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eWOM Information Richness and Online User Review Behavior: Evidence from TripAdvisor

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Abstract: The growing number of online users commenting on review platforms has fueled the development of electronic word–of–mouth (eWOM). At the same time, merchants have improved their requirements for the length and frequency of online reviews. However, few studies have examined the updating mechanism of online reviews length and frequency from the perspective of businesses. This study explores the relationship between online commenting platform users and eWOM and examines how eWOM information richness affects online user review behavior. We used media richness theory (MRT) to quantify the information richness of eWOM content (linguistic, textual, and photographical) to build an empirical framework. For the research data, we used advanced big data analytics to retrieve and analyze TripAdvisor data on restaurant services in nine major tourist destinations, the United States, Mexico, and mainland Europe (including UK, Spain, Netherlands, etc.), over a long period of time. Based on >10 million eWOM, this study used multiple regression to examine the impact of eWOM information richness on online user review behavior, considering the moderating effect of information ambiguity. Our research results show that content information richness positively affects online user review behavior, increasing their frequency and length. Information ambiguity play a moderating role that strengthens this relationship. This supports our theoretical hypothesis. Finally, for greater applicability and reliability, we conducted a comparative study on the degree of differences in the relationship between eWOM and users based on different cultural backgrounds across countries.

Keywords: information richness; cross–cultural; interactive knowledge innovation; online eWOM platform; information ambiguity

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1. Introduction

With the emergence of many online review platforms and apps, such as TripAdvisor and Google, electronic word–of–mouth (eWOM) is playing an increasingly important role in the branding operations of businesses [1–3]. Specifically, for platforms, providing valuable eWOM can enable an increasing number of tourists and businesses to use their software. For customers, a new consumer group is born, users of online commenting platforms, which is a group of consumers who connect, communicate, share information, and purchase goods or services through an Internet platform. For businesses, understanding and participating in the discussions of these groups can help them better understand consumer needs, improve their products and services, and conduct effective marketing campaigns. In this study, "users of online commenting platforms" refers to those groups who are willing to share information on an Internet platform after completing the actual experience of the consumption process offline in restaurants, hotels, etc. [4]. The information from online ratings and eWOM can help them choose satisfactory businesses. Customers' participation in eWOM can build a good platform reputation, and historical eWOM can even help businesses understand the advantages and disadvantages of their product, thus optimizing products [5]. In conclusion, the information from eWOM on online platforms can create a mutually beneficial solution for customers, businesses, and platforms [6].

The competition for traffic among online review platforms is increasingly fierce, especially following the emergence of short video platforms. The rich information of eWOM on online review platforms not only increases a user's stay time, but also enhances user interaction. Therefore, more and more online review platforms are paying attention to the update frequency and length of eWOM and specifying relevant platform rules. On the one hand, platforms require updates of business reviews, such as linking a business ranking with eWOM. Newer reviews have a higher weight in ranking algorithms, while older reviews have a lower weight. New businesses can only obtain star ratings after receiving at least 10 reviews; if the number of recent comment updates is insufficient, the store's star rating may decrease at any time [7]. On the other hand, platforms also have requirements for comments posted by consumers due to the increasing number of fake reviews. For example, TripAdvisor requires a minimum length of at least 200 characters for online consumer reviews (OCRs). Thus, businesses need online reviewers to make greater efforts when posting new reviews.

The emphasis on eWOM also encourages researchers to conduct research on the motivations of users to post eWOM [8,9]. Online ratings and historical reviews improve users' purchase intent [10–12], and historical reviews affects online business reputations [13]. Previous studies have focused on emphasizing the importance of historical reviews to users and businesses, explaining the mechanism of interaction between ratings and reviews [14,15]; rating changes closely relate to changes in reviews information. Many studies have investigated individual factors (personal reputation, altruism, economic incentives, emotional expression) influencing reviews initiators' posting their motivations when ratings show slight differences [16,17]. Furthermore, from users' perspective, reviews updating stems from continuous sharing; from businesses' perspective, users' continued review sharing requires positive interaction with a business' online reviews, reaching psychological consensus pre–posting and satisfying psychological motivations post–posting [18,19].

However, these studies and measures target consumer behavior, putting merchants in a passive position in the eWOM mechanism, and the impact of online reviews has a strong latency. From a research content perspective, most eWOM research has focused on consumers' willingness to consume, emotions, and trust, reflecting historical eWOM information interaction and affecting user business decisions and behaviors [20,21]. Research on eWOM publishing has focused on consumers' sharing motivations, such as altruism, rewards, and emotional venting [22,23]. eWOM affects sales volumes, while users' sharing motivations influence eWOM updates. From the perspective of the consumption process of online reviews, starting with consumers' browsing of eWOM, to generating consumption, and finally posting reviews, each link requires rich information from merchants. This demands information richness to generate consumption willingness and assist in the successful posting of new reviews. However, current research cannot provide a closed–loop conclusion on how eWOM information richness affects final user review posting. This is a relevant research gap. First, multilingual commenting is currently a more typical phenomenon on online commenting platforms, but current research on eWOM and consumer behavior seldom takes into account the impact of this phenomenon on the research results [24]. Second, the mechanism of users' sharing of comments is a well–established topic of research [25], but most of the current research focuses on the study of the subjective reasons of users' sharing of comments, e.g., altruism, emotional outbursts, and so on. However, there is little literature that examines the relationship between the information environment created by eWOM and user sharing mechanisms. This study explores the relationship patterns between users of the growing online review platforms and eWOM, with OCR platforms and merchant operators increasingly focusing on eWOM. Specifically, we focus on merchants and aim to address the following research questions:

How Does the Information Richness of Sellers' Electronic Word of Mouth Affect the Frequency and Length of Users' eWOM Sharing?

To address the above issues and understand the relationship between eWOM and user review behavior, we first used media richness theory (MRT) to quantify eWOM content information richness: linguistic, textual, and photographical [26–28]. For the research data, we used advanced big data analytics to retrieve and analyze TripAdvisor data on restaurant services in nine major tourist destinations, the United States, Mexico, and mainland Europe (including European countries such as the United Kingdom, Spain, France, the Netherlands, etc.), over a long period of time. Based on >10 million eWOM, this study used multiple regression to examine the impact of eWOM information richness on users' online review behavior, controlling for the moderating effect of information ambiguity. Our research results show that content information richness positively affects users' online review behavior, increasing their frequency and length. Information ambiguity play a moderating role that strengthens this relationship. This supports our theoretical hypothesis. Finally, for greater applicability and reliability, we conducted a comparative study on the degree of differences in the relationship between eWOM and users based on different cultural backgrounds across countries.

The remainder of this study is organized as follows. A literature review, the theoretical background, and our hypotheses are provided in Section 2. Section 3 presents the research methods and models. Section 4 presents our research findings. Finally, a discussion and our conclusions are presented in Section 5.

2. Theoretical Background and Hypotheses

2.1. Why Should We Pay Attention to the Frequency and Length of Users' eWOM Sharing?

The frequency and length of users' eWOM sharing can be described in many ways. The concept of eWOM update frequency and length of users discussed in our study was derived from public activity and participation in social media [26].

eWOM has become an indispensable part of Internet consumption. When choosing the most suitable business, customers usually need to browse the homepage of online platform businesses first. eWOM consists of scores and content. On online platforms, the time interval between the latest eWOM and the user's browsing time is a key basis for decision–making. For example, when a company's eWOM updates slowly or does not even have new eWOM for some time, customers may think that the company's attractiveness is declining, and users and companies have less understanding of these eWOM [29,30]. In addition, the investment maintenance of online word–of–mouth marketer is also crucial, higher investment in online word–of–mouth marketing can generate high length eWOM. It is worth noting that the number of words is still an intuitive reflection of the degree of dispersion of eWOM, as lengthy texts about the product itself require time and mental effort. In other words, the more specialized the words involved, the higher the costs for users to generate eWOM. Therefore, the number of words has become a key indicator for customers' written online word–of–mouth investment [31–33]. However, the information value of eWOM decreases over time. In addition, previous research based on information overload theory has shown that the length of eWOM does not necessarily benefit future customers [34]. Therefore, we recognize Shukla et al.'s research on the impact of eWOM richness on user browsing time, which suggests that decision–making depends on online word–of–mouth richness in the market [35]. Therefore, companies should maintain a certain frequency of updates and online word–of–mouth richness on online platforms to maintain their online reputation.

In the marketing literature, eWOM releases and updates primarily emanate from a consumer behavior perspective [36]. First, research examines consumers' sharing motivations. The current literature partitions these into a reward motivation, an altruistic motivation, or emotional venting [37–39]. Meanwhile, scholars introduced the concept of continuous sharing as a single consumer posting two or more reviews [2]. Informed by social cognitive theory and social exchange theory, platform management capabilities for community members determine continuous sharing behaviors. The above literature clearly categorizes consumer groups from the consumer perspective and proposes a mechanism to influence the sharing of reviews between platforms and consumers. However, for businesses, consumer groups are highly heterogeneous, so how platforms and merchants can jointly manage each merchant's eWOM to accomplish review updates constitutes an intriguing research question.

It is noteworthy that a study on public participation in social media analyzed the characteristics of public participation by summarizing the number of shares, online word–of–mouth, and likes [40]. Bottom–up design may be a key characteristic of public participation, which means that formal decision–making power is initiated by the public [41]. In the eWOM community, composed of platform operators and enterprises, users not only act as users, but also as participants [42]. According to research on the motivations of eWOM, compared with the likes and shares by the public on social media platforms, users are more likely to express eWOM about a certain enterprise on online platforms [43,44]. Therefore, this study attempts to measure the process of eWOM updates by comparing online review platforms and social media platforms based on two indicators: frequency and length.

2.2. Media Richness Theory (MRT) and Information Richness

MRT provides a theoretical foundation for information richness from the perspective of communication media [45]. Daft, Lengel, and Trevino proposed a media richness hierarchical structure including four media categories: face–to–face, telephone, address file, and unspecified file [46]. The richness of each medium is based on four criteria: feedback, multiple cues, linguistic diversity, and personal attention. Information can lead to uncertainty, mainly due to differences between the amount of information needed and received and ambiguity of information due to recipient confusion or lack of information [3]. To achieve information transmission, two basic information goals must be fulfilled: meeting information richness and reducing ambiguity [47–49]. As shown in Table 1, recent research on information richness has mainly focused on social media and online and offline sales. It plays a positive role in user participation on social media and omni–channel sales. However, little research has been conducted on the definitions of information richness variables and related business values on online platforms.

According to the existing literature, numerous indicators are utilized to measure the information richness of eWOM. Some studies have referenced the media richness theory (MRT), suggesting that information richness impacts credibility and quality, influencing the breadth and depth of user participation on platforms. Previously, eWOM richness enhanced participation in information processing [26,50]. Therefore, eWOM information richness can be considered an important factor affecting update frequency. However, prior research on eWOM richness has primarily focused on communication channels like texts, images, and videos [27], overlooking language types and rating characteristics. Language types reflect company popularity and internationalization [51]. Currently, limited research addresses multilingual eWOM, single–language analysis yields scant richness data for other languages' eWOM. Hence, this study analyzes corporate eWOM information richness considering language types. The degree of information ambiguity in eWOM is defined by rating differences; greater variation indicates a higher ambiguity [28,52]. In Lee et al.'s study, information richness was defined as "the display format of emergency–related information" in a social media scenario based on MRT theory [53], whereas in our study, using eWOM on an online platform as the scenario, information richness is defined as "the way in which merchants provide traditional information to their customers through eWOM", which comprises the richness of review language categories, text richness, and image richness, respectively.

Ratings are also part of eWOM. Differences in ratings are also a significant indicator of the successful operation of a business community's eWOM. A previous study confirmed that when top-ranked companies experience reputation inflation on online platforms, i.e., when the mean score increases and the variance decreases, their sales can increase in the short term [30]. The research on reputation inflation started from eWOM platforms, and few studies have assessed the relationship between score variance and the eWOM community constructed by individual restaurants. In this study, the degree of information ambiguity in eWOM is defined by rating differences; greater variation indicates higher ambiguity [28,52]. Rating variance was used as an indicator of information ambiguity both to explain the role of ratings in characterizing eWOM information and to verify the mechanism involved in the impact of reputation inflation on the increase in offline sales in prior studies from the perspective of eWOM [40].

Table 1. The related literature on information richness in recent years.

Author(s) (Year)	Research Variable	Research Object	Conclusion
(Li, Zhou, Luo, Benitez, & Liao, 2022) [40]	Information richness	Social media	Impacts of information timeliness and richness on public engagement on social media
(Su & Li 2023) [54]	Information richness	Social media	Posts with high information richness draw more audience engagement than posts with low information richness
(Shandy, Mulyana, & Harsanto, 2023) [55]	Information richness	Social media	Social media richness influences business performance by facilitating information–sharing activities and providing a platform for consumers to engage in transactions
(Shaputra, Fitriani, & Hidayanto 2023) [56]	Media richness	Booking hotels using online travel agencies	Hotel visualizations with high media richness and high interactivity more significantly influence users' trust, perceived value, and attitudes compared to visualizations with low media richness and interactivity

2.3. Hypothesis Development

2.3.1. Language Richness and the Frequency and Length of Users' eWOM Sharing

Language richness refers to the diversity of language types and language expressions used in eWOM. Specifically, the richness of language types represents the participation of users from different language backgrounds and reflects the degree of internationalization of businesses. In the field of e–commerce, Pangarkar et al. observed that a higher degree of internationalization positively affected the performance of medium–sized enterprises [57]. In addition, the emergence of digital platforms has resulted in a greater blurring of language and culture boundaries and the appearance of new participants, roles, and relationships. The disruptive relationships between participants on global online platforms arise from the processes of innovation, digitization, and learning. Language richness is a typical feature of the co–creation service ecosystem to a certain extent [57,58]. Although some studies elucidated that the national and cultural differences in users posed a risk to product sales, eWOM with high language richness increased the number of new users and improved the motivation and enthusiasm of eWOM from the perspectives of performance and knowledge interaction and innovation. To sum up, the language richness in the eWOM of customers can affect the frequency and length of users' eWOM sharing. Therefore, the following hypothesis is proposed.

H1. Language richness positively influences the frequency and length of users' eWOM sharing.

2.3.2. Media Richness and the Frequency and Length of Users' eWOM Sharing

More informative eWOM is more interesting, which can reduce uncertainty and encourage decision–making. Communicators on eWOM platforms have multiple goals, of which only one is to provide accurate information. Before reviewing, new users can read eWOM which in turn affect the written eWOM of these users. A prior study unraveled that the use of rich media forms, such as texts, pictures, and videos, in eWOM on eWOM platforms might increase the diversity and visual appeal of eWOM [53]. Zhou et al. found that information richness positively modulated the relationship between the relevance of information and its dissemination on social media [59]. The research of Li et al. confirmed that information richness exerted a positive regulatory effect on the relationship between the retrospectivity and prospectivity of information and the breadth of public participation [40]. eWOM with high media richness are more prone to capture the attention of readers because eWOM with multiple media can more vividly convey information and evoke emotional resonance. As a result, users may be more motivated to create WOMs about businesses with such eWOM, which may then further promote the frequency and length of eWOM. Therefore, the following hypotheses are proposed based on the above discussion [59].

H2. The richness of text media positively influences the frequency and length of users' eWOM sharing.

H3. The richness of photo media positively influences the frequency and length of users' eWOM sharing.

2.3.3. The Moderating Role of Information Ambiguity

The score differences in eWOM can afflict the information richness of eWOM and the frequency and length of users' eWOM sharing on the online review platforms of businesses. Highly rated eWOM tend to be more attractive, and users may be more inclined to interact with these eWOM, such as by liking, replying, and sharing, which increases the exposure of the eWOM and the interaction between users, thus facilitating the activity and engagement of users [60]. Meanwhile, lowly rated eWOM may generate discussions, responses, or rebuttals and may also engage users to express their views. Rating differences create arguments for different positions, which can stimulate the interest of users holding different views to write new eWOM and their interactions. Low rating differences reflect similar views, which can contribute to reputation inflation and reduce the interest of users in participation.

A recent theoretical model by Epstein and Schneider predicted that a firm's assets will be undervalued by the market if the information surrounding those assets is ambiguous [61,62].This suggests that information ambiguity plays an important role in corporate image. Information ambiguity affects the timeliness and accuracy of information delivery by highly information–rich content. On this basis, the following hypotheses are proposed.

H4a. Information ambiguity strengthens the relationship between language richness and the frequency and length of users' eWOM sharing.

H4b. Information ambiguity strengthens the relationship between the richness of text media and the frequency and length of users' eWOM sharing.

H4c. Information ambiguity strengthens the relationship between the richness of photo media and the frequency and length of users' eWOM sharing.

These four hypotheses are presented in the conceptual framework of Figure 1. In addition to information richness though, other factors also influence the customer–sharing review behavior of a restaurant, such as its ratings, price point, ranking on a platform and whether the restaurant has been registered on the platform [63,64].

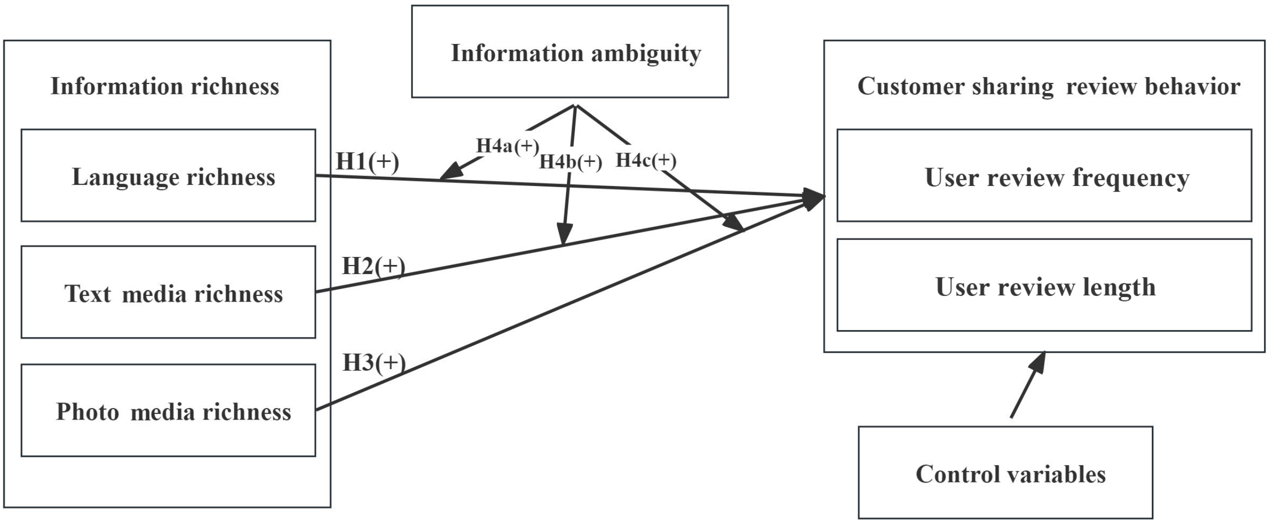

Figure 1. Research model.

3. Research Methods

3.1. Data Collection

The data we used were user reviews crawled online and can be considered secondary data. Data were collected between January 2016 and July 2023 from the website of the online travel product company, TripAdvisor, which is the largest travel website across the world. This company has websites in 30 countries around the world and contain more than 100 million eWOM. In this company, customers can book online tourism products and enjoy offline services. A Python web crawler was developed to randomly collect eWOM on restaurants, which obtained a total of 10,666,784 eWOM on 31,172 restaurants in 9 different countries and regions. Notably, Hu et al. crawled a total of 319,225 eWOM when studying the motivations of picture eWOM on online platforms [5]. Li et al. crawled 87,540 posts and 1,073,606 eWOM in their research on the impact of information timeliness and richness of information on public participation in social media, the sample size in our study far exceeded or approached that used in those studies, suggesting that our sample size was sufficient for this type of study [40].

3.2. Variable Operationalization

3.2.1. Dependent Variables

The dependent variables of this study included the frequency and length of users' eWOM sharing, which were measured from two perspectives. First, like in previous studies, the activity of online user eWOM was measured with the update frequency of the eWOM of each restaurant. The latest 15 reviews were selected because the first page of the platform typically presents approximately 15 reviews. Then, the time interval (days) between each eWOM and the latest eWOM was calculated and then accumulated. This dimension was called "frequency", the smaller the time interval value, the faster the update frequency. Second, there are numerous studies on the definition of the length of users' eWOM sharing at present, and the length of eWOM has been included as an important factor for research on eWOM [65,66]. In our study, the length of users' eWOM sharing was defined using the lengths of the last 15 reviews [67].

3.2.2. Independent Variables

The independent variables of this study were the three dimensions of information richness in eWOM: language richness, text media richness, and photo media richness. The above three independent variables were determined by counting the number of languages, text eWOM, and pictures among the eWOM of each business.

3.2.3. Moderator Variables

Different from information richness, information ambiguity was assessed according to the differences in eWOM ratings. In other words, the information ambiguity between eWOM was calculated with rating variance. Greater variance was associated with higher information ambiguity in the eWOM for the business.

3.2.4. Control Variables

To eliminate the interference of other factors in the results, our study included the rating of each review, real or popular name registration of the business, restaurant price, and ranking of restaurants in the region [68]. Table 2 provides the definitions of the main variables in this study.

Table 2. Description of variables.

Variable	Measured Item	Description
Dependent variable		
The frequency and length of users' eWOM	User review frequency (URF)	For the time (days) it took for a restaurant to update 15 reviews on an online review platform (TripAdvisor)
	User review length (URLen)	When a restaurant on the TripAdvisor platform was updated with 15 reviews, the total number of words in these 15 reviews was the value of this variable
Independent variable		
Information richness	Language richness (Lanr)	The number of languages included in all reviews of a restaurant on an online platform
	Text media richness (Tmr)	The total number of text reviews for a restaurant on an online platform
	Photo media richness (Pmr)	The total number of image reviews for a restaurant on an online platform
Moderator variable		
Information ambiguity	Ambi	The rating variance of a restaurant on an online platform
Control variables		
Score	Score	The rating of a restaurant on an online platform
Registration	Registration	Whether or not a restaurant completed its real name's registration on the platform; the registered were equal to 1, and the unregistered were equal to 0
Price	Price	The price range of the restaurant on the online platform, indicated by three types of symbols, "$, $$, $$$": the higher the number of $ symbols, the higher the price
Rank	Rank	The regional ranking of restaurants on the online platform; the ratio of the actual ranking to the number of regional restaurants

3.3. Data Analysis and Model

Stata 17 was used to analyze our data samples. The summary statistics of the variables are presented in Table 3. Next, multicollinearity was analyzed in Stata. As revealed in Table 3, the variance inflation factor values of all variables in our study were lower than 6 (not greater than the threshold of 10), indicating that multicollinearity was not a problem in our data sample. For text media richness (Tmr), photo media richness (Pmr), and user review frequency (URF), which appeared to be very different from the other variable sizes in the descriptive statistics, we normalized them using a logarithmic transformation. Empirical analysis was performed based on a regression model. We developed a model with the moderating role of emotional valence:

$$URF\ (URLen) = \beta 0 + \beta 1\ Lanr + \beta 2\ Tmr + \beta 3\ Pmr + \beta 4\ Lanr{*}Ambi + \beta 5\ Tmr{*}Ambi + \beta 6\ Pmr{*}Ambi + \beta Zi \quad (1)$$

Table 3. Variable statistics.

Variable	Mean	Std. Dev.	Min.	Max.	VIF
URLen	5684.466	3114.212	1542	53,805	
URF	307.144	336.677	0	2503	
Lanr	8.035	4.201	1	27	1.49
Tmr	342.202	582.716	10	34,298	4.78
Pmr	171.980	330.062	0	25,409	4.33
Ambi	1.341	0.583	0	3.785	2.26
Score	4.092	0.424	3	5	2.78
Registration	0.829	0.376	0	1	1.11
Price	1.945	0.445	1	3	1.07
Rank	0.221	0.184	0.001	1	2.11

4. Findings

4.1. Structural Model

Hierarchical regression was utilized in our study. Considering the changes and differences in the initial values of the variables, the control and dependent variables were standardized. To be specific, the control and dependent variables were subjected to logarithmic transformation. The results are exhibited in Table 4. The results of Models 3 and 6 showed that language richness had a negative impact on the duration of updating reviews (Model 6(Lanr)→H1:β = −0.069, $p < 0.01$) and a positive impact on eWOM length (Model 3(Lanr)→H1:β = 0.0057, $p < 0.05$), which supported H1. This result enriches the research by Denice et al. on multinational enterprise multilingual resource management [69]. Restaurants and hotels in international tourism areas face challenges akin to multinational enterprises: limited Language operating capability (LOC). According to Luo et al., multinational enterprises consist of a parent company and subsidiaries in different countries [70]. Subsidiaries encounter language barriers in communicating with local businesses and networks. Therefore, they have established multilingual communities to ease communication. Online review platforms are also multilingual communities, but with the popularity of web page translation functions on platforms, this reduces the difficulty of communication and knowledge sharing between businesses and reviewers.

Table 4. Hierarchical regression results.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variable	**Ln (URLen + 1)**	**Ln (URLen + 1)**	**Ln (URLen + 1)**	**Ln (URF + 1)**	**Ln (URF + 1)**	**Ln (URF + 1)**
Lanr		−0.015 ***	0.0057 **		−0.061 ***	−0.069 ***
		(−16.54)	(2.561)		(−24.759)	(−11.629)
Ln (Tmr + 1)		−0.020 ***	−0.087 ***		−0.346 ***	−0.272 ***
		(−3.61)	(−6.557)		(−23.411)	(−7.708)
Ln (Pmr + 1)		0.087 ***	0.089 ***		−0.220 ***	−0.256 ***
		(19.65)	(8.683)		(−18.876)	(−9.445)
Ambi			0.053 *			−0.195 ***
			(1.930)			(−2.656)
Lanr*Ambi			−0.014 ***			0.003
			(−9.323)			(0.815)
Ln(Tmr + 1)*Ambi			0.057 ***			−0.065 ***
			(6.392)			(−2.757)
Ln(Pmr + 1)*Ambi			−0.014 **			0.049 ***
			(−1.734)			(4.322)
Score	−0.190 ***	−0.184 ***	−0.032 ***	−0.154 ***	−0.559 ***	−0.804 ***
	(−23.16)	(−21.67)	(−3.144)	(−6.262)	(−24.999)	(−29.637)
Register	0.095 ***	0.063 ***	0.042 ***	−0.391 ***	−0.252 ***	−0.219 ***
	(13.32)	(8.80)	(5.798)	(−18.291)	(−13.259)	(−11.509)
Price	0.157 ***	0.129 ***	0.128 ***	−0.281 ***	−0.092 ***	−0.087 ***
	(26.69)	(21.52)	(21.560)	(−15.844)	(−5.837)	(−5.486)

Table 4. *Cont.*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variable	**Ln (URLen + 1)**	**Ln (URLen + 1)**	**Ln (URLen + 1)**	**Ln (URF + 1)**	**Ln (URF + 1)**	**Ln (URF + 1)**
Rank	−0.231 ***	−0.120 ***	−0.232 ***	1.153 ***	−0.822 ***	−0.609 ***
	(−11.91)	(−5.57)	(−10.477)	(19.747)	(−14.487)	(−10.371)
R–squared	0.052	0.070	0.093	0.069	0.298	0.304

Note (variable code): Lanr: language richness; Ln (Tmr + 1): text media richness; Ln (Pmr + 1): photo media richness; Ambi: information ambiguity; Ln (URLen + 1): user review length; Ln (URF + 1): user review frequency; t–statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results of the analysis of text media richness (Model 3(Ln(Tmr + 1))→H2: β = −0.087, $p < 0.01$; Model 6(Ln(Tmr + 1))→H2: β = −0.272, $p < 0.01$) partially supported H2. Photo media richness (Model 3(Ln(Pmr + 1))→H3: β = 0.089, $p < 0.01$; Model 6(Ln(Pmr + 1))→H2: β = −0.256, $p < 0.01$) negatively influenced the duration of updating eWOM and positively impacted the length of eWOM, which supported H3.

Furthermore, information ambiguity strengthens the relationship between language richness (β = 0.003) and photo media richness (β = 0.049, $p < 0.01$) to user sharing frequency and strengthens the relationship between text media richness (β = 0.057, $p < 0.01$) and the length of users' eWOM sharing. Therefore, the hypotheses of H4a, H4b, and H4c were partially supported.

Our hypotheses expand the emerging empirical literature on eWOM [20,23,71]. Customers posting reviews is customer–driven sharing behavior. Many studies have researched customer motivations for sharing texts and pictures, but their conclusions have centered around customers [34,72]. Our research focuses on the richness of eWOM information from businesses, with the two independent variables of text and picture richness. This information resource serves not only as a knowledge resource for customers, but also as an information resource for businesses. Such information resources can help businesses obtain more frequent and higher–length user sharing.

4.2. Robustness Test

The number of eWOM observations used in the dependent variables was expanded to 30 for additional testing. Our findings (Table 5) demonstrated that most of the studied effects were quantitatively consistent with the results in Table 4. Theoretically, we are relatively confident that our analysis results are reliable and robust.

Table 5. Robustness check using 30 reviews.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variable	**Ln (URLen + 1)**	**Ln (URLen + 1)**	**Ln (URLen + 1)**	**Ln (URF + 1)**	**Ln (URF + 1)**	**Ln (URF + 1)**
Lanr		−0.015 ***	0.0042 **		−0.047 ***	−0.058 ***
		(−19.82)	(2.316)		(−23.894)	(−12.308)
Ln (Tmr + 1)		−0.024 ***	−0.077 ***		−0.347 ***	−0.282 ***
		(−5.14)	(−7.111)		(−29.093)	(−9.921)
Ln (Pmr + 1)		0.090 ***	0.087 ***		−0.203 ***	−0.265 ***
		(24.75)	(10.506)		(−21.712)	(−12.199)
Ambi			0.071 ***			−0.289 ***
			(3.180)			(−4.918)
Lanr*Ambi			−0.012 ***			0.006 *
			(−10.415)			(1.856)
Ln (Tmr + 1)*Ambi			0.046 ***			−0.054 ***
			(6.456)			(−2.865)
Ln (Pmr + 1)*Ambi			−0.009 *			0.0640 ***
			(−1.734)			(4.322)
Score	−0.181 ***	−0.175 ***	−0.035 ***	−0.084 ***	−0.494 ***	−0.677 ***
	(−27.01)	(−25.25)	(−4.443)	(−4.167)	(−27.639)	(−32.278)

Table 5. *Cont.*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variable	**Ln (URLen + 1)**	**Ln (URLen + 1)**	**Ln (URLen + 1)**	**Ln (URF + 1)**	**Ln (URF + 1)**	**Ln (URF + 1)**
Registration	0.106 ***	0.074 ***	0.051 ***	−0.372 ***	−0.238 ***	−0.209 ***
	(18.02)	(12.41)	(8.834)	(−20.969)	(−15.661)	(−13.745)
Price	0.165 ***	0.137 ***	0.135 ***	−0.277 ***	−0.095 ***	−0.090 ***
	(33.79)	(27.57)	(27.793)	(−18.794)	(−7.462)	(−7.138)
Rank	−0.223 ***	−0.113 ***	−0.199 ***	1.062 ***	−0.713 ***	−0.555 ***
	(−13.97)	(−6.47)	(−11.226)	(22.061)	(−15.832)	(−11.966)
R–squared	0.077	0.103	0.137	0.086	0.353	0.360

Note (variable code): Lanr: language richness; Ln (Tmr + 1): text media richness; Ln (Pmr + 1): photo media richness; Ambi: information ambiguity; Ln (URLen + 1): user review length; Ln (URF + 1): user review frequency; t–statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3. Extension

The existing literature confirms the differential impact of cultural factors on the relationship between customers and online reviews. For example, Alei et al. conducted empirical research on Chinese and American consumer groups, finding moderately collectivistic and individualistic responses to online reviews [73]. Another study showed that collectivism and individualism play an important role in group decision–making in cross–cultural teams [74].

However, in addition to collectivism and individualism, Hofstede's cultural theory has developed many dimensions, including power distance, uncertainty avoidance, long–term orientation, indulgence/restraint, and masculinity/femininity [75,76]. Therefore, many studies use these dimensions when analyzing national cases. For example, when studying the factors that influence trust decisions in computer–mediated business transactions, Dan J. Kim divided countries into two categories based on collectivist-strong uncertainty avoidance-high long-term orientation-high context and individualistic-weak uncertainty avoidance-low long-term orientation-low context [77].

In the field of cross–cultural information science, collectivism and individualism are often discussed as independent cultural dimensions. In our discussion topic, long–termism is also an important dimension, since the restaurant reviews in our dataset spanned a long period of time, usually over several years. The longest interval of restaurant reviews in our dataset was more than ten years. Therefore, we incorporated long termism into this study. According to the Hofstede-insights website [78,79], we divided the nine countries (the United States, the United Kingdom, Spain, Mexico, the Netherlands, France, Belgium, Argentina, and Russia) involved in our dataset into two types: Type 1 (individualism–low, long term orientation–low context) and Type 2 (individualism–high, long term orientation–high context). Examples of posts for each category are presented in Table 6.

Table 6. Types of countries.

Category	**Criteria for Classification**	**Countries**
Individualism–low, long term orientation–low context	The Individualism dimension score is less than or equal to 70 and the Long Term Orientation dimension score is less than 59.	the United States, Spain, Mexico, Argentina, and Russia
Individualism–high, long term orientation–high context	The Individualism dimension scores above 70 and the Long Term Orientation dimension scores above 59.	the United Kingdom, Belgium, the Netherlands, France

We divided all reviews into Type 1 (15,729 restaurants and 526,0972 reviews) and Type 2 (15,438 restaurants and 540,5812 reviews). We conducted an analysis procedure consistent with the main analysis, and Tables 7 and 8 show the analysis results of the two cultural type combinations. There are differences in the results between Type 1 (individualism–low, long term orientation–low context) and Type 2 (individualism–high, long term orientation–high context) datasets. Firstly, although language richness and picture richness have the same impact on review update frequency and length, the impact of language richness on review update frequency in the Type 2 dataset (β = −0.087, $p < 0.01$) was greater than that in the Type 1 dataset (β = −0.022, $p < 0.01$), which also occurred for the impact of picture richness on review update frequency. This suggests that being in an individualism–high, long term orientation–high context strengthened the impact of language richness and picture richness on customers' frequency of sharing reviews for the restaurant. The second noteworthy point is that text richness had a greater impact on review update length (β = −0.121, $p < 0.01$) in the Type 1 dataset than in the Type 2 dataset (β = −0.040, $p < 0.05$), indicating that being in an individualism–low, long term orientation–low context strengthened the impact of text richness on customers' length of sharing reviews for this restaurant. Finally, information ambiguity had opposite effects in these two cross–cultural datasets. Information ambiguity had a positive impact in the individualism–low, long term orientation–low context dataset (β = –1.281, $p < 0.01$), while it had a negative impact in the individualism–high, long term orientation–high context dataset (β = 0.335, $p < 0.01$), which also reflects different reactions to information ambiguity between collectivistic and individualistic, long term orientation, and short term orientation cultures. Based on the previous literature, the results of studies conducted only on the cross–cultural background of reviewers are consistent with these findings, and the influence of the collectivistic and long–termism cultural dimensions on customers and enterprises is significant. Our results support the research of Kim et al. from the perspective of user–generated reviews representing consumer trust and enriching consumer behavior research in areas including user–sharing behavior [77,80–83].

Table 7. Results of the Type 1 dataset.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variable	**Ln (URLen + 1)**	**Ln (URLen + 1)**	**Ln (URLen + 1)**	**Ln (URF + 1)**	**Ln (URF + 1)**	**Ln (URF + 1)**
Lanr		−0.010 ***	0.010 ***		−0.040 ***	−0.022 ***
		(−7.930)	(3.333)		(−12.275)	(−2.861)
Ln(Tmr + 1)		−0.095 ***	−0.121 ***		−0.262 ***	−0.544 ***
		(−11.990)	(−6.440)		(−13.111)	(−11.454)
Ln(Pmr + 1)		0.104 ***	0.100 ***		−0.314 ***	−0.310 ***
		(16.550)	(6.650)		(−19.871)	(−8.217)
Ambi			0.126 ***			−1.281 ***
			(3.310)			(−13.315)
Lanr*Ambi			−0.015 ***			−0.016 ***
			(−7.162)			(−2.949)
Ln (Tmr + 1)*Ambi			0.039 ***			0.183 ***
			(3.009)			(5.639)
Ln (Pmr + 1)*Ambi			−0.012			0.030
			(−1.234)			(1.188)
Score	−0.190 ***	−0.194 ***	−0.055 ***	−0.704 ***	−0.566 ***	−0.811 ***
	(−17.440)	(−17.710)	(−4.083)	(−22.366)	(−20.488)	(−23.762)
Registration	0.088 ***	0.057 ***	0.034 ***	−0.365 ***	−0.260 ***	−0.219 ***
	(8.830)	(5.640)	(3.434)	(−12.580)	(−10.228)	(−8.655)
Price	0.140 ***	0.119 ***	0.117 ***	−0.162 ***	0.013	0.024
	(17.300)	(14.540)	(14.415)	(−6.934)	(0.652)	(1.172)
Rank	−0.198 ***	−0.148 ***	−0.216 ***	−0.268 ***	−0.963 ***	−0.749 ***
	(−7.800)	(−5.610)	(−7.971)	(−3.646)	(−14.461)	(−10.946)
R–squared	0.047	0.073	0.094	0.064	0.309	0.323

Note (variable code): Lanr: language richness; Ln (Tmr + 1): text media richness; Ln (Pmr + 1): photo media richness; Ambi: information ambiguity; Ln (URLen + 1): user review length; Ln (URF + 1): user review frequency; t–statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8. Results of the Type 2 dataset.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variable	**Ln (URLen + 1)**	**Ln (URLen + 1)**	**Ln (URLen + 1)**	**Ln (URF + 1)**	**Ln (URF + 1)**	**Ln (URF + 1)**
Lanr		−0.022 ***	−0.004		−0.065 ***	−0.087 ***
		(−16.030)	(−1.178)		(−18.482)	(−10.051)
Ln (Tmr + 1)		0.074 ***	−0.040 **		−0.118 ***	0.191 ***
		(8.270)	(−2.046)		(−5.043)	(3.734)
Ln (Pmr + 1)		0.086 ***	0.095 ***		−0.423 ***	−0.506 ***
		(12.530)	(6.311)		(−23.647)	(−12.743)
Ambi			−0.053			0.335 ***
			(−1.315)			(3.139)
Lanr*Ambi			−0.010 ***			0.011 *
			(−4.666)			(1.861)
Ln (Tmr + 1)*Ambi			0.072 ***			−0.213 ***
			(5.614)			(−6.275)
Ln (Pmr + 1)*Ambi			−0.016			0.081 ***
			(−1.548)			(2.928)
Score	−0.182 ***	−0.067 ***	0.048 ***	0.817 ***	−0.185 ***	−0.415 ***
	(−14.340)	(−4.210)	(2.774)	(22.579)	(−4.465)	(−9.200)
Registration	0.101 ***	0.048 ***	0.032 ***	−0.365 ***	−0.171 ***	−0.140 ***
	(9.940)	(4.610)	(3.147)	(−12.581)	(−6.324)	(−5.187)
Price	0.176 ***	0.127 ***	0.129 ***	−0.302 ***	−0.087 ***	−0.089 ***
	(20.410)	(14.420)	(14.758)	(−12.272)	(−3.790)	(−3.866)
Rank	−0.244 ***	0.203 ***	−0.023	3.779 ***	0.128	0.566 ***
	(−7.940)	(4.780)	(−0.524)	(43.157)	(1.156)	(4.849)
R–squared	0.056	0.085	0.104	0.168	0.320	0.329

Note (variable code): Lanr: language richness; Ln (Tmr + 1): text media richness; Ln (Pmr + 1): photo media richness; Ambi: information ambiguity; Ln (URLen + 1): user review length; Ln (URF + 1): user review frequency; t–statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. Discussion and Conclusions

5.1. Summary of Key Findings

In this study, we utilized over 10 million online, multilingual, restaurant consumer reviews collected from an OCR platform (TripAdvisor.com) in nine countries and processed them through complex big data analysis techniques. We applied a framework to investigate the mechanism between the richness of eWOM restaurant information, information ambiguity, and frequency and length of user–sharing reviews. The innovation of this study is that it explores an old topic in the field of consumer behavior from a new perspective, an area of research with significant business implications. That is, we started from the enterprises that are on online review platforms, to the moderating role of information ambiguity, and then to incorporating the two cultural dimensions of individualism and long–termism into the context of online review information dissemination. More specifically, since the H1–H3 hypotheses held, we found that consumers' behavior of posting reviews on online platforms for specific merchants (in terms of update frequency and content length) was influenced by the information richness of the merchant's eWOM on the platform. Language type, text richness, and image richness all had a positive impact on this behavior of consumers sharing reviews. On the other hand, since the H4a–H4c hypotheses also held, the information ambiguity (generated by ratings) of eWOM can serve as a moderating variable, strengthening the impact of information richness on consumers' behavior of posting reviews for specific merchants. Overall, our research results contribute to a deeper understanding of the mechanism of merchant–centered eWOM and ratings in the role of review updates. Therefore, we have contributed to the emerging research stream of eWOM for businesses (e.g., [3,10,30,84]). The following sections discuss the theoretical and managerial contributions and impacts.

5.2. Theoretical Contributions

This study provides theoretical insights into the existing literature. First, our research explored user enthusiasm for sharing reviews on online business platforms, considering information richness and ambiguity in eWOM as influencing factors. It expands eWOM research focused on businesses. In our study, we propose a measurement method for information richness: treating each enterprise as an individual, defining language richness by calculating language types, and analyzing text media richness and photo media richness by counting text and image reviews for each enterprise. Therefore, compared to previous consumer centered review–sharing behavior research (e.g., consumer motivation [2,85,86], photo sharing [5], and review updating [84]), the research of Berger and others suggests that interesting products drive immediate and ongoing word–of–mouth [87], while our research provides a new answer: "interesting" and rich historical reviews can also drive immediate and ongoing reviews. This study expands upon the opposite of these studies by establishing online reviews sharing mechanisms around businesses.

Second, our research focuses on the role of information richness and differences in online reviews. On social media, previous research has shown that information richness and rating ambiguity positively affect users' commenting on specific businesses [40]. Conversely, our results suggest that rich comment content and ambiguous ratings also negatively impact user engagement. This finding suggests that while rich comment content and ambiguous ratings have been widely confirmed as positive factors, they may also play a negative role in commercial intervention. Therefore, this study enriches MRT theory and previous reputation inflation research by clarifying information richness and these differences' positive and negative effects [30,53].

Finally, our research contributes to the field of cross–cultural research. We also explored the different performances of each variable in two different datasets of Type 1 (individualism–low, long term orientation–low context) and Type 2 (individualism–high, long term orientation–high context). For a long time, the literature on the cross–cultural management of multinational corporations and consumer behavior has discussed these topics separately, leading to many research conclusions about consumer preferences in different countries and cultural backgrounds and how corporations can change their products or services to obtain positive feedback. However, a large body of literature has not answered the question of what role corporate self–image (i.e., reputation) plays in this process. Our research shows that the historical reputation accumulated by corporations through long–term efforts is also valuable in facing cross–cultural markets, whether it is through positive or negative feedback. For a long time, the literature on the cross–cultural management of multinational corporations and consumer behavior has discussed them separately, leading to many research conclusions about consumer preferences in different countries and cultures and how corporations can change products or services to obtain positive feedback [81,88,89]. However, much of the literature has not answered the question: what role does a corporation's self–image (i.e., reputation) play in this process? Our research shows that the historical reputation accumulated by corporations through long–term efforts is also valuable in facing cross–cultural markets, whether it is through receiving positive or negative feedback.

5.3. Practical Significance

This work has some practical implications, including for marketing managers and practitioners, as well as for digital platform managers and developers. Marketing managers and practitioners should be aware that content–rich and rating–rich reviews allow them to obtain continuous and sufficiently long online reviews, while the comment policies of online review platforms have limitations on the length of their published written text, which means that these reviews have a high success rate in passing the platforms' reviews. This is a clear indication of the positive and negative effects of information richness in reviews. This finding should encourage marketing managers to encourage non–native English–speaking consumers to post reviews in their native language, which will increase the language richness of the restaurant; for a seller with an already low rating, not to limit the posting of negative reviews, as the difference in ratings will lead to information ambiguity; and know that the amount of texts and images of historical reviews is a long–term accumulation process, so operating an online platform for reviews should persist for a period of time before it produces results, which may be one year or two years or even ten years. However, research on user–sharing mechanisms can accelerate this process, and our research proves that the realization of this process is positive. Cross–cultural factors also play an important role in this process. Multinational company managers need to pay attention to the important roles of collectivism and individualism in the influencing mechanism of reviews, in order to implement different management measures in countries with different cultures. For example, restaurants in individualist countries need to maintain a large difference in their polarity of reviews, because the information ambiguity caused by rating differences will strengthen the positive effect of information richness on comment update frequency, while restaurants in collectivist countries need to maintain a uniform polarity of reviews, because the information ambiguity caused by rating differences will weaken the positive effect of information richness on comment update frequency.

Online platforms can manipulate the attractiveness of merchants' products and the natural ranking order of sellers, but such behavior clearly violates business ethics [90]. By studying the mechanism of historical reviews on the update frequency and review length of reviews, merchants can adjust and optimize the information structure of historical reviews to completely achieve their own reputation operations management. This approach is low–cost and feasible.

5.4. Conclusion, Limitations, and Future Research Directions

This work contributes to the relationship between online consumer behavior and a firm's reputation, with a focus on restaurant firms that use platforms to publish their eWOM. We empirically measured the relationship between the information richness (texts, photos, and language types) of a firm's historical reviews, the information ambiguity caused by rating differences, and the updates of new reviews based on a quantitative model. Using online reviews from the platform (TripAdvisor), we pursued our goals of investigating online review policies and services involving consumption in different companies and countries. Therefore, this article contributes to the intersection of online review platforms, corporate reputation management, and big data analytics.

This study has important limitations. First, this study was designed to investigate factors such as information richness. However, consumers' post–purchase eWOM may be influenced by many different factors, such as cultural acceptance and social media. Therefore, future research will investigate various factors that affect the new eWOM of online users from different cultural backgrounds, especially emphasizing the roles of social and cultural factors. Second, this study did not consider new forms of eWOM such as short videos related to companies. We believe that the investigation of short video platforms could be included in new research as a next step. Finally, although our study revealed that companies can play a key role in the speed and length of eWOM generation, further research is still needed to determine the mechanisms underlying the new eWOM management of online platforms.

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