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온라인 리뷰의 언어적 특성과 밴드왜건·양극화 효과 간의 연관성 분석
Exploring the Associations between Linguistic Features of Online Reviews and Polarization/Bandwagon Effects

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This study aims to examine the relationships between linguistic features in online reviews and two well-known phenomena in digital consumer behavior: opinion polarization and the bandwagon effect. Opinion polarization is assessed through the skewness of review rating distributions, while the bandwagon effect is measured using lagged regression analysis to determine how earlier ratings influence later ones. The analysis uses approximately 50,000 customer reviews from 50 products and services collected from three major U.S.-based e-commerce platforms. By applying regression analysis, this study empirically explores the statistical connection between specific linguistic features in review texts and both polarization and the bandwagon effect. The results show that lexical density, a measure that combines lexical diversity and review length, has a statistically significant negative relationship with both polarization and the bandwagon effect. Meanwhile, readability was not significantly linked to polarization but was positively related to the bandwagon effect. Unlike previous research, this study emphasizes the role of linguistic features in contributing to information distortion within online review environments, providing a more systematic perspective. These findings offer empirical insights for businesses aiming to establish fair and trustworthy review systems.

Keyword: Online Review, Polarization, Bandwagon, Text Linguistic Features

Ⅰ. Introduction

As online shopping continues to grow, customer reviews have become a key factor in influencing purchasing decisions (Lee and Park, 2020). While this trend enables consumers to access others' experiences easily, it also raises concerns about whether the reviews accurately reflect the overall customer experience. For example, platform-specific features, like how reviews are sorted or visually highlighted in online review systems, may unintentionally emphasize more extreme viewpoints, leading

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to uneven review distributions without intentional manipulation (Jones et al., 2004). Customer reviews posted in such an environment can make it more difficult for consumers to make informed, well-rounded judgments. In response, companies have implemented various strategies to improve the reliability and informational value of their review systems.

Two common issues in online opinion sharing are the polarization effect, where reviews tend to cluster at the extremes of positivity and negativity (Hu et al., 2009), and the bandwagon effect, in which individuals align their evaluations with prevailing opinions rather than their own judgment (Leibenstein, 1950; Chevalier and Mayzlin, 2006). These effects are especially noticeable in digital environments, where algorithmic curation, social reinforcement, and visibility bias can influence how opinions form and are perceived (Muchnik et al., 2013).

Much of the existing research explains these effects from a psychological perspective. Polarization is often associated with self-selection bias, where users with strong experiences are more likely to leave reviews, leading to biased opinion distributions (Duan et al., 2008). Similarly, the bandwagon effect is often associated with herding behavior, where people mimic others′ opinions due to cognitive shortcuts or uncertainty (Schoenmueller et al., 2020). While these insights offer valuable understanding of individual behavior, there are limits to how we comprehend the formation of public opinion online. Unlike in offline settings, opinion formation in online environments is influenced not only by individual psychological traits but also significantly shaped by the structural and design features of the online systems that mediate user interactions (Burbach et al., 2020).

Recent research in information systems (IS) has shifted focus from individual psychology to system-level design mechanisms, examining how platform structures influence collective opinion dynamics. For example, some earlier studies have proposed redesigning user interfaces or modifying review display algorithms to reduce the prominence of highly polarized or overly influential content (Alzate et al., 2021; Zhu, 2021). This shift highlights the importance of socio-technical environments in shaping not only what users share but also how that information develops and spreads within the system.

Building on the above systems-focused perspective, this study examines how linguistic features in individual reviews are related to polarization and the bandwagon effect. Instead of focusing solely on user psychology, we analyze review text attributes such as length, sentiment intensity, readability, and lexical diversity to uncover their connection to broader distributional trends. Using roughly 50,000 customer reviews from leading e-commerce platforms, we examine the relationship between micro-level review text features and macro-level patterns in group opinion dynamics. Importantly, we aim to provide observational insights into how linguistic elements may signal or reinforce informational distortions.

Ⅱ. Literature Review

Recent advancements in powerful tools for analyzing large-scale text data have enabled researchers to surpass traditional statistical methods and delve more deeply into the linguistic features of review texts (Wei et al., 2023). By employing techniques such as text mining and natural language processing (NLP), it is now possible to identify patterns, sentiments, and other textual traits related to polarization and bandwagon effects, without relying solely on self-reported user data.

Recent studies have examined the relationship between specific linguistic features, such as tone, length, readability, and structure, and the perceived helpfulness and credibility of individual reviews (Krishnamoorthy, 2015; Pan and Zhang, 2011; Wang et al., 2019). However, unlike these studies, which focus on analyzing individual reviews, this study shifts its focus to the broader distributional patterns of reviews, exploring how linguistic features are connected to systemic biases in review ecosystems.

Research indicates that users tend to write online reviews mainly with very positive or very negative experiences, while moderate opinions are less common. Even in face-to-face interactions, group opinions often favor extremes, and this tendency becomes more pronounced online because anonymity reduces personal accountability. To determine whether these patterns are present in online review systems, this study analyzes large amounts of text data to identify language patterns associated with polarized ratings.

Along with polarization, the study also examines the bandwagon effect, a phenomenon in which individuals are influenced by recent opinions, regardless of their own experiences. This results in review patterns that may reflect social conformity more than independent judgment. Therefore, the study analyzes the linguistic features of earlier reviews that are likely to trigger such conformity-driven dynamics.

The goal of this study is to identify the linguistic features of review texts that are most likely linked to bias and conformity, two significant challenges to fairness in online review systems. By treating polarization and the bandwagon effect as outcome variables, this study examines how various linguistic features of online reviews function as explanatory factors. Analyzing large-scale review datasets, it aims to uncover the linguistic mechanisms underlying these two phenomena and provide practical insights to enhance the fairness and reliability of online review platforms.

2.1 Two Common Problems of Online Review

Gathering public opinions online is an affordable and efficient way to collect information. However, the collected data may not always accurately represent public opinion. Especially with the recent increase in online shopping, some companies and individual customers with malicious intent post fake reviews, which can significantly impair customers′ ability to make informed purchasing decisions (Paul and Nikolaev, 2021). Existing research highlights two common issues: polarization, where opinions tend to become more extreme, and the bandwagon effect, where people follow the majority opinion regardless of their own beliefs.

2.1.1 J-shaped Distribution & Polarization Effect

A typical pattern observed in online customer reviews is the J-shaped distribution, characterized by a disproportionately high number of 5-star and 1-star ratings, with fewer moderate reviews (Hu et al., 2009). This uneven distribution is often related to self-selection bias, where users with extremely positive or negative experiences are more likely to leave reviews, while those with neutral experiences are less likely to do so (Hu et al., 2008; Schoenmueller et al., 2020). Consequently, online platforms tend to show polarization effect, with consumer opinions clustering at the extremes, raising concerns about whether these reviews accurately reflect overall customer sentiment (DiMaggio et al., 1996; Del Vicario et al., 2017).

Although the concept of polarization has been extensively studied in offline contexts, especially in political science and social psychology, online review environments have distinct structural and communicative features. In offline settings, polarization often occurs during group discussions, social identity formation, and ideological alignment (Moscovici and Zavalloni, 1969; Sunstein, 2002; Iyengar et al., 2012). However, these offline environments also include corrective mechanisms, such as exposure to opposing viewpoints or moderated debates, that help limit extremism. In contrast, online review platforms operate through asynchronous, non-interactive communication, where users post reviews independently and seldom engage in direct dialogue or feedback. These platforms often lack the direct interpersonal correction mechanisms present in offline interactions and are especially vulnerable to algorithmic amplification, which tends to highlight emotionally charged or extreme content (Muchnik et al., 2013). This design increases the visibility and influence of polarized reviews, further shaping public perception.

While early research on review polarization concentrated on cognitive biases, such as confirmation bias and post-purchase rationalization (Kim and Gupta, 2012), more recent studies have shifted their attention to analyzing the linguistic features of reviews as a source of informational distortion. This approach complements psychological explanations by examining how factors such as rhetorical structure, emotional intensity, and word choice influence review perception and subsequent opinion formation. For example, Cantone et al. (2021) found that ideologically charged and emotionally expressive texts, which are common in phenomena such as review bombing, are strongly associated with polarized ratings.

Additionally, recent research has expanded the analytical focus from individual cognition to platform-wide dynamics. Waller and Anderson (2020) observed that polarization in Reddit communities was more affected by the influx of ideologically extreme new users than by changes in the views of existing members. Similarly, Ruch et al. (2022) showed that product categories with moral or political importance on Amazon are more susceptible to rating polarization. These findings highlight the importance of considering how platform structures, user influx, and algorithmic visibility influence individual behavior and language use, thereby shaping collective opinion trends that differ from offline polarization processes.

Overall, existing research suggests that polarization in online review systems stems from a complex interplay among psychological tendencies, linguistic features, and platform design. However, despite increasing awareness of these interconnected factors, only a few studies have combined linguistic analysis with platform-level dynamics to explore how textual elements drive the development of polarization patterns.

To address this gap, this study employs a text-based analytical approach to examine key linguistic features, including review length, sentiment intensity, readability, and lexical diversity, across a large dataset of customer reviews. By examining the link between micro-level textual cues and macro-level public opinion patterns, the study aims to deepen our understanding of how language influences polarization and the bandwagon effect in online review environments.

2.1.2 Bandwagon Effect

Recent studies have increasingly examined the bandwagon effect in online review environments, where individuals tend to match their ratings with the perceived majority, often ignoring their initial opinions (Leibenstein, 1950). Drawing from social psychology and communication theory, this effect mainly arises from two mechanisms: normative influence, where individuals conform to seek social approval, and informational influence, where others' judgments serve as heuristics when facing uncertainty (Cialdini and Goldstein, 2004).

In digital environments where user-generated content is ranked and displayed through algorithms, visible cues such as average star ratings, review counts, and like tallies act as powerful social signals that influence user perception and decision-making (Chevalier and Mayzlin, 2006; Muchnik et al., 2013). Empirical evidence indicates that early positive reviews can significantly affect later ones, potentially causing rating inflation, opinion cascades, and sentiment convergence (Wu and Huberman, 2008; Moe and Schweidel, 2012). These patterns challenge the idea of independent judgment and highlight the path-dependent nature of opinion formation online.

This tendency toward conformity is closely related to cognitive heuristics: when faced with information overload or ambiguity, users often rely on the dominant sentiment as a mental shortcut (Kwek et al., 2020). In such cases, conforming to the majority may come more from a desire for social validation or avoiding cognitive dissonance than from logical reasoning, especially when personal experiences conflict with popular opinions.

Additionally, platform features like sorting reviews by helpfulness or rating can further reinforce this by increasing the visibility and perceived credibility of early or extreme reviews (Dellarocas, 2006). This demonstrates how platform design and content presentation amplify the bandwagon effect. Building on this growing body of research, this study investigates the linguistic features associated with conformity in online reviews.

2.2 Linguistic Features of Review Text

Research has shown that the linguistic features of online reviews can influence user purchasing behavior and opinion polarization. Studies indicate that factors such as strong sentiment language (Wang et al., 2019), review length (Mariani and Borghi, 2020), and clarity (Wang et al., 2019) significantly affect how users perceive and respond to others' online reviews. Building on this, this study aims to explore the relationships between these two information distortion phenomena and the linguistic characteristics of review texts.

Because online text more accurately captures customers' experiences and perceptions than structured metrics like 'helpfulness votes' or 'ratings', recent studies have increasingly focused on analyzing raw customer reviews. This approach allows researchers to gain deeper insights into consumer sentiment, preferences, and behavioral patterns that structured data alone might not reveal (Mariani and Borghi, 2020; Zhao and Wang, 2019). Zhao et al. (2019) conducted an empirical analysis of big data to examine how various attributes of online textual reviews, including subjectivity, diversity, readability, sentiment, and length, impact customer satisfaction with hotels. They aimed to understand how these linguistic features influence customer perceptions and satisfaction levels, providing more detailed insights into consumer behavior beyond numerical ratings.

2.3 Hypothesis Development

In this study, we use the following four quantitative metrics to explore the characteristics of online reviews:

a. Sentence Length (Mariani and Borghi, 2020; Wang et al., 2019; Zhou and Yang, 2019)
b. Sentiment Score (Zhao et al., 2019; Zhou and Yang, 2019)
c. Readability (Mariani and Borghi, 2020; Wang et al., 2019; Woo et al., 2024; Zhao et al., 2019)
d. Lexical Variation (Chang et al., 2020; Mariani and Borghi, 2020)

2.3.1 Review length

Among the various linguistic features of online reviews, review length is often considered one of the most objective and easily measurable indicators. Past studies have consistently demonstrated that longer reviews are perceived as more helpful and trustworthy, especially for utilitarian products that require detailed information (Salehan and Kim, 2016; Pan and Zhang, 2011). Therefore, review length is frequently used as a measure of a reviewer's cognitive effort and level of engagement (Schindler and Bickart, 2012).

Long reviews generally offer more detailed evaluations, covering product features, user experiences, and reasoning that shorter reviews might miss. These qualities enable them to earn higher helpfulness ratings and increase their visibility, as longer reviews are more likely to receive upvotes and be promoted by platform algorithms (Liu et al., 2012). Notably, these reviews are often found at the extremes of the rating scale, mainly 1-star and 5-star reviews, indicating that users with strong opinions tend to invest more time in writing detailed narratives (Mudambi and Schuff, 2010).

Beyond this individual review (micro) level effect, review length also influences system-wide dynamics and the formation of public opinion. When long, emotionally expressive reviews appear early in the review timeline, they often serve as informational anchors that shape the ratings and content of later reviews. This can lead to bandwagon effects, as subsequent reviewers tend to imitate earlier content and ratings as a form of social conformity. Over time, the increased visibility and influence of such extreme reviews may overshadow moderate voices, resulting in rating polarization. In this way, review length functions not only as a sign of engagement but also as a structural factor that impacts opinion formation within online review systems.

Hypothesis 1a: There is a positive relationship between the average length of reviews for a product and the polarization effect.

Hypothesis 1b: There is a positive relationship between the average length of reviews for a product and the bandwagon effect.

2.3.2 Sentiment

As sentiment analysis tools become increasingly popular, sentiment scores have emerged as a crucial metric for analyzing online reviews. These scores quantify the emotional tone of review content and are often used to examine their relationships with trust, purchasing decisions, and product ratings (Chang et al., 2020; Wang et al., 2017). By detecting affective signals in text, sentiment analysis offers insights into how consumers perceive and react to products and services.

Highly valenced reviews, which express strong positivity or negativity, tend to attract more attention and have greater influence (Lee et al., 2017). When these reviews are posted early, they often set evaluative norms that shape the sentiment and language of later reviews. This pattern reflects a bandwagon effect, where users follow dominant emotional cues to make decisions more easily or gain social approval.

Although such behaviors may seem subtle on an individual level, they can accumulate over time, resulting in skewed sentiment distributions and the suppression of moderate opinions. This can lead to rating polarization, especially when early emotional reviews gain prominence through algorithmic promotion. In this way, sentiment strength not only functions as an emotional cue but also triggers shifts in collective opinion.

Hypothesis 2a: There is a positive relationship between the average sentiment score of reviews for a product and the polarization effect.

Hypothesis 2b: There is a positive relationship between the average sentiment score of reviews for a product and the bandwagon effect.

2.3.3 Readability

Readability, or the ease with which a review can be understood, plays a crucial role in shaping user perceptions and behaviors (Woo et al., 2024). Studies have shown that highly satisfied or dissatisfied customers tend to write longer, well-structured, and emotionally expressive reviews, all of which improve readability (Wei et al., 2023; Zhao et al., 2019). Therefore, readability reflects not only the clarity of the writing but also the strength of the sentiment expressed.

Clear and well-organized reviews are consistently perceived as more trustworthy, helpful, and credible (Duan et al., 2008; Wang et al., 2019). Because they are easier to understand, these reviews tend to get more helpfulness votes and are often given higher priority by platform algorithms, boosting their visibility and impact (Gkikas et al., 2022).

When emotionally charged and readable reviews appear early in a product's review timeline, they can set a tone and structure that others follow, increasing the bandwagon effect. Their clarity and perceived authority make them more likely to be copied by later reviewers. However, this dominance can also overshadow more moderate opinions, leading to rating polarization. In this way, readability plays a structural influence, reinforcing both stylistic convergence and evaluative extremes in online review environments.

Hypothesis 3a: There is a positive relationship between the average readability of reviews for a product and the polarization effect.

Hypothesis 3b: There is a positive relationship between the readability of reviews for a product and the bandwagon effect.

Among popular readability metrics, such as Flesch Reading Ease (FRE), Flesch-Kincaid Grade Level (FKGL), SMOG, Coleman-Liau Index (CLI), and Automated Readability Index (ARI), the Gunning Fog Index (FOG) is especially useful for analyzing online reviews. While FRE, FKGL, and SMOG rely on syllable counts or require longer texts (Kong and Hu, 2015; Raja and Lodhi, 2024), FOG handles short, variable-length content more effectively (Wei et al., 2023). Unlike CLI and ARI, which focus on character counts and are designed for formal writing (Tillman and Hagberg, 2014), FOG evaluates sentence and word complexity, important factors in persuasive and emotionally charged reviews. Its simple scoring system and proven relevance to review helpfulness and influence (Mudambi and Schuff, 2010; Wang et al., 2017) make it a balanced, suitable tool for measuring readability in online reviews.

Numerous studies that utilize linguistic features of text as key variables have widely relied on the FOG (Fog Index) as a standard measure of readability (Gkikas et al., 2022; Wei et al., 2023). The FOG Index evaluates readability by analyzing sentence length and the proportion of complex words, offering an intuitive measure of how easy or difficult the text is to comprehend. It estimates the average number of years of education needed to read and comprehend the text effectively (Gunning, 1969; Wei et al., 2023).

According to Stajner et al. (2012), the FOG index is calculated using the following equation:

$$FOG = 0.4 \times \left(\frac{Total\ Words}{Total\ Sentence} + 100 * \frac{Hard\ Words}{Total\ Words}\right)$$

The term "hard words" refers to the number of words in a document that contains more than two syllables per hundred words. A lower FOG Index indicates that the text is easier to understand, while a higher FOG Index suggests that it is more challenging to comprehend. In the study by Wei et al. (2023), the FOG Index and review length were used to predict the sentiment of online reviews. Similarly, Lah et al. (2017) used this measure to forecast review helpfulness. Building on these earlier studies, this research aims to empirically examine the relationship between the FOG Index and phenomena such as polarization and bandwagon effects in online reviews.

2.3.4 Lexical Diversity

Lexical diversity refers to the variety of vocabulary used in a review. It reflects not only language richness but also clarity, accuracy, and conciseness in expression. Reviewers aiming to convey complex ideas often choose more varied and deliberate words, which can enhance the persuasiveness of the review. In individual reviews, lexical diversity has been linked to helpfulness, perceived credibility, and user engagement (Akbarabadi and Hosseini, 2020; Chien et al., 2018). Reviews with broader vocabulary tend to present nuanced arguments and are often seen as more thoughtful and trustworthy.

Lexically rich reviews, particularly those with strong opinions, tend to receive more upvotes and are promoted more frequently by platform algorithms. Their greater visibility serves as an informal template for future reviews. As a result, later reviewers may copy their language, sentiments, and ratings. This imitation can cause bandwagon effects. When these reviews also express extreme sentiments, they can further amplify polarization, overshadowing more moderate or straightforward voices.

In this way, lexical diversity serves as both an indicator of individual review quality and a means of collective influence, shaping how opinions are created, shared, and amplified in online review ecosystems.

Hypothesis 4a: There is a positive relationship between the lexical diversity of reviews for a product and the polarization effect.

Hypothesis 4b: There is a positive relationship between the lexical diversity of reviews for a product and the bandwagon effect.

While advanced measures like MATTR, MTLD, and Voc-D offer statistical accuracy and better control over text length (McCarthy and Jarvis, 2010), this study uses the Type-Token Ratio (TTR) because it is simple, transparent, and practical for short texts, such as online reviews. Since review content is usually brief and highly varied, TTR allows consistent measurement of lexical diversity across a large dataset. Its low computational cost and straightforward interpretation also make it suitable for scalable analysis (Yu, 2010). Additionally, TTR has been widely used in previous research analyzing consumer reviews (Akbarabadi and Hosseini, 2020; Chien et al., 2018).

A commonly used metric to measure lexical diversity is the Type-Token Ratio (TTR) (Yang et al., 2022). Analyzing the Type-Token Ratio (TTR) in online reviews is important for understanding the textual dynamics that influence consumer behavior. TTR, which evaluates lexical diversity, shows the variety of vocabulary used in a text. In the context of online reviews, a high TTR indicates a broad range of vocabulary, suggesting that the review might be more informative, detailed, and thoughtfully written. Such reviews provide diverse perspectives or multifaceted insights about a product or service, potentially helping consumers make well-informed decisions. Conversely, a lower TTR points to more repetitive and possibly less insightful reviews. These likely lack depth and fail to provide a comprehensive understanding of the product, resulting in a less engaging experience for readers.

TTR can be expressed with the following equation.

$$TTR = Types \div Token$$

The Type-Token Ratio (TTR) is calculated as the ratio of the number of unique word types (Types) in a review to the total number of words (Tokens) in that review (Richard, 1987). TTR helps compare texts of different lengths, as shorter texts often have a higher TTR than longer ones. The type-token ratio measures vocabulary variation within a written text. It is shown to be a useful measure of lexical diversity within a text. Analyzing the Type-Token Ratio (TTR) in online reviews is essential for understanding how vocabulary diversity influences consumer behavior (Liu and Hu, 2021). A high TTR indicates reviews with varied vocabulary, suggesting richness and thoughtfulness, whereas a low TTR points to repetitive and less insightful content, resulting in a less engaging experience for readers. Reviews with higher TTRs tend to appear more trustworthy and persuasive, attracting more attention and trust (Chien et al., 2018). This can influence consumer perceptions and brand reputation by providing rich narratives about products or services.

2.4 Linking Micro-Level Linguistic Features of Reviews to Macro-Level Opinion Formation Dynamics

Based on a growing body of research examining the relationships between individual behaviors and overall systemic outcomes, this study suggests that micro-level linguistic features of online reviews, such as length, sentiment intensity, readability, and lexical diversity, may be related to larger structural patterns in overall product evaluations. Keijzer et al. (2024) emphasizes the significance of linking micro-level responses to macro-level trends in understanding how opinions are formed on digital platforms. Additionally, Macy et al. (2019) showed that social cascades are a key mechanism in shaping collective opinions. Their findings suggest that collective opinions are not solely created by aggregating independent judgments but can also be influenced by the structure and sequence of preceding information. This study further suggests that certain ways of presenting information could lead to biased group consensus. Notably, they pointed out that social influence and the immediate informational context may have a greater impact on opinion dynamics than individuals′ fixed beliefs or core values.

Building on this perspective, this study is based on the idea that micro-level features, specifically the linguistic traits of individual reviews, may be related to macro-level patterns in online review ecosystems. Through large-scale data analysis, this study aims to explore the connection between individual expressions and broader trends in review distribution and consumer ratings. In doing so, it aims to enhance understanding of how micro-level behaviors and macro-level structures are interconnected in digital consumer environments.

Ⅲ. Research Model & Methodology

3.1 Data Collection Strategy

The data collection for this study is carefully designed to ensure a diverse and comprehensive dataset. The primary sources are online reviews from three popular e-commerce platforms: Amazon, Sephora, and Yelp. These platforms were chosen due to their popularity and wide range of products and services, which provide a broad spectrum of consumer opinions and experiences.

Reviews from each platform are systematically collected, including review text, star ratings, review dates, and other relevant information available. This study gathers a total of 50,000 customer reviews across 50 different products.

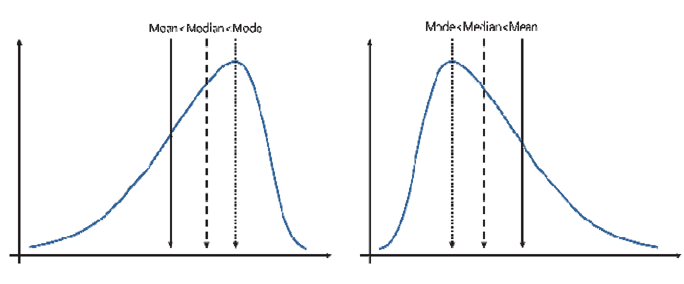
- Amazon: electronics/home 10 devices (SAMSUNG 32-inch Class LED Smart TV 1080P; BISSELL 2252 Vacuum cleaner; …) ~15,000 reviews
- Yelp: 20 restaurants (Kitchen Story; Farmhouse Kitchen Thai Cuisine; …) ~20,000 reviews
- Sephora: 20 beauty products (Dior Dream Skin Perfector; Laneige Lip Balm; …) ~15,000 reviews

3.2 Data Analysis Methods

3.2.1 Polarization Effect

One of the main causes of biased and distorted information in online reviews is the 'Polarization Effect.' This refers to the phenomenon where many customers tend to give ratings of either 1 or 5, leading to a skewed view of a product or service's overall evaluation. It is often hard to find ratings other than 1 or 5 on online stores. This occurs because only extremely satisfied or dissatisfied customers usually feel motivated to leave reviews, which introduces bias into the review data. This study examines whether the overall distribution of customer ratings in online review systems follows a J-shaped pattern and explores the relationship between this phenomenon and the linguistic characteristics of review texts. Majumder et al. (2022) and Koudenburg et al. (2021) used the skewness index to examine the occurrence of opinion polarization in online environments.

Skewness is a statistical measure that describes the shape of a distribution. It indicates the extent to which the distribution is heavily concentrated at one point. This study uses it to examine the polarization in customer review distributions. Skewness shows the distribution's asymmetry. The tail of a negatively skewed distribution points to the left, toward the negative side of the histogram, while the tail of a positively skewed distribution points to the right, toward the positive side (Kopczewska, 2014). If the peak of the review rating distribution is to the left of the mean, the distribution exhibits positive skewness. This means most consumers rate products or services lower than the average. Conversely, if the peak is to the right of the mean, it indicates negative skewness, meaning many customers rate products or services higher than the average. This study utilized the absolute value of skewness derived from the review rating distribution of each product or service to measure the degree of polarization in the distribution.



〈Figure 1〉 Skewness

3.2.2 Bandwagon Effect

The bandwagon effect, a phenomenon in which individuals easily adopt majority opinions or megatrends without critical evaluation, is a key factor in understanding consumer behavior in online reviews. To measure this effect, the study uses an advanced statistical technique, known as lagged regression. While few studies specifically apply lagged regression to quantify the bandwagon effect, some research has looked at how past reviews influence current reviews using time series analysis, a concept similar to lagged regression (Fu, 2012).

Lagged regression is often employed to investigate how previous events or data points influence future outcomes over time (Zhu and Zhang, 2010). This approach can help track how early user reviews or ratings influence later ones, which is central to understanding the bandwagon effect. This study employs a lagged regression model to examine how earlier ratings affect the likelihood of receiving similar ratings in the future. Although Fu (2012) did not employ the lagged regression method directly, it examined time-series data to determine if the number of views at time T (current ratings) on a video archive site was influenced by the views at time T-1 (earlier ratings), confirming the bandwagon effect. To perform lagged regression analysis, we organize reviews for each item by posting date and examine how earlier review ratings influence later ones. In our regression model, the dependent variable is the rating of a review (Y_t), while the independent variables are the ratings of previous reviews (X_{t-1}, X_{t-2}, ⋯, X_{t-k}).

$$Y_t = \beta_0 + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \cdots + \beta_k X_{t-k} + \epsilon_t$$

Where Y_t : Review Score at time t
X_{t-k} : Review Score at time t-k
X_{t-1} : Review Score at time t-1
$\beta_1 \cdots \beta_k$: The coefficient indicating how past review scores

To measure the bandwagon effect in a product's review distribution, we used the moving average of correlation values (β_1 ⋯ β_k) from a lagged regression analysis. These values reflect the impact of previous daily customer ratings on the most recent rating. By analyzing these, we assessed the extent to which past reviews influence current ones. A correlation close to 1 indicates a strong positive relationship, meaning that more positive past reviews tend to lead to more positive recent reviews. Conversely, a correlation close to -1 suggests a strong negative relationship, where more positive past reviews lead to more negative subsequent reviews. A correlation near 0 indicates a weak or negligible connection between past and future reviews.

3.2.3 Review Text Analysis

The study employs a comprehensive method to analyze online reviews by assessing key textual features, including readability (Fog Index, FOG), lexical diversity (Type-Token Ratio, TTR), sentiment scores, and review length. These metrics are calculated using Python and specialized libraries, such as TextBlob, which offer a detailed view of textual dynamics in online reviews. Table 1 shows the descriptive statistics for all variables.

3.2.4 Normalized Variables

In analyzing online reviews, variables like readability scores, sentiment scores, review length, and Type-Token Ratio (TTR) naturally exist on different scales. To compare and analyze these variables effectively, it is necessary to bring them onto a common scale. This study employs min-max normalization, a widely used data preprocessing technique, to achieve consistency.

Min-max normalization is a scaling technique that adjusts data features to a specific range, usually from 0 to 1. This method is especially useful when variables are measured in different units or scales, as it helps to standardize these differences. The min-max normalization is applied using the formula:

$$Normalized\,value = \frac{value - min}{max - min}$$

Here, 'value' is the original value of a data point, 'min' is the minimum value in the dataset for that feature, and 'max' is the maximum value. For each variable (readability score, sentiment score, review length, TTR), min-max normalization was applied. This ensured that each variable was scaled to a range between 0 and 1, enabling consistent and comparable analysis across different data types. It standardizes diverse variables on a common scale, allowing fair comparison and combination in subsequent analyses.

〈Table 1〉 Descriptive Statistics

	N	Mean	SD	Max	Min
Skewness	50	-1.84	0.75	-0.71	-4.16
Bandwagon	50	0.03	0.05	0.23	-0.03
FOG	50	10.23	14.01	82	6.08
TTR	50	0.77	0.06	0.9	0.68
Length	50	68.99	31.32	142.0	19.0
Sentiment	50	0.83	3.78	27.0	0.17

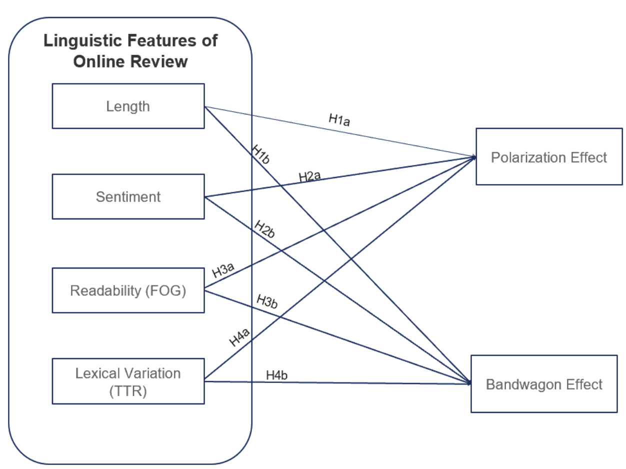
3.3 Research Model

Before conducting regression analysis to examine the effects of four linguistic features of review texts on polarization and the bandwagon effect, we check VIF (Variance Inflation Factors) values to assess multicollinearity among the four independent variables.

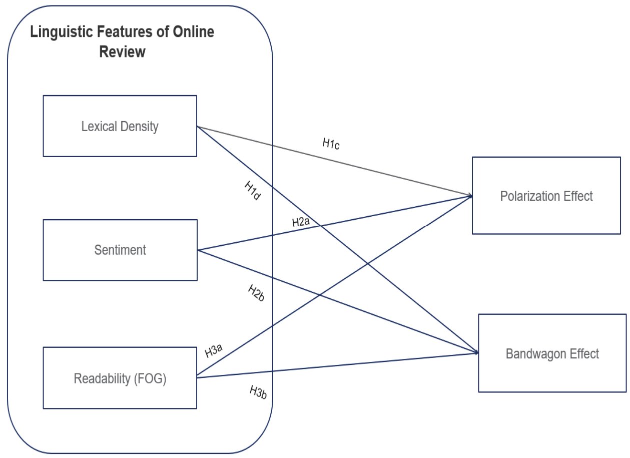
An analysis of Variance Inflation Factors (VIF) shows that FOG and Sentiment have VIF values of 1.04 and 1.16, respectively, indicating a low risk of multicollinearity. In contrast, TTR (Type-Token Ratio) and Length show VIF values of 11.77 and 12.16, both exceeding the commonly accepted threshold of 10, which suggests the presence of severe multicollinearity. Therefore, this study investigates suitable methods to address this issue.

Kim (2019) proposes three methods to reduce multicollinearity. The first involves increasing the sample size to reduce the standard errors of the regression coefficients, thereby enhancing statistical stability. However, Kim (2019) notes that this may not be enough in cases of severe multicollinearity. The second method suggests replacing problematic variables with alternatives that have stronger explanatory power. Since TTR and Length are consistently identified as key variables in this study, removing or substituting them would be inappropriate. The third method involves combining multicollinear variables into a higher-order composite variable.

Following this third approach, this study introduces a new variable, Lexical Density, by combining TTR and Length. This composite measure captures both word diversity and text length, reflecting how densely meaningful content words are packed into a text. For ex-



〈Figure 2〉 Original Research Model



〈Figure 3〉 Revised Research Model

ample, a high lexical density signifies an information-rich and concise review, while a low value suggests a more narrative or emotional style that relies more on function words. Therefore, Lexical Density provides a measurable indicator of textual informativeness and structural complexity and can serve as an important explanatory variable in our regression model.

$$\text{Lexical Density} = \frac{\text{TTR}}{\log(\text{Length} + 1)}$$

Accordingly, this study employed a revised research model (Figure 3), replacing Length and TTR with a new composite variable, Lexical Density, rather than the original model (Figure 2) that included all four linguistic features.

Ⅳ. Research Results

The analysis of the regression model uncovered subtle connections between three linguistic features of online reviews and the phenomena of polarization and the bandwagon effect. The results, shown in Table 2, show the different influences of readability (FOG), lexical density, and sentiment scores on two dependent variables.

First, the analysis showed that Lexical Density has a statistically significant negative impact on Skewness ($t = -6.70$, $p < 0.001$). This indicates that reviews with higher informational density tend to decrease the Skewness in the overall review distribution. In contrast, FOG and Sentiment were not found to have a statistically significant impact on Skewness.

〈Table 2〉 Analysis Results

H	IV	DV	M	t	P
1c	Lexical Density	Polarization[1)]	Skewness	-6.70	0.00***
1d		Bandwagon[2)]	Ave Coefficient	-1.68	0.09*
2a	Sentiment	Polarization[1)]	Skewness	-0.25	0.807
2b		Bandwagon[2)]	Ave Coefficient	-0.24	0.81
3a	Readability (FOG)	Polarization[1)]	Skewness	0.52	0.61
3b		Bandwagon[2)]	Ave Coefficient	1.84	0.07*

IV: Independent Var. DV: Dependent Var. M: Measurement
*p < 0.10, **p < 0.05, ***p < 0.01
1) R-squared of a Regression Model where the dependent variable is Polarization: 0.52
2) R-squared of a Regression Model where the dependent variable is Bandwagon: 0,14

Many previous studies have examined how review length and lexical diversity (TTR: Type-Token Ratio) influence reviewer satisfaction and consumer responses, including helpfulness scores, but their findings have been inconsistent. For example, Zhao et al. (2019) found that review length has a negative effect, while TTR has a positive impact on reviewer satisfaction. Conversely, Wei et al. (2023) suggested the opposite. Lutz et al. (2019) showed that longer reviews lead to higher helpfulness scores. Chua and Banerjee (2016) discovered that review length positively influences the helpfulness of negative reviews but negatively affects the helpfulness ratio of positive reviews.

These conflicting results may occur because review length and lexical diversity do not always reflect the actual amount of information or content density. Not all long reviews are rich in information. Some include meaningful content words, while others are full of emotional or repetitive expressions. The results can vary depending on the review data used in each study. Thus, using review length and lexical diversity to analyze online review systems has significant limitations.

To address these issues, this study introduces Lexical Density as a new variable that measures informational compactness. The analysis shows that this variable significantly reduces the Skewness of review distributions, indicating that more information-dense reviews lead to more balanced consumer evaluations. These findings support recent strategies employed by some companies to limit the number of words in customer reviews, providing practical insights for future online review system design and management.

Secondly, this study analyzed the linguistic features of customer reviews that impact the Bandwagon effect and found that Lexical

Density and the FOG Index showed marginal statistical significance around the 10% level. Specifically, the FOG Index had a positive relationship with the Bandwagon effect, while Lexical Density was negatively related to it.

The FOG Index is a well-known measure of how easily texts can be read, indicating the educational level needed to understand them. A higher FOG score generally reflects more complex sentences and more technical or unfamiliar words, which require higher reading skills. In this study, the average FOG score of the reviews was 7.41, ranging from 6.08 to 8.47, all of which were below the cutoff of 10. This suggests that most people found the reviews easy to read without special knowledge. Previous studies have shown that texts, such as news articles and popular magazines, typically have FOG scores between 5 and 10, while scores below 5 are considered too simple and lacking depth (Gkikas et al., 2022; Wei et al., 2023). The findings indicate that moderately complex reviews with higher FOG scores tend to be more persuasive and more likely to generate Bandwagon responses. In other words, consumers are more inclined to follow reviews that contain some technicality or a formal tone, compared to those written in overly simple language.

In contrast, Lexical Density was found to significantly decrease the Bandwagon effect. High lexical density indicates that the review text is rich in content words, featuring analytical and information-rich language that requires readers to exert cognitive effort. These reviews are more likely to encourage careful and independent judgment rather than instinctive or emotionally influenced reactions, thus reducing susceptibility to Bandwagon behavior. That is, reviews with high lexical density tend to focus on facts and objective information rather than emotional expression, which may reduce emotional contagion and social conformity among consumers.

Ⅴ. Conclusion and Implications

This study investigates the relationship between micro-level linguistic features in online reviews, such as length, sentiment intensity, readability, and lexical diversity, and macro-level patterns in review ecosystems, including rating polarization and the bandwagon effect. Analyzing approximately 50,000 reviews from leading U.S.-based e-commerce platforms, we found that certain linguistic features are significantly associated with imbalanced review dynamics.

In particular, lexical density, a measure of information richness and conciseness, was negatively related to both polarization and the bandwagon effect, indicating that analytical, content-dense reviews might reduce conformity and encourage more independent consumer evaluations. Readability, measured by the FOG Index, was positively correlated with the bandwagon effect, suggesting that reviews written in moderately complex, well-structured language are more likely to influence subsequent reviewers (Krishnamoorthy, 2015; Mudambi and Schuff, 2010).

These findings expand on existing research in information systems by highlighting how linguistic characteristics shape overall opinion patterns. While earlier studies primarily examined how review content influences individual perceptions (e.g., helpfulness, purchase intention), this study demonstrates that textual features of online reviews can also serve as structural signals, affecting collective rating trends (Chevalier and Mayzlin, 2006; Moe and Schweidel, 2012). The results support theories of social influence and information cascades (Cialdini and Goldstein, 2004; Bikhchandani et al., 1992), providing a language-based view on how digital public opinions form (Macy et al., 2019).

Methodologically, the study shows the value of using natural language processing (NLP) techniques on large-scale, long-term review data. Although not causal, the analysis provides strong evidence of associations between linguistic patterns and emerging ecosystem-level behaviors.

Practically, the results suggest that e-commerce platforms should consider incorporating textual features, such as lexical richness and readability, into their review sorting and visibility algorithms. Promoting reviews that are information-rich and analytically structured may help reduce early-stage bias and foster a more balanced and trustworthy review environment (Moe and Schweidel, 2012).

We acknowledge that reliance on observational data and regression methods constrains causal inference, as confounding factors such as product type, reviewer traits, or platform design may influence the observed relationships. Future research should explore these dynamics through experimental or quasi-experimental approaches (Bikhchandani et al., 1992; Macy et al., 2019).

This study focused on examining the relationship between the linguistic features of review texts for a specific product and the overall distribution of those reviews. As a result, it did not include a comparative analysis of which of the two independent variables is more closely related to particular linguistic features of individual reviews. However, the findings demonstrate that linguistic characteristics are strongly connected to distortions in online review information. Therefore, future research should empirically explore, using more refined experimental designs, whether these linguistic features have a greater impact on polarization or the bandwagon effect.

In summary, this research provides empirical evidence that linguistic features in individual reviews are systematically linked to collective judgment patterns in digital marketplaces. These findings lay the groundwork for creating more fair and transparent review systems, based on a deeper understanding of how language shapes opinions on a large scale.

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