


# Semantic Features Revealed in Consumer–Review Studies

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## INTRODUCTION

Consumer reviews are an invaluable resource for assisting online shoppers in determining the quality of a product or service. To date, much research has been conducted in this field. Prior empirical research on consumer reviews has tended to focus on observable aspects of either the reviews themselves (such as review ratings, review volume, and review length) or the reviewers who submit them online (such as reviewer reputation, expertise, social network, and so on). Numerous studies have found that these elements have a significant impact on online buyers' purchase decisions by influencing their purchase intention, perceived usefulness of a review, and, ultimately, product sales. For example, review rating is regarded as a critical factor in determining the perceived usefulness of a review (Hong et al., 2017). A review's star rating indicates how extreme it is (the more stars a review received, the more positive the review is) (Hong et al., 2017). The majority of review sites allow users to rate their interactions with a product or service using a single signal that reflects overall satisfaction. These studies have aided in establishing a link between review ratings, review usefulness, and purchase intent.

However, as some researchers have suggested, condensing a lengthy analysis into a single number may be problematic (Schindler & Bickart, 2012). A single number, such as review rating, may not provide readers with all of the information they needed to make a purchasing decision. As a result, review length has emerged as an important factor to consider in consumer review studies. Review length literally refers to the number of words in a review (Wang et al., 2018). Because reviews are typically written and delivered in text form, the number of words becomes a natural way to quantify the amount of information transmitted in the review. According to Yin et al., review length has a greater impact on a review's perceived helpfulness than other variables (Yin et al., 2014). Short reviews are thought to be shallow and lack a comprehensive evaluation of product features; longer reviews, on the other hand, contain relatively more information, allowing consumers to obtain indirect consumption experiences (Wang et al., 2018). Understanding the textual characteristics of a review will undoubtedly reveal more information to us at this point. As a result, we intend to discuss textual characteristics embedded in consumer reviews in this study.

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## **BACKGROUND**

Textual characteristics in a consumer review can be understood from three perspectives: basic, content, and stylish features (Schindler & Bickart, 2012). Basic features are the previously mentioned observable characteristics, which refer to those review readers can directly observe from reviews, such as review rating (positive or negative), review age (posting date), and review extremity (the average discrepancy between this review's opinion and other reviews), and so on (Cao et al., 2011). Content features refer to the information provided in reviews, whereas stylish features refer to the words used by reviewers to express this information in those reviews (Schindler & Bickart, 2012). Semantic analysis studies typically concentrate on the wording of reviews (content and stylish features) rather than their source (basic features) (Schindler & Bickart, 2012).

Researchers use semantic analysis (also known as opinion mining) to uncover linguistic patterns in consumer reviews. This methodology was used by many researchers to create a concept taxonomy with the goal of capturing product attributes mentioned in consumer reviews as well as the structural relationship between these attributes. Typically, researchers in this field are interested in two variables: sentiment and polarity. In this context, polarity and sentiment are two concepts that are closely related but not interchangeable. Sentiment literally refers to the total amount of sentiment expressed in a text (either positive or negative), whereas polarity refers to the direction of the sentiment expressed in the text, which could be positive, negative, or neutral (Salehan & Kim, 2016). Sentiment analysis on consumer reviews is used to extract semantic cues (the substance of a review, which is the precise meaning of text in this review) from a large volume of online reviews (Sun et al., 2019).

Technically, there are two approaches to consider when conducting a semantic analysis: statistical and lexicon-based approaches (Wimmer & Yoon, 2017). The statistical (or machine learning) approach is a supervised approach that creates classifiers from labeled instances of texts or sentences. This type of approaches perform well as a supervised method when large, labeled instances are available for training and validating classifiers, while the lexicon-based approach identifies a document's orientation based on the semantic orientation of the document's words or phrases (Wimmer & Yoon, 2017). However, when working with dynamic content, such as online consumer reviews, the lexicon-based approach is thought to be more appropriate than the statistical approach, because the time required to update the training set and retrain the classifiers could be significant (Wimmer & Yoon, 2017). As a result, when a training data set is insufficiently large to accumulate the necessary feature frequency information, lexicon-based approaches outperform statistical or machine learning approaches.

The content and style of reviews, according to the most recent research on text-based communication, are important decision inputs that help determine the relative diagnosticity and accessibility of these reviews (Ludwig et al., 2013; Yi & Oh, 2022). It is widely acknowledged that the arguments in a review provide varying levels of information to future consumers depending on the topic of discussion. Product evaluative statements, for example, are more influential than descriptive statements that do not provide product evaluative information because they contain evaluative words on products that can be either positive or negative in valence (Schindler & Bickart, 2012). Furthermore, style words, which are frequently used interchangeably with function words, shape the content of a communication (Ludwig et al., 2013). Pronouns, prepositions, articles, conjunctions, auxiliary verbs, and a few other esoteric categories are examples of style or function words. These categories differentiate not only what people say (sentential meaning), but also how they write (sentential style), and both have diagnostic value that influences decisions (Ludwig et al., 2013).

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