Consuming Regardless of Preference: Consumers Overestimate the Impact of Liking on Consumption

HEEYOUNG YOON
TOM MEYVIS

Given that the central objective of consumption in many contexts is to derive enjoyment or utility, it is reasonable to assume that how much people consume a product will primarily be driven by how much they like it. Yet, the current research finds that, although consumers indeed predict that they will consume a greater amount of options they like more, their actual consumption can be surprisingly insensitive to their preferences. Across six experiments, we find that consumers systematically overestimate the extent to which their consumption amount is determined by their preferences. We propose that how much people actually consume is determined by a variety of factors, including transient motivational states (e.g., hunger or boredom), consumption opportunities, and habits. Compared to these factors, however, people's liking of a product tends to be more salient, better known, and perceived as a more normatively appropriate driver of consumption—leading consumers to focus overly on their preferences when predicting their consumption. We further propose that this prediction error has important implications for consumer welfare, as it can lead to suboptimal inventory decisions (e.g., overpurchasing of favorite products) as well as ineffective self-control strategies (e.g., restricting oneself to mediocre options in order to reduce consumption).

Keywords: preference, prediction bias, consumption amount, consumption experience

Heeyoung Yoon (heeyoung.yoon@unibocconi.it) is an assistant professor of marketing at Bocconi University, Via Roentgen 1, Milan 20136, Italy. Tom Meyvis (tmeyvis@stern.nyu.edu) was a professor of Marketing and Merchants' Council Professor of Retail Management and Consumer Behavior at the Stern School of Business, New York University, 40 West 4th street, New York, NY 10012, USA. Please address correspondence to Heeyoung Yoon. This article is based on part of the lead author's doctoral dissertation completed under the supervision of the second author. The authors are grateful to Cent Bulbul for insightful discussion and Vicki Morwitz for her helpful feedback. The authors also thank Stephanie Tjoa, Chloe Eunha Choi, Jin Kim, research assistants of the Consumer Wellbeing Lab, and the marketing department at New York University for their research assistance. Supplementary materials are included in the web appendix accompanying the online version of this article.

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Many consumer purchases involve two key decisions: (1) deciding *what* to purchase among the available options and (2) deciding *how much* to purchase of the chosen option. Just as a consumer's choice of a product is influenced by situational factors, purchase quantity decisions can be influenced by environmental cues such as price promotions, multiunit prices, purchase quantity limits, or suggested purchase quantities (Ailawadi and Neslin 1998; Gupta 1988; Wansink, Kent, and Hoch 1998). More importantly, deciding how much to buy requires *predicting* how much you will consume—an internal anchor underlying quantity decisions. For instance, how many cherries you buy at a fruit stand should depend on how many you think you will eat. Similarly, how many episodes of a TV show you download in response to a promotional offer should depend on how many episodes you think you will watch.

In this research, we examine how consumers predict how much they will consume—and how this predicted

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amount compares to their actual consumption. We study this in various consumption domains where products are inherently enjoyable to consume (e.g., hedonic products) or at least mildly liked, including consumption of food, entertainment, or even personal care products. Given the nature of the domain of our interest, one obvious factor upon which consumers will base their prediction is how much they like the product or service. In other words, predicted consumption quantity likely depends on preferences: how many cherries or episodes you expect to consume should depend on how much you like those cherries or how much you enjoy that TV show. While this undoubtedly holds for large differences in preferences (you will eat more cherries if you love them than if you dislike them), it is less clear whether this will also hold for smaller differences in preferences. What if the cherries are your favorite type compared to a type that you still like, but like less? What if the TV show is one that you love compared to one that you merely like? We propose that, even in those cases, consumers will continue to predict that they will consume more of the option they like more, yet their actual consumption amount will be surprisingly insensitive to the differences in liking. That is, we expect consumers to predict that a small difference in preference will affect their consumption amount more than it actually does.

Although actual consumption can certainly be affected by preference, it is also influenced by many other factors that do not depend on the liking of the product, including generic motivations (e.g., hunger or boredom), habits, distractions, usage opportunities, and product availability or salience. We propose that there are multiple mechanisms that lead consumers to focus on preference at the expense of these other factors. Specifically, compared to other factors, a consumer's evaluative reaction to a product is (1) more salient at the time of prediction, (2) better known at the time of prediction, and (3) seen as a more normatively appropriate driver of the consumption amount. In the following section, we will elaborate on these unique features of preference and, building on related findings in a diverse set of literatures, explain how they lead to a disproportionate focus on preference in predictions of consumption amount.

PREDICTING CONSUMPTION AMOUNT VERSUS PREDICTING CONSUMPTION ENJOYMENT

Predicted consumption amount is arguably the most obvious consideration when consumers decide whether to make a purchase or how much to purchase (Lemon, White, and Winer 2002), and consumers can, in fact, make better purchase decisions when they estimate product usage before choice (Goodman and Irmak 2013). However, it is not easy for consumers to estimate their future consumption accurately, and they often feel uncertain about it (Luce 1992; Nunes 2000; Tanner and Carlson 2009). Admittedly, it would be much easier to correctly estimate consumption quantity when the unit of consumption is large: for example, predicting the number of movies one will watch would be easier than predicting the number of YouTube video clips. Prediction would also be easier and more accurate when the past consumption amount happens to be salient or when consumption is rationed or scheduled (e.g., taking a pill a day). Unfortunately, however, we often do not accurately recall past consumption quantity (Lansky and Brownell 1982), and we sometimes need to make more granular estimates for our usage frequency or consumption amount (e.g., how many times will I use the metro? How much mobile data will I use?).

Given the evidence suggesting that people do not forecast their own behavior well, it is not surprising that they are also bad at estimating their consumption amounts. However, investigating how people make such predictions would inform us about whether they are systematically biased and if so how. To our best knowledge, the process by which people make *consumption predictions* has not received much attention compared to how purchase quantity or actual consumption quantity is determined (Ailawadi and Neslin 1998; Geier, Rozin, and Doros 2006; Mishra, Mishra, and Masters 2011). A notable exception is Nunes' (2000) work on consumers' preferences for flat rate fees over pay-per-use, which demonstrates that people often overestimate how much they will use a flat fee service because they are biased by the (high) maximum possible consumption amount. Yet, this dearth of research on consumers' predictions of how much they will *consume* contrasts with the copious research on people's predictions of how much they will *enjoy* an experience—a field built on the literature on affective forecasting errors (Gilbert et al. 2004; Loewenstein and Schkade 1999).

One finding that has been consistently observed in affective forecasting research is that people tend to overestimate how much their enjoyment of a consumption experience will be affected by contextual factors or outcome specifications. For instance, people overestimate how much their emotional reaction to a sad story will be affected by knowing whether or not it is fictional (Ebert and Meyvis 2014), how much the joy of winning a gamble will be affected by the prior probability of winning (Buechel et al. 2014), and how much the enjoyment of a jellybean flavor will be affected by their liking of a previous flavor (Novemsky and Ratner 2003). In all these cases, people focus too much on the qualifiers of the experience and under-weigh the essence of the experience: the sadness of the story, the mere joy of winning, or the taste of the jellybean.

Affective forecasters' over-weighting of contextual factors occurs in part because of a decision bias known as "focalism" (Schkade and Kahneman 1998; Wilson et al. 2000). Focalism refers to predictors' tendency to focus

disproportionately on events, objects, or features that are salient at the time of prediction, while failing to sufficiently adjust (or temper) their predictions to account for other features and events that will later also occupy their thoughts and influence their emotions. We propose that while focalism produces *over-weighting* of contextual variables in affective forecasts, it will result in *under-weighting* of contextual variables in forecasts of consumption amounts.

The contextual variables typically examined in affective forecasting studies (e.g., the fictitiousness of a story, the prior probability of a gamble, the taste of the preceding jellybean) are both salient and known at the time of prediction. Yet, when people are assessing their actual enjoyment, they tend to be absorbed by the experience itself, which prevents them from taking any contextual factors into account (Morewedge et al. 2010). Thus, although forecasters tend to focus on contextual variables, these variables have limited influence on actual enjoyment.

We propose that the opposite occurs for consumption quantity. Specifically, we propose that the actions that determine actual consumption quantity (e.g., picking up another cherry or clicking on another episode) are to a great extent influenced by contextual variables, such as momentary hunger, boredom, distraction, or the availability of alternatives. However, these variables tend to be both less salient and less known at the time of prediction. In contrast, consumers' liking of the consumption object is not only salient and known at the time of prediction but will also tend to be perceived as a more normatively appropriate driver of consumption.

Next, we will discuss why liking is particularly salient, known, and appropriate, followed by a discussion of the other (underappreciated) drivers of consumption amount.

LIKING AS A PRIVILEGED PREDICTOR OF CONSUMPTION AMOUNT

We propose that, when consumers predict how much they will consume of a product, they tend to focus on how much they *like* that product because this evaluative reaction is both salient and known. When people consider consumption of a product, their liking of it will be naturally salient as it is the main reason for consumption. More generally, people tend to generate evaluations automatically and effortlessly—as this tells us what to approach and what to avoid (Chen and Bargh 1999; Ferguson and Zayas 2009)—and these evaluations tend to be easily accessible (Fazio et al. 1986). Furthermore, although liking can change over time (e.g., satiation; Frederick and Loewenstein 1999), and although preferences are often constructed and influenced by context (Slovic 1995), people tend to be overly confident about their current preference and believe that it would not change much in the future (Luce 1992; Quoidbach, Gilbert, and Wilson 2013). Thus, because product liking tends to be both salient and (perceived as) known, we expect that consumers who are predicting how much they will consume will focus on this factor and, consequentially, give it too much weight.

Product preference may not only have a disproportionate impact on predictions of consumption amount because it is salient and known (consistent with focalism; Wilson et al. 2000), but also because it seems normatively appropriate to rely on preference. As preference is often a primary motivation for consumption, consumers may feel that they *should* consume greater amounts of products they like more. Although such normative concerns could influence both predictions and behavior, prior research has shown that intentions and norms have a greater impact on predictions than they do on behavior (Kivetz and Tyler 2007; Koehler and Poon 2006; Nordgren, Van Harreveld, and Van Der Pligt 2009; Sherman 1980).

Whereas consumers' liking of a product is particularly salient, known, and normatively appropriate, this does not generally hold for the many other factors that influence actual consumption. As we mentioned earlier, actual consumption is not just driven by liking of the product, but also by various other factors, including general motivational states (e.g., hunger or boredom), usage opportunities, availability of alternatives, habits, and the salience of the product or its accessibility in memory ("is it top of mind?"). These factors do not generally depend on how much consumers like the product, but, compared to product liking, they are less likely to be taken into account during predictions. First, these factors tend to be both less salient and more uncertain than product preference at the time of prediction. Future motivational states, memory accessibility, or consumption context are not present at the time of prediction and are difficult to estimate with any certainty. We often do not know how hungry or bored we will feel later, whether the product will come to mind, how often we will need the product, or whether any substitutes will be available. The greater uncertainty and reduced salience of these transient, situational factors reduce the likelihood that they would be considered at the time of prediction. Furthermore, these additional factors are less likely to be seen as normatively appropriate drivers of consumption. Whereas preference reflects the essential appreciation of the product and the prime reason for consumption, the other factors may seem more incidental and less central to consumption. That is, while consumers may feel that they should consume more of a product if they like it more, it may be less socially desirable for them to consume more of a mediocre product simply because they are bored or because the product happens to be top of mind.

In sum, compared to the many other drivers of consumption, consumers' liking of the product tends to be more salient, better known, and considered to be more normatively appropriate. Given that predictions tend to both unduly focus on factors that are salient and known (i.e., focalism) and be overly principled and normative, we expect consumers to overestimate the extent to which their consumption will be influenced by their preferences. This also aligns with theories advanced by researchers in several

distinct research areas, such as representativeness heuristics, social psychology addressing the inconsistency between social attitudes and behaviors, and the cold-to-hot empathy gap. We further discuss them in the general discussion.

DOES MISPREDICTION OF CONSUMPTION AMOUNT MATTER?

We contend that the proposed effect—consumers overestimating the discerning nature of their consumption—has three distinct negative consequences for consumers: (1) it can produce suboptimal inventory decisions, (2) it can lead consumers to over-invest when they try to strategically increase their consumption, and (3) it can lead consumers to adopt ineffective strategies to intentionally reduce their consumption. First, and most obviously, predicted consumption will drive how much inventory shoppers acquire. If consumers overestimate how much they will consume of a more preferred product, they will end up with excess inventory. Conversely, if they underestimate how much they will consume of a less preferred product, they will run out of inventory. Second, in situations where consumers are trying to increase their consumption of a product or service (e.g., virtuous consumption), they may over-invest in more liked (and perhaps more expensive) alternatives. For instance, a consumer who is trying to increase the amount of water she drinks during the day may decide to pay extra for Fiji water rather than Poland Spring, assuming that she would drink more of the water she likes (slightly) better. Third, and conversely, in situations where consumers are trying to decrease their consumption of a product or service, they may strategically opt for a less preferred option because they erroneously believe that it would decrease consumption. For instance, someone who is trying to reduce time spent watching TV may decide to forgo a better lineup of TV channels, hoping that she would watch TV less if she had a worse lineup.[1] Thus, consumers who wish to reduce their consumption may intentionally opt for a less preferred product or service, which would be a suboptimal decision if they end up consuming as much as they would have otherwise.

We note that the overestimation of the impact of preference can manifest in both directions when comparing predictions to actual consumption—*underestimation* of consumption of less preferred options or *overestimation* of consumption of more preferred options. The direction depends on any factors influencing overall consumption or the prediction of it. For example, people might overestimate the consumption of more preferred options if they are hungry; anticipating eating more and inaccurately predicting how quickly they will get full. Conversely, they may underestimate the consumption of less preferred options if they do not realize how mindless their consumption can be. In most studies, we observe that participants underestimate their consumption of less preferred options (see web appendix H for contrast results in all studies). However, we refrain from making specific predictions about the direction, remaining agnostic as it depends on factors orthogonal to preference, such as the presence of alternative options. Importantly, both cases—overestimation for more preferred options and underestimation of less preferred options—are consistent with our overall claim that consumers overestimate the *impact* of liking on consumption.

OVERVIEW OF STUDIES

We test our hypothesis across six studies. In studies 1–3, we demonstrate that people overestimate the impact of liking on their consumption. Specifically, we find that people overestimate the extent to which their preference for particular flavors of jellybeans influences how many jellybeans they consume (study 1). We replicate this prediction error in a different consumption domain (viewing comics, study 2) and when participants have an alternative consumption option (study 3). In study 4, we demonstrate that the effect also holds outside the lab and for repeated consumption of the same product over time: people overestimate how much the quality of a lip balm will affect the number of times they will apply it during a week. Study 5 shows that overestimating the impact of preference can lead to suboptimal decisions (e.g., insufficient inventory). Finally, we test the mechanism underlying this effect in study 6 and find that the undue reliance on preference during prediction is attenuated when participants are explicitly reminded of how variety can reduce satiation. A summary of the studies is provided in table 1.

In all studies, we removed prediction or consumption outliers that deviated more than three standard deviations above or below the mean. Notably, all results remain consistent even when these outliers are included in the analyses. Further details about outlier removal for each study can be found in web appendix I. The complete study materials and data files are available at https://researchbox.org/207.

STUDY 1: EATING MORE OR LESS PREFERRED JELLYBEANS

In study 1, we tested our main hypothesis by studying the consumption of jellybeans. Participants received 50 jellybeans—either of a more preferred or less preferred flavor—to consume during the experiment session. We expected that people would overestimate how much their

1 We note that this intuition is not as obvious as the first two cases. In fact, rather than choosing a worse line-up with the assumption that she would watch fewer TV shows if she can only access mediocre programming, she could instead opt for a better line-up with the assumption that she would be satisfied with fewer shows if they are really good. However, we observe in a pilot study that people are more likely to have the former intuition (web appendix A).

TABLE 1

SUMMARY OF STUDIES

Study	Context	Design	Main findings
Main text			
1	Eating Jellybeans	2 (liking: more preferred, less preferred) × 2 (response: prediction, consumption) mixed design	• Participants overestimate the impact of their liking for a jellybean flavor on their consumption amount.
2	Viewing Comics	2 (funniness: more funny, less funny) × 2 (response: prediction, consumption) mixed design	• The overestimation of the impact of liking on consumption can be generalized across different consumption domains.
3	Eating Jellybeans	2 (liking: more preferred, less preferred) × 2 (response: prediction, consumption) mixed design	• The overestimation of the impact of liking on consumption occurs when participants have an alternative consumption option. • The overestimation is not explained by underestimation of changes in liking (i.e., satiation).
4	Using Lip Balm	2 (quality: premium, regular) × 2 (response: prediction, consumption) mixed design	• The overestimation of the impact of liking on consumption occurs outside of the lab and when consumption period is extended.
5	Viewing Comics	2 (funniness: more funny, less funny) × 2 (response: prediction, consumption) mixed design	• The overestimation of the impact of liking on consumption leads to a suboptimal purchase quantity decision.
6	Viewing Photographs	2 (liking: more preferred, less preferred) x 2 (response: prediction, consumption) × 2 (reminder: yes, no) mixed design	• Reminding participants of how variety can reduce satiation (VRS) before predictions attenuates the prediction bias.
Supplemental studies in the web appendix			
S1	Eating Jellybeans	2 (liking: more preferred, less preferred) between-subjects	• The overestimation of the impact of liking on consumption occurs when people are making prediction for others and when participants are incentivized to make an accurate prediction.
S2	Eating Jellybeans	2 (liking: more preferred, less preferred) × 2 (response: prediction, consumption) within-subject	• Participants overestimate the impact of their liking for jellybean flavors on their consumption amounts when they make predictions for and eat both flavors of jellybeans.
S3	Eating Jellybeans	2 (liking: more preferred, less preferred) × 2 (response: prediction, consumption) × 4 (duration: 5, 10, 15, 20 min) mixed design	• The overestimation of the impact of liking on consumption occurs from the initial stage of consumption (inconsistent with an underestimation of satiation account).
S4	Viewing Comic	2 (funniness: more funny, less funny) × 2 (boredom reminder: yes, no) between-subjects	• The effect of funniness on the predicted number of comics to view is reversed when participants are reminded of boredom (another driver of consumption).
S5	Viewing Comic	2 (funniness: more funny, less funny) × 2 (experience of boredom: yes, no)	• The actual experience of boredom (another driver of consumption) does not attenuate the impact of funniness on the predicted number of comics to view (inconsistent with the empathy gap account).
S6	Viewing Photographs	One cell	• The overestimation of the impact of liking on consumption replicates when preference is measured (instead of being manipulated). • The less they like the photographs the more they underestimate how many photographs they will view.

actual jellybean consumption would depend on whether they received their more preferred or less preferred flavor.

Method

Fifty-nine undergraduate students (48% male) participated for course credit in a 1-hour-long session, during which they participated in multiple unrelated studies. There were no outliers in this study. The study used a 2 (liking: more preferred vs. less preferred) × 2 (response: prediction vs. consumption) mixed design with liking as a between-subjects factor.

Participants first received two jellybeans: one cotton candy-flavored jellybean and one cherry-flavored jellybean. They then tasted each of these jellybeans, rated how

much they liked each flavor (−4 = *tastes awful*, 0 = *tastes neither good nor bad*, 4 = *tastes great*), and indicated which flavor they liked better (see table 2 for the average ratings of the more preferred and less preferred options across all studies). They were then informed that we would flip a coin to determine which one of these two flavors they would receive in a cup containing 50 jellybeans. They were also informed that they could eat as many of the assigned jellybeans as they wanted during the remainder of the session. We then asked them to predict, for each flavor, how many of the 50 jellybeans they would eat if that flavor was selected. The order of flavors was counterbalanced. Next, the experimenter flipped a coin and participants were provided with a cup of 50 jellybeans of the flavor determined by the coin flip. Participants then proceeded to participate in other unrelated surveys, during which they could eat as many of the assigned jellybeans as they wanted. After the session ended, a research assistant, who was blind to the hypothesis, counted the remaining jellybeans to determine how many each participant ate during the session.

Results and Discussion

For each participant, we first identified which flavor they were assigned to and used the prediction for that flavor (though all participants made predictions for both flavors), which enabled us to compare their consumption to the corresponding prediction. We ran a repeated-measures ANOVA with response (prediction vs. consumption) as a within-subject factor and liking as a between-subjects factor. As hypothesized, we found a significant two-way interaction ($F(1, 57) = 10.75$, $p = .002$, $\eta_p^2 = 0.159$), indicating that participants overestimated the impact of their flavor preference on consumption (figure 1). Although participants expected to eat more jellybeans when they received their preferred flavor as compared to their less preferred flavor ($M_{\text{MorePref}} = 18.9$, SD = 15.8, $M_{\text{LessPref}} = 11.5$, SD = 12.4; $F(1, 57) = 4.01$, $p = .05$, $\eta_p^2 = 0.066$),[2] they actually consumed slightly more jellybeans when they received the less preferred ones ($M_{\text{MorePref}} = 19.7$, SD = 18.5, $M_{\text{LessPref}} = 22.9$, SD = 19.0; $F < 1$). Thus, compared to participants' predictions, their actual consumption was surprisingly insensitive to their preference.

In this study, the prediction bias was driven by participants underestimating their consumption of the less preferred jellybeans ($M_{\text{prediction}} = 11.5$, SD = 12.4, $M_{\text{consumption}} = 22.9$, SD = 19.0; $F(1, 57) = 26.12$, $p < .001$, $\eta_p^2 = 0.314$) rather than overestimating their consumption of the more preferred jellybeans ($M_{\text{prediction}} = 18.9$, SD = 15.8, $M_{\text{consumption}} = 19.7$, SD = 18.5; $F < 1$). However, as mentioned before, we do not formulate any hypotheses about participants' prediction bias within each preference condition. In the end, this prediction bias will depend on the specifics of each study (including the nature of the other surveys people participated in while consuming jellybeans).[3] As such, we will focus our analysis on testing whether the effect of preference is more pronounced on prediction than on consumption, while remaining agnostic as to whether this difference is driven by underestimating consumption of less preferred options or overestimating consumption of more preferred ones.

While the results of this study support our hypothesis that consumers tend to overestimate the impact of preference on consumption amount, there are several plausible alternative accounts. First, it is possible that participants' responses were driven by self-presentation concerns (Goffman 1978). That is, participants indicated that they would consume a greater amount of the more preferred jellybeans because it seemed like an appropriate response even though they did not actually believe that they would consume different amounts of the two flavors. Second, rather than answering the question we asked them (i.e., predicting their consumption), they may have wanted to reaffirm that they preferred one flavor over the other (response substitution, e.g., Gal and Rucker 2011). To address these possibilities, we ran a follow-up study ($N = 64$) where participants predicted others' consumption rather than their own consumption and provided incentives for accurate estimates. Replicating the pattern of predictions in study 1, participants still estimated that those who received their preferred flavor consumed significantly more jellybeans ($M = 25.8$, SD = 11.6) than those who received their less preferred flavor ($M = 14.2$, SD = 9.5; $F(1, 61) = 104.92$, $p < .001$, $\eta_p^2 = 0.632$), suggesting that the effect does not depend on self-presentation concerns or response substitution (see web appendix B for full description of this study).

Second, it is possible that this overestimation is dependent on the fact that people made predictions for both flavors but consumed only one of them. As such, the presence of both flavors may have led predictors to focus on the liking gap, overestimating the effect of preference during prediction (Hsee and Zhang 2004). In fact, it is often the case that predictions of consumption are made in the presence of multiple alternatives (the options in a store) whereas consumption is limited to a single alternative (the purchased option)—and this can certainly contribute to our proposed effect. However, in a second follow-up study ($N = 157$; supplemental study 2, web appendix C), we replicated the finding when participants did not only make predictions for both flavors but were also given both flavors of jellybeans to consume.

2 When we compared the predictions for both flavors within participants, we also found that participants predicted to eat significantly more jellybeans of the more-preferred flavor than the less-preferred flavor ($M_{\text{MorePref}} = 18.4$, SD = 14.9, $M_{\text{LessPref}} = 11$, SD = 13.6; $F(1, 58) = 42.92$, $p < .001$, $\eta_p^2 = 0.425$).

3 For instance, predictions are more likely to be underestimates if the other surveys are more boring than expected, but they are more likely to be overestimates if the jellybeans are more filling than expected.

TABLE 2

PREFERENCE RATINGS FOR JELLYBEANS, COMIC SETS, LIP BALMS, AND PHOTOGRAPH SETS

	Liking for Jellybeans "How much do you like this flavor?" – 4 = *tastes awful*, 0 = *tastes neither good nor bad*, 4 = *tastes great*					
Study	Cotton candy	Very cherry	*t*-value	More preferred	Less preferred	*t*-value
1	2.07*** (1.81)	1.20*** (2.41)	3.11**	2.49*** (1.63)	0.80* (2.30)	8.58***
3	1.66*** (1.84)	1.22*** (2.31)	1.52 ($p = .134$)	2.43*** (1.38)	0.62* (2.10)	9.50***
	Liking for comic sets "How funny do you think comics from set A is?" 1= *not funny at all*, 7 = *very funny*					
	More preferred		Less preferred		*t*-value	
2	4.87 (1.18)		4.10 (1.52)		2.88*	
5	4.16 (1.48)		3.08 (1.29)		12.99***	
	Liking for lip balms "How would you rate the quality of this lip balm?" 1 = *poor quality*, 7 = *high quality*					
	Premium		Regular		*t*-value	
4	5.04 (1.09)		4.48 (1.27)		2.89**	
	Liking for photographs "How pleasant of unpleasant was it to view photographs from Set A [B]?" – 4 = *very unpleasant*, 0 = *neither pleasant or unpleasant*, 4 = *very pleasant*					
	More preferred		Less preferred		*t*-value	
6	3.51*** (0.85)		2.05*** (1.51)		– 23.28***	

NOTE.—Standard deviations are in parentheses; for studies 1, 3, and 6, average ratings significantly higher than the mid-point (=0) are identified with * above the mean.
*$p < .05$.
**$p < .01$.
***$p < .001$.

STUDY 2: VIEWING COMICS

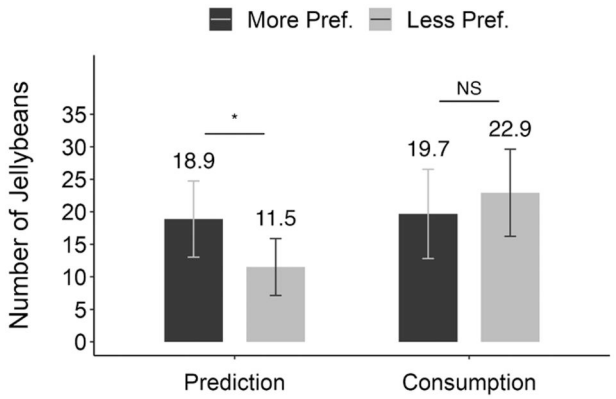
Study 2 had three primary objectives. First, we aimed to test our effect in a different domain (i.e., viewing of comics). Second, we wanted to examine whether the effect also occurs when participants' preference is not measured prior to the predictions (and thus made salient). To achieve this, we pretested comics to create sets that people *generally* like more or less, thus removing the need to measure participants' personal preferences. Third, participants in this study were exposed to only one set of comics (either the more liked set or the less liked set). That is, participants made one prediction for either one of the comic sets and viewed the same set during the consumption stage. Lastly, in this study, we employ an effortful consumption context. In the previous studies, participants could have consumed jellybeans mindlessly and habitually (Ogden et al. 2013; Wood and Neal 2009). To the extent that consumers are underestimating the mindlessness of their consumption decisions, this could lead them to overestimate how discerning they will be to small differences in liking. To examine this, we asked participants to enter a captcha every time they consume a comic to make the consumption decisions more mindful.

Pretest

To create two different sets of comics that would differ in terms of how much people like them, we ran a pretest on Amazon Mechanical Turk with 248 participants (41% male, $M_{age} = 37.4$). Each participant was presented with a subset of 60 comics that were randomly selected from a database of 240 comics and rated how funny each comic was (1 = *not at all*, 7 = *very funny*). The top 80 comics were selected as the funny (more preferred) comics whereas those ranking between 81st and 160th were selected as the less funny (less preferred) comics. As there was substantial divergence between male and female

FIGURE 1

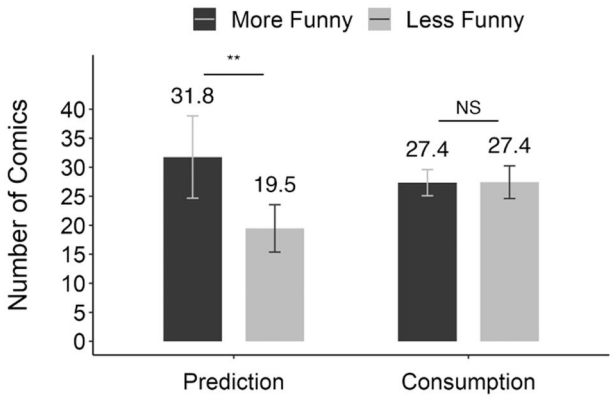
PREDICTED VERSUS ACTUAL JELLYBEAN CONSUMPTION IN STUDY 1



NOTE.—All error bars in this article denote the 95% confidence interval; $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

FIGURE 2

PREDICTED VERSUS ACTUAL COMICS VIEWED IN STUDY 2



ratings, we selected two separate sets of comics for each gender.

Method

One hundred eleven undergraduate students participated in exchange for course credit or a small monetary reward (43% male, $M_{age} = 21.1$). Two outliers were removed from the analyses, leaving us with 109 data points. This study used a 2 (funniness: more funny vs. less funny) × 2 (response: prediction vs. consumption) mixed design with liking as the between-subjects factor.

Depending on condition, participants were either assigned the set of 80 less funny comics or the set of 80 more funny comics. Note that participants were only told that they were assigned a set of 80 comics and were unaware that there was another set of comics that differed in funniness. To allow participants to learn how funny the set of comics was, participants were first shown five comics which were randomly drawn for each participant from their assigned set. To make sure participants would not simply click through all the comics, participants had to enter a captcha (a 3-digit number, see web appendix N) to view each comic (both in the sample phase and in the main experience). After they viewed the five sample comics, they predicted how many of the 80 comics they thought they would view during the next 5 minutes, knowing that they could view as many as they wanted but could not do anything else. Next, they actually viewed comics for 5 minutes. After the 5 minutes had elapsed, they indicated how funny they thought the comics were (1 = *not funny at all*, 7 = *very funny*), which served as a manipulation check.

Results and Discussion

Manipulation Check. As intended, participants in the more funny condition rated the comics as funnier than those in the less funny condition did ($M_{\text{More Funny}} = 4.9$, SD = 1.2, $M_{\text{Less Funny}} = 4.1$, SD = 1.5; $F(1, 101) = 8.30$, $p = .005$, $\eta_p^2 = 0.076$).

Consumption Amount. A repeated-measures ANOVA revealed a significant main effect of funniness ($F(1, 107) = 6.13$, $p = .015$, $\eta_p^2 = 0.054$), which was qualified by an interaction with response type ($F(1, 107) = 8.09$, $p = .005$, $\eta_p^2 = 0.07$; figure 2). As expected, participants who received the funnier comics predicted that they would view significantly more comics than did those who received the less funny comics ($M_{\text{More Funny}} = 31.8$, SD = 27.3, $M_{\text{Less Funny}} = 19.5$, SD = 15.0; $F(1,107) = 8.26$, $p = .005$, $\eta_p^2 = 0.072$). However, the actual number of comics viewed did not significantly differ between the two conditions ($M_{\text{More Funny}} = 27.4$, SD = 8.7, $M_{\text{Less Funny}} = 27.4$, SD = 10.4; $F < 1$).

In sum, consumers' overestimation of the impact of liking replicated in a different domain of consumption and persisted even though they did not rate the comics prior to predicting and were only exposed to a single set of comics. It should also be noted that participants in this study did not engage in any other activities during consumption. This focused attention, and the fact that participants had to enter a captcha to request a comic (rather than just grabbing a jellybean from a cup), indicates that the effect is not limited to mindless consumption decision contexts.

STUDY 3: EATING JELLYBEANS AND M&M'S

In the previous studies, participants had no other food to consume than the jellybeans and no other material to view

than the comics. It is therefore possible that the effect only obtains when people have no consumption alternative (e.g., because they do not fully consider that the less preferred jellybeans or the less funny comics will be the only items to consume). To test whether the effect generalizes to consumption contexts in which consumers do have alternatives available, study 3 provided participants with M&M's in addition to jellybeans. This study also had two additional objectives. First, participants were not asked to indicate their jellybean flavor preference prior to making predictions. This allowed us to further test whether participants' overestimation of the impact of preference was dependent on making this preference salient prior to the prediction (a possibility that study 2 had already ruled out for predictions of comics viewing). Second, this study also addressed the possibility that, rather than overestimating the impact of small differences in liking on consumption, participants were actually overestimating the difference in liking itself (or, more precisely, how this difference would persist over time). Given that people sometimes satiate more quickly to products they like more (DePaoli and Khan 2014), it is possible that participants satiated more quickly to the more preferred flavor than to the less preferred one. If this indeed happened and participants were unaware of this, they may have overestimated the difference in liking, which may have caused them to overestimate the difference in consumption. To test this possibility, we also measured how people's liking for the assigned jellybean flavor changed during the session.

Method

Sixty-eight undergraduate students participated in exchange for course credit (57% male). One outlier, three participants for whom the consumption amount was missing,[4] and one participant who did not indicate a preferred flavor were removed from the analysis. This study used a 2 (liking: more preferred vs. less preferred) × 2 (response: prediction vs. consumption) mixed design with liking as the between-subjects factor.

Participants were told that they would receive a cup of 50 M&M's chocolates and a cup of 50 jellybeans (either cotton candy or cherry flavored), of which they could eat as many as they wanted during the session. They then tasted a sample jellybean of each flavor and predicted how many jellybeans they would eat if they received a cup of 50 cherry jellybeans or 50 cotton candy jellybeans, respectively. After making predictions, they indicated which flavor they liked better (1 = *very cherry*, 2 = *cotton candy*) and how much they liked each flavor (−4 = *tastes awful*, 0 = *tastes neither good nor bad*, 4 = *tastes great*). Participants then flipped a coin and received 50 jellybeans of the corresponding flavor as well as a cup of 50 M&M's, after which they ate as many as they wanted for the remainder of the session. At the end of the session, we asked participants how much they enjoyed the taste of the jellybeans they ate during the session (1 = *not at all*, 7 = *very much*) and how their liking of the assigned jellybean flavor changed with consumption ("Did the additional [cotton candy] jellybeans taste better or worse than the first [cotton candy] jellybean you sampled?"; −4 = *tasted worse*, 0 = *tasted the same*, 4 = *tasted better*).

Results and Discussion

Consumption Amount. A repeated-measures ANOVA revealed a significant interaction of liking and response type ($F(1, 61) = 5.65$, $p = .021$, $\eta_p^2 = 0.085$; figure 3). Replicating our earlier findings, participants expected to eat significantly more of the preferred jellybeans than of the less preferred jellybeans ($M_{\text{MorePref}} = 21.0$, SD = 17.2, $M_{\text{LessPref}} = 12.5$, SD = 9.0; $F(1, 61) = 5.9$, $p = .018$, $\eta_p^2 = 0.088$), even though participants actually consumed a similar amount of jellybeans regardless of whether they received their more or less preferred flavor ($M_{\text{MorePref}} = 17.6$, SD = 19.5, $M_{\text{LessPref}} = 16.6$, SD = 16.5; $F < 1$). Thus, the prediction error persisted, even when participants did not indicate their preference before the prediction, and even though they had an alternative consumption option.

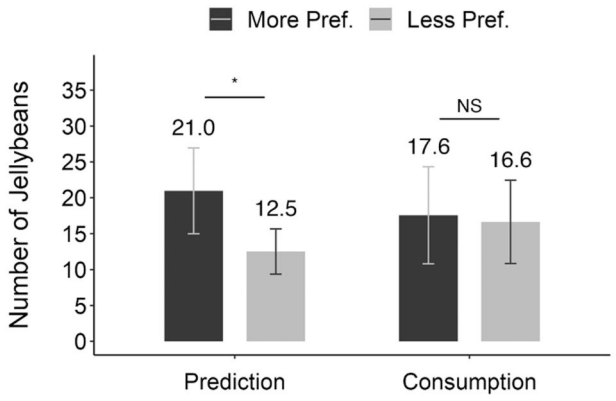
Changes in Liking. Participants in the more preferred condition did not report enjoying the jellybeans significantly more than did those in the less preferred condition ($M_{\text{MorePref}} = 4.2$, SD = 1.5, $M_{\text{LessPref}} = 3.8$, SD = 1.8; $F < 1$), which suggests that participants may indeed have satiated more to their more preferred flavor. However, when asked whether the additional jellybeans tasted better or worse than their first jellybean, participants in the more preferred condition did not report greater satiation ($M_{\text{MorePref}} = -0.5$, SD = 2.1, $M_{\text{LessPref}} = -0.7$, SD = 1.7; $F < 1$). In fact, while the reported reduction in enjoyment was reliable in the less preferred condition ($M = -0.7$, SD = 1.7; compared to 0: $t(30) = -2.36$, $p = .025$, $d = -0.42$), it was not in the more preferred condition ($M = -0.5$, SD = 2.1; compared to 0: $t(29) = -1.32$, $p = .198$, $d = -0.24$), contradicting the idea that those in the more preferred condition may have experienced greater satiation.

To further examine the dynamic process during consumption, we ran a separate study ($n = 141$, see supplemental study 3 in web appendix D for details) in which we measured predicted versus actual jellybean consumption *over time*. If the surprising insensitivity of consumption to preference is caused by a reduced difference in preference over time (e.g., because of differential satiation), then participants' consumption should initially differ between options, but become more similar over time. Instead, we

4 The number of remaining jellybeans for these participants was not recorded by the research assistants, as those participants took the remaining jellybeans with them after the session, making it impossible to assess consumption.

FIGURE 3

PREDICTED VERSUS ACTUAL JELLYBEANS CONSUMED IN STUDY 3



observed that consumption of less versus more preferred jellybeans was already very similar initially and, if anything, became slightly more discerning over time. Together, these findings indicate that participants were overestimating the impact of preference, rather than overestimating the persistence of preference.

STUDY 4: PREDICTING AN EXPERIENCE OUTSIDE THE LAB: USING LIP BALM

So far, our studies have demonstrated that people overestimate the influence of liking on the number of items consumed in a lab setting. In the next study, we wanted to examine if this effect generalizes to the repeated consumption of the same product outside the lab. Specifically, we tested whether participants overestimated how much the quality of a lip balm would affect their usage over a week. In this study, we operationalized preference using quality. While this approach differs from that of other studies, we assumed preference would align with quality when consumers are aware of quality differences and when other attributes remain constant. Participants were informed about the quality of the two lip balms, which shared similar attributes such as a minty scent and nearly identical shape and size. Moreover, they were offered to participants free of charge. Given the quality information, similarities in other attributes, and the absence of cost considerations, leaving quality as the primary input to preference, we assumed that participants would prefer to receive the more expensive premium lip balm over the cheaper generic lip balm.[5]

Method

The study used a 2 (quality: premium vs. regular) × 2 (response: prediction vs. consumption) mixed design with quality as the between-subjects factor. The data were collected in two surveys spaced 1 week apart. The first survey was completed by 328 undergraduate students (39% male); out of which 180 (33% male) also participated in the second survey. Five outliers, 23 participants who reported that they had lost or disposed of the lip balm,[6] and one person who was allergic to an ingredient in the lip balm were removed from the analysis, leaving us with 151 responses. Participants were compensated with either course credit or a monetary reward to participate in the first week, and one person from those who participated in the second survey was randomly selected to receive a $100 Amazon gift card.

To manipulate the quality of the lip balm (and, by assumption, participants' average preference), we selected a premium organic lip balm (Beauty by Earth Peppermint Beeswax, $2.60) as the high-quality option and a more affordable, generic lip balm (Blistex, $0.93) as the regular quality option. In the first survey, which participants completed in the lab, they were told that they would receive one of these two lip balms to take home with them. Participants were shown the actual lip balms, as well as the product descriptions and prices, which were taken from Amazon.com (appendix A). To make sure that participants could make fully informed predictions, they were asked to examine the lip balms and write a few sentences about each. Next, for each lip balm (in counterbalanced order), they predicted how many times they would apply it in the next 7 days (0–100 times). They then flipped a coin, which determined which lip balm they actually received. After receiving the lip balm, we asked them to compare the quality of the two lip balms (1 = *beauty by Earth is higher quality*, 0 = *they are of the same quality*, −1 = *Blistex is higher quality*).

One week later, they were contacted again via email with a survey link. In this second survey, we asked them how much they actually used the lip balm ("How many times in the past 7 days did you apply this product?," 0–100 times) and how they would evaluate it based on their experience ("How would you rate the quality of this lip balm?"; 1 = *poor quality*, 7 = *high quality*). Lastly, they indicated whether they had lost the lip balm or disposed of it.

Results and Discussion

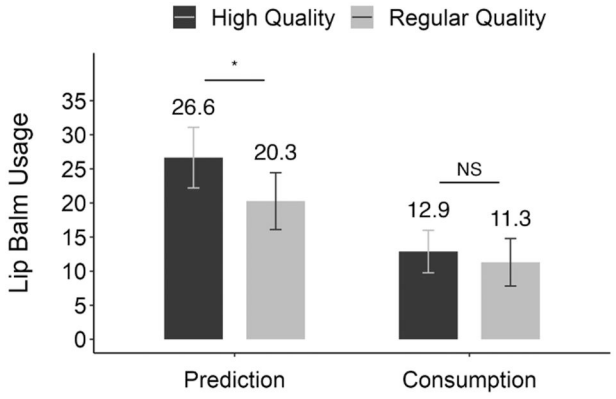
Since the order of product presentation did not interact with the manipulation ($F < 1$), we collapsed across the order conditions in our analysis.

5 Indeed, in a separate survey (N=100), we found that 74% of participants preferred the higher-quality lip balm (compared to 50%: $z = 4.70$, $p < .001$), and the preference rating was also higher for the higher-quality lip balm than for the regular-quality one ($M_{\text{High Quality}} = 5.34$, SD = 1.40, $M_{\text{Reg. Quality}} = 4.68$, SD = 1.37; $t(99) = -3.36$, $p < .001$, $d = .34$). However, we acknowledge that quality and preference are distinct constructs, and consumers may use quality differently than preference when estimating their consumption in other contexts, as we will further discuss in the general discussion.

6 This number did not differ by condition ($\chi^2 < 1$).

FIGURE 4

PREDICTED VERSUS ACTUAL LIP BALM USAGE IN STUDY 4



Quality Manipulation Check. As intended, a majority of participants (66%) perceived Beauty by Earth to be of higher quality (compared to 50%: $z = 3.74$, $p < .001$, 95% CI = [57%, 73%]), with only 7% of participants selecting Blistex instead. The remaining 27% indicated that they were of the same quality.

Consumption Amount. Participants generally overestimated how often they would apply the lip balm ($F(1, 149) = 69.99$, $p < .001$, $\eta_p^2 = 0.32$). More importantly, and as expected, actual lip balm use was less sensitive to the quality of the assigned lip balm than participants predicted, though this interaction effect was only marginally significant ($F(1, 149) = 3.11$, $p = .08$, $\eta_p^2 = 0.02$; figure 4). Although participants predicted that they would use the lip balm more often if they received Beauty by Earth ($M_{\text{High Quality}} = 26.6$, SD = 19.5, $M_{\text{Reg. Quality}} = 20.3$, SD = 18.7; $F(1, 149) = 4.20$, $p = .042$, $\eta_p^2 = 0.027$), their reported usage was similar regardless of the lip balm they had received ($M_{\text{High Quality}} = 12.9$, SD = 13.7, $M_{\text{Reg. Quality}} = 11.3$, SD = 15.6; $F < 1$).

Perception After Consumption. Even after using the assigned lip balm for a week, those who received Beauty by Earth still rated their lip balm as higher quality than those who received Blistex ($M_{\text{High Quality}} = 5.0$, SD = 1.1, $M_{\text{Reg. Quality}} = 4.5$, SD = 1.3; $F(1, 148) = 8.38$, $p = .004$, $\eta_p^2 = 0.054$). This suggests that the limited impact of the quality difference on actual consumption was not driven by the dissipation of the perceived quality difference itself.

In sum, study 4 provides evidence suggesting that consumers' overestimation of the impact of small quality differences can generalize to the repeated use of a product over an extended period outside the lab.

STUDY 5: SUBOPTIMAL PURCHASE DECISIONS

The objective of this study was to test a possible consequence of the prediction bias: suboptimal purchase quantity decisions. If consumers overestimate how much their consumption depends on how much they like a product, they may over-purchase a more preferred product or under-purchase a less preferred one. To test this idea, we again presented participants with a set of comics, but this time they had to first commit to the number of comics they wanted to request, after which they could only view the requested comics. As in study 2, for each comic requested, participants were asked to enter a captcha. In this study, however, they completed the captchas altogether, and they were explicitly told the number of captchas would be determined by the number of comics they requested. The idea was to make requesting a comic "costly" and to make the process similar to purchase situations. Then, following the actual viewing of the comics, they were asked whether they wished they had requested more or fewer than they had actually requested.

Method

A total of 471 undergraduate students participated in exchange for course credit (44% male). Unfortunately, 98 of these students either experienced technical problems or did not follow the instructions.[7] Responses from these participants as well as additional four outliers were removed from the analysis, leaving us with a total of 369 participants (see web appendix P for details about the data exclusion). The study used a 2 (funniness: more funny vs. less funny) × 2 (response: prediction vs. consumption) mixed design with funniness as the between-subjects factor.

In this study, we used two sets of comics varying in their level of funniness, as in study 2. Participants were first informed that they would be able to request comics to view during a 4-minute period and that they would have to enter as many 6-digit captchas as the number of comics they requested. They would not be able to view more comics than they had requested. Next, participants were shown five sample comics randomly drawn from the 50 comics of set A (the less funny set), after which they rated how funny they were (1 = *not at all funny*, 7 = *very funny*), and indicated how many comics they would commit to request if they were assigned set A (by entering a number between 0 and 50). They were then shown five comics randomly drawn from set B (the more funny set) and answered the

7 Participants were removed because they either (1) self-reported engaging in other activities, fast-forwarding the music, or experiencing technical problems during the comics-viewing experience ($n = 58$), (2) terminated the experience before the four minutes had elapsed ($n = 36$), or (3) received the wrong number of comics due to a programming error ($n = 4$).

same two questions. Participants then flipped a coin to determine the set they would receive, after which they entered as many captchas as they had committed to request from the assigned set.[8] During the next 4 minutes, they listened to piano music while viewing the comics they requested (without the option of viewing more than they initially committed to). After the 4 minutes had passed, they were asked to look back at their experience and indicate whether they felt they should have requested fewer or more comics than they actually did (−100 = *I should have requested a lot fewer*, 100 = *I should have requested a lot more*). Lastly, to again test the satiation account, we asked whether the comics they viewed during the 4 minutes were more or less funny than the comics they had initially sampled from that set (−4 = *much less funny*, 0 = *the same*, 4 = *much more funny*).

Results and Discussion

Manipulation Check. As intended, the sample comics from set B were rated as funnier than those from set A ($M_{\text{More Funny}} = 4.2$, SD = 1.5, $M_{\text{Less Funny}} = 3.1$, SD = 1.3; $t(367) = -13.0$, $p < .001$, $d = -0.676$).

Number of Comics Requested and Viewed. As predicted, participants requested more comics when they were assigned to the more funny set than when they were assigned to the less funny set ($M_{\text{More Funny}} = 15.5$, SD = 14.3, $M_{\text{Less Funny}} = 9.9$, SD = 8.5; $F(1, 367) = 20.6$, $p < .001$, $\eta_p^2 = 0.053$). Unlike in previous studies, the effect of the assigned set persisted for actual consumption: participants viewed significantly more comics when they had been assigned the funnier set ($M_{\text{More Funny}} = 13.9$, SD = 12.0, $M_{\text{Less Funny}} = 9.6$, SD = 7.9; $F(1, 367) = 16.3$, $p < .001$, $\eta_p^2 = 0.043$), though this difference was still less pronounced for consumption than for requested amount ($F(1, 367) = 9.94$, $p = .002$, $\eta_p^2 = 0.026$). It was to be expected that, compared to previous studies, consumption would more closely mirror prediction (request), since participants could not view more comics than they had requested and had no incentive to view fewer either (as entering the captchas was separated from the consumption stage, which made viewing costless).

Desired Corrections. More critically, the main objective of this study was to examine whether overestimating the impact of preference could result in suboptimal decisions, as reflected by participants' post-consumption evaluations of their decision. While participants generally wished they had requested more rather than fewer comics ($M = 15.2$, SD = 38.0; compared to 0; $t(368) = 7.69$, $p < .001$, $d = 0.40$), this happened to a greater extent for those who received the less funny set ($M_{\text{More Funny}} = 11.4$, SD = 35.6, $M_{\text{Less Funny}} = 19.3$, SD = 40.1; $F(1, 367) = 4.0$, $p = .046$, $\eta_p^2 = 0.011$). Consistent with our prior findings, this indicates that participants were especially likely to underestimate how many of the less funny comics they would want to view, resulting in an insufficient inventory of comics.

It should be noted that, due to the experiment logistics (web appendix O), some participants had to wait more than others after finishing the 4-minute experience and before proceeding with the dependent measures, which could have introduced noise by creating additional boredom. Indeed, when we limit the analysis to those who spent exactly 4 minutes on the task ($n = 243$), the effect of the preference manipulation on their desired correction of the purchase decision is more pronounced ($M_{\text{More Funny}} = 8.7$, SD = 33.4, $M_{\text{Less Funny}} = 20.3$, SD = 40.4; $F(1, 241) = 6.05$, $p = .015$, $\eta_p^2 = 0.024$; see web appendix Q for more detailed results by task duration).

Running Out of Comics. If participants who received the less funny comics were indeed more likely to have under-requested, they should also be more likely to have viewed all the comics they had requested (thus running out of comics to view). Consistent with participants' assessment of their decisions, we observe that those who received the less funny set were more likely to go through their entire requested inventory than those who received the more funny set ($M_{\text{More Funny}} = 86\%$, $M_{\text{Less Funny}} = 94\%$; $\chi^2(1) = 6.14$, $p = .013$, $\varphi = 0.129$). The full set of results is summarized in table 3.

Changes in Liking. Finally, we also examined whether participants liked the comics they ended up viewing (during the 4-minute period) more or less than those they had sampled from that set. Liking for the comics in the assigned set did change over time, and the nature of this change depended on the set they had been assigned ($F(1, 348) = 12.2$, $p = .001$, $\eta_p^2 = 0.034$). For those who received the better set, the comics viewed during the experience seemed even funnier than the sample ($M_{\text{More Funny}} = 0.4$, SD = 1.7; compared to 0: $t(180) = 3.0$, $p = .003$, $d = 0.225$), but for those who received the worse set, the comics viewed during the experience seemed even less funny than the sample ($M_{\text{Less Funny}} = -0.2$, SD = 1.5; compared to 0: $t(168) = -1.89$, $p = .06$, $d = -0.145$). This suggests that the liking difference increased rather than decreased over the course of the study, providing additional evidence against an unanticipated reduction in the difference in liking (e.g., by differential satiation).

In sum, this study indicates that the prediction error documented in the previous studies can lead to suboptimal decisions. Those who were assigned the less funny set of comics committed to requesting fewer comics and were,

8 Although most participants ($n = 227$) completed the captchas before consumption, a sizeable number ($n = 142$) completed them afterwards. We added this variation in order in case participants would have forgotten about the effort (cost) by the time they had to evaluate their decision. However, since the effect of the manipulation did not differ by order ($F < 1$), we collapsed across order conditions.

TABLE 3

COMICS REQUESTED, VIEWED, AND DESIRED CORRECTIONS (STUDY 5)

	More funny	Less funny	
Number of comics requested	15.5 (14.3)	9.9 (8.5)	$F = 20.6^{***}$
Number of comics viewed	13.9 (12.0)	9.6 (7.9)	$F = 16.3^{***}$
Desired correction	11.4 (35.6)	19.3 (40.1)	$F = 4.0^{*}$
Proportion of participants who viewed all comics requested	86%	94%	$\chi^2 = 6.14^{*}$

NOTE.—Standard deviations are in parentheses.
$^{*}p < .05$.
$^{***}p < .001$.

after the experience, more likely to state that they wished they had requested more (compared to those who had received the funnier set). These results illustrate that consumers' overestimation of the impact of their preferences on their consumption can lead them to underinvest in less preferred ones.

So far, we have demonstrated that people tend to overestimate the extent to which small differences in preference influence their consumption and that the overestimation can result in suboptimal quantity decisions. Our results suggest that this effect does not rely on the distinction bias, self-presentation concerns, the absence of consumption alternatives, the salience of prior preference ratings, unexpected mindlessness of consumption, or the misprediction of satiation. Although some of these mechanisms may certainly contribute to this bias, we propose that it is generally driven by an inherent focus on preference, which leads consumers to insufficiently account for the influence of other factors that affect consumption. In the next study, we examine whether we can reduce this prediction bias by drawing attention to such a factor, specifically the role of variety in reducing satiation.

STUDY 6: DEBIASING BY REMINDING OF THE ROLE OF VARIETY IN REDUCING SATIATION

So far, we have demonstrated that consumers excessively focus on their liking of a product when predicting how much of it they will consume. We suggest that preference is an intuitive determinant of consumption behavior because it is inherently a more salient, known, and normative factor than other drivers of consumption. Based on this assumption, we attempted to reduce this prediction bias by reminding participants of other drivers of consumption: specifically, how satiation can be addressed by variety. We note that satiation is not just another determinant of consumption amount. First of all, as liking often falls faster for things we like more (DePaoli and Khan 2014), it can reduce the preference gap between the more preferred and the less preferred options over time.[9] Moreover, satiation can encourage people to consume options they prefer less in addition to their favorites, as doing so will increase variety in their consumption, thereby slowing down the satiation (Sevilla, Lu, and Kahn 2019). Thus, considering how *variety can reduce satiation* should offset the impact of preference on consumption predictions.

In this study, participants predicted how many photographs they would view from a more or a less preferred set of photographs. However, prior to making their prediction, half of them were reminded of satiation and the role of variety in reducing it (variety to reduce satiation [VRS]). They read that one's enjoyment from repeated consumption of similar products tends to decrease over time and that one way to combat this decline in enjoyment is to increase variety. Then, they were asked to think about their experience of viewing the photographs and to predict the extent to which they would get tired of it (1) if they view photographs from only one book and (2) if they view photographs from both books. We expected that reminding participants of satiation and its relation to variety-seeking before predicting consumption amount would reduce the prediction bias. Specifically, the debiasing would be driven by a reduced difference in predicted amounts between the more and the less preferred sets, rather than changes in consumption.

Method

A total of 480 Mturk participants (44% male, M_{age} = 44.3) participated in the experiment in exchange for monetary compensation. We did not remove any observations and pre-registered this study on AsPredicted.org.[10] This study used a 2 (liking: more preferred vs. less preferred) × 2 (response: prediction vs. consumption) × 2 (reminder of VRS: yes vs. no) mixed design with liking as the within-subject factor. We counterbalanced the order in which the two photograph sets were presented to participants.

We used two sets of nature photographs: mountains and deserts. Participants first viewed five sample photographs that were randomly drawn from each set. They then rated how much they like the photographs from each set, respectively (e.g., "How pleasant or unpleasant was it to view photographs from set A [B]?"; $-4 = very\ unpleasant$, $0 = neither\ pleasant\ nor\ unpleasant$, $4 = very\ pleasant$) and indicated which set they liked better ($1 = set\ A$, $2 = set\ B$).

Participants were then informed that they would have access to two photograph sets just like the ones they sampled and that they could view as many photographs as

9 Though we did not find this pattern in our studies (see studies 3, 5, and 6), we do not preclude this possibility and consumers' intuition of it, given that experiences in our studies lasted only a relatively short time.

10 https://aspredicted.org/661_61R

they wanted. For the reminder manipulation, half of the participants (reminder condition) read that "no matter how much we like something initially, we tend to get bored with it after repeating the same type of experiences" and that "one way to fight boredom is to introduce variety." They then indicated how much they would get tired of it if they viewed photographs from only one set [both sets] ("How much do you think you would get tired of it if you view photos from only one set [both set A and B]?"; $1 = I$ *wouldn't get tired of it*, $7 = I$ *would get tired of it*). The other half (no-reminder condition) did not receive these questions.

We crossed this reminder condition with response type. Participants in the prediction condition predicted the number of photographs they would view from each set during the next 3 minutes. In contrast, those in the consumption condition did not make any prediction and proceeded directly to the viewing page, where they viewed as many photographs from the two sets as they wanted (appendix B). While these measures served as our key dependent variables, we also measured actual consumption after predictions in the prediction condition (figure 5) to conduct additional replication analysis of the overestimation bias within this condition. We report the replication in web appendix R.

Lastly, to test whether participants actually experienced satiation during the experience, we measured whether they enjoyed the photographs they viewed during the 3 minutes more or less than the five samples they viewed before they made predictions ("Did you find the additional photographs in set A [B] (i.e., the photographs you viewed during the 3 minutes) more or less enjoyable than the first five samples you viewed from set A [B]?" $-4 = less\ enjoyable$, $0 = the\ same$, $4 = more\ enjoyable$).

Results and Discussion

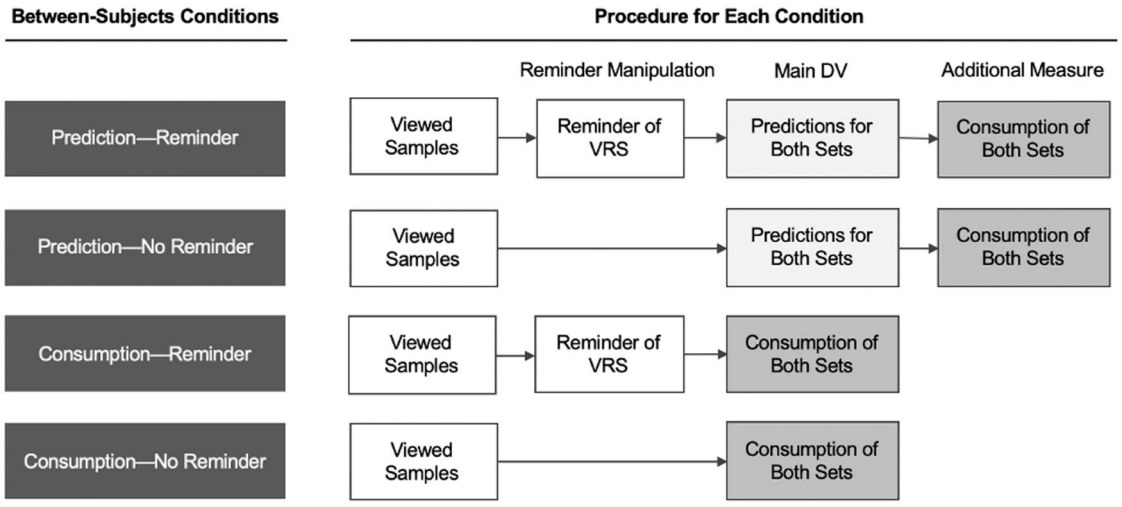
Intuition About the Impact of Variety on Satiation. Participants intuited that they would get less tired of the viewing experience if they were to view photographs from both sets, compared to only one set ($M_{\text{one set}} = 4.2$, $SD = 1.6$ vs. $M_{\text{both sets}} = 3.2$, $SD = 1.5$; $t(246) = 10.70$, $p < .001$, $d = 0.681$).

Liking × Response Type × Reminder Interaction. Replicating our finding that participants mispredict the impact of preference on consumption amount, a repeated-measures ANOVA revealed a significant interaction between liking and response type ($F(1, 476) = 4.16$, $p = .042$, $\eta_p^2 = 0.009$). However, as predicted, this two-way interaction was qualified by a significant three-way interaction, indicating that reminding participants of VRS attenuated their prediction bias ($F(1, 476) = 4.85$, $p = .028$, $\eta_p^2 = 0.010$, figure 6).

Next, we tested the prediction bias by the reminder conditions. First, replicating the prior studies, we found the prediction bias in the no-reminder condition ($F(1, 231) = 7.97$, $p = .005$, $\eta_p^2 = 0.033$). As in the previous studies, participants predicted that they would view more

FIGURE 5

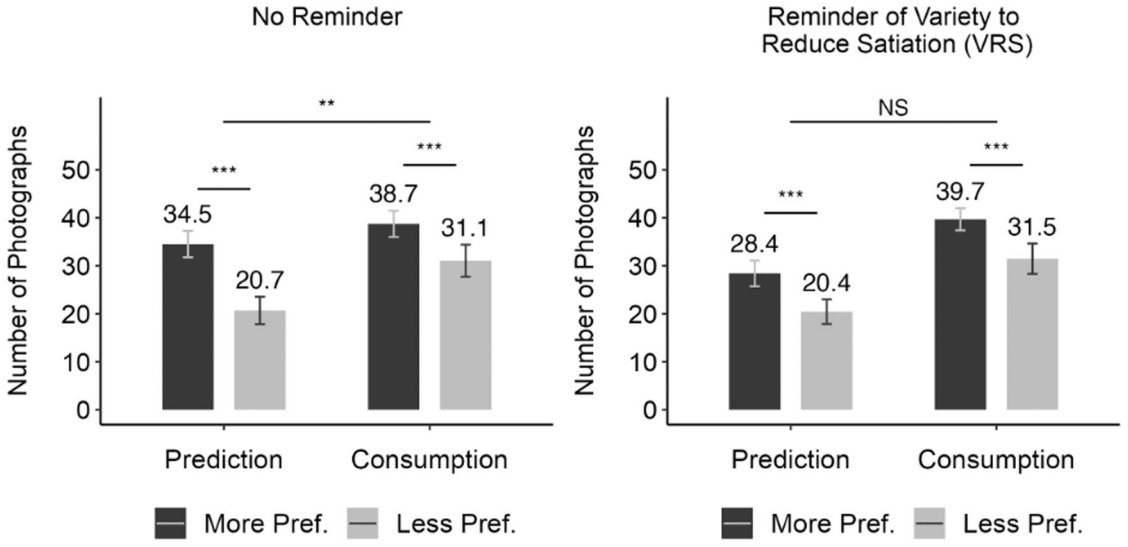
PROCEDURE OF STUDY 6



NOTE.—Black boxes on the left side indicate between-subjects conditions. The right side of the figure illustrates the procedure of the experiment for each condition.

FIGURE 6

THE EFFECT OF LIKING AND REMINDER ON THE NUMBER OF PHOTOGRAPHS PREDICTED TO BE VIEWED VS. VIEWED



photographs from the more preferred than from the less preferred set ($M_{\text{MorePref}} = 34.5$, SD = 15.5, $M_{\text{LessPref}} = 20.7$, SD = 16.0; $F(1, 231) = 84.20$, $p < .001$, $\eta_p^2 = 0.267$). Unlike most of the previous studies, participants did in fact view more photographs from the more preferred than from the less preferred set ($M_{\text{MorePref}} = 38.7$, SD = 14.7, $M_{\text{LessPref}} = 31.1$, SD = 18.1; $F(1, 231) = 24.12$, $p < .001$, $\eta_p^2 = 0.095$), although this difference was significantly less pronounced than they predicted. It is arguably not surprising that the effect of preference did not fully disappear during consumption, as participants now could actively choose to view from the set they preferred.

In the reminder condition, however, we found that the prediction bias was eliminated ($F < 1$). Though participants also predicted that they would view more photographs from the more preferred than from the less preferred set ($M_{\text{MorePref}} = 28.4$, SD = 14.9, $M_{\text{LessPref}} = 20.4$, SD = 14.2; $F(1, 245) = 32.98$, $p < .001$, $\eta_p^2 = 0.119$), this difference in the predictions between the sets was reduced significantly after the reminder and became similar to the difference between the sets in their actual consumption amounts ($M_{\text{MorePref}} = 39.7$, SD = 13.4, $M_{\text{LessPref}} = 31.5$, SD = 18.3; $F(1, 245) = 38.21$, $p < .001$, $\eta_p^2 = 0.135$). Specifically, in the reminder condition, participants predicted they would view about eight more photographs and, in fact, did view about eight more photographs from the more preferred than the less preferred set on average.

Finally, we confirm that the elimination of the prediction bias results from a decreased impact of preference on prediction rather than an increased impact of liking on actual consumption. The effect of preference on prediction was significantly reduced (from approximately 14 to 8 photographs) when participants were reminded of VRS ($F(1, 237) = 8.99$, $p = .003$, $\eta_p^2 = 0.037$). However, the reminder did not change the impact of liking on the actual number of photographs viewed ($F < 1$).[11]

Changes in Liking. We also examined whether the photographs they viewed during the 3 minutes were more or less enjoyable than the sample. Participants indeed change how much they liked the photographs from both sets. However, instead of experiencing satiation, participants reported that the photographs viewed during the experience were even more enjoyable than the sample both for the more preferred set ($M_{\text{MorePref}} = 1.7$, SD = 1.8; compared to 0: $t(479) = 20.19$, $p < .001$, $d = 0.921$) and for the less preferred set ($M_{\text{LessPref}} = 0.7$, SD = 1.7; compared to 0: $t(479) = 8.67$, $p < .001$, $d = 0.395$). While the magnitude of this change varied by set ($t(479) = 10.23$, $p < .001$, $d = 0.467$), the increase in liking was greater for the more preferred than for the less preferred set, resulting in a greater liking gap between the sets. This further provides evidence that the prediction bias is not driven by an unanticipated

11 As additional measure, participants in the prediction condition also viewed photographs for 3 minutes after making predictions. The additional analysis, comparing predicted and actual consumption amounts within participants in the prediction condition, revealed the same results. See web appendix R for details.

reduction in the difference in liking over time (i.e., by differential satiation).

GENERAL DISCUSSION

Many consumer decisions require us to predict how much we will consume. For instance, we may have to decide how many cherries to purchase at a fruit stand, choose a popcorn bucket size at a movie theater, select the number of events to include in a season pass, or decide whether to pay extra for a premium tier of service that increases the amount of content (music, videos, games, etc.) we can consume. Although many variables may affect consumption, we have proposed that consumers will particularly focus on how much they *like* the product—as this liking tends to be salient, known, and a normatively appropriate driver of consumption. You expect to eat more cherries when you like them more, and you expect to play more games when you enjoy them more. Yet, while this may be accurate for large differences in liking (e.g., products they dislike versus like), our studies indicate that when the difference in liking is small it has surprisingly little impact on actual consumption amounts.

Across six studies, we find that participants systematically overestimate how much their preference for a product will influence their consumption amount. This holds true for a variety of products (jellybeans, comics, photographs, and lip balm), when participants are only aware of one product (study 2), when both products are available during consumption (study 6, supplemental study 2), when there are other products they can consume instead (study 3), both inside and outside the lab (study 4), and when predictions are incentivized for accuracy (supplemental study 1). Moreover, this undue focus on preference can lead participants to make suboptimal quantity decisions (study 5).

We have proposed that preference enjoys a privileged status as a predictor since it is salient, known, and perceived to be an appropriate driver of consumption—this is less applicable to many other drivers of consumption, such as temporary motivational states, usage opportunities, or accessibility in memory. For instance, consumers may be immediately aware of how much they like a jellybean flavor or a set of comics, but they are less likely to anticipate how hungry or bored they will be. Based on this reasoning, we assumed that we could debias participants by making these other factors salient (study 6). Specifically, by asking participants to think about how much they would get tired of the experience for both situations where they view photographs from only one set or from both sets, we prompted them to realize how satiation could be reduced by consuming less preferred options as well as the more preferred ones. This study suggests that only when people are explicitly reminded of factors that would undermine the effect of liking itself will they adjust their reliance on preference during prediction.

Similarly, in a follow-up study (supplemental study 4, web appendix E), we reminded participants of another driver of consumption, *boredom*, by asking participants to indicate how bored they would be if they would not view any comics during the session. Yet, rather than reducing the effect of preference, this manipulation *reversed* the effect of preference: participants who had considered boredom predicted they would view more comics if they had been assigned to the less funny set (rather than more funny set)—presumably because they expected to need more comics to provide sufficient entertainment. This suggests that people can be nudged to take other factors into account by making them more salient, but this does not mean that they will stop relying on preference. These results suggest that it is challenging to steer consumers away from relying on preference when forecasting consumption amounts, which attests to the privileged status of preference as an intuitive determinant of consumption behavior.

Another way to attenuate the prediction bias is to introduce an intervention that would more align consumption with preferences, versus attempting to adjusting consumers' predictions to be more in line with their actual behavior. We theorize that, unlike predictions, actual consumption behavior is driven by many other circumstantial and incidental factors, which weakens the impact of preference on the amount people consume. Based on this reasoning, we expect that consumption could be more discerning if an external cue would constantly remind consumers of their preference or of the quality of the product while they consume it. One possible way marketers could remind consumers of product quality or preference is through product packaging. For example, even though a consumer may prefer Duvel beer slightly more than Blue Moon, he would drink similar amounts of both beers. However, to the extent that a beer mug bearing the brand logo constantly reminded him that he is drinking his favorite beer, perhaps he would drink more than he would have otherwise.

Alternative Accounts

As we have discussed earlier, participants may be wrong about their liking itself (or the enduring strength of their liking) rather than being wrong about the impact of preference. We initially considered this as a likely explanation. However, we did not observe a decrease in the liking gap during the consumption stage in studies 3, 5, and 6. In fact, we found the liking gap increased during the consumption period, but still participants' consumption amount was not

tied to their preferences as much as they thought (or not at all). Furthermore, when we observed consumption of jellybeans over time (supplemental study 3, web appendix D), we also found that consumption became more aligned with preference over time, which is the opposite of what the satiation account would predict.

Another explanation for the prediction error is a cold-to-hot empathy gap: our limited ability to fully appreciate how we would behave when we are in a more visceral, emotional state, such as experiencing anger, hunger, sexual arousal, or boredom (Loewenstein, O'Donoghue, and Rabin 2003). For instance, when we are satiated, we may underestimate the extent to which feelings of hunger can lead us to consume less preferred food; and when we are currently entertained, we may underestimate how much boredom will make us seek out content, even if it is mediocre. Although we view the cold-to-hot empathy gap as one mechanism that can lead consumers to overestimate how discerning their consumption will be, we do not consider it as a necessary condition. That is, it is unlikely that participants in our studies overestimated the impact of preference on their consumption of comics because they could not fully anticipate what it would feel like to be truly bored during the actual experience. In fact, in supplemental study 5 (web appendix F), we found that, even when participants experienced a motivational state that is a key driver of consumption (i.e., boredom) immediately before making predictions, neither did it change their predictions nor reduce the impact of their preference for the assigned comics. This suggests that the key problem does not seem to be an inability to imagine this motivational state, but rather an inability to spontaneously take it into account (unless explicitly primed with it).

Theoretical Contribution and Practical Implications

The present research builds on, and extends, classic findings in judgment and decision-making, social psychology, and consumer research. Our findings most closely mirror Kahneman and Tversky's (1973) observation that predictions are often insufficiently regressive due to people's reliance on the representativeness heuristic. When predicting their future consumption, people directly translate the most salient input—how much they like a particular product—into a consumption amount, without sufficiently regressing this prediction to account for additional factors that muddy the relationship between liking and consumption. This perspective is also similar to the concept of "attribute substitution": consumers replace the difficult task of predicting consumption amount with the easier question of how much they like the product (Kahneman and Frederick 2002). This is also consistent with the idea that people often make difficult numeric estimates (e.g., calorie content) by relying on their qualitative judgments, such as whether the option is good or bad (Chernev and Gal 2010). It should be noted that while our effects can be aptly described as examples of insufficiently regressive predictions, they do require the additional assumption of liking as a privileged predictor. That is, we show that consumers rely on liking even when it shows only minor variation, while simultaneously under-weighting other factors even when having some information on these factors (e.g., their current hunger, duration of consumption)—unlike in the Kahneman and Tversky (1973) studies, in which participants only had a single predictor available to them.

Our findings are also in line with a long-standing literature in social psychology on the disconnect between attitudes and behavior (Ajzen and Fishbein 1977; Chaiken and Stangor 1987; LaPiere 1934; Wicker 1969). While this literature has mostly focused on how social behavior tends to be highly contextualized (and thus not as strongly determined by the underlying social attitude), our studies indicate that this also applies to attitudes toward products and consumption behavior. Furthermore, our findings indicate that people do not intuitively understand this disconnect between attitudes and behavior, and thus underestimate the extent to which consumption is driven by contextual factors rather than by their liking of the product.

The current research also contributes to the extensive literature on consumer forecasts of hedonic experiences. While prior research in this area has largely focused on predictions of enjoyment (i.e., affective forecasting), we focus on predictions of consumption amount. On the one hand, our research indicates that consumers treat these two predictions as highly similar. That is, they expect their consumption amount to mostly depend on their enjoyment. On the other hand, the nature of consumers' prediction error is quite different for these two types of predictions. In affective forecasts, people tend to focus too much on contextual variables and under-weight the essence of the experience (e.g., they focus on the probability of winning rather than the joy of winning itself; Buechel et al. 2014). In contrast, we observe that when consumers predict consumption, they overly focus on the essence of the product (how much do I like it?) and under-weight the many contextual variables that influence consumption (such as momentary hunger, boredom, distraction, consumption opportunities, etc.).

This research also adds to the literature examining purchase quantity decisions and consumption quantity. Predictions about consumption amount are closely related to both purchase quantity decisions and actual consumption amounts, and prior literature has often used these terms interchangeably. However, consumption predictions are distinct from purchase quantity decisions, and as we demonstrate, they often deviate from actual consumption. Consumption prediction is an internal anchor that consumers rely on to make purchase quantity decisions, similar to the other external factors (e.g., bulk discounts, purchase quantity limits), and it sometimes nullifies the impact of these external factors on purchase decisions (e.g., see study 3 in Wansink et al. 1998). Our findings shed light on a disconnect between quantity predictions and consumption quantity and the implication of this disconnect on the quality of purchase quantity decisions (i.e., suboptimal quantity decision).

Aside from contributing to these different literatures, the current research also has important implications for consumer welfare. First, consumers' undue focus on their preferences may prevent them from optimally managing their inventory. They may over-purchase products they are particularly fond of, but under-purchase products they like somewhat less. These errors may be mitigated by encouraging consumers to also consider other drivers of consumption. For instance, a consumer may be less likely to splurge on dazzling stiletto shoes when she is forced to consider how soon she will get tired of them or how rarely occasions will arise that she can wear them. Conversely, when buying snacks for a long trip it may be good to consider the length of the trip and the lack of other food options along the way, rather than focusing on the mediocre quality of the available snacks. Second, consumers' exaggerated focus on their preferences may also lead them to adopt ineffective strategies to manage their consumption. Buying premium rather than regular fruit probably does not increase your fruit intake as much as you would expect. Similarly, canceling your streaming services, leaving you with inferior TV programming with commercial interruptions, probably does not decrease your TV viewing as much as you would hope for. Rather than trying to manage their consumption by managing the quality of their options, consumers may be better off focusing on goal reminders and alternative activities.

Consumers' biased forecasting of their consumption behavior also holds implications for marketing managers. Our results suggest that sellers of less-popular or lower-quality brands (e.g., private labels) should attempt to increase consumers' expected consumption, both by enhancing the attractiveness of their products and by highlighting factors unrelated to liking, such as variety-seeking. As for popular or higher-quality products, although our findings suggest that consumers will buy more of them, this bias still may have adverse consequences for sellers of premium products. Although it is certainly beneficial in the short run if consumers over-purchase their product, there is always the risk that consumers may infer that they do not really like their product as much as they thought when they struggle to consume all they have purchased. If my fondness for Belgian chocolates leads me to purchase them in large quantities, the surprising difficulty of working my way through my entire purchase may make me reconsider my love for these chocolates. As such, premium brands do not only benefit from offering small quantities because of the association with scarcity and sophistication, but it may also help consumers to avoid over-purchasing. Finally, premium brands in categories perceived as guilty pleasures (e.g., chocolates or wine) should also be aware that consumers may be more inclined to switch to more mediocre alternatives when they aim to limit their consumption in these categories. However, consumers may simultaneously also hold the countervailing lay belief that they need fewer pieces of a premium product (than of a less preferred alternative) to achieve the same level of utility. This implies that premium brands in a sinful category could position themselves as facilitating self-control ("I'll drink less wine if I drink better wine") rather than undermining it ("I'll drink more wine if I drink better wine").

Boundary Conditions and Directions for Future Research

Admittedly, the prediction bias depends somewhat on the fact that the task of estimating consumption amounts is difficult—especially when the unit of consumption is small. As mentioned earlier, this difficulty with quantity estimation can make people rely more on qualitative information, or replace it with easier question they can answer with known information (e.g., how much they like it). Our findings suggest that people rely unduly on preference compared to other qualitative information or known factors (e.g., how hungry they are). However, to the extent that the bias relies on the inherent difficulty of making quantity estimates, we expect that our effect could be reduced or even eliminated when it is easy for people to predict their consumption amount. For example, when consumption is rationed or scheduled (e.g., an apple a day), consumers

would be able to easily calculate their future consumption amount. Also, when explicit information about previous consumption amount is available, people may be able to rely on that number which would be salient, known, and normatively appropriate to anchor on—just like their preference. To the extent that these diagnostic quantity anchors are salient, they would offset the effect of preference on predictions.

Furthermore, our research focuses almost exclusively on the consumption of products that are liked. Arguably, people consume products they like (or at least mildly like) in most consumption situations, which makes this prediction bias (i.e., the overestimation of the impact of preferences) relevant in many cases. However, people sometimes consume products they do not like—especially when the product is necessary or purely made for utilitarian purpose (e.g., a vacuum cleaner, medicine). We expect that the effect would be attenuated in these situations, as preference would not be a primary reason why the product is consumed, making preference less salient, and less normatively appropriate to consider. Still, future work should examine whether people show the same prediction bias even when the product is purely functional or mildly disliked.

Future research might also examine the effect of price or anchor-based promotions on consumption predictions. We predict that, although these factors would influence consumption predictions, the extent to which promotions or discounts influence predicted consumption could also depend on how much consumers like the product. For example, consumers may inaccurately predict that they would increase consumption more dramatically when the price for their favorite product is discounted compared to a product they like less. Although stockpiling of both more preferred and less preferred options can increase the rate of consumption by the heightened product salience (Chandon and Wansink 2002), our findings would suggest that consumers may not predict it because future product salience is difficult to foresee and less normatively appropriate. This might prevent consumers from stockpiling a discounted product they do not particularly prefer which they would have otherwise consumed.

Lastly, we employed product quality as an operationalization of preference in study 4, assuming that participants would generally prefer to receive higher-quality products over lower-quality ones. In fact, quality and liking can be correlated, aligning with the perspectives in standard economic models that often associate higher preference with higher quality (Anderson 2008). However, we acknowledge that preference and quality could be orthogonal, and consumers may not overestimate the impact of quality in the same way they do with liking (or not at all). While quality could be another normative factor for estimating consumption quantity, it remains less clear whether quality information is as readily available, known, or salient as one's preference. The availability and salience of quality may depend on other factors such as consumers' expertise in the domain. In this regard, consumers may overly rely on quality, similar to liking, especially when they possess sufficient knowledge to appreciate quality or when it is made salient by firms. Moreover, as higher quality may imply a higher price, consumers may not necessarily overestimate their consumption of higher-quality products due to budget constraints. Future research could explore the role of quality and shed light on various mechanisms by which quality influences consumers' predictions and quantity decisions.

DATA COLLECTION STATEMENT

Data were collected using the NYU Stern Marketing Department Subject Pool, the paid pool of the NYU Stern Behavior Lab, Amazon Mechanical Turk, and Prolific from the autumn 2015 to the autumn 2022. Trained research assistants at New York University collected data for the lab studies (studies 1, 2, 3, 4, 5, pilot study, and supplemental studies 1, 2, and 3) under the supervision of the first author. The first author managed the collection of data using Mturk for study 6 and supplemental studies 4 and 5. The first author managed the collection of data using Prolific for supplemental study 6. The first author analyzed all studies and discussed the results with the second author. Data files and study materials are available at https://researchbox.org/207.

APPENDIX A

LIP BALM DESCRIPTION USED IN STUDY 4

Beauty by Earth Peppermint Beeswax Lip Balm

$2.60

DESCRIPTION

- REFRESH YOUR SMILE: Best for healing cracked, chapped lips with vitamin E and shea butter for intensive moisture. This delicious creamy balm is the perfect set for men. women and kids. Revitalize your smile with our light eco friendly minty salve.
- ORGANIC AND GLUTEN FREE: Every tube of luxury lip balm we make is filled with 100% certified organic ingredients. That means you'll never have to worry about what you're putting on your lips.
- NOURISH AND PROTECT: Spending time out in the sun or wind... Your lips need good hydration. Our balm gives you essential protection no matter your environment by creating a barrier between you and the elements.

Blistex Lip Balm

$0.93

DESCRIPTION

- Helps prevent dryness and chapping to soothe irritated lips.
- Temporarily protects and helps relieve chapped or cracked lips.
- Helps prevent sunburn.
- Contains three long-lasting protectants, seals in moisture to alleviate dryness and prevent reoccurrence.
- Glides on comfortably to provide complete coverage and avoid further irritation of chapped lips.

APPENDIX B

STIMULI USED IN STUDY 6: A SCREENSHOT OF THE PHOTOGRAPHS VIEWING PAGE

Set A
Photographs of Mountains

1	2	3	4	5	6	7	8	9	10
11	12	13	14	15	16	17	18	19	20
21	22	23	24	25	26	27	28	29	30
31	32	33	34	35	36	37	38	39	40
41	42	43	44	45	46	47	48	49	50

Set B
Photographs of Deserts

1	2	3	4	5	6	7	8	9	10
11	12	13	14	15	16	17	18	19	20
21	22	23	24	25	26	27	28	29	30
31	32	33	34	35	36	37	38	39	40
41	42	43	44	45	46	47	48	49	50

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