

Article

Cumulative Online Reputation and Automobile Sales: Evidence from the Chinese Market

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Abstract

Online consumer reviews provide an important source of information for automobile purchase decisions, yet relatively little is known about the informational value of cumulative electronic word-of-mouth (eWOM) ratings that reflect long-term online reputation. This study examines whether cumulative eWOM ratings are associated with subsequent automobile sales and explores their relationship with subsequent changes in monthly ratings and rating entropy. We combine monthly automobile sales data from Chezhu Zhijia with more than one million individual consumer reviews collected from Autohome between January 2013 and December 2025. Review-level data are aggregated to the automobile model-month level to construct cumulative eWOM measures, and the hypotheses are examined using two-way fixed-effects models. The results show that cumulative eWOM ratings are positively associated with subsequent automobile sales. Higher cumulative ratings are also associated with more favorable changes in subsequent monthly ratings and lower rating entropy. The positive association between cumulative eWOM ratings and automobile sales becomes stronger as product age increases and varies with cumulative rating entropy. These findings remain qualitatively unchanged across a broad set of robustness and additional analyses. This study highlights the informational value of cumulative online reputation for high-involvement durable goods and provides new evidence on the conditions under which accumulated consumer evaluations are associated with market outcomes.

Keywords: electronic word-of-mouth; online reputation; cumulative average eWOM rating; automobile sales; high-involvement products

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1. Introduction

Electronic word-of-mouth (eWOM) provides direct evaluations of products from consumers who have already completed their purchases, making it an important source of information for subsequent buyers [1,2]. Because these evaluations originate from consumers with actual ownership or usage experience, they are generally perceived as more credible and relevant than firm-generated information [1,2]. Compared with low-cost consumer goods, automobiles are high-involvement durable goods that require greater information search and more careful evaluation before purchase decisions are made [3,4]. Such decisions involve substantial financial commitment and perceived risk, leading consumers to rely extensively on information generated by previous buyers to

reduce uncertainty [5,6]. Prior research further suggests that purchasing high-involvement products depends more heavily on eWOM learning than on simple observational learning because consumers actively seek diagnostic information from others' experiences [3–5]. As digital platforms continue to accumulate large numbers of consumer reviews and ratings, online reputation has become an increasingly important informational signal in automobile markets [2,5].

Extensive research has examined the role of eWOM in markets for low-involvement products, including movies, books, and video games [7–9]. Early studies primarily investigated short-term eWOM characteristics and showed that review volume was closely associated with product sales [9–11]. Dellarocas et al. (2007) [12] further demonstrated that online reviews could serve as indicators of product sales before official sales information became available. Subsequent studies reported that review volume often exhibited a stronger association with product sales than review valence [13], and consumer-generated reviews continued to be associated with product performance after launch [14]. More recently, Delre and Luffarelli (2023) [15] showed that cumulative eWOM volume and valence remained positively associated with product performance throughout the product lifecycle, although this association gradually weakened over time. Collectively, these studies establish eWOM as an important informational signal that helps consumers and researchers understand product performance in markets for low-involvement products.

Comparatively fewer studies have examined eWOM in the context of high-involvement durable goods such as automobiles. Existing studies have shown that review volume is positively associated with automobile sales, whereas ratings exhibit nonlinear associations with market performance [3]. Liu et al. (2022) further demonstrate that both eWOM volume and rating are positively associated with automobile sales [16]. Other studies have reported heterogeneous effects across different information sources, including user-generated, firm-generated, and professionally generated content [17]. Zhao et al. (2024) [18] further suggested that automobile consumers rely more heavily on review volume than on review ratings when evaluating alternative products. Although these studies have improved understanding of eWOM in automobile markets, they have focused primarily on short-term eWOM characteristics, such as review volume, variance, and average rating [3,17,18]. Comparatively less attention has been devoted to cumulative eWOM ratings, which summarize consumer evaluations accumulated over extended periods and may better represent long-term online reputation. Whether cumulative ratings provide additional informational value beyond short-term eWOM signals therefore remains unclear. Likewise, little is known about how cumulative ratings are associated with subsequent consumer evaluations or the conditions under which these associations become stronger or weaker.

To address these questions, this study combines monthly automobile sales data obtained from Chezhu Zhijia with individual consumer reviews collected from Autohome to construct an automobile model-by-month panel covering January 2013 to December 2025. The final dataset contains 40,703 automobile-month observations for 985 automobile models and 1,019,679 individual consumer reviews. Monthly review data are aggregated to construct cumulative eWOM ratings, cumulative rating entropy, review volume, and other eWOM measures. Using a two-way fixed-effects framework, we examine the association between cumulative eWOM ratings and subsequent automobile sales while controlling for eWOM characteristics and other market factors. We further examine the relationships between cumulative ratings and subsequent monthly rating changes and rating entropy, as well as the moderating roles of product age and cumulative rating entropy. This empirical design enables us to evaluate the informational value of

cumulative online reputation from both market performance and subsequent consumer evaluation perspectives.

This study makes several contributions to the literature. First, it extends the eWOM literature by shifting attention from short-term review characteristics to cumulative eWOM ratings as a proxy for long-term online reputation in the context of high-involvement durable goods. Second, it broadens the understanding of accumulated online reputation by examining its associations with both automobile sales and subsequent consumer evaluations, together with the conditions under which these associations vary. Third, it complements the literature on signaling theory and online reputation by providing evidence on the informational value associated with accumulated consumer evaluations. From a practical perspective, the study offers implications for online review platforms, automobile manufacturers, and consumers in evaluating and managing cumulative online reputation.

The remainder of this paper proceeds as follows. Section 2 introduces the theoretical background and reviews the relevant literature. Section 3 develops the research hypotheses. Section 4 describes the dataset, variable definitions, and empirical methodology. Section 5 presents the empirical results and robustness analyses. Section 6 concludes the paper, discussing implications and limitations.

2. Theoretical Background and Literature Review

2.1. Theoretical Background

This study is primarily grounded in signaling theory and the online reputation literature [19,20]. Signaling theory argues that market participants rely on observable signals to infer unobservable product quality under conditions of information asymmetry [20]. In online review environments, cumulative eWOM ratings aggregate evaluations from a large number of consumers over an extended period and therefore represent a long-term reputation signal rather than a temporary assessment. Compared with short-term ratings, cumulative ratings reflect the historical consistency of consumer evaluations and provide a more stable representation of online reputation [19,21]. From this perspective, cumulative eWOM ratings may contain informational value beyond that conveyed by short-term review characteristics.

In addition to signaling theory, this study builds on consumer behavior research that distinguishes between high-involvement durable goods and low-involvement experience goods [22–24]. Consumers purchasing automobiles typically undertake more extensive information search and evaluation because these decisions involve greater financial commitment, longer ownership periods, and higher perceived risk [25,26]. As a result, accumulated online reputation may serve a different informational role in the automobile market than in markets for products such as movies, books, or video games, where purchase decisions generally involve lower levels of involvement and uncertainty. Building on these theoretical perspectives, this study examines the informational value of cumulative eWOM ratings and the conditions under which this accumulated reputation is associated with automobile sales.

2.2. Literature Review

Electronic word-of-mouth (eWOM) has become an important source of information in consumer decision making because it reflects the experiences and evaluations of previous consumers and provides valuable quality signals for potential buyers [27,28]. However, the role of eWOM is not uniform across product categories. Consumer information processing depends on product characteristics such as purchase involvement, perceived risk, and decision complexity. Compared with low-involvement products,

purchasing durable goods such as automobiles requires greater financial commitment, longer usage horizons, and more extensive information search [22,23]. Consumers therefore tend to evaluate information more systematically and place greater emphasis on credible and stable signals accumulated over time rather than on isolated recent reviews. These differences suggest that the informational value of eWOM may vary substantially between low-involvement and high-involvement products.

Most existing eWOM research has focused on low-involvement experience goods, including movies, books, hotels, and video games [7–10,29–31]. This literature has primarily examined short-term eWOM characteristics, particularly review volume and review valence, and their association with product performance. Prior studies generally report a positive association between review volume and sales, whereas the effect of review valence varies across contexts [9,30]. For example, review valence significantly affects hotel bookings [29], and its influence is particularly pronounced for lower-rated hotels [30]. In the gaming industry, review valence is especially impactful for less popular games and those offering rich network experiences [7]. Other studies suggest that the relationship between review valence and sales may be nonlinear and depend on product characteristics such as innovation, price, or consumer involvement [3,31,32]. Although these studies demonstrate the importance of online reviews, they mainly emphasize eWOM signals generated during a relatively short period of the product life cycle.

Research on eWOM in high-involvement durable goods, particularly automobiles, has expanded in recent years. Existing studies have examined how review attributes, multidimensional ratings, and textual information are associated with automobile sales [3,32–34]. For example, functional and hedonic ratings exhibit different nonlinear associations with vehicle sales [32], while product-specific attributes such as comfort and handling are closely associated with electric vehicle demand [34]. These studies substantially advance our understanding of eWOM in the automobile market. Nevertheless, they primarily focus on short-term review characteristics and pay relatively little attention to the long-term informational value embedded in accumulated consumer evaluations.

Compared with short-term ratings, cumulative eWOM ratings summarize all historical consumer evaluations and therefore provide a more comprehensive representation of long-term online reputation. Because cumulative ratings are accumulated over many consumers and a longer period, they are generally more stable and less affected by short-term fluctuations than individual monthly ratings. Existing evidence on cumulative eWOM remains limited. Delre and Luffarelli (2023) [15] showed that cumulative review valence is positively associated with movie box office revenue, although this association weakens over the product life cycle. Other studies suggest that early reviews shape subsequent evaluations through path-dependent processes [35,36], and cumulative review valence remains closely associated with subsequent review valence over time [15]. These findings indicate that accumulated online evaluations contain persistent informational value. However, the existing evidence is still largely derived from low-involvement products with relatively short life cycles. Whether cumulative online reputation exhibits similar informational value in high-involvement durable goods remains largely unexplored.

Building on the online reputation perspective, this study conceptualizes cumulative average eWOM rating as a proxy for cumulative online reputation and draws primarily on signaling theory to explain its informational value. A cumulative rating summarizes historical consumer experiences and serves as an observable signal of product quality under information asymmetry. We examine whether cumulative online reputation is associated with automobile sales, whether it is associated with subsequent changes in monthly ratings and the diversity of future rating distributions, and whether these

relationships vary with product age and cumulative rating entropy. By focusing on the Chinese automobile market, this study extends the literature from short-term eWOM to accumulated online reputation and provides new evidence on the informational value of cumulative consumer evaluations for high-involvement durable goods.

3. Hypotheses Development

Product reputation plays a critical role in consumer decision-making, particularly for high-involvement durable goods. In the online environment, the cumulative average rating of consumer reviews serves as a readily observable proxy for a product's long-term reputation. Unlike monthly eWOM metrics, which capture short-term fluctuations, the cumulative rating aggregates all historical evaluations since the product's launch. This measure is prominently displayed on review platforms and is visible to all consumers, making it a salient signal of overall product quality. To understand the informational value of cumulative eWOM rating as a proxy for online reputation in the automobile market, this study examines three aspects: (1) the association between cumulative eWOM rating and automobile sales, (2) the associations between cumulative eWOM rating and subsequent changes in monthly ratings as well as rating entropy, thereby characterizing the dynamic evolution of cumulative online reputation, and (3) whether these associations with automobile sales vary according to product age and cumulative rating entropy.

3.1. Cumulative eWOM Rating and Automobile Sales

The cumulative nature of eWOM average rating enables it to reflect consumers' long-term evaluations of product quality. Both recent and accumulated eWOM provide valuable information for consumer decision making [37]. Previous studies have primarily focused on the relationship between short-term eWOM and product sales using low-involvement products such as movies, games, and books [7,8,10]. Several studies further report that cumulative eWOM measures, including cumulative rating and cumulative eWOM volume, are positively associated with box office revenues in the movie industry, although these associations become weaker over the product lifecycle [9,15]. These findings suggest that cumulative evaluation metrics contain information relevant to market performance. However, most evidence on the informational value of cumulative eWOM has been developed in the context of low-involvement experience goods, particularly the movie industry [10,11,38,39]. Whether cumulative eWOM ratings provide similar informational value for high-involvement durable products, such as automobiles, has received much less attention [25,40].

Compared with low-involvement products, automobile purchases typically involve greater financial commitment and more extensive information search [3,4,16,33]. Consumers therefore rely on multiple sources of information when evaluating alternative products. The cumulative average eWOM rating summarizes historical evaluations from previous consumers over an extended period and provides a stable representation of accumulated online reputation. Because this measure is based on a large number of reviews collected over months or years, it is less susceptible to short-term fluctuations than recent ratings. Accordingly, cumulative eWOM rating may provide additional information beyond current monthly ratings when consumers evaluate automobile models. From this perspective, a positive association between cumulative eWOM rating and subsequent automobile sales is expected. Accordingly, we propose the following hypothesis:

H1. *Cumulative eWOM average rating is positively associated with automobile sales.*

3.2. Subsequent Rating Characteristics

The cumulative average rating summarizes consumers' long-term evaluations of an automobile across all previous reviews. It reflects the overall direction of historical consumer evaluations and represents the accumulated online reputation of the product over time [41]. By contrast, monthly ratings capture short-term evaluation outcomes that may fluctuate as new consumers enter the market and new reviews are posted. Because cumulative ratings are built through the continuous aggregation of historical evaluations, they provide a stable reference point against which subsequent monthly evaluations can be interpreted [8,16,21]. If cumulative ratings summarize historical consumer evaluations, subsequent monthly ratings are expected to evolve around this accumulated benchmark rather than independently of it [42,43]. Examining monthly rating changes therefore provides a more direct way to understand whether historical cumulative reputation is associated with the direction of subsequent evaluation dynamics.

Informational cascade theory suggests that individuals often use accumulated public evaluations as an important source of information when forming their own judgments in sequential decision environments [44]. A favorable cumulative rating reflects a long history of positive evaluations and provides a salient public signal that may be associated with more favorable subsequent evaluations [45]. Similarly, the anchoring-and-adjustment heuristic proposes that existing summary evaluations provide a cognitive reference point when individuals make judgments under uncertainty [46]. Rather than determining the absolute level of subsequent ratings, a higher cumulative rating may be associated with more positive changes in subsequent monthly ratings relative to previous evaluations [47]. Therefore, we hypothesize:

H2a. *Cumulative average eWOM rating is positively associated with subsequent monthly changes in eWOM rating.*

Unlike the average monthly eWOM rating, rating entropy captures the diversity of the rating distribution rather than its central tendency. In information theory, entropy quantifies the uncertainty or diversity of a probability distribution, with lower values indicating that observations are concentrated in fewer categories and higher values reflecting greater diversity across categories [48,49]. Prior research has shown that consumers evaluate not only average ratings but also the distribution of ratings because the distribution provides additional information about product quality and evaluation uncertainty [42]. Examining rating entropy therefore provides a complementary perspective on the dynamic characteristics of cumulative online reputation. If cumulative ratings summarize long-term consumer evaluations, products with higher accumulated ratings are expected to exhibit a more concentrated distribution of subsequent evaluations. A favorable cumulative reputation summarizes consistently positive historical evaluations. As a result, subsequent consumers may be more likely to form evaluations within a narrower range and is expected to be associated with lower diversity in future rating distributions.

From a signaling perspective, cumulative ratings summarize a large body of historical evaluations and serve as a publicly observable signal of prior consumer evaluations. According to signaling theory, credible signals help reduce information asymmetry by conveying otherwise unobservable product quality under conditions of imperfect information [20,50]. Because cumulative ratings are aggregated over a long period and across many reviewers, they provide a relatively informative summary of historical consumer evaluations. When subsequent reviewers observe such a signal, their evaluations are expected to be more concentrated, resulting in lower rating entropy. Similarly, the anchoring-and-adjustment heuristic suggests that existing summary

evaluations provide an important cognitive reference point when consumers form subsequent judgments under uncertainty [46]. As a common reference becomes more salient, subsequent evaluations may become less dispersed across rating categories, leading to lower rating entropy. Therefore, we propose:

H2b. *Cumulative average eWOM rating is negatively associated with the entropy of subsequent monthly eWOM ratings.*

3.3. Moderating Roles of Product Age and Cumulative Rating Entropy

Prior research has shown that the influence of online reviews varies across the product life cycle. The impact of review volume on product sales is generally stronger during the early stage after product launch and tends to decline over time [51]. Cumulative average eWOM rating differs from review volume because it summarizes consumer evaluations accumulated over an extended period. A favorable cumulative rating that has been maintained for a longer time may therefore represent a more stable and credible reputation signal than an equally favorable rating established over a shorter period. As product age increases, the cumulative rating incorporates evaluations from a larger and more diverse group of consumers. According to the law of large numbers, larger samples generally provide more stable estimates of underlying population characteristics [42]. Consequently, cumulative rating based on a longer accumulation period may provide a more informative summary of historical consumer evaluations.

Product age may also affect how consumers interpret cumulative reputation signals. The elaboration likelihood model suggests that consumers rely on different types of information depending on their familiarity with a product and the amount of information available [22]. As a product remains in the market for a longer period, consumers are exposed to a richer set of historical evaluations and product-related information. Under such conditions, cumulative ratings may become a more informative reference for evaluating product quality than during the early stage of the product life cycle. Previous research similarly reports that the informational value of cumulative eWOM becomes more prominent over time as historical evaluations continue to accumulate [15]. Furthermore, cumulative ratings based on a relatively small number of early reviews may be more susceptible to random fluctuations or early adopter bias [52]. As additional reviews accumulate over time, the cumulative rating is likely to reflect a broader range of consumer experiences. These considerations suggest that the association between cumulative eWOM rating and automobile sales may become stronger as product age increases. Accordingly, we propose the following hypothesis:

H3a. *Product age positively moderates the relationship between cumulative eWOM rating and automobile sales.*

In online review systems, cumulative rating entropy reflects an additional dimension of cumulative online reputation by describing how diverse historical consumer evaluations are rather than how favorable they are on average. From an information perspective, cumulative rating entropy may strengthen the informational value of cumulative eWOM ratings. Signaling theory suggests that consumers rely on observable market signals to infer unobservable product quality when direct evaluation is difficult [20]. For high-involvement products such as automobiles, consumers typically seek comprehensive information before making purchase decisions [53]. A cumulative average rating summarizes the overall evaluation of a product, whereas cumulative rating entropy provides complementary information about the diversity of historical consumer experiences. A moderate degree of diversity allows potential buyers to observe multiple

perspectives on product performance rather than a single, highly homogeneous evaluation pattern. Previous research has shown that information diversity enhances perceived information quality and helps consumers make more informed decisions [54,55]. A reputation signal supported by diverse historical evaluations may therefore be perceived as more credible because it reflects experiences from heterogeneous consumers rather than highly uniform opinions.

At the same time, greater cumulative rating entropy also reflects a higher degree of diversity among historical evaluations. Previous studies have shown that heterogeneous online reviews may increase information processing difficulty because consumers must reconcile inconsistent product experiences across reviewers [55]. Information overload theory further suggests that more diverse information increases consumers' cognitive processing burden when evaluating alternatives [56]. Consequently, although greater rating diversity may enrich the information contained in cumulative online reputation, it may also make product evaluation more complex. The overall moderating role of cumulative rating entropy therefore depends on the relative importance consumers assign to informational richness and evaluative diversity when interpreting cumulative online reputation. Given these competing theoretical arguments, cumulative rating entropy is expected to moderate the relationship between cumulative eWOM rating and automobile sales. Therefore, we propose:

H3b. *Cumulative rating entropy moderates the relationship between cumulative eWOM rating and automobile sales.*

4. Methodology

4.1. Data

To investigate the association between cumulative eWOM ratings and subsequent automobile sales, we combined data from four sources: automobile sales, online consumer reviews, consumer search attention, and automobile prices. Monthly automobile sales data were obtained from Chezhu Zhijia (16888.com) (accessed on 8 January 2026), one of China's major automobile information platforms that reports monthly vehicle sales and market information. Consumer eWOM data were collected from Autohome (<https://www.autohome.com.cn/>) (accessed on 8 January 2026), the largest automobile eWOM platform in China. Each automobile model has a dedicated webpage displaying both an overall cumulative rating and individual consumer reviews. Following prior research, we further controlled for consumer attention and automobile prices [57,58]. Consumer attention was proxied by the Baidu Search Index, using either the automobile model name or a combination of the brand and model name when the model-name alone was ambiguous. Automobile price was measured using the average transaction price reported by consumers on Autohome.

We first collected monthly automobile sales records from January 2013 to December 2025 and matched them with individual consumer reviews from Autohome, yielding 1,148,670 review records. Because automobile sales are reported monthly and consumers typically post reviews after accumulating some ownership experience, we aggregated the review data to the automobile-model-by-month level. Monthly review statistics, including review volume, average rating, rating entropy, cumulative rating, and cumulative rating entropy were then constructed. This procedure resulted in an initial panel comprising 52,781 automobile-month observations for 1473 automobile models. To examine the association between prior cumulative ratings and subsequent automobile sales, all explanatory and control variables were lagged by one month, whereas the dependent variable was measured in the subsequent month. Observations without valid lagged values were removed after variable construction, resulting in the exclusion of 6248

automobile-month observations while retaining 1371 automobile models. Finally, because consumer attention is measured using the Baidu Search Index, automobile models without valid Baidu Search Index keywords were excluded to ensure comparable measurement of consumer attention across the sample. The final dataset contains 40,703 automobile-month observations, representing 985 automobile models and 1,019,679 individual consumer reviews.

4.2. Variables

This study focuses primarily on the cumulative average eWOM rating ($CumRating_{i,t-1}$), which captures the long-term reputation accumulated through consumers' historical evaluations. Unlike a monthly average rating, the cumulative rating incorporates all individual review ratings posted from an automobile model's launch through the end of month $t - 1$. As new reviews become available, the cumulative rating is continuously updated to reflect the complete history of consumer evaluations. Because our empirical analysis examines subsequent outcomes, all reviews posted in the focal month are excluded from the calculation to ensure that the cumulative rating is predetermined with respect to the dependent variable. Accordingly, for automobile model i , $CumRating_{i,t-1}$ is defined as the weighted average of all historical monthly ratings prior to month t , where the weights are the corresponding monthly review volumes, as shown in Equation (1).

$$CUMRating_{i,t-1} = \frac{\sum_{k=1}^{t-1} Rating_{i,k} \times Volume_{i,k}}{\sum_{k=1}^{t-1} Volume_{i,k}} \quad (1)$$

In Equation (1), i denotes the automobile model, t denotes the focal month, and k indexes each historical month from the model's launch through month $t - 1$. $Rating_{i,k}$ represents the average rating of automobile model i in month k , and $Volume_{i,k}$ denotes the number of eWOM reviews posted in that month. Consequently, $CUMRating_{i,t-1}$ represents the cumulative average rating calculated from all individual reviews posted prior to month t .

To further examine the dynamic relationship between cumulative reputation and newly generated eWOM, we additionally construct two monthly measures: the average monthly rating change and the monthly rating entropy. While the change in the monthly average rating reflects how newly generated evaluations change relative to the previous month, the rating entropy reflects the diversity of consumers' evaluations. Entropy, originally proposed by Shannon (1948) [48], measures the uncertainty or dispersion of a probability distribution and has been widely applied to quantify information diversity and disagreement across categories. In online review settings, greater diversity in rating distributions reflects a wider range of consumers evaluations [42]. A higher entropy indicates that ratings are distributed more evenly across different score levels, suggesting greater diversity in consumer evaluations, whereas a lower entropy indicates stronger consensus. Accordingly, we use rating entropy to capture the diversity of consumers' rating. The rating entropy is calculated as follows:

$$RatingEntropy_{i,t} = - \sum_{s=1}^5 p_{i,t,s} \ln(p_{i,t,s}) \quad (2)$$

For each automobile model, all individual review ratings posted in month t are first classified into five rating categories. Specifically, ratings greater than or equal to 1 and less than 2 are assigned to Category 1; ratings greater than or equal to 2 and less than 3 to Category 2; ratings greater than or equal to 3 and less than 4 to Category 3; ratings greater than or equal to 4 and less than 5 to Category 4; and ratings equal to 5 to Category 5. In Equation (2), s denotes the rating category ($s = 1, 2, 3, 4, 5$), and $p_{i,t,s}$ represents the proportion of reviews for automobile model i in month t that fall into rating category s . A

higher value of $RatingEntropy_{i,t}$ indicates greater dispersion of ratings across the five categories, reflecting greater diversity and uncertainty in consumer evaluations.

Furthermore, to explore the boundary conditions of the relationship between cumulative eWOM rating and automobile sales, we focused on two moderators capturing the temporal accumulation of reputation and the potential effect of rating diversity. Specifically, we calculated the cumulative time (in months) from the model's launch month to month $t - 1$ as a moderator representing temporal accumulation ($Age_{i,t-1}$). Following the same cumulative procedure described for $CUMRating_{i,t-1}$, we recursively calculate the cumulative rating entropy ($CumEntropy_{i,t-1}$) using all reviews posted prior to month t . This cumulative measure captures the long-term diversity in consumers' historical evaluations.

The dependent variable is monthly automobile sales ($logSales_{i,t}$). The logarithmic transformation mitigates the influence of the highly skewed distribution of sales and allows the estimated coefficients to be interpreted in proportional terms. Detailed definitions of the dependent, independent, moderating, and control variables are presented in Table 1.

Table 1. Detailed variable descriptions.

Variable	Definition
$logSales_{i,t}$	Natural logarithm of the monthly sales volume of automobile model i sold in month t .
$CumRating_{i,t-1}$	Cumulative average eWOM rating for automobile model i , calculated using all individual consumer review ratings posted prior to month t .
$\Delta Rating_{i,t}$	Month-to-month change in the average eWOM rating for automobile model i , measured as the difference between the average monthly ratings in months t and $t - 1$.
$RatingEntropy_{i,t}$	Information entropy of consumer ratings for automobile model i in month t , measuring the diversity of monthly consumer evaluations.
$Age_{i,t-1}$	Number of months since the launch of automobile model i measured up to month $t - 1$.
$CumEntropy_{i,t-1}$	Cumulative information entropy of consumer ratings for automobile model i , calculated using all individual consumer review ratings posted prior to month t , measuring the historical diversity of cumulative consumer evaluations.
$logVolume_{i,t-1}$	Natural logarithm of the monthly eWOM review volume for automobile model i in month $t - 1$.
$Rating_{i,t-1}$	Average monthly eWOM rating for automobile model i in month $t - 1$.
$Rating^2_{i,t-1}$	Squared value of the average monthly eWOM rating for automobile model i in month $t - 1$.
$logSVI_{i,t-1}$	Natural logarithm of the Baidu Search Index for automobile model i in month $t - 1$, used as a proxy for consumer attention.
$logPrice_{i,t-1}$	Natural logarithm of the average transaction price (10,000 RMB) of automobile model i in month $t - 1$, calculated from consumer-reported purchase prices.
$logPrice^2_{i,t-1}$	Squared value of the natural logarithm of the average transaction price of automobile model i in month $t - 1$.

4.3. Model Specification

To examine the relationship between cumulative eWOM average ratings and automobile sales, we estimated a two-way fixed-effects model in which monthly automobile sales serve as the dependent variable and the cumulative eWOM average rating is the primary explanatory variable. The specification includes automobile-model fixed effects and month fixed effects to account for time-invariant heterogeneity across automobile models and common temporal shocks. The model is specified as follows:

$$logSales_{i,t} = CUMRating_{i,t-1} + logVolume_{i,t-1} + Rating_{i,t-1} + Rating^2_{i,t-1} + logSVI_{i,t-1} + logPrice_{i,t-1} + logPrice^2_{i,t-1} + u_i + \lambda_t + \varepsilon_{i,t} \quad (3)$$

To account for other factors that may be associated with automobile sales, we include several control variables. Prior research suggests that eWOM review volume is associated with product awareness and market performance [9]. We therefore control for the lagged monthly eWOM review volume ($logVolume_{i,t-1}$) and the lagged average monthly eWOM

rating ($Rating_{i,t-1}$). Because previous studies have reported a potential nonlinear association between rating valence and sales [32,47], we additionally include the squared term of the lagged average monthly rating ($Rating_{i,t-1}^2$). Consumer attention is controlled for using the lagged Baidu Search Index ($logSVI_{i,t-1}$). We also control for the average transaction price ($logPrice_{i,t}$) and its squared term ($logPrice_{i,t}^2$) to account for potential nonlinear price effects. Detailed definitions of all variables are provided in Table 1.

We next examined whether cumulative eWOM ratings are associated with subsequent changes in newly generated eWOM. If cumulative eWOM ratings capture consumers' long-term evaluations of an automobile model, they may be associated not only with subsequent changes in monthly ratings but also with rating distribution of newly generated reviews. To examine these relationships, we estimated two fixed-effects models using the cumulative average eWOM rating as the primary explanatory variable.

For Model 2, the dependent variable is the month-to-month change in the average rating ($\Delta Rating_{i,t}$), defined as the difference between the average monthly rating in month t and that in month $t - 1$. Using the change in ratings rather than the monthly rating allows the analysis to focus on subsequent variation in newly generated evaluations. To distinguish historical cumulative reputation from the most recent monthly evaluation, the cumulative rating is calculated using all individual reviews posted up to month $t - 2$ ($CUMRating_{i,t-2}$). For Model 3, the dependent variable is the information entropy of monthly ratings in month t ($RatingEntropy_{i,t}$), which measures the dispersion of consumers' rating distributions across the five rating categories. Both models include automobile-model and month fixed effects, as specified in Equations (4) and (5).

$$\Delta Rating_{i,t} = CUMRating_{i,t-2} + logVolume_{i,t-1} + Controls_{i,t-1} + u_i + \lambda_t + \varepsilon_{i,t} \quad (4)$$

$$RatingEntropy_{i,t} = CUMRating_{i,t-2} + logVolume_{i,t-1} + Controls_{i,t-1} + u_i + \lambda_t + \varepsilon_{i,t} \quad (5)$$

where the control variables include the lagged monthly eWOM volume ($logVolume_{i,t-1}$), the lagged monthly average rating ($Rating_{i,t-1}$) and its squared term ($Rating_{i,t-1}^2$), the lagged Baidu Search Index ($logSVI_{i,t-1}$), and the lagged automobile price ($logPrice_{i,t}$) and its squared term ($logPrice_{i,t}^2$). Detailed definitions of these variables are provided in Table 1.

Finally, we examined whether the association between cumulative eWOM rating and automobile sales varies with two characteristics of accumulated online reputation, namely the duration of reputation accumulation and the degree of historical rating diversity. The first characteristic is the length of reputation accumulation, measured by the automobile model's age in months ($Age_{i,t-1}$). Older products typically accumulate a longer history of consumer evaluations, allowing us to examine whether the association between cumulative reputation and automobile sales differs across stages of the product life cycle. The second characteristic is the consistency of historical consumer evaluations, measured by the cumulative rating entropy ($CumEntropy_{i,t-1}$). Cumulative rating entropy captures the dispersion of historical consumer ratings and reflects the informational diversity embedded in accumulated reputation.

Based on Model 1, we estimated two additional fixed-effects models by separately introducing the interaction between $CUMRating_{i,t-1}$ and each moderator. Model 4 includes the interaction between $CUMRating_{i,t-1}$ and $Age_{i,t-1}$, whereas Model 5 includes the interaction between $CUMRating_{i,t-1}$ and $CumEntropy_{i,t-1}$. Both models retain the same control variables and fixed-effects structure as Model 1. The specifications are presented in Equations (6) and (7).

$$logSales_{i,t} = CUMRating_{i,t-1} + Age_{i,t-1} \times CUMRating_{i,t-1} + Age_{i,t-1} + Controls_{i,t-1} + u_i + \lambda_t + \varepsilon_{i,t} \quad (6)$$

$$logSales_{i,t} = CUMRating_{i,t-1} + CumEntropy_{i,t-1} \times CUMRating_{i,t-1} + CumEntropy_{i,t-1} + Controls_{i,t-1} + u_i + \lambda_t + \varepsilon_{i,t} \quad (7)$$

5. Empirical Analysis and Results

5.1. Descriptive Statistics

Table 2 presents the descriptive statistics for all variables used in the empirical analyses. For monthly automobile sales and eWOM volume, we additionally report their original values prior to logarithmic transformation to provide a clearer picture of the sample distribution. The mean of monthly automobile sales is 5964.118 units, with a standard deviation of 8274.595. This large standard deviation indicates substantial variation in sales across different automobile models and months. The mean of monthly eWOM volume is 25.426 reviews per model per month, with a standard deviation of 34.913, suggesting considerable heterogeneity in review activity across models and over time.

Table 2. Descriptive statistics.

Variable	Obs	Mean	Std. Dev	Min	Max
$Sales_{i,t}$	40,703	5964.118	8274.595	1.000	230,703.000
$\log Sales_{i,t}$	40,703	7.789	1.653	0.000	12.349
$CumRating_{i,t-1}$	40,703	4.454	0.247	2.500	5.000
$\Delta Rating_{i,t}$	40,703	−0.003	0.337	−4.000	3.920
$RatingEntropy_{i,t}$	40,703	0.462	0.331	0.000	1.424
$Age_{i,t-1}$	40,703	38.808	33.514	1.000	155.000
$CumEntropy_{i,t-1}$	40,703	0.628	0.196	0.000	1.333
$Volume_{i,t-1}$	40,703	25.207	34.916	1.000	620.000
$\log Volume_{i,t-1}$	40,703	2.472	1.305	0.000	6.430
$Rating_{i,t-1}$	40,703	4.435	0.346	1.000	5.000
$Rating^2_{i,t-1}$	40,703	19.792	2.906	1.000	25.000
$\log SVI_{i,t-1}$	40,703	10.569	1.781	0.000	15.503
$\log Price_{i,t-1}$	40,703	2.607	0.592	0.000	6.471
$\log Price^2_{i,t-1}$	40,703	7.149	3.171	0.000	41.876

The cumulative average eWOM rating has a mean of 4.454 and a standard deviation of 0.247, with a minimum value of 2.5. These values indicate that, on average, consumers in the sample were generally satisfied with their purchased automobile models, and that the variation in long-term reputation across models is relatively small. The average monthly eWOM rating change has a mean close to zero (−0.003) and a standard deviation of 0.337, suggesting that monthly ratings remain relatively stable over time while still exhibiting meaningful month-to-month variation across automobile models.

The monthly rating entropy has a mean of 0.462 and ranges from 0 to 1.424. Given five rating categories, the theoretical upper bound of entropy is $\ln(5) = 1.609$. The observed values therefore fall within the expected range. The cumulative rating entropy has a higher mean of 0.628 and a smaller standard deviation (0.196), suggesting that the diversity of accumulated ratings is relatively more stable than the diversity observed within a single month.

The average automobile age is 38.808 months, indicating that the sample contains both newly launched and mature automobile models. The remaining control variables also exhibit sufficient variation across observations, providing adequate cross-sectional and temporal variation for the subsequent fixed-effects analyses.

5.2. Baseline Association with Automobile Sales

We first examined the association between cumulative average eWOM rating and automobile sales using Model 1. The regression results are reported in Table 3, where the

dependent variable is the natural logarithm of automobile sales in the month t ($\log Sales_{i,t}$). Column (1) presents the baseline specification including automobile-model and month fixed effects, with standard errors clustered at the automobile-model level. The coefficient on cumulative average eWOM rating is positive and statistically significant at the 1% level (coefficient = 1.088), indicating a positive association between cumulative rating and subsequent automobile sales.

Table 3. Association between cumulative eWOM average rating and automobile sales.

Variable	DV: $\log Sales_{i,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$CumRating_{i,t-1}$	1.088 *** (3.540)	0.918 *** (3.216)	1.293 *** (4.424)	1.321 *** (4.680)	1.292 *** (4.516)	1.292 *** (4.598)	0.735 *** (3.666)
$\log Volume_{i,t-1}$		0.374 *** (22.678)	0.375 *** (22.590)	0.340 *** (20.768)	0.326 *** (19.976)	0.326 *** (18.803)	0.209 *** (16.337)
$Rating_{i,t-1}$			1.575 *** (4.994)	1.409 *** (4.481)	1.416 *** (4.596)	1.416 *** (6.540)	0.136 (0.561)
$Rating^2_{i,t-1}$			−0.222 *** (−5.729)	−0.199 *** (−5.166)	−0.200 *** (−5.296)	−0.200 *** (−7.369)	−0.018 (−0.630)
$\log SVI_{i,t-1}$				0.156 *** (6.641)	0.154 *** (6.746)	0.154 *** (6.676)	0.104 *** (7.544)
$\log Price_{i,t-1}$					1.935 *** (4.994)	1.935 *** (4.489)	0.234 (0.722)
$\log Price^2_{i,t-1}$					−0.252 *** (−4.357)	−0.252 *** (−3.883)	−0.039 (−0.815)
Constant	2.942 ** (2.149)	2.777 ** (2.181)	−1.495 (−1.036)	−2.900 ** (−2.032)	−5.969 *** (−4.247)	−5.969 *** (−4.442)	2.330 * (1.884)
Automobile FE	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y
Brand-Year FE	N	N	N	N	N	N	Y
Within R ²	0.005	0.146	0.152	0.174	0.179	0.179	0.058
Between R ²	0.005	0.281	0.288	0.299	0.301	0.301	0.301
AIC	120,766.7	114,517.6	114,256.1	113,180.9	112,961.8	112,961.8	101,496.9
BIC	120,775.3	114,534.8	114,290.6	113,224.0	113,022.1	113,022.1	101,557.2
F-statistics	12.53	259.69	135.55	116.63	89.58	80.42	45.63
Observations	40,703	40,703	40,703	40,703	40,703	40,703	40,703

Notes: Robust standard errors clustered at the automobile-model level are reported in Columns (1)–(5) and (7). Column (6) reports two-way cluster-robust standard errors clustered at both the automobile-model and month levels. t -statistics are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Columns (2) through (5) in Table 3 sequentially introduce the control variables. After controlling for lagged monthly eWOM volume in Column (2), the coefficient on cumulative rating remains positive and statistically significant (coefficient = 0.918). Column (3) further controls for the lagged monthly average rating and its squared term. The estimated coefficient on cumulative rating increases to 1.293 and remains significant at the 1% level. Column (4) additionally includes consumer attention measured by the Baidu Search Index. The coefficient changes only slightly to 1.321, suggesting that the estimated association between cumulative rating and automobile sales is not materially affected by the inclusion of consumer search attention. Finally, Column (5) further controls for the average transaction price and its squared term. The coefficient on cumulative rating remains highly stable (coefficient = 1.292, $p < 0.01$), indicating that the

estimated association is largely unchanged after accounting for pricing differences across automobile models. Columns (6) and (7) provide additional sensitivity analyses. Column (6) reports two-way clustered standard errors at the automobile-model and month levels. The estimated coefficient on cumulative rating remains virtually identical to that reported in Column (5) and continues to be statistically significant at the 1% level. Column (7) further incorporates brand-by-year fixed effects. The estimated coefficient on cumulative average eWOM rating decreases from 1.292 to 0.735 but remains positive and statistically significant at the 1% level, suggesting that the main findings are robust to the inclusion of additional fixed effects.

Across all specifications, the estimated coefficient on cumulative average eWOM rating remains positive and statistically significant despite the sequential inclusion of additional control variables and alternative model specifications. Overall, the results provide consistent empirical support for H1 and indicate that automobile models with higher cumulative average eWOM ratings tend to be associated with higher subsequent automobile sales. Table 3 also reports the within- R^2 , between- R^2 , AIC, BIC, and F-statistics for each specification to facilitate model comparison.

5.3. Associations with Subsequent Ratings

We next examined the association between cumulative eWOM ratings and subsequent monthly review dynamics using Model 2 and Model 3. Model 2 takes the change in the monthly average rating from month $t - 1$ to month t as the dependent variable, whereas Model 3 uses the monthly rating entropy in month t as the dependent variable. The regression results are reported in Table 4. Column (1) reports the results using the cumulative rating calculated up to month $t - 2$, thereby separating the cumulative reputation measure from the most recent monthly rating included as a control variable. Column (2) further computes the cumulative rating up to month $t - 3$, excluding more recent rating information from the cumulative measure. In both specifications, the coefficient on cumulative average eWOM rating is positive and statistically significant at the 1% level. The estimated coefficients are 0.300 and 0.257, respectively. These findings indicate that automobile models with higher historical cumulative ratings tend to experience more positive subsequent changes in monthly ratings. The positive association remains statistically significant even when the cumulative rating is constructed using information only up to month $t - 3$. This result indicates that the association is not confined to the most recent ratings incorporated into the cumulative measure. Instead, earlier accumulated eWOM ratings continue to contain information that is associated with subsequent changes in monthly ratings. Columns (3) and (4) report the results for Model 3. Using cumulative average ratings calculated up to month $t - 2$ and month $t - 3$, respectively, the estimated coefficients are -0.143 and -0.093 , both statistically significant at the 1% level. These results indicate that higher cumulative ratings are associated with lower rating entropy in subsequent monthly reviews. Since rating entropy captures the diversity of consumer evaluations across different rating categories, the negative coefficients suggest that automobile models with stronger accumulated reputations tend to receive subsequent evaluations with lower rating diversity. The results reported in Table 4 are consistent across alternative lag structures and provide empirical support for H2a and H2b.

Table 4. Association between cumulative eWOM average rating, monthly rating change, and rating entropy.

Variable	DV: $\Delta Rating_{i,t}$		DV: $RatingEntropy_{i,t}$	
	(1)	(2)	(3)	(4)
$CumRating_{i,t-2}$	0.300 ***		-0.143 ***	

	(7.736)		(−3.987)	
$CumRating_{i,t-3}$		0.257 *** (6.959)		−0.093 *** (−2.587)
$logVolume_{i,t-1}$	0.019 *** (8.677)	0.019 *** (8.475)	0.064 *** (24.836)	0.064 *** (24.169)
$Rating_{i,t-1}$	−1.632 *** (−22.625)	−1.654 *** (−22.446)	0.378 *** (6.757)	0.388 *** (6.765)
$Rating^2_{i,t-1}$	0.098 *** (11.043)	0.100 *** (11.083)	−0.052 *** (−7.376)	−0.054 *** (−7.403)
$logSVI_{i,t-1}$	−0.004 * (−1.668)	−0.004 * (−1.739)	0.014 *** (4.120)	0.015 *** (4.184)
$logPrice_{i,t-1}$	0.116 (1.506)	0.107 (1.374)	−0.083 (−1.106)	−0.101 (−1.306)
$logPrice^2_{i,t-1}$	−0.016 (−1.390)	−0.015 (−1.276)	0.008 (0.683)	0.011 (0.915)
Constant	3.776 *** (14.711)	4.027 *** (15.767)	0.310 (1.421)	0.089 (0.412)
Automobile FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Within R ²	0.408	0.406	0.065	0.065
Between R ²	0.098	0.101	0.462	0.469
AIC	5125.0	5392.0	13,758.8	13,594.5
BIC	5185.1	5451.9	13,819.0	13,654.5
F-statistics	1053.47	1022.61	106.71	101.73
Observations	39,800	38,887	39,800	38,887

Notes: All models are estimated with cluster-robust standard errors clustered at the automobile-model level. *t*-statistics are reported in parentheses. *** $p < 0.01$, * $p < 0.10$.

5.4. Boundary Conditions

Finally, we examined whether the association between cumulative average eWOM rating and automobile sales varies with the characteristics of cumulative reputation. The regression results are reported in Table 5. Columns (1) and (2) present the moderating effect of cumulative age ($Age_{i,t-1}$). Columns (3) and (4) use the logarithm of cumulative age as an alternative measure ($logAge_{i,t-1}$). Columns (5) and (6) examine the moderating effect of cumulative rating entropy ($CumEntropy_{i,t-1}$), while Columns (7) and (8) replace cumulative rating entropy with the cumulative proportion of extreme ratings as an alternative measure ($CumExtreme_{i,t-1}$). The interaction between cumulative rating ($CumRating_{i,t-1}$) and cumulative age ($Age_{i,t-1}$) is positive and statistically significant in both specifications, with coefficients of 0.025 and 0.024, respectively. These results indicate that the positive association between cumulative average eWOM rating and automobile sales becomes stronger as an automobile model remains longer in the market. Columns (3) and (4) report consistent findings when cumulative age is measured using its logarithmic transformation. The interaction coefficients remain positive and statistically significant at the 1% level, providing additional support for the robustness of H3a.

Table 5. Moderating effects on the relationship between cumulative eWOM average rating and automobile sales.

Variable	DV: $logSales_{i,t}$							
	$Age_{i,t-1}$		$logAge_{i,t-1}$		$CumEntropy_{i,t-1}$		$CumExtreme_{i,t-1}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$CumRating_{i,t-1}$	1.199 ***	0.932 ***	−0.233	−0.118	−0.735	0.125	0.977 ***	1.178 ***

	(3.516)	(3.237)	(−0.709)	(−0.415)	(−1.562)	(0.291)	(2.860)	(3.714)
$CumRating_{i,t-1} \times Mod_{i,t-1}$	0.025 ***	0.024 ***	0.564 ***	0.556 ***	2.511 ***	1.515 ***	4.367 ***	3.232 ***
	(4.831)	(4.993)	(7.104)	(7.488)	(4.629)	(3.169)	(3.429)	(3.069)
$Mod_{i,t-1}$	−0.125 ***	−0.113 ***	−2.991 ***	−2.800 ***	−12.204 ***	−7.568 ***	−21.207 ***	−15.534 ***
	(−5.384)	(−5.298)	(−8.390)	(−8.425)	(−4.928)	(−3.499)	(−3.424)	(−3.058)
$logVolume_{i,t-1}$		0.253 ***		0.263 ***		0.326 ***		0.326 ***
		(18.928)		(19.111)		(20.108)		(20.054)
$Rating_{i,t-1}$		0.564 **		0.654 **		1.263 ***		1.444 ***
		(2.091)		(2.403)		(4.176)		(4.666)
$Rating_{i,t-1}^2$		−0.077 **		−0.095 ***		−0.180 ***		−0.203 ***
		(−2.359)		(−2.869)		(−4.875)		(−5.363)
$logSVI_{i,t-1}$		0.134 ***		0.132 ***		0.153 ***		0.154 ***
		(6.778)		(7.294)		(6.892)		(6.810)
$logPrice_{i,t-1}$		1.036 **		0.491		1.686 ***		1.877 ***
		(2.575)		(1.325)		(4.481)		(4.854)
$logPrice_{i,t-1}^2$		−0.147 **		−0.090		−0.226 ***		−0.246 ***
		(−2.437)		(−1.587)		(−4.039)		(−4.256)
Constant	3.006 **	−0.721	10.415 ***	5.704 ***	11.766 ***	0.553	3.552 **	−5.340 ***
	(1.967)	(−0.453)	(6.991)	(3.722)	(5.501)	(0.284)	(2.338)	(−3.570)
Automobile FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Within R ²	0.134	0.213	0.145	0.236	0.017	0.185	0.007	0.180
Between R ²	0.133	0.352	0.134	0.324	0.033	0.322	0.018	0.320
AIC	115,115.1	111,228.4	114,595.3	110,023.5	120,275.9	112,641.1	120,686.1	112,914.2
BIC	115,141.0	111,305.9	114,621.1	110,101.1	120,301.7	112,718.6	120,711.9	112,991.7
F-statistics	66.34	74.16	159.70	92.04	22.27	71.91	11.93	70.01
Observations	40,703	40,703	40,703	40,703	40,703	40,703	40,703	40,703

Notes: All models are estimated with cluster-robust standard errors clustered at the automobile-model level. *t*-statistics are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$. To conserve space, $Mod_{i,t-1}$ represents the moderator variable included in each specification. The specific moderator used in each model is indicated in the corresponding column heading.

Columns (5) and (6) in Table 5 report the moderating effect of cumulative rating entropy ($CumEntropy_{i,t-1}$). The interaction term between cumulative average rating and cumulative rating entropy is positive and statistically significant at the 1% level in both specifications. This finding indicates that the positive association between cumulative average eWOM rating and automobile sales becomes stronger when historical ratings exhibit greater informational diversity. Compared with uniformly favorable evaluations, a moderate degree of variation in historical ratings may provide consumers with a richer and more authentic representation of product quality, thereby enhancing the informational value of cumulative reputation. Columns (7) and (8) replace cumulative rating entropy with the cumulative proportion of extreme ratings ($CumExtreme_{i,t-1}$). The interaction term remains positive and statistically significant across both specifications. This consistency suggests that the moderating role of rating diversity is robust to alternative operationalizations. These results indicate that cumulative reputation appears to be more strongly associated with automobile sales when historical evaluations exhibit greater diversity rather than complete uniformity.

The moderating analyses suggest that both the duration and the diversity of accumulated reputation are associated with the relationship between cumulative eWOM ratings and automobile sales. As reputation accumulates over time, the association between cumulative ratings and sales becomes stronger. In addition, cumulative ratings appear to be more informative when historical evaluations exhibit greater diversity in

consumer ratings. These findings suggest that consumers may value not only the overall level of accumulated ratings but also the diversity embedded in historical evaluations when interpreting cumulative online reputation.

5.5. Robustness Checks and Additional Analyses

Table 6 reports robustness checks using alternative measures of the dependent and key independent variables. Columns (1) to (3) replace the logarithm of monthly automobile sales with the inverse hyperbolic sine (IHS) transformation. Column (1) re-estimates the baseline model for H1. The coefficient on $CumRating_{i,t-1}$ remains positive and statistically significant at the 1% level (coefficient = 1.290), which is highly comparable to the baseline estimate reported in Table 3. Columns (2) and (3) examine the two moderating effects under the IHS specification. The interaction between $CumRating_{i,t-1}$ and $Age_{i,t-1}$ remains positive and statistically significant at the 1% level (coefficient = 0.024). Likewise, the interaction between $CumRating_{i,t-1}$ and $CumEntropy_{i,t-1}$ remains positive and statistically significant at the 1% level (coefficient = 1.512). These results indicate that the main findings are robust to an alternative transformation of automobile sales. Columns (4) to (6) report an alternative construction of the cumulative eWOM rating. Instead of calculating the cumulative rating from all historical individual review scores, the alternative measure is obtained by recursively averaging the monthly average ratings. Under this alternative definition, the coefficient on $CumRating_{i,t-1}$ remains positive and statistically significant at the 1% level (coefficient = 1.304) in Column (4). The interaction between $CumRating_{i,t-1}$ and $Age_{i,t-1}$ also remains positive and statistically significant (coefficient = 0.025), as reported in Column (5). Similarly, the interaction between $CumRating_{i,t-1}$ and $CumEntropy_{i,t-1}$ remains positive and statistically significant at the 1% level (coefficient = 1.736) in Column (6). The results remain qualitatively consistent under the alternative construction of the cumulative eWOM rating, providing further evidence for the robustness of the main empirical findings.

Table 6. Alternative measure of automobile sales and cumulative eWOM average rating.

Variable	IHS Sales			Monthly Average CumRating		
	(1)	(2)	(3)	(4)	(5)	(6)
$CumRating_{i,t-1}$	1.290 *** (4.516)	0.932 *** (3.239)	0.124 (0.292)	1.304 *** (5.335)	0.976 *** (3.542)	−0.025 (−0.085)
$CumRating_{i,t-1} \times Age_{i,t-1}$		0.024 *** (4.988)			0.025 *** (5.293)	
$Age_{i,t-1}$		−0.113 *** (−5.293)			−0.117 *** (−5.555)	
$CumRating_{i,t-1} \times CumEntropy_{i,t-1}$			1.512 *** (3.168)			1.736 *** (4.468)
$CumEntropy_{i,t-1}$			−7.554 *** (−3.499)			−8.524 *** (−4.846)
$\log Volume_{i,t-1}$	0.325 *** (19.985)	0.253 *** (18.939)	0.326 *** (20.117)	0.321 *** (19.684)	0.252 *** (17.381)	0.323 *** (19.862)
$Rating_{i,t-1}$	1.416 *** (4.600)	0.565 ** (2.097)	1.263 *** (4.181)	1.305 *** (4.181)	0.417 (1.524)	1.150 *** (3.733)
$Rating_{i,t-1}^2$	−0.200 *** (−5.301)	−0.078 ** (−2.365)	−0.180 *** (−4.879)	−0.189 *** (−4.907)	−0.064 * (−1.920)	−0.168 *** (−4.444)
$\log SVI_{i,t-1}$	0.154 *** (6.743)	0.134 *** (6.776)	0.153 *** (6.889)	0.154 *** (6.780)	0.134 *** (6.708)	0.152 *** (6.919)
$\log Price_{i,t-1}$	1.931 *** (4.995)	1.033 ** (2.574)	1.682 *** (4.483)	1.898 *** (4.897)	0.926 ** (2.318)	1.673 *** (4.433)
$\log Price_{i,t-1}^2$	−0.251 *** (−4.358)	−0.146 ** (−2.436)	−0.225 *** (−4.039)	−0.249 *** (−4.314)	−0.130 ** (−2.193)	−0.225 *** (−4.043)
Constant	−5.257 ***	−0.019	1.255	−5.635 ***	−0.353	1.538

	(−3.746)	(−0.012)	(0.646)	(−4.257)	(−0.226)	(0.989)
Automobile FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Within R ²	0.179	0.214	0.186	0.179	0.211	0.186
Between R ²	0.301	0.352	0.322	0.299	0.348	0.322
AIC	112,715.8	110,976.8	112,394.0	112,954.9	111,340.6	112,615.1
BIC	112,776.1	111,054.3	112,471.5	113,015.2	111,418.2	112,692.6
F-statistics	89.68	74.27	72.00	88.15	73.90	71.39
Observations	40,703	40,703	40,703	40,703	40,703	40,703

Notes: All models are estimated with cluster-robust standard errors clustered at the automobile-model level. *t*-statistics are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

To examine whether the main findings are driven by major changes in the Chinese automobile market during the sample period, we conduct subsample analyses across different market periods. The results are reported in Table 7. Specifically, Columns (1)–(3) restrict the sample to observations before December 2019, thereby excluding the COVID-19 period as well as the subsequent rapid expansion of the new-energy vehicle market. Columns (4)–(6) further exclude observations during the COVID-19 period (from Dec. 2019 to Jan. 2023) and re-estimate the models using the remaining observations. Columns (1)–(3) show that the main findings remain consistent in the pre-December 2019 subsample. In Column (1), the coefficient on $CumRating_{i,t-1}$ is 1.552 and remains statistically significant at the 1% level. Columns (2) and (3) further show that the interaction terms between $CumRating_{i,t-1}$ and $Age_{i,t-1}$ and between $CumRating_{i,t-1}$ and $CumEntropy_{i,t-1}$ remain positive and statistically significant at the 1% level, with coefficients of 0.033 and 1.436, respectively. These results indicate that the documented relationships are present even before the COVID-19 period and the rapid expansion of the new-energy vehicle market. Columns (4)–(6) report the results after excluding observations during the COVID-19 period. The coefficient on $CumRating_{i,t-1}$ remains positive and statistically significant at the 1% level in Column (4). The interaction effects with $Age_{i,t-1}$ and $CumEntropy_{i,t-1}$ also remain positive and statistically significant at the 1% level in Columns (5) and (6). The findings remain robust when the COVID-19 period is excluded from the sample.

Table 7. Subsample analyses across different market periods.

Variable	DV: $\log Sales_{i,t}$					
	Subsample Before Dec. 2019			Excluding COVID-19 Period		
	(1)	(2)	(3)	(4)	(5)	(6)
$CumRating_{i,t-1}$	1.552 *** (5.453)	0.388 (1.386)	0.269 (0.746)	1.496 *** (5.086)	0.862 *** (2.936)	−0.005 (−0.011)
$CumRating_{i,t-1} \times Age_{i,t-1}$		0.033 *** (4.852)			0.031 *** (6.172)	
$Age_{i,t-1}$		−0.159 *** (−5.439)			−0.145 *** (−6.434)	
$CumRating_{i,t-1} \times CumEntropy_{i,t-1}$			1.436 *** (2.726)			2.021 *** (4.043)
$CumEntropy_{i,t-1}$			−7.432 *** (−3.176)			−9.876 *** (−4.392)
$\log Volume_{i,t-1}$	0.351 *** (13.113)	0.270 *** (12.723)	0.358 *** (13.293)	0.331 *** (18.000)	0.262 *** (18.271)	0.332 *** (18.278)
$Rating_{i,t-1}$	1.354 *** (2.959)	0.354 (1.064)	1.092 ** (2.502)	1.173 *** (3.551)	0.484 * (1.666)	0.988 *** (3.027)
$Rating_{i,t-1}^2$	−0.192 ***	−0.050	−0.160 ***	−0.164 ***	−0.062 *	−0.141 ***

	(−3.380)	(−1.186)	(−2.942)	(−4.077)	(−1.748)	(−3.546)
$\log SVI_{i,t-1}$	0.387 ***	0.337 ***	0.372 ***	0.167 ***	0.144 ***	0.164 ***
	(5.767)	(5.491)	(5.709)	(6.075)	(5.725)	(6.218)
$\log Price_{i,t-1}$	2.261 ***	0.235	1.866 ***	1.865 ***	0.851 **	1.515 ***
	(6.315)	(0.667)	(5.315)	(4.537)	(2.149)	(3.876)
$\log Price_{i,t-1}^2$	−0.286 ***	−0.027	−0.240 ***	−0.242 ***	−0.117 **	−0.203 ***
	(−5.562)	(−0.522)	(−4.780)	(−3.979)	(−1.966)	(−3.514)
Constant	−10.047 ***	1.208	−2.285	−6.459 ***	−0.206	1.851
	(−5.616)	(0.746)	(−1.103)	(−4.429)	(−0.129)	(0.973)
Automobile FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Within R ²	0.228	0.300	0.239	0.189	0.231	0.200
Between R ²	0.456	0.480	0.468	0.313	0.370	0.327
AIC	59,331.6	57,166.1	59,019.7	81,713.7	80,073.4	81,318.9
BIC	59,387.6	57,238.1	59,091.7	81,772.1	80,148.4	81,393.9
F-statistics	68.32	67.74	57.64	77.10	64.94	63.34
Observations	22,122	22,122	22,122	30,862	30,862	30,862

Notes: All models are estimated with cluster-robust standard errors clustered at the automobile-model level. *t*-statistics are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 8 reports several additional analyses that further examine the robustness of the main findings and explore heterogeneity in the value of cumulative eWOM ratings. Column (1) replaces the month fixed effects with year-by-month fixed effects to control more flexibly for common time-specific shocks. Under this more demanding time fixed-effects specification, the coefficient on $CumRating_{i,t-1}$ remains positive and statistically significant at the 1% level, with an estimated coefficient of 0.949. This result indicates that the positive association between cumulative eWOM rating and automobile sales remains after accounting for more detailed time variation. Columns (2) and (3) further examine whether earlier cumulative ratings continue to contain information associated with subsequent automobile sales. Specifically, Column (2) replaces the cumulative rating measured up to month $t - 1$ with the cumulative rating measured up to month $t - 2$, while Column (3) further shifts the cumulative measure to month $t - 3$. The estimated coefficients remain positive and statistically significant at the 1% level, with values of 1.070 and 1.182, respectively. These results suggest that cumulative ratings constructed from earlier review histories remain positively associated with subsequent automobile sales.

Table 8. Additional analyses.

Variable	DV: $\log Sales_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
$CumRating_{i,t-1}$	0.949 *** (3.059)			1.512 *** (4.414)	1.491 *** (4.632)
$CumRating_{i,t-2}$		1.070 *** (4.152)			
$CumRating_{i,t-3}$			1.182 *** (4.625)		
$CumRating_{i,t-1} \times High Price_{i,t-1}$				−0.497 * (−1.739)	
$CumRating_{i,t-1} \times New Energy_{i,t-1}$					−1.332 *** (−2.632)
$High Price_{i,t-1}$				2.331 * (1.789)	
$\log Volume_{i,t-1}$	0.298 ***	0.338 ***	0.343 ***	0.326 ***	0.326 ***

	(20.404)	(19.838)	(19.622)	(19.944)	(20.007)
$Rating_{i,t-1}$	0.763 ***	1.380 ***	1.419 ***	1.371 ***	1.411 ***
	(2.808)	(4.582)	(4.523)	(4.418)	(4.599)
$Rating_{i,t-1}^2$	-0.108 ***	-0.190 ***	-0.196 ***	-0.194 ***	-0.199 ***
	(-3.285)	(-5.112)	(-5.069)	(-5.098)	(-5.303)
$logSVI_{i,t-1}$	0.129 ***	0.155 ***	0.157 ***	0.154 ***	0.155 ***
	(6.314)	(6.532)	(6.349)	(6.731)	(6.736)
$logPrice_{i,t-1}$	0.754 *	1.787 ***	1.625 ***	1.837 ***	1.922 ***
	(1.935)	(4.637)	(4.260)	(4.775)	(4.980)
$logPrice_{i,t-1}^2$	-0.108 *	-0.242 ***	-0.220 ***	-0.248 ***	-0.250 ***
	(-1.867)	(-4.212)	(-3.900)	(-4.355)	(-4.332)
Constant	-0.975	-4.753 ***	-5.075 ***	-6.674 ***	-6.099 ***
	(-0.636)	(-3.666)	(-3.928)	(-4.207)	(-4.375)
Automobile FE	Y	Y	Y	Y	Y
Month FE	N	Y	Y	Y	Y
Year-Month FE	Y	N	N	N	N
Within R ²	0.117	0.183	0.187	0.179	0.179
Between R ²	0.301	0.310	0.302	0.307	0.321
AIC	108,676.3	110,086.3	107,296.1	112,930.4	112,920.5
BIC	108,736.6	110,146.4	107,356.1	113,007.9	112,989.4
F-statistics	72.12	88.54	87.62	70.18	79.18
Observations	40,703	39,800	38,887	40,703	40,703

Notes: All models are estimated with cluster-robust standard errors clustered at the automobile-model level. t -statistics are reported in parentheses. *** $p < 0.01$, * $p < 0.10$.

Columns (4) and (5) in Table 8 examine whether the association between cumulative eWOM rating and automobile sales differs across product categories. In Column (4), a dummy variable indicating high-priced automobile models ($High Price_{i,t-1}$) is introduced together with its interaction with $CumRating_{i,t-1}$. High-priced models are defined as those with an average transaction price above the sample median of approximately RMB 132,000. The interaction coefficient is -0.497 and is statistically significant at the 10% level, suggesting that the positive association between cumulative eWOM rating and automobile sales is weaker for high-priced automobile models. One possible explanation is that consumers purchasing higher-priced automobiles may rely on a broader set of information, including brand reputation, product quality, and professional evaluations, thereby reducing the relative importance of accumulated online reputation.

Column (5) in Table 8 examines heterogeneity between new-energy vehicles and conventional internal combustion engine vehicles. The interaction term between $CumRating_{i,t-1}$ and the new-energy vehicle indicator ($New Energy_{i,t-1}$) is negative and statistically significant at the 1% level, with an estimated coefficient of -1.332. This result suggests that the positive association between cumulative eWOM rating and automobile sales is weaker for new-energy vehicles. A possible explanation is that consumers considering new-energy vehicles may obtain information from multiple specialized channels, including technology-oriented communities, charging infrastructure information, and manufacturer communications, thereby reducing their relative reliance on cumulative online reputation when making purchase decisions.

The additional analyses provide further evidence that the main findings remain robust under more granular time fixed-effects specifications and alternative cumulative rating windows. They also suggest that the informational value associated with cumulative eWOM ratings varies across automobile segments.

6. Conclusions, Implications and Limitations

6.1. Conclusions

This study provides new evidence on the informational value of cumulative eWOM ratings from the perspective of online reputation. Using a two-way fixed-effects framework, we find that cumulative average eWOM rating is positively associated with subsequent automobile sales, suggesting that cumulative consumer evaluations contain valuable information beyond short-term eWOM signals. We further show that higher cumulative ratings are associated with more favorable subsequent rating changes and lower rating entropy in new monthly reviews. These findings indicate that accumulated online reputation is closely related to both the direction of subsequent consumer evaluations and the degree of rating diversity reflected in future ratings. We also examine two boundary conditions of the relationship between cumulative eWOM rating and automobile sales. The positive association becomes stronger as an automobile model remains in the market for a longer period, suggesting that the informational value associated with accumulated reputation increases over time. In addition, cumulative rating entropy positively moderates this relationship. This finding suggests that cumulative reputation appears to be more informative when it is accompanied by a moderate degree of rating diversity rather than complete uniformity. Collectively, these results indicate that cumulative online reputation reflects not only the average level of consumer evaluations but also the richness and credibility of the information embedded in historical reviews.

The main findings remain consistent across a wide range of supplementary analyses, providing further evidence for the robustness of the informational value associated with cumulative eWOM ratings. The positive association between cumulative ratings and automobile sales persists under alternative variable constructions, stricter empirical specifications, and different sample periods. Additional analyses further suggest that the informational value of cumulative eWOM ratings varies across product contexts. Specifically, the association is relatively weaker for high-priced automobiles and new energy vehicles, where consumers are likely to have access to a broader set of information beyond online eWOM review. These findings indicate that cumulative eWOM rating represents a robust and informative signal of online reputation, while its relative informational value depends on the market context in which consumers evaluate products.

6.2. Theoretical Implications

This study contributes to the eWOM literature by demonstrating the informational value of cumulative eWOM rating as a long-term indicator of online reputation. While prior studies have primarily focused on short-term eWOM characteristics, such as review volume and average rating within a short time window [9–11], our findings suggest that the historical accumulation of consumer evaluations represents a distinct source of information that is positively associated with subsequent automobile sales. This perspective extends the measurement of online reputation from short-term evaluations to accumulated reputation and highlights the importance of considering the temporal dimension of eWOM.

Second, this study advances the understanding of when cumulative online reputation is more informative. We show that the positive association between cumulative eWOM rating and automobile sales becomes stronger as products remain longer in the market. In addition, this association is strengthened when cumulative ratings exhibit greater diversity, as reflected by cumulative rating entropy and the proportion of extreme ratings. These findings suggest that consumers evaluate not only the average level of

historical ratings but also the perceived credibility of the accumulated reputation signal embedded in the distribution of consumer evaluations. This enriches the literature by showing that the informational value of cumulative online reputation depends on its temporal accumulation and rating diversity.

Third, this study provides additional evidence on the dynamic characteristics of cumulative online reputation. We find that higher cumulative ratings are associated with more favorable subsequent rating changes and lower rating entropy. These findings suggest that accumulated online reputation is closely related to the subsequent evolution of consumer evaluations. These analyses provide a complementary perspective on how cumulative reputation and subsequent eWOM are dynamically associated over time.

6.3. Practical Implications

From a practical perspective, online review platforms may benefit from presenting cumulative reputation more explicitly. Our findings suggest that the historical accumulation of consumer evaluations contains additional information. Displaying cumulative ratings together with the accumulation period may help consumers better interpret long-term reputation. For automobile manufacturers, the findings highlight the importance of maintaining favorable customer evaluations over time. Online reputation should be viewed as a cumulative asset rather than a collection of isolated monthly ratings. Sustained product quality and customer satisfaction contribute to the gradual accumulation of favorable reputation, which is more strongly associated with automobile sales for products with longer market histories. For consumers, cumulative ratings may provide complementary information beyond short-term fluctuations in monthly ratings. The findings also suggest that rating distributions deserve attention in addition to average ratings. Moderate diversity in historical evaluations may reflect more authentic consumer experiences than complete rating uniformity, thereby providing a richer basis for evaluating product reputation.

6.4. Limitations and Future Research

Despite these contributions, several limitations provide opportunities for future research. First, the empirical analyses are based on the Chinese automobile market using data from the Autohome platform. As one of China's largest automobile review platforms, Autohome provides a rich source of consumer-generated eWOM and detailed product evaluations. However, platform-specific characteristics, including review-writing practices, user composition, and reputation formation mechanisms, may influence the observed relationships. Future studies could examine whether similar patterns emerge on other online review platforms or in different national markets to further assess the generalizability of the findings. Accordingly, the findings should be interpreted as evidence from the Chinese automobile market and the Autohome platform, and their generalizability to other online review platforms and market settings warrant further investigation.

Second, to measure consumer attention, this study incorporates the Baidu Search Index. To ensure consistent measurement across automobile models, the final sample is restricted to models with valid search keywords throughout the observation period. Although this approach improves the comparability of the consumer attention measure, it also limits the sample to automobile models for which reliable search-volume information is available. Future research may explore alternative measures of consumer attention that provide broader coverage across different product categories and market segments.

Third, this study primarily examines the relationship between cumulative eWOM rating and automobile sales. To better understand the dynamic characteristics of

cumulative ratings, we further examine their associations with subsequent changes in monthly ratings and rating entropy. These analyses document how cumulative reputation is related to the evolution of subsequent eWOM, but do not provide direct evidence on the behavioral mechanisms driving these relationships. Future research could incorporate richer behavioral data, reviewer characteristics, or exogenous variation in platform design to identify these underlying mechanisms and further clarify how cumulative online reputation shapes subsequent consumer evaluations.

Finally, our analyses document the dynamic associations between cumulative online reputation, subsequent eWOM characteristics, and automobile sales. The mechanisms underlying these relationships may involve multiple forms of social influence and information processing, which cannot be directly distinguished using the current data. Future research could combine behavioral experiments, platform interventions, or richer reviewer-level information to further examine the processes through which accumulated online reputation shapes subsequent consumer evaluations and market outcomes.

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