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RESEARCH ARTICLE

The effect of subjectivity and objectivity in online reviews: A convolutional neural network approach

Sang Kyu Park[1] | **Taikgun Song**[2] | **Aner Sela**[2]

[1]Hong Kong University of Science and Technology, Hong Kong, Hong Kong
[2]University of Florida, Gainesville, Florida, USA

Correspondence
Sang Kyu Park, Hong Kong University of Science and Technology, Hong Kong, Hong Kong.
Email: sangkyu.park@ust.hk

Abstract
User reviews are now an essential source of information for consumers, exerting strong influence on purchase decisions. Broadly speaking, reviews rated by consumers as more helpful exert a greater influence downstream. The current research examines how the linguistic characteristics of a review affect its helpfulness score. Using a convolutional neural network (CNN), this research analyzes the linguistic subjectivity and objectivity of over 2 million reviews on Amazon. The results show that, ceteris paribus, both linguistic subjectivity and objectivity have a positive impact on review helpfulness. However, contrary to consumers' intuition, when subjectivity and objectivity are combined in the same review, review helpfulness increases less than their respective separate effects would predict, especially for hedonic products. We conceptualize that this results from the increased complexity of messages mixing subjective and objective sentences, which requires more effortful processing. The findings extend the literature on online reviews, word-of-mouth, and text analysis in marketing, and offer practical implications for marketing communication and facilitation of reviews.

KEYWORDS
neural network, online reviews, subjectivity, text analysis, word-of-mouth

INTRODUCTION

User reviews are now a standard part of the consumer information search process, with approximately 90% of consumers reading reviews prior to purchase (Podium, 2017). Needless to say, online reviews have an enormous impact on consumer choice, and prior research provides a rich understanding of many factors that affect the impact of online reviews (Berger & Milkman, 2012; Chen & Xie, 2008; Chevalier & Mayzlin, 2006; Dai et al., 2020). Of particular relevance, a growing body of research has investigated how a review's influence is affected by its linguistic characteristics, including emotional valence (Rocklage & Fazio, 2020; Yin et al., 2014), abstractness (Schellekens et al., 2010), figurativeness (Kronrod & Danziger, 2013), and endorsement language (Packard & Berger, 2017). One important characteristic of user reviews is the linguistic subjectivity versus objectivity of their claims. Considering that objective information is often seen as more useful, because it generalizes beyond idiosyncrasies (Olson et al., 1983; Spears et al., 2009), one might intuit that objectivity should increase review helpfulness while subjectivity should decrease it. But does this intuition hold empirically and for all types of goods?

We examine how linguistic subjectivity and objectivity independently and jointly affect the perceived helpfulness of a review. Based on the natural language processing literature, we define subjectivity as aspects of language used to express opinions or personal evaluations and objectivity as those used to convey facts (Hatzivassiloglou & Wiebe, 2000; Pang & Lee, 2004). We train convolutional neural network (CNN) algorithms on top of two pretrained word embeddings (GloVe and Word2vec) to classify each sentence within a product review as either subjective or objective. For instance, the algorithm classifies the sentence "it feels solid, fits snugly, and looks great" as a subjective sentence and "the instructions

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come in several languages" as an objective sentence (see web Appendix A for more detail). Analyzing over 2 million Amazon reviews in 13 product categories, we find that subjectivity alone has a positive influence on review helpfulness, as does objectivity alone—but, in contrast to laypeople's intuitions, we find that the interaction between subjectivity and objectivity is negative, such that their combined presence increases helpfulness less than the sum of their individual effects would predict. We hypothesize that this negative joint effect occurs because reviews containing a mix of subjective and objective sentences are more difficult to process than reviews that are solely subjective or solely objective, and reviews that are more difficult to process are less likely to be perceived as helpful. We also find that the negative joint effect of subjective and objective sentences is more pronounced for reviews of hedonic goods, and we hypothesize this is because consumers are less inclined to spend cognitive effort in hedonic domains (Hsee & Rottenstreich, 2004; Kahneman & Frederick, 2007; Pham, 1998).

This research makes several important contributions. First, we extend the literature on online reviews and consumer word of mouth (e.g., Berger & Milkman, 2012; Packard & Berger, 2017; Rocklage & Fazio, 2020) by documenting a novel influence of subjectivity and objectivity on review helpfulness. In doing so, we empirically demonstrate that subjectivity predicts review helpfulness after controlling for emotionality, which suggests that the two are related but distinct constructs. Second, our findings extend and qualify prior attitude and persuasion research which has suggested that objective messages are generally more effective than subjective ones (Darley & Smith, 1993; Edell & Staelin, 1983; Ford et al., 1990; Holbrook & Hirschman, 1982). We show that this is not always true, at least in the context of online user reviews. Third, by modeling each sentence in a review rather than only the linguistic style of the review as a whole or counting the number of certain words, we provide new and more nuanced insights into online review data through the use of multiple advanced text analysis techniques such as deep learning (CNN), topic modeling (Latent Dirichlet Allocation; LDA), and sentiment analysis (Valence Aware Dictionary for Sentiment Reasoning, hereafter VADER).

PRIOR RESEARCH ON SUBJECTIVITY AND OBJECTIVITY

Prior research on attitude and persuasion demonstrates that objective messages are often more effective than subjective messages for advertisement claims in that objective messages are more credible (Holbrook & Hirschman, 1982), lead to more favorable thoughts about the target (Edell & Staelin, 1983), increase purchase intentions (Darley & Smith, 1993), and are less susceptible to doubt (Ford et al., 1990). One key reason why objectivity has an advantage in firm-generated messages is because consumers are often skeptical about claims made by firms, and objective claims are more trustworthy than subjective ones (Darley & Smith, 1993; Ford et al., 1990).

Similar to objective and subjective claims in persuasive messages, online user reviews can be differentiated based on whether the review contains objective facts or subjective descriptions (e.g., Chang et al., 2014; Lee & Lee, 2009; Liu et al., 2018; Xia & Bechwati, 2008). Experimental studies have operationalized objectivity as the number of product attributes described in a review (Xia & Bechwati, 2008) and as the similarity between the product description and the review (Otterbacher, 2009). The findings in this literature on user reviews are mixed: Objective reviews are considered more helpful in general as they provide more accurate information (Lopez & Garza, 2022; Schindler & Bickart, 2005; Xia & Bechwati, 2008), but subjective reviews can also increase purchase likelihood in certain situations, such as for hedonic options (Liu et al., 2018).

The literature on natural language processing often defines subjectivity as the linguistic expression of experienced personal states such as opinions and evaluations (Ghose & Ipeirotis, 2011; Hatzivassiloglou & Wiebe, 2000; Pang & Lee, 2004; Wiebe et al., 2004). This definition focuses on the personal nature of expression based on private experiences, so it includes emotional expressions as one manifestation of subjectivity. Again, the findings are mixed: Subjective reviews are perceived as less helpful than objective reviews in the context of hotels, for example (Li et al., 2011; Zhao et al., 2019), but the opposite is true for reviews of well-known travel destinations (Bigne et al., 2021).

These divergent findings have motivated us to take a closer look at the relative impact of subjectivity and objectivity on review helpfulness. We adopt the same definition of subjectivity used in the natural language literature (i.e., expressions that convey opinions), but we analyze the impact of subjectivity and objectivity in the following ways. First, we train a CNN to classify as subjective or objective each *sentence* in a review, rather than the *entire* review (c.f., Bigne et al., 2021). Sentence-level classification enables us to assess both the independent and joint effects of subjectivity and objectivity, which has not been done in prior research. Second, in addition to Word2vec (Ghose & Ipeirotis, 2011), we use the Global Vectors for Word Representation (GloVe) word-embedding model to train our algorithm and compare the results from those obtained with Word2vec. This provides robustness checks and bolsters our findings. Third, we test the moderating role of hedonic versus utilitarian product categories on the effect of review subjectivity, objectivity, and their interaction effect on helpfulness, which has not been investigated previously. Fourth, we use LDA to control for the effect of review topic (e.g., what specifically people praise or complain about), which allows us to better identify subjectivity and objectivity as distinct from specific types of complaints or issues on which consumers may write in their reviews.

THIS RESEARCH

Intuitively, objective information is useful for determining the value of a product or service. Prior research has found that reliance on others' judgment increases with objectivity (Gorenflo & Crano, 1989; Nan et al., 2023; Olson et al., 1983; Spears et al., 2009) because objective information applies to everyone equally and can be verified (Dai et al., 2020; Simonson & Rosen, 2014). But in addition to objective facts, consumption decisions and outcomes are often also shaped by subjective experiences, emotions, and evaluation (Alba & Williams, 2013; Crowley et al., 1992; Dhar & Wertenbroch, 2000; Kahneman et al., 1991; Lin et al., 2006). Since subjective experience is a crucial aspect of consumption, subjective expressions in reviews may also be important and helpful for others—especially given that subjective product information can be gathered only after experience or speculation, whereas objective information often is already present in the product description or is available when searched for. In other words, the subjective opinions and evaluations expressed in reviews may be more uniquely informative than objective expressions. Although experiences are idiosyncratic (Eliashberg & Sawhney, 1994), reviews are a medium through which people can empathize with other consumers to predict their own consumption experiences. To the extent that one consumer's experience and evaluation are seen as diagnostic of another's, subjectivity in online reviews should also be helpful (Yaniv et al., 2011).

Based on the evidence for the value of both objectivity and subjectivity in online product reviews, we predict:

> **H1.** Holding objectivity constant, review helpfulness increases with the number of subjective sentences it contains.

> **H2.** Holding subjectivity constant, review helpfulness increases with the number of objective sentences it contains.

Although we expect positive, independent effects of subjectivity and objectivity, we propose that their interaction effect may be negative rather than synergistic, such that expressing both subjectivity and objectivity within a single review increases review helpfulness less than if the two types of sentences were used separately. That is because mixed reviews (i.e., subjective *and* objective) are more effortful to process than more monolithic reviews. Prior research suggests that information processing demands are higher when consumers encounter pieces of information that appear unrelated or disjointed (Maheswaran & Chaiken, 1991; Shugan, 1980), and that mixed, inconsistent, and incoherent messages reduce processing fluency (Schwarz, 2015; Schwarz et al., 2021). In the context of online reviews, subjective sentences— that is, expressions of opinion—and objective sentences—that is, expression of facts—often represent fundamentally distinct types of information and require different assessment strategies. For example, objective facts may be taken at face value whereas subjective opinions might need to be discounted or qualified by certain assumptions about the person who wrote the review. When a review contains either objective or subjective content, evaluation of the review's validity and personal relevance is simplified because review recipients can consistently employ one of these comprehension strategies, whereas a mixed review that includes both content types may require significantly greater cognitive vigilance and closer monitoring of the arguments to assess their validity (e.g., "is this a fact or an opinion?"). This is likely to make mixed reviews more difficult to process than reviews containing only objective or subjective sentences. Research suggests that people rely less on reviews that contain mixed messages or even conflicting styles (Forman et al., 2008; Moradi et al., 2023), because such features make the review seem more ambiguous. Extending these prior findings, we propose that mixed objective and subjective reviews are more difficult to process than reviews that are either objective or subjective which, in turn, makes them seem less helpful than their respective separate positive effects would predict. This attenuating effect of combining objectivity and subjectivity should be pronounced under conditions where consumers are already inclined to process information with less cognitive diligence.

> **H3.** Compared with the sum of their individual effects, combining objective and subjective sentences in the same review increases review helpfulness to a lesser extent.

One important distinction that is relevant to objective and subjective arguments is the one between hedonic and utilitarian goods. Hedonic choices are often driven by subjective feelings and emotions whereas utilitarian choices are driven more by objective facts and logical reasoning (Batra & Ahtola, 1991; Botti & McGill, 2011; Holbrook & Hirschman, 1982; Khan et al., 2005; Sela et al., 2009). Consequently, the effect of subjectivity and objectivity on review helpfulness is likely to depend on whether the product for which a review is written is predominantly hedonic or utilitarian. Because the benefits derived from hedonic goods lie in subjective experiences (Sela et al., 2009; Zeithaml, 1988), we expect subjective sentences to be seen as more helpful than objective sentences in product reviews for hedonic purchases, whereas the opposite is true for utilitarian purchases.

Further, consumers tend to rely on affective and effortless processing when evaluating affect-rich, hedonic products (Hsee & Rottenstreich, 2004; Kahneman & Frederick, 2007; Pham, 1998). Because mixed reviews (i.e., those containing both subjective and objective sentences) are more cognitively demanding to process, as discussed above, compared with reviews that are distinctly objective or subjective, consumers are even less likely to process them carefully and view them as helpful in hedonic product categories, where they are already less inclined to exert cognitive effort. This should exacerbate the negative joint effect of subjectivity and objectivity on review helpfulness, compared with predominantly subjective or objective reviews, in hedonic domains.

> **H4.** The negative effect of mixing subjectivity and objectivity in the same review, predicted in H3, is more pronounced for hedonic products, compared with utilitarian products.

In the next section, we explain the CNN we trained to analyze over 2 million Amazon reviews. Our method deviates from dictionary-based word counting, commonly adopted in the marketing literature, in which text is analyzed according to a list of words predetermined to fall into categories such as positive words or negative words (e.g., LIWC). Before we present the methods, however, we wish to differentiate our study from the two studies that are most similar to our research: Bigne et al. (2021) and Ghose and Ipeirotis (2011). Ghose and Ipeirotis (2011) similarly investigate the influence of subjectivity and objectivity on review helpfulness, but they capture the relative effect of subjectivity in comparison to objectivity, while we capture the effect of subjectivity and objectivity separately. Our work further extends Ghose and Ipeirotis (2011) in that we use a CNN instead of a random forest model and also control for the effect of review sentiment and topic. Also, Ghose and Ipeirotis focus on reviews for DVD's, digital cameras, and audio/video players specifically, while our scope is broader in that we investigate 13 different product categories. Bigne et al. (2021) use recurring neural networks with Word2vec as an embedded layer to study the effects of subjectivity and objectivity on review helpfulness. We additionally use GloVe as an alternative embedded layer on top of CNN to increase the robustness of our findings, and our more granular classification (at the sentence-level rather than at the review-level) allows us to assess both the independent and joint effects of subjectivity and objectivity. Furthermore, we provide richer understanding of the data by holding constant both review valence and topic to test our effect. Lastly, we investigate how the effects of subjectivity and objectivity in reviews are moderated by utilitarian and hedonic product categories, which have not been examined by Bigne et al. (2021) and Ghose and Ipeirotis (2011).

DATA AND ANALYSES

We classified each sentence in each review as subjective or objective using two separate CNNs with either GloVe or Word2vec, two of the most popular word-embedding models. GloVe was trained on over 6 billion word tokens from Wikipedia and Gigaword 5 (Pennington et al., 2014), and Word2vec was trained on over 100 billion words from Google News (Mikolov et al., 2013). These models of word vectors serve as general-purpose feature extractors and allow the algorithm to leverage semantic information, which improves CNN performance on classification tasks even for datasets on which the model was not trained (Kim, 2014; Razavian et al., 2014).

We used a one-dimensional CNN and fine-tuned the parameters by training the algorithm on a dataset from prior research that has 10,000 sentences pre-labeled as either objective or subjective (Pang & Lee, 2004). This dataset contains 5000 movie snippets coded as subjective sentences and 5000 sentences from IMDb plot summaries coded as objective sentences. We split the subjectivity dataset in half for training and testing. For the training phase, we conducted a grid-search for the optimal learning rate for parameter tuning between 0.001 and 0.01 with 0.001 increments. Based on the results, we used 0.005 as the learning rate with 10 epochs. For each sentence, the algorithm outputs the log-odds of a sentence being objective over subjective. Thus, we relied on binary classification of each sentence as either objective or subjective rather than log-odds per se, because the log-odds generated by our CNN do not necessarily imply the extremity of subjectivity or objectivity. In the testing phase, we found that the CNN with GloVe reached 91% accuracy (30% loss), while the CNN with word2vec reached 89% accuracy (25% loss). The results suggest that both algorithms performed very well, so we used both for the main analyses. The code for the CNN used for our analyses as well as the materials for our studies (pretests, the pilot study, and the supplementary study) are available in our OSF repository (https://osf.io/6ws3c/?view_only=e181f369937e43b6a68a8af8def61e42).

We analyzed product reviews posted on Amazon from 2008 to 2014 (McAuley et al., 2015) in 13 categories: Baby, Beauty, CDs and Vinyl, Cell Phones and Accessories, Clothing, Shoes and Jewelry, Electronics, Grocery and Gourmet Food, Health and Personal Care, Home and Kitchen, Movies and TV, Sports and Outdoors, Tools and Home Improvement, and Toys and Games. We used 5-core datasets which contain the review data for reviews for products that have at least five reviews, written by users who have written at least five reviews.

We focus on the helpfulness rating as our dependent variable because it is known to affect purchase decisions (Chen et al., 2008; Dai et al., 2020). On Amazon.com, shoppers are unobtrusively asked to vote on the helpfulness of reviews posted by others ("Was this review helpful to you?" "yes" or "no"). We defined our dependent variable, *Review Helpfulness*$_i$, as review's number of "yes" votes divided by the total number of helpfulness votes, following previous research (Dai et al., 2020). We excluded reviews that did not receive any votes (Dai et al., 2020; Forman et al., 2008). Moreover, we excluded six observations that had a higher number of "yes" votes than the total number of helpfulness votes (including them did not significantly alter the results). There were 2,470,106 reviews in the dataset after the exclusion.

We segmented the review into sentences using periods, exclamation marks, and question marks as the delimiter, with the exception of periods followed by an integer as they represent decimal points. The 2,470,106 reviews were disintegrated into 23,840,717 sentences. The decomposed sentences were submitted to both of the trained algorithms (one embedded with GloVe, the other embedded with Word2vec), and each sentence was labeled either as objective or subjective based on the algorithm's output. Overall, the algorithm trained with GloVe classified 73% of sentences as subjective and 27% as objective, and the algorithm trained with Word2vec classified 66.9% of sentences as subjective and 33.1% as objective (see Table 1 for a summary of classifications across product categories; see web Appendix A for examples of sentences classified as subjective and objective). The two algorithms had 85.8% convergence on the final classification. Our focal independent variables were the number of objective sentences and the number of subjective sentences in the review.

For control variables, following prior research (Dai et al., 2020), we collected the length of the review's title (in words), length of the review (in words), review age (days since it was written), and star rating (1–5) given to the product. Also, given that emotional valence may affect review helpfulness (Rocklage & Fazio, 2020), we used VADER (Hutto & Gilbert, 2014), a sentiment lexicon that outperforms human raters and LIWC, to calculate the review's sentiment (positive or negative) and controlled for its effect in our analyses. All variables were standardized.

Following prior research on review helpfulness (Dai et al., 2020; Forman et al., 2008), we ran the following OLS regressions for our analyses, where i indexes each review. The first regression tests the effect of review subjectivity and objectivity without product category variables:

$$\begin{aligned}\text{Review Helpfulness}_i = a_0 + b_1(\#\text{of subjective sentences}_i)\\ + b_2(\#\text{of objective sentences}_i)\\ + b_3(\#\text{of subjective sentences}_i * \#\text{of objective sentences}_i)\\ + b_4(\text{sentiment}_i) + b_5(\text{star rating}_i) + b_6(\text{title length}_i)\\ + b_7(\text{review length}_i) + b_8(\text{review age}_i) + \varepsilon_i\end{aligned} \tag{1}$$

The second regression tests the moderating effect of hedonic product category, as well as the effect of subjectivity and objectivity after controlling for product category effects. We relied on results from two pretests to code each product category as either hedonic or utilitarian. In the first pretest, we explained to participants what hedonic (affectively driven, based on sensory or experiential pleasure, speaks to your emotions, and is associated with fun and enjoyment) and utilitarian (cognitively driven, based on functional benefits, speaks to your rationality, and is associated with practicality and usefulness) purchases are and asked them to rate the extent which they perceived each of the 13 categories as hedonic or utilitarian (1 = definitely hedonic, 7 = definitely utilitarian). One hundred and one participants rated baby (M = 4.84), cell phones and accessories (M = 4.33), grocery and gourmet food (M = 5.11), health and personal care (M = 5.36), home and kitchen (M = 5.28), and tools

TABLE 1 The proportion of sentences classified as subjective and objective.

	GloVe		Word2vec		
Product category	Subjective	Objective	Subjective	Objective	Classification convergence
Baby	67.5%	32.5%	57.8%	42.2%	83.2%
Beauty	82.3%	17.7%	73.9%	26.1%	85.6%
CDs and Vinyl	69.7%	30.3%	67.8%	32.2%	85.1%
Cell phones and accessories	74.1%	25.9%	68.1%	31.9%	84.8%
Clothing, shoes, and jewelry	76.2%	23.8%	66.7%	33.3%	84.1%
Electronics	76.1%	23.9%	68.9%	31.1%	84.7%
Grocery and gourmet food	80.0%	20.0%	72.8%	27.2%	86.3%
Health and personal care	75.5%	24.5%	66.0%	34.0%	83.6%
Home and kitchen	76.2%	23.8%	68.1%	31.9%	84.2%
Movies and TV	68.6%	31.4%	64.7%	35.3%	89.1%
Sports and outdoors	74.6%	25.4%	65.9%	34.1%	83.5%
Tools and home improvement	73.4%	26.6%	66.1%	33.9%	83.9%
Toys and games	63.1%	36.9%	56.9%	43.1%	85.2%

and home improvement ($M=5.69$) as utilitarian (vs 4; all p's < 0.02). Beauty ($M=2.51$), CDs and vinyl ($M=2.19$), clothing, shoes, and jewelry ($M=3.7$), movies and TV ($M=2.02$), sports and outdoors ($M=2.96$), toys and games ($M=2.05$) were rated as hedonic (vs 4; all p's < 0.04). The average rating for electronics category was directionally higher than the midpoint ($M=4.14$ vs 4; $t(100)=1.04$, $p=0.30$), so we ran the second pretest with 99 participants where we mentioned a few subcategories for Electronics (e.g., computers, office electronics) for clarification and found that electronics category was perceived as utilitarian ($M=4.71$ vs 4; $t(98)=5.27$, $p<0.001$). We coded each of the 13 product categories as either hedonic or utilitarian based on these results, and this dummy variable was not standardized. Figure 1 shows the distribution of subjective and objective sentences in a review for hedonic and utilitarian products.

Product category (hedonic vs utilitarian) was included as a dummy variable along with its interaction terms in the regression:

$$
\begin{aligned}
\text{Review Helpfulness}_i &= a_0 + b_1(\text{\#of subjective sentences}_i) \\
&+ b_2(\text{\#of objective sentences}_i) \\
&+ b_3(\text{\#of subjective sentences}_i * \text{\#of objective sentences}_i) \\
&+ b_4(\text{hedonic}_i) + b_5(\text{hedonic} * \text{\#of subjective sentences}_i) \\
&+ b_6(\text{hedonic}_i * \text{\#of objective sentences}_i) \\
&+ b_7(\text{hedonic}_i * \text{\#of subjective sentences}_i * \text{\#of objective sentences}_i) \\
&+ b_8(\text{sentiment}_i) + b_9(\text{star rating}_i) + b_{10}(\text{title length}_i) \\
&+ b_{11}(\text{review length}_i) + b_{12}(\text{review age}_i) + \varepsilon_i
\end{aligned} \tag{2}
$$

While the effects of subjectivity and objectivity (H1–H3) were confirmed in both regressions, we report the results from both regressions for completeness and for ease of comparison as we use the first regression to test hypotheses 1, 2, and 3 for each product category individually.

RESULTS

The results were similar for analyses using CNN with GloVe and with Word2vec as embedded layers, demonstrating robustness. Models 1 and 2 refer to our first regression model using GloVe and Word2vec, respectively, and models 3 and 4 refer to our second regression model (i.e., including product category moderators) using GloVe and Word2vec, respectively. Table 2 summarizes the results of our analyses.

Consistent with hypotheses 1 and 2, both the number of objective sentences and the number of subjective sentences had positive impacts on review helpfulness across all four models. Holding all else constant, an increase in the number of subjective sentences increased the likelihood that the review would be perceived as helpful, consistent with the findings of Bigne et al. (2021) on a TripAdvisor dataset. The results suggest that the positive effect of subjectivity may not be captured when subjectivity is measured in relation to objectivity (e.g., calculating the ratio of subjective sentences).

More importantly, the coefficient for the interaction term, *number of subjective sentence* × *number of objective sentences*, is negative and significant across all four regression models (H3). This implies that combining subjective and objective language has a subtractive rather than a synergistic effect, such that it increases helpfulness to a lesser extent compared with when objective or subjective sentences are used alone (Figure 2). Note that the interaction was significant after controlling for review length (controlling for review length using the number of characters instead of number of words in a review did not change our conclusions; see web Appendix B).

We additionally found that review valence positively predicted review helpfulness, such that positive reviews were more likely to be perceived as helpful consistent with the findings in prior research (e.g., Pentina et al., 2018; Ullah et al., 2015). All other control variables had a positive impact on review helpfulness, except for the age of the review, where older reviews were less likely to be perceived as helpful. While older reviews may have had more time to receive votes, many products on Amazon are frequently updated or replaced, rendering older reviews to be more likely outdated and therefore less helpful.

As a robustness check, we also tested H1–H3 after controlling for the topics within the reviews using LDA model. We searched for the optimal number of topics using a grid-search algorithm (between 2 and 10 topics) and extracted five topics based on the results from multidimensional scaling. The five topics seemed to represent recommendation (associated words: buy, product, review, recommend etc.), overall impression (associated words: good, watch, bad, quality etc.), performance (associated words: great, time, work, long etc.), usability (associated words: use, light, easy, nice etc.), and entertainment value (associated words: movie, film, love, story etc.). We used this factor variable to control for the main topic for each review. All three hypotheses were confirmed after controlling for the topic of the reviews (see web Appendix C for details of the analyses and the list of topics and the associated words for each topic).

One may wonder why consumers write reviews using both subjective and objective sentences, given that our analyses found their interactive effect to be negative, compared with their respective separate effects. In a pilot study, we found that this is because laypeople have the intuition that contradicts our findings. Specifically, we told participants that an objective sentence is a statement of facts and that a subjective sentence is a statement of personal opinions and asked them to imagine reading a review containing both types of sentences. They were then asked to predict whether the combination of subjective and objective sentences would enhance, reduce, or have no effect on review helpfulness (see web Appendix D for details). We found that a majority of participants

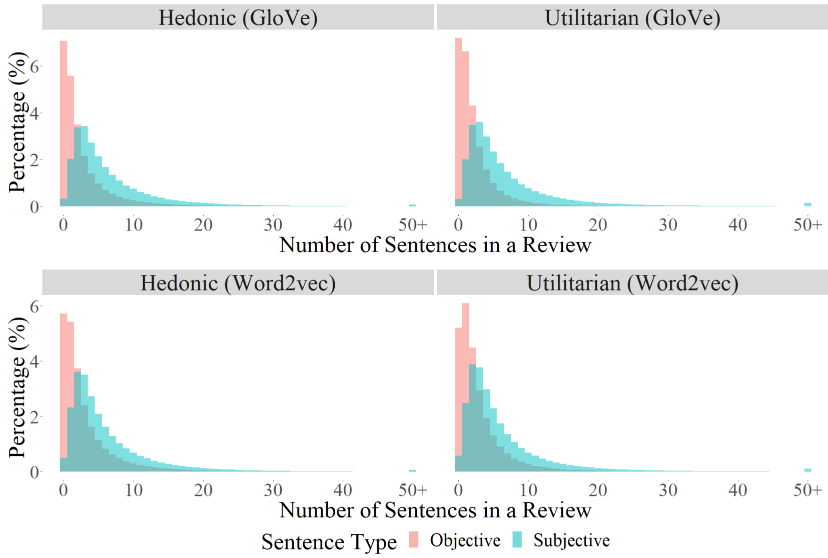

FIGURE 1 Proportion of reviews that contain each number of subjective and objective sentences.

recruited from Prolific ($N=201$) expected subjective and objective sentences to have a synergetic effect, such that they expected the combined effect to be positive (86.6%; vs the chance level 33.3%; $\chi^2(1)=256.93$, $p<0.001$). In line with this result, reviews that contain at least one subjective and one objective sentence accounted for 70%–76% of our sample (depending on whether GloVe or Word2vec model is used). This suggests that while people can naturally switch between objective and subjective sentences when writing a review, avoiding this natural tendency and focusing on either objective or subjective statements can, counterintuitively, further increase review helpfulness and impact.

Next, models 3 and 4 test the moderating role of hedonic and utilitarian product category. Consistent with our prediction (H4), the interactive effect of subjective and objective sentences was more negative for hedonic products, as indicated by the negative coefficient for the three-way interaction term. Also in line with our conceptualization, subjective sentences had a greater impact on review helpfulness than objective sentences for hedonic products. In particular, the sum of the coefficients for the number of subjective sentences (GloVe=0.01777; Word2vec=0.0213) and the interaction between the number of subjective sentences and the hedonic product category variable (GloVe=0.0468; Word2vec=0.03402) was greater than the sum of the coefficients for the number of objective sentences (GloVe=0.05141; Word2vec=0.04827) and the interaction between the number of objective sentences and the hedonic product category variable (GloVe=−0.0212; Word2vec=−0.01476). We did not control for the effect of topics for testing product category moderator because topics modeled using LDA inherently capture product category variance leading to a conceptual overlap and collinearity. Instead, we controlled for the topics for reviews within each product category separately below.

Although not central to our prediction, we also found that the coefficient for the hedonic product category variable was negative, which suggests that reviews were in general perceived as less helpful for hedonic products compared with utilitarian products. This is consistent with the finding in previous research that reviews are perceived as less helpful for purchases involving experiential goods compared with material goods (Dai et al., 2020).

We also ran the first regression for each of the 13 product categories individually. We report the results pertaining to H1–H3 (i.e., coefficients for number of subjective sentences, number of objective sentences, and their interaction term) in Table 3 for brevity. H3 was confirmed for all of the categories, and hypotheses 1 and 2 were supported for most of the categories with a few exceptions.

For the algorithm trained with GloVe, the coefficient for number of subjective sentences was not statistically significant for grocery and gourmet food category, and the coefficient for number of objective sentences was not significant for clothing, shoes, and jewelry category, although they were both directionally consistent with H1 and H2. We speculate that for the former, consumers may be looking for more factual statements (e.g., nutrition facts) while for the alter, the actual experience of the product is of particularly high importance, such that objective statements may be less helpful. Similarly, for the algorithm trained with Word2vec, H1 was not supported for CDs and grocery and gourmet food category, and H2 was not supported for beauty, CDs and vinyl, and clothing, shoes, and jewelry category.

TABLE 2 Standardized beta coefficients.

	Model 1	Model 2	Model 3	Model 4
	GloVe	Word2vec	GloVe	Word2vec
Predictor variables				
Number of subjective sentences	0.06922	0.05824	0.01777	0.02130
	(0.001404)	(0.001372)	(0.001640)	(0.001589)
Number of objective sentences	0.02484	0.03734	0.05141	0.04827
	(0.001026)	(0.001059)	(0.001615)	(0.001503)
Interaction (Number of subjective × Number of objective sentences)	−0.01103	−0.01206	−0.00921	−0.01081
	(0.000134)	(0.000139)	(0.000181)	(0.000192)
Hedonic			−0.25670	−0.25710
			(0.001247)	(0.001239)
Interaction (Hedonic × Number of subjective sentences)			0.04680	0.03402
			(0.001647)	(0.001631)
Interaction (Hedonic × Number of objective sentences)			−0.02120	−0.01476
			(0.001878)	(0.001778)
Interaction (Hedonic × Number of subjective × Number of objective sentences)			−0.00454	−0.00273
			(0.000261)	(0.000271)
Sentiment	0.00394	0.00479	0.01728	0.01746
	(0.000692)	(0.000693)	(0.000688)	(0.000690)
Star rating	0.26558	0.26522	0.25929	0.25930
	(0.000677)	(0.000677)	(0.000673)	(0.000673)
Title length	0.02515	0.02463	0.02248	0.02216
	(0.000639)	(0.000639)	(0.000633)	(0.000634)
Review length (words)	0.05684	0.06065	0.07954	0.08197
	(0.001638)	(0.001640)	(0.001645)	(0.001642)
Review age (days)	−0.03057	−0.02989	−0.04714	−0.04699
	(0.000617)	(0.000617)	(0.000618)	(0.000618)
Multiple R-squared	0.08773	0.08783	0.1041	0.1042

Note: All coefficients were statistically significant at $p<0.001$. Values in parentheses represent standard errors.

To control for the effect of topics, we again selected the optimal number of topics based on the results from multidimensional scaling and relative term frequencies within topics for each product category. For example, for reviews in health and personal care category, the selected number of topics were five, and the topics were related to supplements (associated words: help, supplement, pill, effect, etc.), satisfaction (associated words: recommend, good, great, buy etc.) hair removal (associated words: shave, hair, razor, long, etc.), cleansing (associated words: clean, brush, use, light, etc.), and scent (associated words: good, love, smell, scent, etc.). We then identified the main topic for each review and controlled for its influence on review helpfulness. We found that controlling for the topic of the reviews did not significantly change our conclusions, such that hypotheses 1, 2, and 3 were all confirmed across the 13 categories (see web Appendix E for details of the analyses and the list of topics and the associated words for each topic). There was only one exception: Akin to the results when topics were not controlled for, the coefficient for the number of subjective sentences for grocery and gourmet food became insignificant.

Supplementary analyses

Additionally, we conducted two sets of supplementary analyses to corroborate our findings.

First, as an additional accuracy check, we compared the extent to which the classifications by our CNNs map onto lay consumers judgments in a follow-up study. To do so, we sampled 130 sentences that had a relatively higher likelihood (i.e., fifth percentile) of being classified as a subjective sentence and another 130 that had a relatively higher likelihood of being classified as an objective sentence by the model trained on GloVe for each the 13 product categories (the classification of these sentences for model trained on Word2vec were also consistent). We recruited 1002 participants from Prolific and told them that an objective sentence is a "statement of facts," whereas a subjective sentence is a "statement of personal

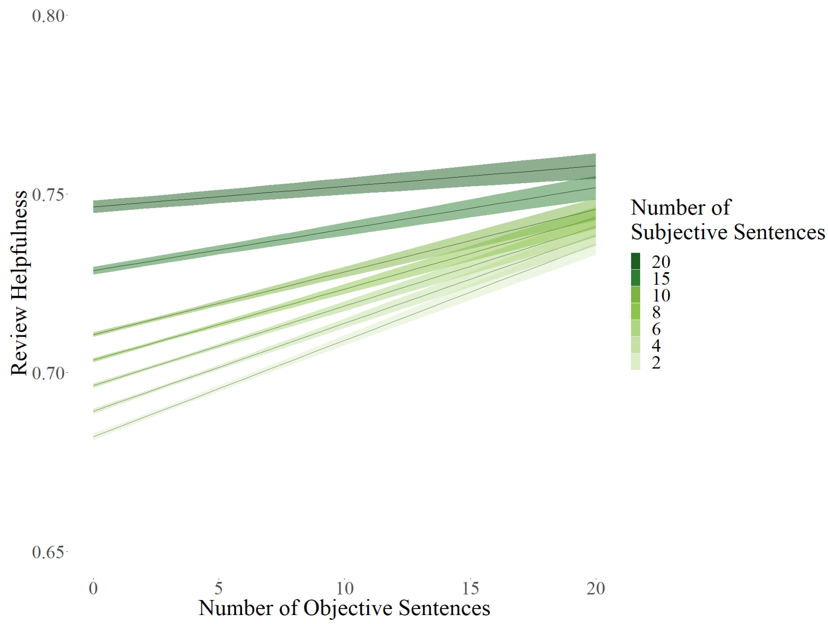

FIGURE 2 Predicted review helpfulness by the number of objective and subjective sentences.

opinions or feelings" (see web Appendix F for details) with a few example sentences that the model was trained on. Participants were then presented with two subjective and two objective sentences from a randomly chosen product category and were asked to classify the sentences either as subjective or objective. Overall, we found that participants' classification of the sentences converged with the models' classification most of the time for both subjective (88.22%) and objective (85.27%) sentences, where the convergence rate was higher for subjective sentences $F(1, 1001)=11.021$, $p=0.001$). Participants agreed 88.21% of times for classifying subjective sentences and 86.32% of times for objective sentences. Thus, the pattern of results suggests that our models classified reviews in a manner consistent with lay consumers.

Second, we explored whether isolating and testing the effect of relatively "neutral" sentences (i.e., sentences with scores close to 0) altered our conclusions. For ease of reference, we converted the scores from our CNNs to probability using a sigmoid function, such that probabilities lower than 50% indicated a subjective sentence and probabilities greater than 50% indicated an objective sentence. We first classified sentences with probabilities lower than 33% as strongly subjective, higher than 66% as strongly objective, and those in between as neutral. We ran the first regression equation with the number of neutral sentences and its interaction with the number of subjective and objective sentences as additional independent variables. Note that the interaction results should be interpreted with caution because the category "neutral sentences" is a pool of objective and subjective sentences that are classified with a lower confidence. We found that the two-way interactions were all negative and significant. These results are consistent with our conceptualization in that they imply the interactive effect of subjectivity and objectivity is negative, given that neutral sentences are also either subjective or objective per our CNNs. We also found that the coefficient for three-way interaction was positive and significant. This indicates that the negative interactive effect of subjectivity and objectivity weakens when a review has more neutral sentences with less distinct subjective or objective characteristics, according to our CNNs. Consequently, this result supports our findings, as it suggests the negative interactive effect is more pronounced for sentences classified with higher certainty. The conclusions were identical when we classified sentences with 45%~55% probability as neutral instead of 33%–66% (see web Appendix G for results), further support the robustness of the conclusions drawn from our CNNs.

In sum, we find that both subjectivity and objectivity can have a positive influence on the extent to which a review is considered helpful. Nonetheless, while consumers tend to expect a synergetic effect between objective and subjective sentences, we find that their interactive effect is negative, such that it increases helpfulness to a lesser extent compared with when objective or subjective sentences are used alone. Although the negative interactive effect of subjective and objective sentences is consistent across different product categories and robust after controlling for valence, topic, etc., we find that it is more pronounced for reviews for hedonic products.

GENERAL DISCUSSION

Online reviews have now become one of the most important sources of information for consumers (e.g., Chen &

TABLE 3 Standardized beta coefficients for number of subjective sentences, number of objective sentences, and their interaction term for each product category.

	Number of subjective sentences		Number of objective sentences		Interaction	
Product categories	**GloVe**	**Word2vec**	**GloVe**	**Word2vec**	**GloVe**	**Word2vec**
Hedonic						
Beauty	0.04983	0.05905	0.02778	0.01797$_{n}$	−0.01040	−0.00965
	(0.01175)	(0.01125)	(0.01031)	(0.00978)	(0.00165)	(0.00157)
CDs and vinyl	0.00665*	0.00233$_{n}$	0.01107	0.00260$_{n}$	−0.00895	−0.00711
	(0.003504)	(0.003320)	(0.002668)	(0.002803)	(0.000307)	(0.000285)
Clothing, shoes, and jewelry	0.12658	0.13288	0.00043$_{n}$	−0.00105$_{n}$	−0.02622	−0.02250
	(0.013673)	(0.013078)	(0.010062)	(0.010111)	(0.003794)	(0.003319)
Movies and TV	0.07115	0.07432	0.03636	0.03610	−0.01744	−0.01966
	(0.002701)	(0.002623)	(0.001708)	(0.001808)	(0.000271)	(0.000296)
Sports and outdoors	0.06055	0.07478	0.05662	0.04096	−0.02066	−0.01918
	(0.00922)	(0.00887)	(0.00674)	(0.00661)	(0.00109)	(0.00101)
Toys and games	0.05255	0.05380	0.03976	0.04058	−0.01970	−0.02083
	(0.01263)	(0.01207)	(0.00791)	(0.00859)	(0.00179)	(0.00181)
Utilitarian						
Baby	0.04158	0.06125	0.04968	0.03340	−0.01977	−0.02025
	(0.01388)	(0.01316)	(0.00946)	(0.00989)	(0.00208)	(0.00215)
Cell phones and accessories	0.02019*	0.03174	0.07965	0.06921	−0.01013	−0.00956
	(0.011748)	(0.010946)	(0.008159)	(0.008457)	(0.000863)	(0.000846)
Electronics	0.02562	0.03580	0.05799	0.04524	−0.01204	−0.01119
	(0.002722)	(0.002560)	(0.002112)	(0.002037)	(0.000242)	(0.000226)
Grocery and gourmet food	0.003477$_{n}$	−0.01773$_{n}$	0.03820	0.05568	−0.00945	−0.00987
	(0.013652)	(0.01315)	(0.010802)	(0.01054)	(0.002090)	(0.00206)
Health and personal care	0.04331	0.03681	0.06644	0.07409	−0.00906	−0.01378
	(0.007568)	(0.007596)	(0.005478)	(0.005251)	(0.000621)	(0.000805)
Home and kitchen	0.03839	0.03802	0.01723	0.02752	−0.00297	−0.00567
	(0.005686)	(0.005426)	(0.004193)	(0.004044)	(0.000344)	(0.000491)
Tools and home improvement	0.04800	0.04940	0.03930	0.05059	−0.00541	−0.0101
	(0.011219)	(0.01057)	(0.007954)	(0.00801)	(0.000699)	(0.00102)

Note: All coefficients were statistically significant at $p<0.05$ unless otherwise indicated. An asterisk (*) denotes coefficients marginally significant at $p<0.10$ and the subscript n denotes insignificant coefficients. Values in parentheses represent standard errors. All analyses were conducted with control variables included in the regression.

Xie, 2008; Dai et al., 2020; Forman et al., 2008; Rocklage & Fazio, 2020). Given the impact of reviews on other consumers' purchase intentions (Chen et al., 2008), understanding what kind of reviews are more influential is of both theoretical and practical importance. In this research, we focus on subjectivity and objectivity of a review and investigate how they affect the perceived helpfulness of a review. To answer this question, we trained a convolutional neural network embedded with word vector models (GloVe and Word2vec) to account for the semantic information contained in words, and classified review sentences into either objective or subjective sentences for over 2 million reviews posted on Amazon.

Theoretically, we extend prior research on online user reviews and word of mouth (e.g., Berger & Milkman, 2012; Packard & Berger, 2017; Rocklage & Fazio, 2020) by demonstrating the effect of subjectivity, objectivity, and their interaction effect on review helpfulness. First, we have found that subjectivity, rather than objectivity, has a stronger positive effect in hedonic domains. Second, we found that the interactive effect of subjectivity and objectivity is negative, especially in hedonic domains. This finding is particularly interesting since one may expect the combined effect of subjective and objective sentences to be additive given that subjective and objective sentences each have a positive main effect on review helpfulness. Taken together, our findings highlight that linguistic subjectivity and objectivity affect review helpfulness in a more nuanced manner than previously assumed, both within and across product categories.

These contributions were made possible by our use of a neural network approach, which allowed us to assess the impact of subjectivity and objectivity independently rather than in relative terms (cf. Bigne et al., 2021; Chen & Tseng, 2011; Forman et al., 2008) and to provide insight beyond dictionary-based approaches. Using multiple text analysis techniques, including CNN, LDA, and sentiment analyses (VADER), offer richer and more robust insights into review data.

Our findings also contribute to research on objectivity and subjectivity persuasion more generally. While prior persuasion research finds that objective arguments are often more effective than subjective arguments (e.g., in advertisements; Ford et al., 1990), we find that both subjective and objective statements can have a positive impact on user-generated messages in online consumer reviews, and that subjective statements have a stronger effect in hedonic contexts. This is consistent with the notion that subjective advertising claims are more credible in hedonic product categories (Becker et al., 2019).

Practically, our findings provide insight for writing and facilitating reviews. In our survey, 86.6% of respondents expected the combined effect subjective and objective sentences to enhance review helpfulness and only 9% expected it to reduce review helpfulness. Similarly, over 70% of reviews in our Amazon.com dataset contained at least one subjective and one objective sentence. This suggests that the majority of users might inadvertently undermine the impact of their reviews by combining objective and subjective perspectives. We also found that people wrote more objective statements than would be ideal for hedonic products and more subjective sentences for utilitarian products (see Figure 1), perhaps in an attempt to write a well-rounded review. Rather than encouraging shoppers to "write a helpful review," marketers might want to more specifically encourage customers to focus on subjective experiences when reviewing hedonic products and objective benefits when reviewing utilitarian goods.

More broadly, beyond online reviews, our findings suggest that communications might be more persuasive if they focused on either subjective or objective arguments, rather than using them both. Further research may investigate this possibility.

This research offers several other directions for future research. First, subjectivity and objectivity may vary in terms of their extremity. Our models generate a probability or certainty score to classify each sentence as subjective or objective, but they are unable to capture the extremity of subjectivity or objectivity (admittedly, extremity is not well defined in this linguistic context to begin with). And although our hypotheses were supported even when we used these probability scores as independent variables rather than a binary classification of subjective and objective sentences, these probability scores do not necessarily capture the extremity of subjectivity or objectivity (just like attitude certainty does not necessarily capture attitude extremity; Tormala & Rucker, 2007). Future research may extend our findings using other techniques to capture the extremity of subjectivity and objectivity and testing their influence on review helpfulness.

Second, prior research suggests that reviewer characteristics affect the extent to which shoppers rely on reviews (Zhang et al., 2016). The Amazon.com data used in this research did not include reviewer characteristics such as expertise or the number of reviews written that may significantly affect review credibility, but future research may investigate platforms that do provide such information (e.g., TripAdvisor) and examine potential interactions between linguistic subjectivity and objectivity and reviewer characteristics. Similarly, future research may examine whether linguistic subjectivity and objectivity interacts with user-uploaded images or videos, which were unavailable in our data.

DATA AVAILABILITY STATEMENT

The data and analyses that support the findings of this study are openly available in OSF at https://osf.io/6ws3c/?view_only=e181f369937e43b6a68a8af8def61e42.

ORCID

Sang Kyu Park https://orcid.org/0000-0001-9371-9142
Aner Sela https://orcid.org/0000-0003-2292-9665

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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