Decision Making in Applied Contexts: The Dynamic Relations Between Signals and Stakes

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Abstract

This paper explores decision-making with multiple signals in applied contexts, focusing on online shopping with consumer feedback. The richness of crowdsourced information and the growth of e-commerce highlight the importance of understanding how different consumer feedback signals are weighted across product types. Participants allocated 100 points among eight common consumer feedback signals for products differing in emotional, commitment, and monetary values. A pilot study confirmed the product choice validity, assessing a separate group of participants' inclination to purchase target products for emotional needs and long-term use. Results reveal an increased reliance on crowdsourced information weight heightened decision stakes. While the overall signal importance ranking remains consistent across products, negative information gains significance, and average ratings diminish in importance for high-stakes decisions. The findings carry theoretical and practical implications, shedding light on the nuanced decision dynamics in applied contexts.

Keywords: Decision making, signal weighting, Consumer feedback

Introduction

Decision-making in applied contexts is both intriguing and indispensable. The present paper focuses on online shopping for two primary reasons. First, online shopping, especially when coupled with consumer feedback, offers a dynamic and immersive environment for us to explore how people weigh various signals in their decision-making processes. Second, the prevalence of online shopping, which has become a routine for many, adds necessity and urgency to the current exploration. The behavioral shift caused by COVID-19, along with busy lifestyles, has led to substantial growth in online shopping. In the U.S., the online retail share surged from 5% to 15% between 2011 and 2020. Globally, spending on e-commerce exceeded \$4.9 trillion in 2021, with projections estimating a further rise to \$7 trillion by 2025 (Diaz-Gutierrez et al., 2023).

The significance of ratings and reviews in shaping consumer decisions cannot be overstated. While there is a consensus that these factors collectively impact decision-making processes, variations arise when examining individual signals such as rating valence, volume, and variance (Floyd et al., 2014; Purnawirawan et al., 2015). Consumer feedback, an umbrella term that encompasses ratings (quantitative information) and reviews (qualitative information), contains variety even within these two broad types. Ratings include at least valence, volume, and variance, while reviews capture things such as sentiments and relevance. In the extensive literature on consumer feedback systems, a robust finding is the influential role of review volume in driving sales (Duan et al., 2008). As social animals, people often exhibit herd behavior, opting for more popular products, even when they are statistically confirmed to be of lower quality (Powell et al., 2017). Surprisingly, for average ratings – the signal that typically comes to mind when it comes to consumer feedback – differential effects have been observed. While a one-star increase on Yelp.com correlates with a 5-9% revenue growth (Luca, 2016), average ratings do not reliably predict movies' box office revenues (Duan et al., 2008). Consumers believe things can be "too good to be true," with the highest purchase likelihood occurring when the average rating is between 4.2 and 4.5 stars (Collinger, 2016). Experimental variations, such as the presence of other types of signals, could have contributed to some of the discrepancies. Additionally, differences in industry nature and the products they offer may serve as a critical source of the observed inconsistencies as well.

This paper addresses a crucial question: do people assign different importance weights to various signals based on the product type? Research suggests that not all signals are perceived equally (Mudambi & Schuff, 2010). For utilitarian products where a consistent taste is expected, average ratings can serve as a relatively reliable cue for predicting outcomes, leading consumers to prioritize this signal. In contrast, for hedonic products where taste dissimilarity is anticipated and sometimes preferred, consumers may place greater emphasis on understanding fellow consumers' prior experiences in depth. This distinction in expectations is further evident in how people interpret negative reviews, attributing negativity to product-related reasons for utilitarian products and reviewer-related reasons for hedonic products. Additionally, decision-makers seek similarities to such an extent that their decisions are influenced by coincidences, like shared birthdays and birthplaces (Burger et al., 2004). Hence, it also makes sense to hypothesize that signals other than aggregated statistical information, such as the most relevant review to the searcher, will also hold significant weight among various signals. This question also carries significant practical implications, as practitioners often ponder how to leverage consumer feedback systems and prioritize information that can effectively facilitate consumer decision-making.

Product Dimensions

While products can be categorized along various dimensions, we selected three common ones based on both previous literature and personal experiences: emotional, commitment, and monetary. Rather than encompassing the entire spectrum of products, these three dimensions serve as a good starting

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point to investigate whether consumer feedback signals hold varying levels of importance depending on product type. For simplicity, the term “products” in the remainder of this paper refers to both goods and services.

Emotional: Beyond functionality, products fulfill emotional needs such as identity signaling and self-expression. For instance, individuals purchase designer bags to signal to the world their status, styles, and aesthetics. The purchases serve as a fashion statement. An illustrative example of how certain products satisfy emotional needs can be seen in Season 3 Episode 4 of the comedy show *Friends,* where Monica and Rachel provide Chandler with ice cream to console him over his relationship issues. They even had tiers of ice cream prepared for different levels of crises, starting with low-cal, non-dairy, and soy-based options for non-terminal issues to the “real” ice cream when damage cannot be repaired.

Commitment: The commitment to products varies significantly based on individual consumption goals and product characteristics. Disposable items, designed for single use before recycling or disposal, contrast with durable appliances like fridges and microwaves, meant for prolonged use. While theoretically, one can replace appliances after each use, it is not a common practice.

Monetary: Purchases exhibit variations in cost. While the average cost of an energy drink is $2.50 - $5.00 for a 16-ounce can (of course, if individuals drink one energy drink per day, it adds up to a large sum annually as well), the average of a washer and dryer set is $1,000 to $2,300.

All these three dimensions represent gradients as opposed to dichotomies (e.g., a product either offers emotional value or not). Take the emotional value of cars as an example, some owners purchase cars simply for commuting purposes, whereas others purchase them to signal status and wealth, loving how they feel about themselves behind a steering wheel. Similarly, while “diamonds are a girl’s best friend,” guys may feel differently about these shining tones. For commitment value, people vary in how often they would like to replace their wardrobes, some get new clothes for every new season while others only purchase when the current ones are worn out. While emotional, commitment, and monetary values are relative, the monetary value is more quantifiable than the other two. Taken together, a pilot study was conducted to ensure the validity of our experimental constructs. We wanted to make sure that there is overall consistency across perceptions towards the emotional and commitment value of chosen products.

Pilot Study

A pilot study was conducted to confirm that the eight selected products for the experiment did indeed vary in terms of emotional, commitment, and monetary values.

Participants. One hundred thirty-four students from a major university in Canada completed the pilot study as part of course requirements.

Materials. Table 1 shows the eight products, differing across three dimensions – emotional, commitment, and monetary.

Procedure. Participants evaluated each product for its emotional and commitment value. For emotional value, they indicated the extent to which they purchased [product name] to experience emotions such as happiness, sadness, etc. Regarding commitment, participants indicated the extent to which they intended to stick with the chosen [product name] for an extended period. Responses were recorded on a 7-point Likert scale, ranging from 1 (not at all) to 7 (very much).

Table 1. Product variations across three dimensions.

Monetary: Low

Commitment / Emotional	Low	High
Low	Energy Drink $3 - $10	Calculator $10 - $30
High	Ice Cream $5 - $10	Decorative Wall Art $20 - $40

Monetary: High

Commitment / Emotional	Low	High
Low	One-time Moving Company Service $500 - $700	Washing Machine $800 - $1100
High	Luxury Massage $300 - $400	High-end Shoes $500 - $700

Results. A series of one-sample t-tests were conducted to compare average responses with 4, the mid-point of a 7-point Likert scale. Products with significantly below (above) 4 responses were considered to be at a low (high) level of the corresponding dimension. Pilot data confirmed our product selection (ps < .05), affirming that the three dimensions captured distinct aspects of a product and that the eight products fell into their respective cells.

Experiment

This experiment explored signal importance variations across distinct product types, representing diverse decision contexts.

Participants. Data were collected from 101 Prolific users who met the following requirements: 1) Located in the U.S. or Canada, and 2) have had at least 300 successful submissions with over a 99% approval rate on Prolific.

Materials. We reviewed numerous consumer feedback systems and identified eight common signals, spanning across quantitative and qualitative information: 1) average ratings, 2) the number of reviews, 3) amount of 1-, 2-, 3-, 4-, and 5-star ratings, respectively, 4) the most helpful positive reviews overall, 5) the most helpful negative reviews overall, 6) the most helpful positive reviews from the past month, 7) the most helpful negative reviews from the past month, and, 8) the most relevant review (based on the searcher). The difference between the most helpful positive (negative) review overall versus from the past month lies in recency. "Most recent" is provided by many sites as a sorting method. People prioritize ratings and reviews from the past 2-4 weeks (BrightLocal, 2023). Hence, we were interested in exploring differences in the significance of the most positive (negative) review overall versus from the past month. Consumer feedback signals and products were randomized.

Procedure. Prolific users allocated 100 points among eight signals for eight purchases in the pilot study. The most important categories received the highest number of points. Equal points were allowed, with the option to allocate 0. Participants were instructed to approach each situation as they would in real life. For purchases where participants typically would not rely on consumer feedback, they were asked to imagine doing so and allocate points accordingly. Additionally, participants also indicated their likelihood of relying on consumer feedback for each product, ranging from extremely unlikely to extremely likely.

Results

In brush strokes, people's reliance on consumer feedback varies by product type, as shown by a chi-square test, $X^2(42, N = 101) = 293.1$, $p < .001$. Table 2 displays the frequency of participants selecting the likelihood of viewing consumer feedback for a target purchase. Visual inspection suggests that product costs drive the likelihood of consulting consumer feedback, and a chi-square test confirmed this intuition, $X^2(6, 101) = 235.4$, $p < .001$. The shift in the likelihood of viewing suggests that while people rely on ratings and reviews, their reliance increases with the cost of purchases.

Having established differences in people's reliance on consumer feedback by product type, we sought to understand the varying importance of signals and patterns across different products. This question can be addressed from two angles: analyzing the importance ranking of the eight signals and examining the points allocated to each signal across different levels of emotional, commitment, and monetary value. As the results remained consistent when considering all responses compared to only those indicating at least a slight likelihood of viewing consumer feedback for the target purchase, we reported the findings based on all responses.

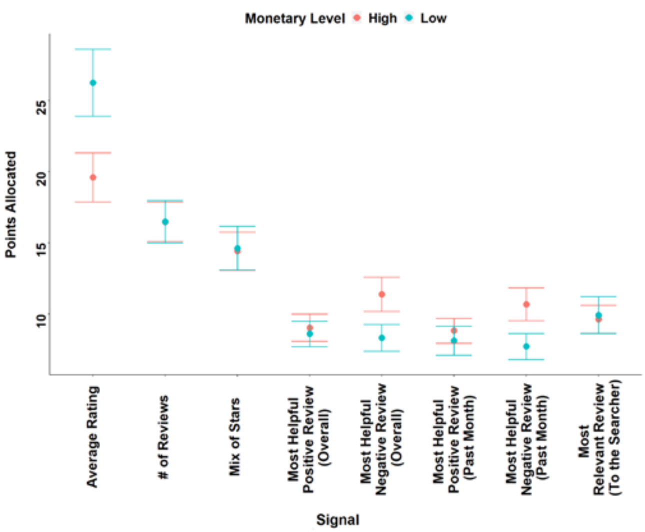
To assess the impact of emotional, commitment, and monetary value on the use of consumer feedback signals, we started with the most comprehensive linear-mixed effect model. This model featured a four-way interaction between signal types, commitment value, emotional value, and monetary value, along with all the relevant sub-terms (e.g., two-way and three-way interactions) as fixed effects. Participants were included as a random effect. We performed model selection using the "step" function in R. The final model selected is a simpler one with signal types, monetary value, and their interaction as fixed effects. The two-way interaction between signal types and the monetary level was significant, $F(7, 6448) = 10.185$, $p < .001$. This suggests that the importance of signals varies depending on the monetary level involved.

Table 2. Participant likelihood choices for viewing consumer feedback for target purchases.

	Extremely Unlikely	Moderately Unlikely	Slightly Unlikely	Neither	Slightly Likely	Moderately Likely	Extremely Likely
Calculator ($10 – 30)	11 (11%)	4 (4%)	3 (3%)	9 (9%)	26 (26%)	31 (31%)	17 (17%)
Decorative Wall Art ($20 – 40)	13 (13%)	14 (15%)	9 (9%)	7 (7%)	22 (22%)	19 (19%)	17 (17%)
Energy Drink ($3 – 10)	19 (19%)	11 (11%)	3 (3%)	15 (15%)	17 (17%)	25 (25%)	11 (11%)
Ice Cream ($5 – 10)	13 (13%)	12 (12%)	10 (10%)	10 (10%)	19 (19%)	25 (25%)	12 (12%)
High-end Shoes ($500 – 700)	5 (5%)	5 (5%)	3 (3%)	2 (2%)	9 (9%)	22 (22%)	55 (55%)
Luxury Massage ($300 – 400)	2 (2%)	1 (1%)	1 (1%)	6 (6%)	13 (13%)	24 (24%)	54 (54%)
One-time Moving Company Service ($500 – 700)	1 (1%)	0 (0%)	0 (0%)	3 (3%)	8 (8%)	19 (19%)	70 (70%)
Washing Machine ($800 – 1100)	2 (2%)	0 (0%)	0 (0%)	2 (2%)	4 (4%)	18 (18%)	75 (75%)

Note. Cells represent the frequency of participants selecting the likelihood of viewing consumer feedback for a target purchase. Proportion in cells = $\frac{cell\ value}{number\ of\ participants\ (N=101)}$.

There was also a significant main effect across various types of signals, $F(7, 6448) = 118.4$, $p < .001$, indicating that the eight signals hold different weights in decision-making processes. The significance of the two terms is robust, as supported by the results of 1000 bootstrapped samples. For post-hoc tests of the interaction between signal types and the monetary level, we conducted pairwise comparisons with Tukey adjustments. Three comparisons yielded significant results: 1) Participants allocated <u>fewer</u> points to average ratings when the monetary value was high ($M = 19.59$, $SD = 17.60$) than when the monetary value was low ($M = 26.23$, $SD = 23.98$), $t(6448) = -7.06$, $p < .001$. 2) Participants allocated more points to the most helpful negative review overall when the monetary value is high ($M = 11.38$, $SD = 12.28$) than when the monetary value is low ($M = 8.32$, $SD = 9.61$), $t(6448) = 33.252$, $p = .0012$. 3) Participants allocated more points to the most helpful negative review from the past month when the monetary value is high ($M = 10.68$, $SD = 111.89$) than when the monetary value is low ($M = 7.71$, $SD = 9.37$), $t(6448) = 3.158$, $p = .0016$. All the remaining five comparisons across signals at high versus low monetary levels did not differ, *ps* > .1 (Figure 1). Simply put, as products become more expensive, average ratings become less important for shoppers while negative sentiments (including from both overall and the past month) become increasingly more important in their decisions. The absence of two-way interactions between signals and commitment, as well as signals and emotional value, implies that the levels of emotional and commitment value had no impact on the number of points received by each signal.



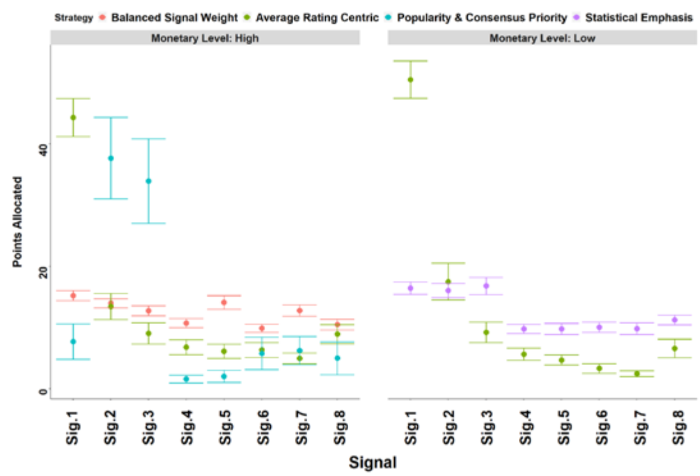
Note. Due to space constraints, “the number of reviews” was relabeled into “# of reviews” and “the amount of 1-, 2-, 3-, 4-, and 5-star ratings” was relabeled into “mix of stars.”

Figure 1. The allocated points to various signals indicate their significance, with higher points denoting more crucial roles in decision-making. Red (blue) data points illustrate point allocation for high-cost (lost-cost) purchases. As purchase costs increased, negative information gained increasing importance, while the importance of average ratings significantly diminished as product costs escalated.

Analyzing the main effect of signals revealed a consistent trend across products, with average ratings, the number of reviews, and the amount of 1-, 2-, 3-, 4-, and 5-star ratings as the top three important signals. At an aggregated level, the top 3 secured their positions with a substantial margin (Figure 1). Specifically, average ratings were allocated significantly more points than signals ranked 2-8, the number of reviews was allocated significantly more points than signals ranked 3-8 (except the difference between the 2nd and 3rd signals was marginally significant with a *p-value* of .06), and the amount of 1-, 2-, 3-, 4-, and 5-star ratings respectively was allocated significantly more points than signals ranked 4-8, *ps* < .001. All signals are important to purchase decisions, as supported by comparisons between allocated points and zero, *ps* <.001.

In summary, signal importance holds steady across products. However, for higher-cost purchases, negative information (regardless of when it was generated) becomes more influential, and the role of average ratings becomes less dominant compared to cheaper buys.

So far, we have explored signal importance from an aggregated perspective. We also examined common patterns in our point allocation task, by taking a more granular angle. Due to the substantial impact of the monetary level, we separately analyzed strategies for high and low monetary levels, aiming to paint a more nuanced picture of signal importance based on stakes. For this purpose, we employed Principal Component Analysis (PCA), followed by k-means clustering. The NbClust methods (Charrad et al., 2014) revealed that the optimal number of clusters varied between high (3 clusters) and low (2 clusters) stakes. Table 3 provides an overview of the diverse strategies uncovered, which are further illustrated in Figure 2. Between the low- and high-monetary levels, we identified both distinct and shared patterns in signal weighting.



Note. Sig.1 = average ratings, Sig.2 = the number of reviews, Sig.3 = amount of 1-, 2-, 3-, 4-, and 5-star ratings, respectively, Sig.4 = the most helpful positive reviews overall, Sig.5 = the most helpful negative reviews overall, Sig.6 = the most helpful positive reviews from the past month, Sig.7 = the most helpful negative reviews from the past month, Sig.8 = the most relevant review (based on the searcher).

Figure 2. Variations in strategies by the monetary level. Different colors represent different strategies, and the same color represents the same strategy.

Table 3. Strategy overview by the monetary level.

Monetary Levels	**Strategies**	**Definitions**
High (distinct)	Balanced Signal Weight	Give balanced consideration to both aggregated statistics and negative sentiments
High (shared)	Average Rating Centric	Prioritize average ratings with significant importance

High (distinct)	Popularity & Consensus Priority	Prioritize the popularity of a product and the dispersion of opinions it receives
Low (shared)	Average Rating Centric	Prioritize average ratings with significant importance
Low (distinct)	Statistical Emphasis	Prioritize aggregated statistical information over textual information

Despite different patterns, one consistent theme is that as involved stakes increased, there was a heightened need for going beyond average ratings for more diverse signals to understand potential risks. Some prepared themselves for the worst possible outcome by reading the most helpful negative sentiments, while others investigated the histories behind average ratings by looking into the number of people who have reviewed the product and the dispersion in their opinions to evaluate the probability of getting negative outcomes. After all, different star rating distributions can result in the same average ratings (Yu et al., 2022) but with varying levels of uncertainty in outcomes.

Discussion

These results align with both theoretical accounts and real-life experiences. The fall in the weight of average ratings and the rise in the weight of negative information accompanying higher-cost purchases can be attributed to at least two interrelated factors: the willingness to take risks and the level of involvement. People tend to be more risk-seeking with lower-cost items but exhibit more risk aversion with higher-cost items. Making a $3 purchase is vastly different from making a $1000 purchase. Everything else being equal, life's lessons reveal that individuals invest more thoughtful consideration when parting with $1,000 as opposed to $3. The shift from seeking risk with small amounts of money to avoiding risk with larger amounts, first introduced by Markowitz (1952) and later called the "peanut effect" by Prelec and Loewenstein in 1991, does not mean that individuals have to actively seek risks with smaller amounts, which corresponds to the more commonly used definition of the peanut effect (Weber & Chapman, 2005). Several demonstrations have supported the peanut effect. The findings have been particularly robust for gains, with more inconsistencies observed for losses (Hogarth & Einhorn, 1990; Casey, 1991, 1994; Fehr-Duda et al., 2010).

Spending $3 on an energy drink that tastes like water is no big deal. The potential gain or loss associated with a $3 purchase perhaps may not even justify the time invested in sifting through consumer feedback and the associated information integration efforts. In other words, the risk is minimal, leading to less motivation to prepare for worst-case scenarios by reading about the horror stories shared by others. In addition, relatively inexpensive or low-risk products often result in low involvement, translating to quick and routinized decision-making (Jain, 2019). This is consistent with our observation that a significantly larger proportion of participants indicated a lack of interest in viewing consumer feedback for low-cost items. Even when they do, attention is disproportionally allocated to aggregated statistics. On the contrary, acquiring a satisfactory washer after spending $800 invokes a drastically different experience and expectations. Heightened risk aversion stemming from an $800 purchase prompts decision-makers to contemplate various negative outcomes and assess their tolerance for them. In such situations, while aggregated statistics remain crucial for the big picture, negative qualitative information becomes significantly more important. This leads to a substantial increase in the weight given to the most helpful negative reviews, both overall and within the past month. Clearly, when it comes to important decisions, people want to know about various possible negative scenarios, and this aligns with the negativity bias – a human tendency to pay more attention to negative things (Rozin & Royzman, 2001). In the end, it is not so much about whether an outcome exceeds expectations; after all, who does not love a good surprise?

At least two reasons why average ratings, the number of reviews, and the amount of 1-, 2-, 3-, 4-, and 5-star ratings emerged as top signals in the present study. First, these signals are the most frequently encountered consumer feedback on websites, often requiring no additional clicks for display. The prevalence of these signals (compared to others) as well as everyday online shopping experiences may have reinforced their perceived importance. Second, and perhaps more importantly, while each signal evaluated in the present study is only one piece of information, the amount of information embedded in each signal is not equivalent. Average ratings, the number of reviews, and the amount of 1-, 2-, 3-, 4-, and 5-star ratings are all aggregated information, offering group insights. In contrast, detailed reviews, while containing more characters, represent the perspective of only one individual. Even the most helpful reviews, though selected based on group opinions, ultimately convey the experience of a single person.

General Discussion

The present study provides four key insights for the literature on decision-making and information integration. First and foremost, our findings emphasize the central role of crowdsourced information in shaping decisions, particularly in contexts with heightened stakes. Second, delving deeper, at the aggregated level, the study sheds light on the consistent ordering of signal importance within consumer feedback across various product types, even when considering differences in monetary, emotional, and commitment values. Third, examining weight changes by different levels of the three dimensions provides a more nuanced picture. Specifically, we observed a distinct pattern where monetary considerations (which can be interpreted as the decision stakes) elevate the importance of the most helpful negative reviews while diminishing the importance of average ratings. Fourth, at the individual level, we identified distinct yet common patterns in signal weighting between low and high decision stakes. Despite different approaches, a consistent theme surfaced: as the stakes increased, individuals tended to factor in a broader range of signals when evaluating risks.

This study suggests a dynamic relationship between signal weighting and the perceived stakes of a decision. In low-stake situations, aggregated information carries substantially more weight as a quick judgment shortcut, likely due to a lower need for involvement given the low cost of rectifying wrong decisions. High-stake situations, on the other hand, demand a more holistic understanding, giving more weight to negative information to assess potential risks.

Importantly, the significance of different signals does not inherently reveal the specific role each signal plays in the decision process. Consider review volume – used as a key signal in high-stakes scenarios, individuals may vary in how they integrate it. Some may use it strictly as a threshold to dismiss options below a certain popularity level, while others may use it as an indicator to understand how much confidence they should place in other signals.

Interestingly, the study reveals that neither commitment nor emotional value significantly influences the weights of decision signals. While people generally dislike losses, the aversion intensity varies based on the nature of the loss. It seems that monetary losses take precedence over the failure to satisfy emotional needs or the inability to commit as intended. People are more inclined to consider the financial implications first, contemplating how much money they would potentially waste if the decision does not yield desirable outcomes, as opposed to considering how much less happy they might be. While monetary losses lead to emotional losses as well, the change in the size of a wallet appears more direct and prominent. Despite manipulating monetary, commitment, and emotional values in the experiment, participants predominantly assessed risks from a monetary perspective. The observed pattern in this study suggests that the specific purchases to be made matter less than their costs. Perhaps this inclination stems from the quantifiability of monetary gains and losses, making it easier for people to grasp the stakes involved. This implies that intentionally directing individuals to contemplate risks from alternative perspectives might lead decision-makers to prioritize different signals. It is important to highlight that the primary focus of the present study is on intention rather than behavior. Given the common occurrence of gaps between intentions and behaviors (Sheeran & Webb, 2016), the subsequent step involves investigating the alignment between stated intentions and observed behaviors in the context of online decision-making with consumer feedback.

The present study has covered a wide range of consumer feedback signals, including statistical information such as average ratings and review volume as well as written comments of different sentiments and recency. There are, however, other types of signals with high prevalence and significance that were excluded from the study, particularly photos and videos. As the adage goes "A picture is worth a thousand words," pictures and videos seem to hold special weights when it comes to crowdsourced information as well. Many sites with consumer feedback systems, such as Amazon.com, have a filter option that allows consumers to single out reviews with images and videos. Video reviews, on their own, have gained increasing traction. So much so that YouTube has become the second most popular search engine after Google (Wagner, 2017), with numerous channels dedicated to unboxing and product reviews. Participants in our study also expressed interest in visual signals when queried about additional desirable information. Future research could explore the impact of introducing videos and pictures as signals. Unlike textual reviews, video reviews offer visual and auditory cues, allowing viewers to experience products from different perspectives. In addition, video reviews reveal information about the reviewers, such as voice and physical appearances, that is otherwise unavailable through textual reviews (Penttinen et al., 2022). From a cognitive perspective, textual reviews often lean towards the most easily justifiable reasons (Shafir et al., 1993), and the fear of consequences associated with discussing specific topics (Zhang et al., 2010) may diminish the representativeness of information in textual reviews. These distinctions make it worthwhile to explore the importance of videos and pictures relative to other signals we have evaluated in the present study. Video reviews, a comparatively recent addition to the consumer feedback sphere, bring an immersive dimension to the evolving landscape of e-commerce. In this dynamic space, we expect new signals, such as frequent mentions with sentiment breakdowns, to emerge and become prevalent, driven by technological advancements. Just as passengers have learned that anything less than a 5 on Uber is considered negative, individuals possess the ability to understand how to interpret and integrate various signals, be they existing or new. Investigating how people navigate consumer feedback engines offers researchers invaluable insights into information integration and decision making.

Our study sheds light on the perplexing question of signal prioritization for practitioners by revealing the hierarchical importance of commonly implemented signals, offering guidance on what to prioritize for display on consumer feedback sites. Businesses can enhance their implementation and marketing strategy by prioritizing key signals, depending on their data infrastructure capacity. The consistent ranking of signals simplifies their decisions. Particularly, for decision contexts characterized by high stakes, our findings underscore the critical need to ensure easy accessibility to negative information.

While the present study centers on online consumer decision-making, the adaptable nature of our paradigm suggests potential applications in diverse contexts where crowdsourced information influences decision-making, such as review performance assessments. This understanding of signal importance serves as valuable insights for system developers, guiding the development of systems aligning with effective decision strategies.

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