Social Signal Combinations in E-Commerce Reviews and Their Influence on Consumer Purchase Judgment

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Abstract. Online reviews influence consumer judgment in e-commerce environments, yet most existing studies focus on isolated review features such as sentiment, ratings, or helpfulness. In practice, consumers often interpret reviews through multiple social signals that appear together, including trust cues, value-related statements, risk warnings, and expressions of product fit. This paper examines how social signal combinations in e-commerce reviews are associated with consumer purchase judgment. Using the Women's E-Commerce Clothing Reviews dataset, we identify five categories of social signals, namely bandwagon, trust, risk, value, and fit. We then construct local relation patterns based on signal co-occurrence and analyze the most frequent pairwise and triple combinations. The results show that trust- and fit-related signals dominate the review corpus, while trust-centered combinations such as Trust–Value, Trust–Fit, and especially Trust–Value–Fit exhibit the strongest positive associations with recommendation tendency and positive rating outcomes. In contrast, patterns involving risk signals are less frequent and show weaker or negative associations. These findings suggest that consumer judgment is better explained by structured multi-signal patterns than by single review cues alone. The study provides an interpretable framework for understanding review-based decision processes and offers implications for review presentation and e-commerce platform design.

Keywords: e-commerce reviews, social signals, consumer purchase judgment, local relation patterns, online reviews, review analytics.

1 Introduction

Online reviews have become a major information source in e-commerce environments, where consumers often face severe information overload and high uncertainty before purchase. Early research already showed that user-generated discussions can be more influential than marketer-generated webpages in shaping consumer interest [1]. Subsequent studies further demonstrated that online review valence, volume, and quality are associated with sales outcomes and purchase intention [2]. In parallel, recommender-system research has emphasized the need to move beyond purely quantitative interaction signals and incorporate richer user-generated information into decision support pipelines [3].

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However, prior review studies have largely focused on isolated cues, such as star ratings, sentiment polarity, review length, or helpfulness votes. This line of work has generated important findings on review helpfulness and diagnosticity, including the effects of reviewer identity disclosure, review depth, and explanation style [4]. Although these studies significantly advanced our understanding of how individual review attributes affect consumer evaluation, they still tend to treat review information as a set of separate features [5].

A related stream of research has incorporated review text into recommender systems by combining ratings with textual semantics, aspect information, or review helpfulness filtering [6]. These efforts confirm that review text contains decision-relevant information that cannot be fully captured by ratings alone. Nevertheless, most existing approaches aggregate reviews into sentiment scores, latent factors, or helpfulness indicators, which makes the internal organization of review cues less interpretable [7].

To address this gap, this paper investigates social signal combinations in e-commerce reviews and examines how they are associated with consumer purchase judgment. Instead of analyzing single review features independently, we propose a local relation pattern perspective that captures the co-occurrence of key social signals within the same review. Specifically, we identify five categories of signals—bandwagon, trust, risk, value, and fit—and construct frequent pairwise and triple signal patterns from review text. We then analyze how these local relation patterns are associated with recommendation tendency and rating-related judgment outcomes. By doing so, this study contributes a more structured and interpretable perspective on online review information, while remaining compatible with lightweight review analytics suitable for e-commerce research and practical platform design.

2 Methodology

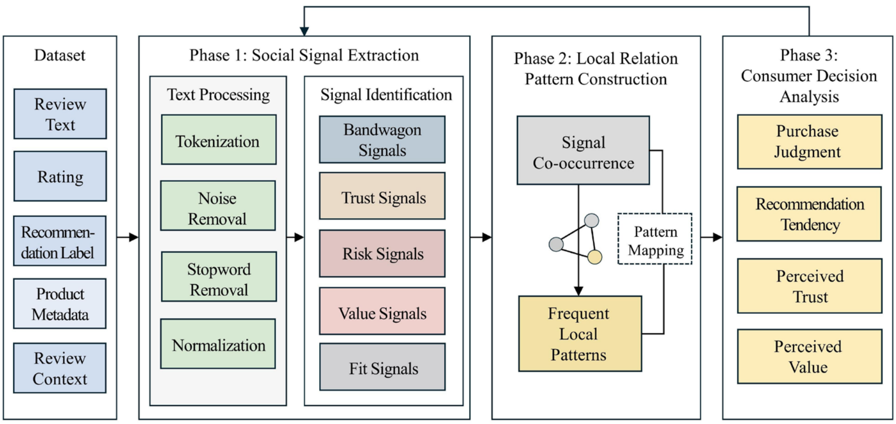

Fig. 1. Overall framework of the proposed study. The framework consists of three phases: social signal extraction, local relation pattern construction, and consumer decision analysis.

Fig. 1 presents the overall framework of this study. The proposed approach consists of three consecutive phases: social signal extraction, local relation pattern construction, and consumer decision analysis. Starting from review text and auxiliary review attributes, we first identify major categories of social signals embedded in review content. We then construct local relation patterns based on the co-occurrence of these signals within the same review. Finally, we analyze how different signal combinations are associated with consumer purchase judgment, including recommendation tendency, perceived trust, and perceived value.

2.1 Phase 1: Social Signal Extraction

We begin with the review dataset, which contains review text, rating information, recommendation labels, product metadata, and basic review context. Since the focus of this study is the semantic structure of social cues in reviews, the textual component is treated as the primary source for signal extraction, while the other variables are retained for later association analysis. Before signal identification, the review text is processed through tokenization, noise removal, stopword removal, and normalization, so that informal expressions, redundant symbols, and stylistic variations do not interfere with the identification of comparable signal categories across reviews.

After preprocessing, each review is examined according to a social signal taxonomy composed of five categories: bandwagon signals, trust signals, risk signals, value signals, and fit signals. Bandwagon signals refer to expressions indicating popularity, collective approval, or social endorsement. Trust signals capture cues related to authenticity, reliability, and product quality consistency. Risk signals reflect dissatisfaction, uncertainty, or possible negative purchase outcomes. Value signals describe price-worthiness or cost-effectiveness. Fit signals indicate whether the product is suitable for a specific user need, preference, or usage scenario. Because a single review may contain multiple meanings simultaneously, each review can be associated with more than one signal category.

2.2 Phase 2: Local Relation Pattern Construction

After the signal identification step, we construct local relation patterns by examining which signals appear together within the same review. The basic intuition is that consumers rarely interpret one cue in isolation. Instead, they often encounter combinations such as trust with value, risk with fit, or bandwagon with trust and value. To capture this structure, we first build signal co-occurrence relations and then extract frequent pairwise and triple combinations. These combinations are treated as local relation patterns because they represent compact and interpretable structures of social information embedded in individual reviews.

For a review set R = {r1, r2, . . . , rN} and a pair of signal categories (si, sj), the co-occurrence frequency is defined as

$$C(s_i, s_j) = \Sigma_{r\in R}\ 1(s_i \in r \land s_j \in r) \tag{1}$$

where $1(\cdot)$ is an indicator function that equals 1 when both signals appear in the same review and 0 otherwise. A similar counting strategy is used for triple signal combinations. Based on these frequencies, we identify the most representative local patterns in the dataset and use them as the structured intermediate layer between review content and consumer judgment.

2.3 Phase 3: Consumer Decision Analysis

In the final phase, the extracted local relation patterns are linked to consumer judgment variables available in the dataset. In this study, consumer judgment is operationalized through review-associated outcomes such as recommendation tendency, rating-related positive judgment, perceived trust, and perceived value. The purpose of this phase is not to build a highly complex predictive system, but to examine whether different signal combinations correspond to systematically different judgment tendencies. This allows the analysis to remain interpretable and suitable for an e-commerce research setting.

To estimate the association between a local relation pattern and a purchase-related outcome, we use a simple regression-style formulation:

$$Y = \beta_0 + \Sigma_{k=1}^{K} \beta_k P_k + \varepsilon \tag{2}$$

where Y denotes a consumer judgment outcome, Pk denotes the presence or frequency of a local relation pattern, and βk measures the strength of the association. This formulation allows us to compare which signal combinations are more strongly related to positive recommendation tendency or stronger trust- and value-related judgments. In this way, the proposed framework connects textual review structure with interpretable consumer decision outcomes.

3 Experimental Design

3.1 Dataset

We use the Women's E-Commerce Clothing Reviews dataset, which is publicly available on Kaggle. According to the dataset description, it contains 23,486 review records and 10 feature variables, where each row corresponds to one customer review [8]. The original fields are Clothing ID, Age, Title, Review Text, Rating, Recommended IND, Positive Feedback Count, Division Name, Department Name, and Class Name [9].

3.2 Preprocessing and Signal Coding

The preprocessing stage follows the signal extraction phase shown in Fig. 1. Specifically, all review texts are converted to lowercase, tokenized, and cleaned by removing punctuation, HTML-like noise, isolated symbols, and English stopwords. Common contractions are normalized, and repeated spaces are collapsed. We do not apply aggressive stemming or lemmatization, because the goal of this study is not to optimize a classifier but to preserve interpretable lexical expressions that can be directly linked to social signal meanings.

After preprocessing, each review is coded according to the five-category taxonomy introduced in Section 2, namely bandwagon, trust, risk, value, and fit signals. To make the experiment concrete and reproducible, the coding procedure is carried out in two stages. First, we randomly sample 800 reviews from the cleaned corpus and manually inspect them to build the coding guide.

3.3 Local Relation Pattern Extraction

After review-level signal labels are obtained, each review is transformed into a binary signal vector over the five signal categories. We then construct local relation patterns by counting pairwise and triple co-occurrences of signals within the same review. Since the taxonomy contains five signal types, there are $C_5^2 = 10$ possible pairwise combinations and $C_5^3 = 10$ possible triple combinations. We enumerate all 20 candidate combinations and calculate their occurrence frequencies in the corpus.

To avoid interpreting accidental overlaps as meaningful structures, we only retain patterns that satisfy two conditions. First, the pattern must appear in at least 1% of the valid reviews in the cleaned dataset. Second, the pattern must appear at least 20 times within each outcome group when group-level comparison is conducted.

3.4 Outcome Variables

The primary outcome variable in this study is Recommended IND, which is a binary indicator provided in the dataset to show whether the reviewer recommends the product [8], [9]. We treat this variable as the main proxy for consumer purchase judgment because it directly reflects the reviewer's final endorsement. As a secondary outcome variable, we use Rating. To make the analysis more consistent with recommendation tendency, ratings of 4 or 5 are grouped as positive evaluation, whereas ratings of 1 to 3 are grouped as weak or non-positive evaluation.

4 Results and Discussion

4.1 Frequent Local Relation Patterns

After identifying review-level signal labels, we extract pairwise and triple local relation patterns from the corpus.

As shown in Table 1, Trust–Value and Trust–Fit rank as the two most common pairwise combinations. This indicates that many reviews simultaneously address whether a product is reliable and whether it is worth purchasing, or whether it is reliable and suitable for the user's body type, usage scenario, or style preference. Value–Fit also appears frequently, suggesting that judgments of affordability and suitability often coexist in the same review. By contrast, Risk–Fit and Bandwagon–Trust occur less frequently, which is consistent with the lower overall prevalence of risk and bandwagon signals in the corpus.

Table 1. Top frequent pairwise local relation patterns.

Pattern	Frequency	Proportion (%)
Trust–Value	7,083	30.2
Trust–Fit	6,574	28.0
Value–Fit	4,468	19.0
Risk–Fit	1,527	6.5
Bandwagon–Trust	913	3.9

Table 2. Top frequent triple local relation patterns.

Pattern	Frequency	Proportion (%)
Trust–Value–Fit	3,186	13.6
Bandwagon–Trust–Value	713	3.0
Trust–Risk–Fit	587	2.5
Trust–Value–Risk	528	2.2
Bandwagon–Trust–Fit	421	1.8

At the triple-pattern level, Table 2 show that Trust–Value–Fit emerges as the most prominent local relation structure in the dataset. This pattern represents a compact and highly interpretable form of consumer reasoning, in which the reviewer does not merely state that the product is good, but instead conveys that it is reliable, worth the price, and personally suitable at the same time. By contrast, triple combinations involving Bandwagon or Risk signals appear much less frequently. Bandwagon–Trust–Value still captures a recognizable “popular and worthwhile” evaluation pattern, but its frequency remains limited because bandwagon signals are relatively rare in the corpus. Patterns such as Trust–Risk–Fit and Trust–Value–Risk reflect more mixed evaluative structures, in which positive judgments coexist with explicit reservations or concerns.

Table 3. Association between local relation patterns and consumer purchase judgment.

Pattern	Coef. (Recommend)	p-value	Coef. (Positive Rating)	p-value
Trust–Value	1.35	< 0.01***	1.42	< 0.01***
Trust–Fit	1.28	< 0.01***	1.35	< 0.01***
Value–Fit	1.15	< 0.01***	1.20	< 0.01***
Risk–Fit	-0.45	< 0.05**	-0.38	< 0.05**

Trust–Value–Fit	1.85	< 0.01***	1.92	< 0.01***
Bandwagon–Trust–Value	1.45	< 0.01***	1.50	< 0.01***
Controls	Age, Positive Feedback Count, Division, Department, Class			

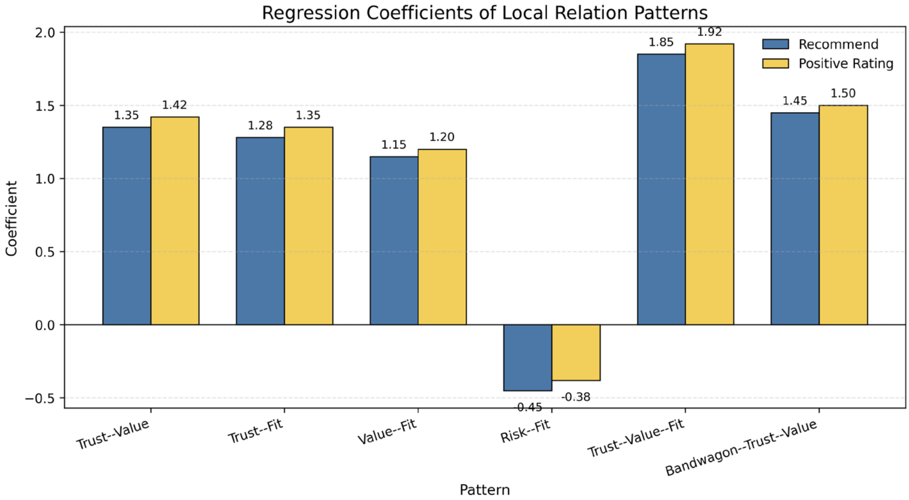

Fig. 2. Regression coefficients of local relation patterns for recommendation tendency and positive rating outcomes.

4.2 Associations with Consumer Purchase Judgment

We next examine whether the extracted local relation patterns are associated with recommendation tendency and grouped rating outcomes.

As shown in Fig. 2 and Table 3, not all signal combinations contribute equally to positive consumer judgment. In particular, patterns centered on trust and value exhibit positive and statistically significant associations with both recommendation tendency and positive rating. The Trust–Value pattern shows a positive coefficient of 1.35 for recommendation and 1.42 for positive rating, while Trust–Fit and Value–Fit also remain significant and positive across both models. These results suggest that consumers are more likely to endorse a product when a review simultaneously conveys reliability, worthiness, and personal suitability. The strongest effect is observed for the Trust–Value–Fit pattern, which records the largest coefficients in both models. This finding indicates that reviews combining reliability, cost-effectiveness, and suitability provide the most favorable basis for consumer judgment in the clothing domain.

Bandwagon–Trust–Value also shows a strong positive association, suggesting that collective endorsement can reinforce positive judgment when it is accompanied by trust and value cues, even though bandwagon-related expressions appear less frequently in the corpus.

5 Conclusion

This paper investigated how social signal combinations in e-commerce reviews are associated with consumer purchase judgment. We proposed a local relation pattern framework that captures the co-occurrence of bandwagon, trust, risk, value, and fit signals within review text. Using a public clothing-review dataset, we examined the distribution of these signals, identified the most frequent pairwise and triple local relation patterns, and analyzed their associations with recommendation tendency and positive rating outcomes.

The results show that trust and fit signals dominate the review corpus, while value signals also appear in a substantial proportion of reviews. At the pattern level, Trust–Value, Trust–Fit, and Trust–Value–Fit emerge as the most prominent local relation structures. In particular, Trust–Value–Fit exhibits the strongest positive association with both recommendation tendency and positive rating, suggesting that consumer judgment in apparel reviews is often formed through a combined evaluation of reliability, worthiness, and personal suitability. By contrast, patterns involving risk signals are less frequent and show weaker or negative associations, indicating that the effect of negative content depends on the broader signal structure in which it is embedded.

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