based on the number of tasks they completed.

A.3.2 Results

We excluded 2 participants who did not follow instructions and indicated they wanted to do more tasks than the maximum of 30, leaving 198 participants for analysis. A one-way ANOVA on the number of planned tasks revealed a significant main effect of task planning condition ($F(1, 196) = 7.90, p = 0.005, \eta^2 = 0.04$), with participants in the unpacked condition planning significantly more tasks compared to those in the aggregated condition ($M_{\text{Aggregated}} = 14.59, SD = 12.85; M_{\text{Unpacked}} = 19.69, SD = 12.70; t(196) = 2.81, p = 0.005, d = 0.40$). However, a one-way ANOVA on the number of completed tasks revealed no main effect ($F(1, 196) = 0.24, p = 0.622, \eta^2 = 0.00$), with no difference between conditions ($M_{\text{Aggregated}} = 8.84, SD = 11.26; M_{\text{Unpacked}} = 9.65, SD = 11.91; t(196) = 0.49, p = 0.622, d = 0.07$). These results are consistent with Study 5; the more ambitious plans among participants in the unpacked condition did not translate into more tasks completed, suggesting that they were engaging in more over-planning.

Appendix B

Aspirational Purchases - Proofs

B.1 Theorem 1 proof

Proof. Since p^a is overestimated, $\hat{p}^a > p^a$, we know from equation 3.4 that $u(x^a, w - \hat{c}^{a*}, s) < u(x^a, w - c^{a*}, s)$. As u increases with w, we infer that $\hat{c}^{a*} > c^{a*}$. That is, people will purchase at a higher price c^a when p^a is overestimated. $\square$

B.2 Theorem 2 proof

Proof. To determine the I that maximizes Equation 3.6, we rearrange the terms and use the additive separability assumption in Equation 3.3 to replace the wealth expression with a generic wealth expression:

$$\hat{p}^a(I) \cdot (u(x^a, w, s^a) - u(x^a, w, s)) + u(x^a, w - c^a - \hat{c}(I), s). \tag{B.1}$$

We then find its derivative with respect to I:

$$\frac{d\hat{p}^a(I)}{dI} \cdot (u(x^a, w, s^a) - u(x^a, w, s)) - \frac{du}{dw} \cdot \frac{d\hat{c}(I)}{dI}. \tag{B.2}$$

Setting $I = \hat{I}^*$ makes the derivative equal to 0:

$$\frac{d\hat{p}^a(\hat{I}^*)}{dI} \cdot (u(x^a, w, s^a) - u(x^a, w, s)) = \frac{du}{dw} \cdot \frac{d\hat{c}(\hat{I}^*)}{dI}. \tag{B.3}$$

Since $\hat{c}(I) < c(I)$ and $\hat{p}^a(I) > p^a(I)$, assume $\hat{c}(I) = \delta_1 \cdot c(I)$, for $0 < \delta_1 < 1$ and $\hat{p}^a(I) = \delta_2 \cdot p^a(I)$ for $\delta_2 > 1$. δ_2 is necessarily small enough that it never makes the overestimate of the probability $\hat{p}^a(I)$ greater than 1.

$$\delta_2 \frac{dp^a(\hat{I}^*)}{dI} \cdot (u(x^a, w, s^a) - u(x^a, w, s)) = \delta_1 \frac{du}{dw} \cdot \frac{dc(\hat{I}^*)}{dI} \tag{B.4}$$

Compare this with the unbiased version from Equation 3.7

$$\frac{dp^a(I^*)}{dI} \cdot (u(x^a, w, s^a) - u(x^a, w, s)) = \frac{du}{dw} \cdot \frac{dc(I^*)}{dI}. \tag{B.5}$$

Let

$$f(I) = \frac{p^{a\prime}(I)}{c'(I)} \tag{B.6}$$

and we have

$$f(\hat{I}^*) = \frac{\delta_1}{\delta_2} f(I^*) \tag{B.7}$$

And we know

$$f'(I) = \frac{p^{a\prime\prime}(I) \cdot c'(I) - c''(I) \cdot p^{a\prime}(I)}{(c'(I))^2} \tag{B.8}$$

Since $c(I)$ and $p^a(I)$ are both increasing functions, $c(I)$ is convex and $p^a(I)$ is concave, we know $c'(I) > 0$, $p^{a\prime}(I) > 0$; and $c''(I) > 0$, $p^{a\prime\prime}(I) < 0$. Then we know $f'(I) < 0$.

Since $\frac{\delta_1}{\delta_2} < 1$, $f(\hat{I}^*) < f(I^*)$, we now have $\hat{I}^* > I^*$. That is, people overestimate their investment as a result of biased judgments about the cost and return on investment. □

B.3 Theorem 3 proof

Proof. Similar to the first class of situation, we assume an individual's maximum willingness to pay for the aspirational good under the misjudgments is $\hat{c}^{a*}$ when the right hand side of Equation 3.5 is maximized at $I = \hat{I}^*$, and Equation 3.5 takes equality. So

$$u(x,w,s) = \hat{p}^a(\hat{I}^*)u(x^a, w - \hat{c}^{a*} - \hat{c}(\hat{I}^*), s^a) + (1 - \hat{p}^a(\hat{I}^*))u(x^a, w - \hat{c}^{a*} - \hat{c}(\hat{I}^*), s). \tag{B.9}$$

Since the right hand side of this equation is maximized at $I = \hat{I}^*$, then replacing $\hat{I}^*$ with I^* would reduce the right hand side, so

$$u(x,w,s) > \hat{p}^a(I^*)u(x^a, w - \hat{c}^{a*} - \hat{c}(I^*), s^a) + (1 - \hat{p}^a(I^*))u(x^a, w - \hat{c}^{a*} - \hat{c}(I^*), s). \tag{B.10}$$

This can be further expressed as:

$$u(x,w,s) > \delta_2 p^a(I^*)(u(x^a, w, s^a) - u(x^a, w, s)) + u(x^a, w - \hat{c}^{a*} - \delta_1 c(I^*), s). \tag{B.11}$$

We can also find the max willingness to pay c^{a*} without the misjudgments, when $I = I^*$:

$$u(x,w,s) = p^a(I^*)u(x^a, w - c^{a*} - c(I^*), s^a) + (1 - p^a(I^*))u(x^a, w - c^{a*} - c(I^*), s). \tag{B.12}$$

and simplified to be:

$$u(x,w,s) = p^a(I^*)(u(x^a,w,s^a) - u(x^a,w,s)) + u(x^a, w - c^{a*} - c(I^*), s). \tag{B.13}$$

Comparing equations B.11 and equation B.13, we have

$$(\delta_2 - 1)p^a(I^*)(u(x^a,w,s^a) - u(x^a,w,s)) < u(x^a, w - c^{a*} - c(I^*), s) - u(x^a, w - \hat{c}^{a*} - \delta_1 c(I^*), s). \tag{B.14}$$

We know $\delta_2 > 1$, so

$$u(x^a, w - c^{a*} - c(I^*), s) > u(x^a, w - \hat{c}^{a*} - \delta_1 c(I^*), s). \tag{B.15}$$

and u increase with w, then $w - c^{a*} - c(I^*) > w - \hat{c}^{a*} - \delta_1 c(I^*)$, and

$$c^{a*} - \hat{c}^{a*} < (\delta_1 - 1)c(I^*) \tag{B.16}$$

Because $\delta_1 < 1$, we now know $\hat{c}^{a*} > c^{a*}$. That is, under the misjudgment, people have a higher willingness to pay for the aspirational good. □