Exploring Utilitarian Product Reviews: How Do Emotional, Social and Cognitive Dimensions Differ in Positive and Negative Reviews?

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Online reviews are a vital source of information for both consumers and businesses. For business, reviews are not simply positive or negative, but are sources of information that reveal how consumers think, feel, and respond to products/services. As such, it makes sense to look toward underlying linguistic and psychological patterns. Prior research indicates that positive and negative reviews may vary in terms of cognitive, social, and emotional. However, the impact of these factors depends on context. Factors such as product category, the platform on which the review was posted, and the cultural background of the reviewers can influence the impact of varying processes on reviews. As such, in the current study, we explore how positive and negative reviews of earphone reviews differ in terms of their emotional, social and cognitive processes. Given that earphones are a multifaceted product, they shed light on varying processes present in the reviews.

Keywords: online reviews, cognitive, social, affective, LIWC

INTRODUCTION

Online reviews are a vital source of information for both consumers and businesses. On the consumer side, it can influence perception and ultimately the product choice. On the business side, reviews can be used to gather feedback about products/services to improve offerings. Reviews are, therefore, not simply positive or negative, but are sources of information that can reveal how consumers think, feel, and respond to products/services. As such, it makes sense to expand analysis beyond positive/negative valence and look toward underlying linguistic and psychological patterns.

Prior research indicates that positive and negative reviews may vary in terms of cognitive, social, and emotional processes (Vinson & Dale, 2014; Lam et al., 2019; D'Acunto & Volo, 2021). To capture these nuanced differences, both positive and negative reviews should be analyzed separately. For example, a positive review may show satisfaction and trust whereas a negative review could highlight frustration, disappointment, or unmet expectations.

The Linguistic Inquiry and Word Count (LIWC) tool is a widely used framework that has been employed by other researchers to investigate the characteristics of positive and negative language. LIWC extracts key linguistic and psychological features such as tone, analytical thinking, social orientation, and cognitive processing. As previously mentioned, studies have shown differences in how positive and negative reviews manifest these variables. A simple example is that, as expected, negative reviews tend to contain more words associated with anger or problem-solving, whereas positive reviews tend to contain more words associated with affiliation, certainty, and/or reward.

However, the impact of these factors depends on context. Factors such as product category, the platform on which the reviews were posted, and the cultural background of the reviewers can influence the main effect of varying processes on reviews. For instance, cultural norms strongly influence the directness and emotional expression of both praise and criticism.

As such, in the current study we are interested to explore how positive and negative reviews of earphone reviews differ in terms of their emotional, social and cognitive processes. Earphone is a multifaceted product. These are primarily utilitarian and experience products, with hedonic elements when marketed for lifestyle, music enjoyment, or luxury. Therefore, it is intriguing to note the differences between the positive and negative views of such a complex product. It sheds light on varying processes present in the reviews.

LITERATURE REVIEW

LIWC **(**Linguistic Inquiry and Word Count**)** is a text analysis software tool (Boyd et al., 2022) used in many prior studies to analyze texts and explore the psychological meaning of the text. LIWC counts words in different meaningful categories and helps researchers comprehend various aspects of the text data namely, emotional, cognitive etc. It is more than a word count software since each category has psychological meaning associated with it (Tausczik & Pennebaker, 2010). Research has shown that, in some instances, LIWC performs superior to many Machine Learning (ML) algorithms that are employed to extract the hidden psychological, social and other processes in the text (del Pilar Salas-Zárate et al., 2014); Olagunju et al., 2020).

There are studies that have explored the comparison of positive and negative reviews using LIWC. The body of studies suggests that positive and negative reviews differ in terms of their emotional, social, and cognitive processes. Next, we summarize their findings in detail.

- ***Emotional language Difference:*** It is quite intuitive that positive reviews contain more positive words, and negative reviews contain significantly more negative words. Studies have supported this notion (Vinson & Dale, 2014; Lam et al., 2019; D’Acunto & Volo, 2021). Studies have also found that the emotional tone is higher in positive reviews than in negative reviews (Ferreira et al., 2023; Lam et al., 2019). However, Yin and Sadowski (2024) found no significant difference. Positive reviews are found to have more analytical content (Lam et al., 2019) and tentativeness (Evans et al., 2019). The authors also found that doubt increased trust in positive reviews, but less so in negative reviews. On the other hand, negative reviews are high in Authenticity (Ferreira et al., 2023).
- ***Social process variable***s: Manchaiah et al., (2021a and 2021b) found higher values of social engagement and social processes in positive reviews compared to negative reviews. Vinson and Dale (2014) found that social words are frequent both in positive and negative reviews. Yin and Sadowski (2024) found that social words specially ‘we” were used more in corporate platform and less on an independent platform.
- ***Cognitive Process Variables:*** In the cognitive variables domain of LIWC, the analytical word is the most research variable. The studies show that positive reviews contain more analytic scores compared to negative reviews (Vinson & Dale, 2014; lam et al., 2019). Vinson and Dale (2014) also found that there is a nonlinear relationship between review valence and cognitive word use. Meyer and Okuboyejo, 2021 claims that positive reviews are higher for therapeutic features and the negative reviews are lower for other features.
- ***Contextual factors:*** There seem to be some contextual factors that affect how these processes show up in positive and negative reviews. Product category, platform and cultural context were reported to have varying effects on the polarity of the reviews. One study found cultural differences where Europeans showing more sentiment and North Americans showing more satisfaction and Asians were less satisfied and more analytic in negative reviews (D’Acunto & Volo, 2021). The study was conducted in luxury hotel context.

In the context of depression apps, supportive and entertainment features were associated with more positive reviews (Meyer & Okuboyejo, 2021). The authors also found that medical assessment features were associated with more negative reviews. In the context of hearing aids, financial concerns were linked to lower ratings (Manchaiah et al., 2021a). All these studies were performed on various platforms, including Yelp, Reddit, Spotify community, Hellopeter, etc., which may also contribute to the varying effects on review valence.

Knowing that, depending on the context, the emotional, social, and cognitive processes in positive and negative reviews may differ, we explore Amazon earphone reviews. We divided our data into positive and negative reviews and ran the LIWC analysis on some categories. The definitions of these categories are provided below:

TABLE 1
DEFINITION OF LIWC VARIABLES

Summary Language Variable:

Category	***Abbreviation***	***Definitions/most frequently used exemplars***
Analytical thinking	Analytical thinking	Metric of logical, formal thinking
Clout	Clout	Language of leadership, status
Authentic	Authentic	Perceived honesty, genuineness
Emotional Tone	Tone	Degree of positive (negative) tone
Psychological processes		
Affiliation	Affiliation	we, our, us, help
Achievement	Achieve	work, better, best, working
Power	Power	own, order, allow, power
Cognition	Cognition	is, was, but, are
All-or-none	Allone	all, no, never, always
Cognitive processes	Cogproc	but, not, if, or, know
Insight	Insight	know, how, think, feel
Causation	cause	how, because, make, why
Discrepancy	Discrep	would, can, want, could
Tentative	Tentat	if, or, any, something
Differentiation	Differ	but, not, if, or
Memory	Memory	remember, forget, remind, forgot
Affect	Affect	good, well, new, love
Emotion	Emotion	good, love, happy, hope
Social processes	Social	you, we, he, she
Social behavior	SocialBehav	said, love, say, care
Communication	Comm	said, say, tell, thank*
Social referents	Socrefs	you, we, he, she
Family	Family	parent*, mother*, father*, baby
Friend	Friend	friend*, boyfriend*, girlfriend*, dude
Culture	Culture	car, united states, govern*, phone
Politics	Politic	united states, govern*, congress*, senat*
Ethnicity	Ethnicity	american, french, chinese, indian
Technology	Tech	car, phone, comput*, email*
Lifestyle	Lifestyle	work, home, school, working
Religion	Relig	god, hell, christmas*, church
Allure	Allure	have, like, out, know
Perception	Perception	in, out, up, there

Category	*Abbreviation*	*Definitions/most frequently used exemplars*
Attention	Attention	look, look* for, watch, check
Politeness	Polite	thank, please, thanks, good morning
Conflict	Conflict	fight, kill, killed, attack
Moralization	Moral	wrong, honor*, deserv*, judge

DATA AND METHODOLOGY

We have used an earphone review dataset collected from Amazon.com. This dataset (Kat, 2019) is publicly available for research purposes at the Kaggle (www. Kaggle.com) website. It has also been used in prior research (Ahmad & Richard, 2024). The dataset included 14337 Amazon reviews, along with their review titles, review bodies, and star ratings for the 10 latest Bluetooth earphone devices as of mid-2019. Among all the reviews, 2493 reviews had a one-star rating, 939 reviews had a two-star rating, 1503 reviews had a three-star rating, 3189 reviews had a four-star rating, and 6213 reviews had a five-star rating. The mean rating of the reviews is 3.68.

Following prior literature (Pan & Zhang, 2011), reviews with a four-star and five-star rating constitute positive reviews, while those with a two-star rating and a one-star rating are considered negative reviews. Some research also uses the arithmetic mean of the star rating of a review as their valence (Dellarocas et al., 2007; Duan et al., 2008). Reviews with a star rating of three are considered neutral and were not used in this study.

Now, LIWC software was run on the dataset. We included review title and review body in the text analysis. Once the dataset had values for each of the reviews on different parameters (such as Analytic, clout, emotional tone etc.), we divided the dataset into two groups. The positive reviews were denoted by 1 and the negative reviews were denoted by 0. Here, we conducted an independent sample t-test to examine any differences between positive and negative reviews. It was found that the two groups did not have equal variances; therefore, a Welch's t-test was conducted. The result is discussed in the following section.

RESULT

The following result yielded from the LIWC and t-test analyses. The result revealed that some of the variables had significantly higher value in positive reviews than the negative reviews. Table [2] shows the list of the variables. The significant variables are in bold.

TABLE 2
VARIABLES WHICH HAVE SIGNIFICANTLY HIGHER VALUES IN POSITIVE REVIEWS THAN NEGATIVE REVIEWS (IN BOLD)

Variable	t	df	p
Analytic	**-13.570**	**6253.877**	**< .001**
Clout	**-28.573**	**8271.093**	**< .001**
Authentic	**34.472**	**6037.216**	**< .001**
Tone	**-84.237**	**3367.935**	**< .001**
Affiliation	**-3.272**	**8408.506**	**0.001**
Achieve	**-9.534**	**11560.522**	**< .001**
Discrep	**-4.611**	**8027.787**	**< .001**
Memory	-0.819	11441.614	0.413
Affect	**-31.096**	**9528.485**	**< .001**
Emotion	**-27.610**	**9992.982**	**< .001**
Socrefs	-0.735	6770.034	0.462
Family	**-2.306**	**9771.392**	**0.021**

Variable	t	df	p
Friend	**-4.622**	**9278.135**	**< .001**
Culture	-1.692	7353.972	0.091
Politic	-0.517	9418.313	0.605
Tech	-1.623	7334.215	0.105
Relig	-0.877	12738.308	0.380
Allure	**-38.032**	**12242.024**	**< .001**
Perception	-0.534	6244.805	0.593
Attention	**-2.039**	**7965.776**	**0.041**

TABLE 3
VARIABLE WHICH HAVE SIGNIFICANTLY HIGHER VALUES IN NEGATIVE REVIEWS THAN POSITIVE REVIEWS (IN BOLD)

Variable	t	df	p
Power	**12.519**	**3996.150**	**< .001**
Cognition	**36.448**	**6904.113**	**< .001**
Allnone	**3.791**	**6177.864**	**< .001**
Cogproc	**21.009**	**5822.556**	**< .001**
Insight	0.796	6858.498	0.426
Cause	**3.206**	**5972.707**	**0.001**
Tentat	**3.701**	**5912.978**	**< .001**
Differ	**31.217**	**4571.450**	**< .001**
Social	**3.260**	**5942.401**	**0.001**
Socbehav	**3.889**	**5799.725**	**< .001**
Moral	**4.642**	**4207.526**	**< .001**
Comm	**2.379**	**7457.166**	**0.017**
Lifestyle	**3.454**	**6992.796**	**< .001**
Conflict	**3.449**	**4554.598**	**< .001**

It can be seen that positive reviews tend to be high in terms of analytic, clout, authenticity, tone, affiliation, achievement, discrepant, affect, emotion, family, friend, allure, and attention. It reflects persuasive and multifaceted communication. From the variables, it suggests that the negative reviews are logically structured and very detailed (high analytic), while also expressing confidence and authority (high clout) in a manner that feels credible and personally revealing (high authenticity). The overall sentiment is emotionally expressive (high affect and emotion) which is not a surprise given these are positive reviews. However, these positive reviews also contain gaps that may be opportunities for improvement (high discrep). Frequent references to relationships (family, friends, and affiliations) and aspirational themes (achieving, allure) frame the product reviewed as both socially and personally valuable. High attention scores indicate that these reviews describe specific product features. Overall, these traits make the review not only credible and engaging but also highly influential for potential consumers.

On the other hand, the negative reviews have high scores in the categories that reflect a socially engaged, cognitively rich, and thematically complex description of the product. High-power language suggests that the reviewer discusses control, influence, or dominance, highlighting the product's disadvantages. Increased cognition, cogproc, and cause scores indicate active reasoning, explanation, and cause-effect thinking. It reveals that the reviewer is not just describing features but explaining its shortcomings. Negative reviews seem to need more cognitive power to be written. High, all-none, tentative, and differing values point to the thought process that considers exceptions, possibilities, and contrasts. Strong social, social behavior, and communication scores reveal that the product is evaluated in the context of interpersonal interactions, communication, and broader social roles, while moral and lifestyle language highlights the ethical aspects of a poorly functioning product. The presence of conflict terms suggests that the reviews address problems, trade-offs, or competing perspectives, and hence conflicting ideas are presented. Overall, these linguistic patterns signal thoughtful, socially aware, and critically engaged negative reviews that go beyond simple criticism when compared to positive reviews.

CONTRIBUTION

The current study explores the textual pattern of positive and negative reviews. The reviews of these two types seem to differ in terms of cognitive engagement, social processes, themes, confidence, and conflict, among others. The positive reviews focus on friends and family whereas negative reviews focus on social behavior. The positive ones are more analytical, while the negative ones are more cognitively engaged. Positive reviews appear to carry more credibility than negative reviews. Future research may investigate the specific psychological processes associated with each of these differences.

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