EXPLORING CUSTOMER SATISFACTION ACROSS LANGUAGE BACKGROUNDS: A HYBRID FRAMEWORK ON MULTILINGUAL EWOM

Jie Lin
School of Economics and Management
Tongji University
linjie@tongji.edu.cn

Xueyu Liu[1]
School of Economics and Management
Tongji University
2210458@tongji.edu.cn

Shuaiyong Xiao
School of Economics and Management
Tongji University
syxiao@tong.edu.cn

Haowen Lin
Computer Science Department
University of Southern California
haowenli@usc.edu

ABSTRACT

In international travel, customers are willing to express their experiences and feelings about the trip by posting reviews on platforms in their native language. According to Customer-based Discrepancy Theory, customers with different language backgrounds will form different anchors when browsing or reading eWOM in the corresponding language due to the differences in expression forms, nouns, and other information in different languages, and even if they have consistent offline consumption experience, customers with different language backgrounds may have different satisfaction levels due to the differences in established anchors. Prior studies have been leveraging reviews to understand the information contained in eWOM in different languages, however, the analyses of multilingual reviews still face challenges. The current joint linguistic and statistical analysis methods suffer from information overload in terms of massive online data. In this paper, we address the above challenges by utilizing cross-linguistic deep learning and multiple linear regression model of attribute-level effects on customer satisfaction. The results of the data experiment in English, Spanish, French & Dutch based on online restaurant reviews from both Yelp and TripAdvisor platforms show that there are significant differences in restaurant satisfaction across customer groups with different language backgrounds. Furthermore, there are differences in the impact of attributes level satisfaction such as restaurant service between customer groups with different language backgrounds. Our findings contribute to the development of effective marketing strategies for corporate policies for international travel services by providing a more responsive experience for customers from different language backgrounds.

Keywords: Multilingual eWOM; Cross-lingual sentiment analysis; Customer satisfaction; Customer based discrepancy theory; Multiple linear regression model.

1. Introduction

Due to the differences in economic levels among countries and regions, people from different countries and language backgrounds come to new customer destinations in pursuit of globalized trade, migration, travel, etc. The multilingual business environment brings about many opportunities and challenges to today's service industries, such as the restaurant industry (Ramanathan et al., 2022). On the one hand, especially for offline service products, customer groups from different language backgrounds enrich the local customer population and bring about more business opportunities. On the other hand, the business environment of multilingual scenarios also brings diverse product experience, and customer groups from different countries and cultural backgrounds show distinct satisfaction with the products and services. A noticeable case is the preference for food. A recent study on the differences in the attributes of the diets of people living in different countries shows that customers in France, Greece, and Spain prefer fresh products without any additional flavors or preparation compared to customers in other European countries (Dudinskaya et al., 2021).

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[1] Corresponding author
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To better serve international customers, the localized services industry needs to understand consumer differences in different contexts and upgrade its products or services to achieve the business goals of increasing sales and product or service reputation in unfavorable situations such as the current economic downturn. On online platforms, cultural contexts have a more complex composition: country, ethnicity, religious beliefs, etc., while linguistic context is a more accessible label, especially when dealing with immigrants from immigrant countries or multiracial countries, differentiating the differences in satisfaction between groups through language is a more effective research path.

With the rapid development of international online travel platforms (e.g. Tripadvisor), an increasing number of customers are posting reviews through online word of mouth, which is multilingual, public, and highly communicative on the internet and will also become an important basis for subsequent customer decisions when purchasing products or services, possibly even becoming more important for conveying business information than are promotions. Previous studies have confirmed that the improvement of word-of-mouth evaluation has a positive impact on store sales (Cheung & Thadani, 2012; Huerta-Álvarez et al., 2020; Zhang et al., 2020). At the same time, service industry operators have a limited understanding of business and products at the linguistical dimension, with such an understanding being clearly difficult and prone to information overload to obtain the restaurant attributes of customer groups from different cultural backgrounds from limited customer information using traditional joint linguistic and statistical analysis methods (Critchfield & Doepke, 2018; Feng & Ren, 2020; Lee et al., 2016).

In particular, artificial intelligence, such as deep learning, has been widely used in online word-of-mouth data mining (Cheng et al., 2023), such as sentence-level topic classification and sentiment analysis tasks using natural language processing algorithms, and the emotional polarity of customer reviews of products in service industries, such as the hotel industry, which is generally classified as positive, negative, or neutral. Commercial organizations obtain attributes through the distribution of sentiment polarity and then launch marketing activities such as personalized user recommendations and product interaction innovation (Berezina et al., 2015; Ho et al., 2020; Zhang et al., 2016). With the development of cross-lingual machine translation, multilingual sentiment analysis has developed significantly in terms of accuracy (Pfeiffer et al., 2020). However, limited literature has used cross-linguistic deep learning to study specific marketing directions such as product attributes and interaction innovations for multilingual online word-of-mouth data. On the one hand, although the research on consumer preferences based on eWOM has always been a spotlight in the field of information science, their conclusions are mainly based on word-of-mouth data of a single language, or customers with the same language background. However, in a multilingual environment, eWOM is usually composed of English (the international common language) and the local mother tongue. When countries with multiple official languages, such as Belgium (the official languages are French, Dutch, and German), the language type and quantity distribution of comments will be more complex. Therefore, whether the previous conclusions of consumer preference research based on a single language are still applicable in multilingual eWOM data is questionable. On the other hand, in practice, translation software can well solve the problem of multilingual environments for customers and multinational enterprises. Currently, many online review platforms offer Google translation, effective for products with international standards like automobiles and mobile phones. However, for culture-involving industries like catering and tourism, translation software struggles with accurate translation of professional terms like dish names and scenic spots. Therefore, studying product attributes from multilingual online reviews can help companies better understand the anchors and perceived differences in satisfaction formation of customers from different language backgrounds, so that they can target and improve their services and products.

According to customer based discrepancy theory, satisfaction is the judgment result of the difference between the expectation or expectation of the product or service and the actual experience ((Churchill & Surprenant, 1982). The emergence of online review platforms has created a new consumer culture. Generally, the differences between their previous status and subsequent perception of eWOM are mainly composed of online browsing comment history and offline dining experience. Online browsing comment history is the main factor determining customers' previous status. There are differences in the content of eWOM they read between customers with different language backgrounds. For example, customers who only speak French are more likely to browse eWOM in French language. It is worth noting that customers from different countries who use the same language, such as customers from Brazil and Portugal, will have priority to read Portuguese eWOM; In terms of the offline dining experience, different language backgrounds will also affect the subsequent perceived differences, such as menu, service communication, diet preference and so on. From the above, we can find that there are group differences in the satisfaction of customers with different language backgrounds to comment online. The existing literature focuses on the research of consumer preference differences in the context of cultural differences but ignores the interoperability and communication speed of online platforms, whether users with the same language background are forming a new product preference difference by browsing online eWOM in the same language (Chang et al., 2015; Chen et al., 2015; Chen & Zahedi, 2016; Clemmensen, 2012; Cohen & El-Sawad, 2007; Cyr et al., 2009; Dibbern et al., 2012).

To the best of our knowledge, little research has analyzed the role of multilingual grouping on the relationship between online user reviews and user behavioral intentions from a restaurant perspective as described above. This paper expects to adopt the abovementioned ideas to study the following issues.

Question 1: Is there a significant difference in customer satisfaction with online reviews based on language background?

Question 2: Is the direction of the influence of restaurant attributes on satisfaction consistent across customers with different language backgrounds, which attributes influence satisfaction to a greater extent, are there differences in the extent to which attributes affect satisfaction among customers from different linguistic backgrounds?

To fill the gap in quantitative analysis methods in the field of multilingual customer preference, we propose a method based on a combination of deep learning models and multiple regression models. With the deep learning model, the aspect words and emotional polarity contained in online user reviews can be obtained automatically and analyzed statistically, and the multiple regression mathematical models can finish the multi-attribute analysis, which can avoid the problem of linguistic specialization compared with traditional joint analysis methods. This paper addresses the question 1 and 2 with several novel design artifacts as follows.

1) It analyzes customer group differences in cross-cultural contexts from the perspective of multilingual online customer reviews. To achieve this, it leverages a cross-lingual deep learning model to extract aspect word-sentiment polarity pairs from online user reviews. The model effectively solves the problem of lack of label resources in some language datasets by using the methods of transfer learning and label projection.

2) It investigates online review sentiment differences among customers of different language backgrounds by developing a statistical model of eWOM. The number of emotional polarities of five attributes such as food, environment, and location of the restaurant is counted. The difference between this study and other studies is that the above indicators are counted separately for different languages.

3) It adopts a multiple linear regression model to analyze the differences in the impact of merchant attributes on satisfaction for customer groups with different language backgrounds. The model solves the problem of discussing the factors influencing the satisfaction of user groups from a restaurant perspective. The use of the model refines the applied methodology of this study, which can be used by merchants in the future to measure their attributes for different language groups.

The rest of the article is organized as follows. Section II discusses the background of our study. Section III presents the theoretical framework and the study data, followed by the data analysis and results in Section IV. Section V discusses the implications and results of this study. Finally, Section VI summarizes the current work and presents the limitations of this study as well as suggestions for future research.

2. Literature Review

Based on the current mainstream research on customer culture differences, this paper establishes linguistic distinctions between customers' cultural differences as the basis of the study. We identified three research streams on differences in attribute related to multilingual backgrounds, including factors affecting restaurant word-of-mouth in multilingual environments, arguing that there are differences in satisfaction with restaurants among customer groups from multilingual backgrounds and differences in attributes of restaurants among customer groups from multilingual backgrounds.

2.1. Multilingual electronic word of mouth

Multilingual electronic word of mouth (eWOM) is a phenomenon that has emerged during the internationalization of online review platforms. While eWOM is one of the main factors influencing customers' purchasing decisions, the diversity and decentralization of the backgrounds of the groups generating eWOM complicate the process of browsing eWOM and obtaining valid information for other consumers(Öğüt & Onur Taş, 2012). Empirically, consumers tend to seek out reviews written by reviewers with backgrounds similar to their own, such as being from the same country or city, having the same religious beliefs, and traveling to the same destinations, and these different background groups have also been identified as important heterogeneity factors in related studies (Cao & Yang, 2016; Daries et al., 2018; Ghazali et al., 2022).

Therefore, in previous studies, the distinction between customers' cultural backgrounds is often rooted in the cultural dimension between countries. A common approach is to compare the responses of customers from different cultures to questions on certain dimensions such as individualism-collectivism, power distance, uncertainty avoidance, and masculinity-femininity, which are derived from Hofstede's theory and are widely used in cross-cultural business research (Galariotis & Karagiannis, 2020; Zhang et al., 2022). Hofstede is not the only type of cultural classification approach, Trompenaars' and Hampden Turner's seven dimensions of national culture. Scholars also try to develop some new dimensions from new perspectives, such as horizontal and vertical individualism, global expansion and supported cultural values (Chu et al., 2019; Peter & Shaun, 1995).

Recently, it has been noted that although the data source for most studies is English, English is only one of more than 6,500 languages spoken today, and differences in the way knowledge is attributed to different languages in a multilingual environment pose a challenge to studies based on monolingual data (Machery et al., 2021). The role that language can play as a carrier of cultural values, different languages have different degrees of expressiveness because of differences in their linguistic structure and grammar (Ravi & Ravi, 2015). Methods for conducting cross-linguistic research on customer cultural differences include surveys, interviews, etc., as well as quantitative data analysis using statistical methods. Other approaches focus on analyzing language use and communication patterns, such as the use of metaphors, idioms, and other cultural markers that reflect cultural values and attitudes, which are characterized by higher accuracy rates; knowledge of the underlying logic of language has begun to be applied to cross-linguistic deep learning research, such as machine translation (Ahmad et al., 2022; Karayiğit et al., 2022). Therefore, it is necessary to consider new research methods and more linguistic varieties of electronic word of mouth to understand consumer groups in different regions of the world in terms of satisfaction as well as the attributes of goods that influence satisfaction.

Table 1: Overview of Relevant Research about Factors Influencing Customer Satisfaction with Restaurants

Authors	**Attributes**	**Platform for obtaining online review data**	**Research topic**
(Chakraborty et al., 2022)	Food, service, ambiance, value, and location	Yelp restaurant review data	Attribute Sentiment Scoring with Online Text Reviews
(Zhu et al., 2022)	Location, service, price, environment, and dish	The website Ctrip.com	Consumer preference analysis based on text comments and ratings
(Vo-Thanh et al., 2022)	The quality of the dishes, the service, and the customers’ experience with the service staff and chefs	TripAdvisor	The link between perceived innovativeness and customer satisfaction in the fine-dining catering segment
(Pantelidis, 2010)	Food, service, ambience, price, menu, and decor	www.london-eating.co.uk	Electronic meal experience by a content analysis of online restaurant comments

2.2. Cross-lingual sentiment analysis with deep learning

In the selection of the NLP model, we need to consider some challenges existing in the current cross-language ABSA task, the labeling problem of different language samples (Conneau et al., 2020). At present, the common methods to solve the labeling problem in the research community are zero sample learning and translation-based labeling method. First, the relevant texts of this study are usually written by ordinary users using various abbreviations or dialects, and the number of samples in different languages is unevenly distributed. However, the language-specific knowledge learned by zero samples is purely from the pre-training process, in which low-resource languages may be underrepresented (Zhang et al., 2021), so it is not suitable for this study. The use of translation target language data with projection labels is a reasonable idea to compensate for language-specific knowledge (Li et al., 2020). However, the performance of this translation-based method largely depends on the quality of translation and label projection. If the expected label quality is not satisfactory, the task-specific knowledge in the translation data will also be limited.

In recent years, the development of multi-lingual pre-training models have significantly improved the downstream cross-lingual tasks. Based on that, a method called MTI-ACS-D is proposed, which could tackle the problems mentioned above. MTI-ACS-D establishes a strong translation-based baseline for the cross-lingual ABSA task based on an alignment-free label projection approach and an aspect code-switching (ACS) mechanism, by distilling the proposed model on the unlabeled target data, the performance can be further improved, the results of this model show SOTA performance on the ABSA task in the Sem2016 public dataset (Zhang et al., 2021). We will therefore use the above approach to obtain more accurate aspect terms and sentiment polarity in the multilingual review dataset.

2.3. The study of factors influencing customer satisfaction with restaurants

User preferences for commercial products in the hospitality and food service industries have been the focus of research in various disciplines, including marketing, psychology, and tourism. Researchers typically choose multiple dimensions through which to measure users' product experience. Several studies have investigated those service quality dimensions that are most important to customers. For example, Berry et al. (Berry et al., 1988) developed the SERVQUAL model, which identifies five dimensions of service quality, namely, physical equipment, reliability, responsiveness, assurance, and empathy, which can be considered influential factors that affect final customer evaluations (Berry et al., 1988). Several studies have applied the SERVQUAL model to study user preferences for hotel and restaurant services. For example, Ladhari et al. (Ladhari et al., 2008) used the SERVQUAL model to study the most important service quality dimensions for customers in fast-food restaurants, finding that the reliability dimension is the most important factor influencing customer satisfaction. In recent years, most researchers have tended to use the original label classification of publicly available datasets to identify the influencing factors. For example, Zhu et al. (Zhu et al., 2022) classified the influencing factors into five major categories, the environment, location, cuisine, service, and price, through classification in the public review dataset of Meituan, a Chinese online platform for travel and customer eWOM. Research on the differences in service satisfaction of people with different backgrounds for the same influencing factors has also been carried out. Otero et al. (Otero et al., 2018) proposed an explanatory model of social service satisfaction for these users with Spanish immigrants and found that the difference in satisfaction depends on the user's gender and place of residence, which also indicates that there are some differences in the evaluation of service categories among people with different geographical and cultural backgrounds.

2.4. Literature on Customer-based Discrepancy Theory

The study of Discrepancy Theory is the study of the difference between prior states and subsequent perceptions (Jiang et al., 2010). In marketing, customer satisfaction is an important component of Customer-based Discrepancy Theory research. Consumer satisfaction is typically defined as "post-selection evaluation, following a hedonic continuum from unfavorable to favorable, of whether a specific purchase experience is at least as good as expected"(Jun et al., 2001). Generally, satisfaction from Customer-based Discrepancy Theory arises from consumer cognitive comparison. Comparison requires each person to establish an anchor point, with a context-relevant natural state to compare with the anchor point, to achieve personal expectations or perceptions of the anchor point and natural state, and to judge these using a (potentially complex) relationship, determining how satisfaction is derived from the two components (anchor point and natural state) (Szymanski & Henard, 2001).

The emergence of eWOM has transformed customer consumption processes and anchor point and cognitive comparison establishment. People often first browse online reviews for pre-consumption choices, creating personal anchors. Offline dining or accommodation experiences form a natural, context-related state target. In multilingual online review environments, there are differences in anchor establishment for customers with different language backgrounds, due to differences in review content viewed. English speakers are more likely to read English reviews, while French speakers are more likely to read French reviews. Even with consistent offline consumption experiences, customers with different language backgrounds may have differing satisfaction levels due to different previously established anchor points.

3. Proposed Method

This study is divided into three phases aimed at collecting user reviews and conducting quantitative analysis on an online platform. The first phase is to process the collected multilingual eWOM data, including deep learning-based sentiment analysis. The second phase is to preliminarily explore the variability of restaurant satisfaction among customer groups with different language backgrounds. The third stage is to explore the differences in the influence of restaurant attributes on the satisfaction of customers from different language backgrounds by constructing a multiple regression model.

3.1. Theoretical framework

To study customers' evaluations of merchants, many theories and ideas have been proposed. In addition to the traditional SERVQUAL model, there are also improved versions of the SERVQUAL model and the Usage and Attitude (U&A) research method, in which the study of usage habits and attitudes is the core issue in customer behavior research (referred to as U&A) (Dyke et al., 1999; Kononiuk & Gudanowska, 2022; Luyen & Thanh, 2022; Park et al., 2018; Son et al., 2013). At present, the model to study customer usage habits and attitudes is a relatively mature and commonly used market research model, which is widely used in customer research. According to the Fishbcin model, the sum of customers' preference weights for a given product or brand represents their overall attitude toward the brand (Ahtola, 1975; Wilson et al., 1975). This preference relationship involves the decision information obtained through a two-by-two comparison of the decision maker for the evaluated object, first proposed in 1977 by Saaty (Saaty, 1977) on a 1-9 scale, which specifically describes the decision maker's preference for two aspects after comparison. Due to the uncertainty of the decision problem and the data dimensionality of the decision process, which would result in multiple weighted decision matrix inputs and multiple alternative ratings on each criterion, researchers have used multicriteria analysis to solve such problems. In a recent study on food service quality attributes, Zhu et al. (Zhu et al., 2022) proposed a new multi-attribute decision-making approach based on these traditional multi-attribute analysis methods, using product attributes to compose a hesitant fuzzy dataset for two-by-two comparisons, categorizing online restaurant reviews into five categories—service, price, environment, location, and cuisine.

To investigate the answers to the above question, this paper constructs an empirical model of customer online evaluation using five attributes (environment, location, deliverables, tangible assets, and service), with attributes and sub-attributes as shown in Table 2 and Figure 2, to explore the differences in these attributes across users from different language backgrounds. In this paper, an environmental attribute is defined as "an attribute that can influence the user experience inside a restaurant through nonphysical media". It creates conditions such as music, atmosphere, and other elements that can affect the mood of diners through visual and auditory means. Studies have shown that when the type and level of service are homogeneous, the service environment becomes an important differentiator of customer appreciation (Newman, 2007). Studies in the retail industry have shown that ambiance affects the product image and service and product expectations of customers (Sharma & Stafford, 2000). We focus on those customer reviews that contain elements of atmosphere, background music, and color related to the environment (Baker et al., 1994; Doucé, 2022; Khalil et al., 2023; Zhao & Guan, 2022). This study introduces a new concept: deliverables. According to the SERVQUAL model, deliverables should fall under the category of reliable delivery and assurance dimensions, with the deliverables of restaurants being food and drinks (Park et al., 2018).

Table 2: Table of Attributes and Similar Attributes

Attribute	Similar attribute
	Place
Location	Restaurant
	Parking lot
	Scenic spot
Deliverables	Food
	Wine
	Meal
	Meat
	Desserts
	Soup
	Cake
Service	Waiter
	Staff
	Wine list
	Wine menu
	Menu
	Sommelier
Environment	Atmosphere
	Music
	Landscape
	Weather
Tangible assets	Chair
	Table
	Wine glass
	Plate

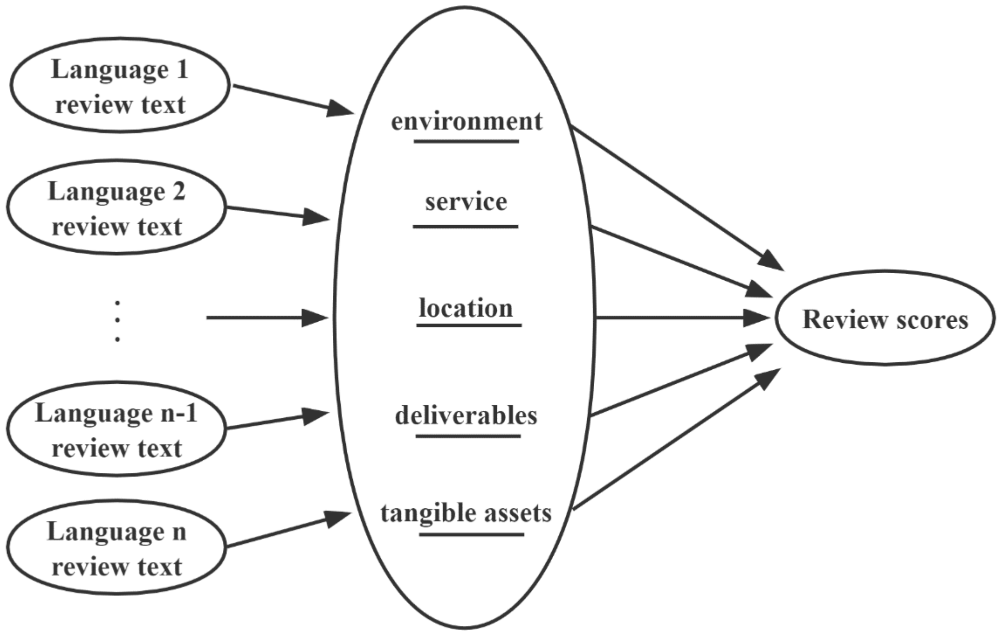

Figure 2: Theoretical Framework.

3.2. Data Collection and Preprocessing

We collected data from two platforms, Yelp and TripAdvisor, to understand whether and how the linguistic background of reviewers affects online review ratings on different online review platforms. Yelp is an online review platform from the United States and the largest review site in the U.S (Qiu et al., 2020). TripAdvisor was also founded in the U.S., but has a much larger user base, with offices in 49 markets around the world and coverage of 7 million hotels, attractions, and restaurants in countries around the world, TripAdvisor was also founded in the U.S., but has a much larger user base, with offices in 49 markets around the world and coverage of 7 million hotels, attractions, and restaurants in countries around the world. Both platforms selected for this study play an important role in the travel industry: they are two of the leading OCR platforms in the travel, tourism, and hospitality industries. The choice of language type is very important and has a direct impact on the way we crawl the data. In this study, we chose English, French, Spanish, and Dutch review data for our research. All four languages originated in Europe and have a wide distribution of groups, with countries in the Americas, Africa, and other regions far from the European continent as official languages.

The data was collected in early 2024 using two crawlers developed in the Python programming language (using the Selenium and Beautiful Soup libraries). First, to collect a large enough sample, we focused on the most popular cities in the country where each language originated: Barcelona in Spain, London in the UK, Paris in France, and Amsterdam in the Netherlands, in addition to some cities in the US and Belgium. We used a crawler to retrieve the list of all reviewed restaurants on the reference platforms. Second, we collected all eWOM from the two platforms (i.e., Yelp and TripAdvisor) covering restaurants in the destinations over the period 2000-2024. Third, unlike other studies using text analysis techniques (e.g., Xiang et al., 2017; Zhao et al., 2019), we kept multilingual online reviews written in English, French, Spanish, and Dutch in our final database. Online review platforms provide the language type of the review, and we complete the language type filtering based on this label. A total of 226,359 eWOMs were retrieved: 148,418 eWOMs from Yelp and 77,941 eWOMs from TripAdvisor. These data are therefore based on many reviews extracted from different, mainly European, restaurant services in several countries.

The four research steps of the cross-language deep learning model sentiment analysis, as shown in Figure 3.

Step 1.1 Crawling restaurant reviews in different languages from the TripAdvisor and Yelp platforms, with review data containing text reviews, restaurant names, and overall ratings.

Step 1.2 Preprocessing the text data of reviews, removing text data such as special symbols and duplicate data, and removing restaurants with fewer than 10 reviews, which become the final data input into the model.

Step 1.3 Obtaining the aspect words and emotional polarity of restaurant attributes using the multilingual ACS model, which are assigned to the training and test sets at a ratio of 8:2. The standard dataset is input into the model for validation.

Step 1.4 The terms for each aspect were categorized into five categories: deliverables, location, service, environment, and tangible assets, and each attribute was scored according to the sentiment polarity of the output, with a score of 5 for positive sentiment, 3 for neutral sentiment, and 1 for negative sentiment. If the sentiment polarity of an attribute is missing, it defaults to a score of 3.If an attribute occurs multiple times in a review, the sentiment polarity score is averaged.

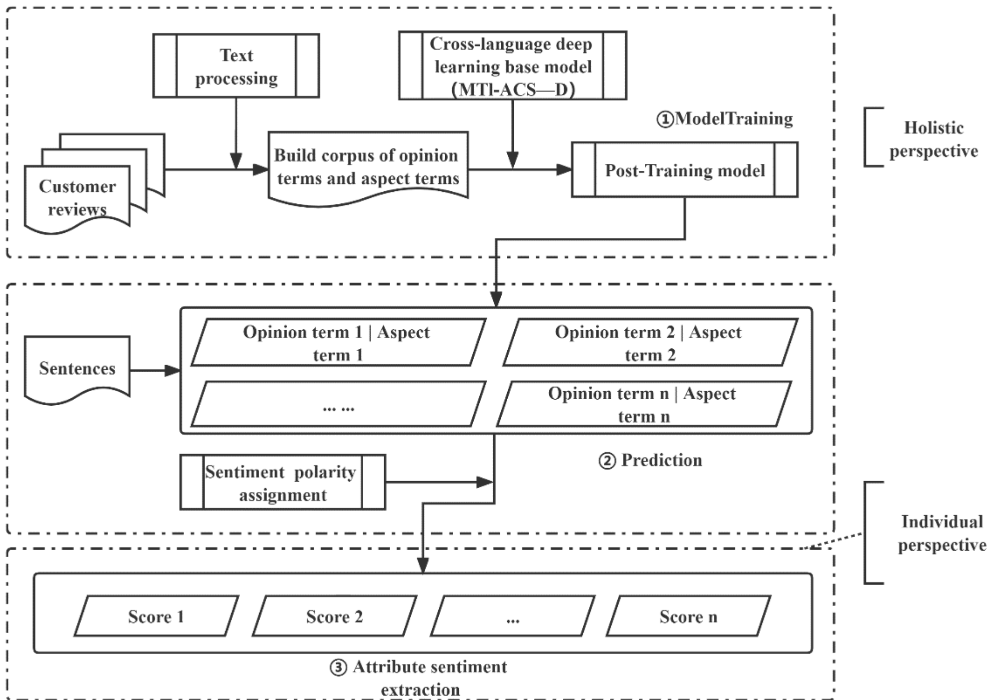

Figure 3: Flow Chart of Text Data Processing and Sentiment Analysis Model Scoring.

3.3. Variables

The variable of focus, "Restaurant Attributes", is known from the description in the Data Processing section that each review that has been processed by the deep learning model receives a score for five attributes, and this score ranges from 1-5.

Table 3: Variables Description.

Variable	Description
Rating	Online review ratings posted by online reviewers that summarize their satisfaction with the restaurant in numbers.
Deliverables	Deliverables are defined as the products that a restaurant as a business delivers to its customers, which primarily include all food, liquor, and condiments.
Location	Location is defined as the factors that influence a restaurant's location, including notable landmarks, attractions, and easy access to transportation.
Service	Service is defined as all the people who serve in a restaurant (including restaurant managers, greeters, doormen, waiters, and sommeliers, etc.), in addition to the service behaviors provided by these people, such as presenting dishes, and welcoming ceremonies.

Environment	The environmental attribute is defined as "an attribute that can influence the user experience inside a restaurant through nonphysical media". It creates conditions such as music, atmosphere, and other elements that can affect the mood of diners through visual and auditory means.
Tangible assets	Tangible assets, as a dimension of service quality impact, with the upgrading of restaurants have also emerged, one after another, with more tangible assets, including beds, sofas, tables, and other equipment that can provide convenience to customers.
Price	The price range of the restaurant on the online platform is indicated by three types of symbols: "$, $$, $$$", the higher the number of $ symbols, the higher the price
Review Length	It represents the number of words included in each online review.
Destination Country	This is a categorical variable indicating the city in which the rated restaurant is located (Mariani et al., 2023).
Country of the reviewer	This is a categorical variable indicating the country of origin of the reviewer.
Year	It represents the year in which the review has been written.

Several control variables were used, including type of trip, type of group, destination city, year, chain, and star rating. Destination Country and Country of the reviewer are two categorical variables used to consider the heterogeneity of the restaurant and the reviewer at the country-culture level. Price is a categorical variable describing the price point of the restaurant, Price is a categorical variable that describes the price point of a restaurant, which is categorized according to the price point of the hotel (from $ to $$$$), and the notation varies across different review platforms, e.g., TripAdvisor adopts the notation "$,$$-$$$,$$$$". Review Length is also a variable of interest, which is expressed with different levels of complexity in different languages, some of which have different levels of complexity. The level of complexity varies from language to language, with some languages being concise and others being lengthy. Overall, the above controls have been used in the existing tourism and restaurant literature to identify and explain the determinants of online review ratings (Gao et al., 2018). Consistent with the existing literature (Mariani et al., 2018), online review ratings were used as the dependent variable to address our research question, which represents the ratings posted by online reviewers to express their satisfaction with the restaurant.

Tables 4a and 4b illustrate the descriptive statistics of the variables considered for the period 2000-2024. We use the multicollinearity test to model the construction of the model. The results, as shown in Table 4.c, show that the VIF values of all independent and control variables are less than 5, indicating that the model has no multicollinearity problem, and the model is well constructed.

Table 4a: Descriptive Statistics for the TripAdvisor Sample.

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Rating	77941	4.372	1.036	1	5
Price	77941	2.404	.559	1	3
Review Length	77941	449.699	455.478	4	22097
Location	77941	3.487	1.019	1	5
Service	77941	3.964	1.244	1	5
Environment	77941	3.336	.812	1	5
Tangible assets	77941	3.187	.742	1	5
Deliverables	77941	4.111	1.182	1	5

Table 4b: Descriptive Statistics for the Yelp Sample.

Variable	Obs	Mean	Std. Dev.	Min	Max
Rating	148418	4.055	1.149	1	5
Price	148418	2.277	.71	1	4
Review Length	148418	547.338	498.009	1	5000
Location	148418	3.441	1.091	1	5
Service	148418	3.476	1.282	1	5
Environment	148418	3.331	.827	1	5
Tangible assets	148418	3.215	.841	1	5
Deliverables	148418	4.064	1.225	1	5

Table 4c: Results of the Multicollinearity Test.

Variable	Yelp VIF	TripAdvisor VIF
Price	1.032	1.086
Review Length	1.029	1.071
Destination Country	1.072	1.097
Country of the reviewer	1.415	1.080
Year	1.072	1.036
Location	1.030	1.037
Service	1.085	1.156
Environment	1.039	1.040
Tangible assets	1.027	1.031
Deliverables	1.078	1.125

3.4. Techniques and Model Adopted

In response to research question 1, common analytical methods currently used include one-way ANOVA, but the prerequisite requires that the distribution of the variables conforms to a normal distribution. However, as shown in Figure 4, the datasets for the two platforms do not show a normal distribution because the ratings are negatively skewed, meaning that there are many more high ratings than low ratings. Therefore, the analysis was conducted using the Kruskal-Wallis method; this method is considered the nonparametric equivalent of one-way ANOVA, which makes no distributional assumptions.

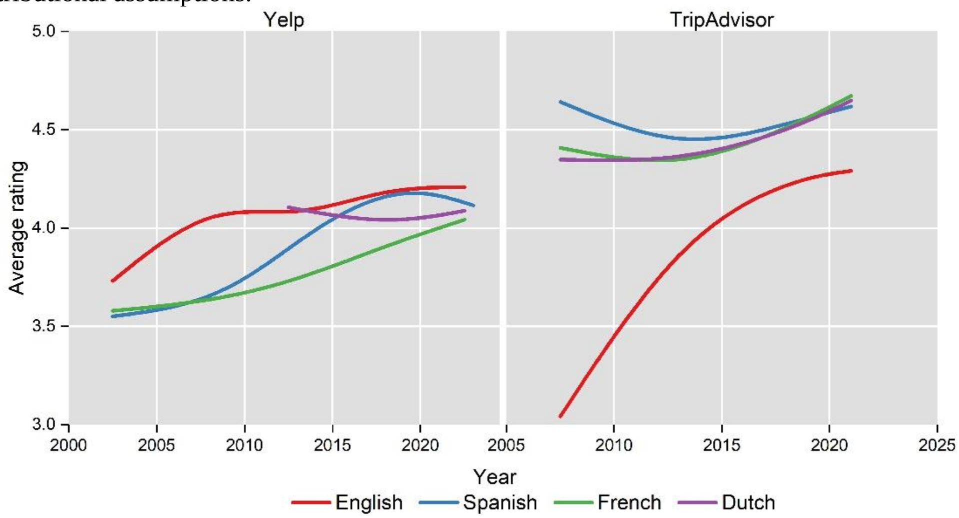

Figure 4: Ratings by Language and Year

For Research Question 2, a model specification was developed based on the sample indicated in the research design (Mariani et al., 2023), as shown in the following equation:

$$\begin{aligned} Rating_i = \beta_0 + \beta_1(Deliverables) + \beta_2(Location) \\ +\beta_3(Service) + \beta_4(Environment) + \beta_5(Tangible\ assets) \\ +Price + Review\ Length + Destination\ Country + Country\ of\ the\ reviewer \\ +Year + \varepsilon \end{aligned} \tag{1}$$

It is clear from the equation that the model explores the extent to which a restaurant's attributes in serving customers influence online review ratings (digitized customer satisfaction). It is clear from the model that the reference dependent variable is online review ratings, which was regressed against the focused independent variables (Deliverables, Location, Service, Environment, Tangible assets) and a range of other control variables. The control variables include Price, Review Length, Destination Country, Country of the reviewer, and Year.

4. Results

To address research question 1, Kruskal-Wallis compared means between groups and tested the probability of a random observation in each group against a random observation in another group. This analysis was performed using StataSE 17 software with a significance threshold set at 0.05. The results, as shown in Table 5, the p-values for the ratings (satisfaction) were below the significance value for all groups (linguistic categorization), thus confirming the significant differences in ratings between groups.

Our findings in Question 1 are consistent with Antonio et al. that customer groups with different language backgrounds differ in their ratings (numerical satisfaction) in multilingual environments (Antonio et al., 2018). Meanwhile, our study in Question 2 extends their findings by explaining the reasons for this difference at the restaurant attribute level.

Similar to past studies, the model results show that the sentiment scores of restaurant attributes (Deliverables, Location, Service, Environment, and Tangible assets) all positively affect the ratings of online reviews (see Tables 6 and 7, respectively) (Zhu et al., 2022). Our use of a multiple linear model can handle more diverse and complex data while considering reviewer identity characteristics, restaurant characteristics, and temporal characteristics, which are heterogeneous factors that have rarely been discussed simultaneously in past multilingual data.

Further, we found differences in the impact of attribute sentiment scores on ratings obtained from review data in different languages on both Yelp and TripAdvisor platforms, a finding that answers research question 2. The group posting English-language reviews has an impact on ratings on the Deliverables attribute (Yelp: 0.983, $p < 0.01$; TripAdvisor: 0.441, $p < 0.01$) differed from other language groups (e.g., Dutch: Yelp: 0.635, $p < 0.01$; TripAdvisor: 0.524, $p < 0.01$), and these were also seen on the other four attributes; while the group posting Spanish reviews differed from the group posting French reviews on the five attributes were less different (e.g. Deliverables attributes: Yelp: 0.698 (Spanish); 0.649 (French), $p < 0.01$; TripAdvisor: 0.900 (Spanish); 0.924 (French), $p < 0.01$).

Finally, about the order of the correlation coefficients of the attributes. In the results of Table 6, there is no controversy in the most important attribute, the customers of our languages think that the attribute of “Deliverables” is the most important. However, for the second most important attribute, English-speaking customers chose the attribute “Services” and Dutch-speaking customers chose the attribute “Tangible assets”.

Table 5. Kruskal–Wallis ratings test results.

Rating			
	Chi squared	**df**	**p value**
Language(Yelp)	5708.979	3	0.0001
Language(TripAdvisor)	1367.791	3	0.0001

Table 6: Econometric Modeling Results of the Impact of Yelp Platform Reviews on Ratings.

	English	Spanish	French	Dutch
	Rating	Rating	Rating	Rating
Deliverables	0.983***	0.698***	0.649***	0.635***
	(67.63)	(9.15)	(27.22)	(5.35)
Location	0.338***	0.180***	0.229***	-0.016
	(37.42)	(3.84)	(15.11)	(-0.17)
Service	0.476***	0.450***	0.316***	0.283***
	(62.12)	(11.19)	(25.08)	(4.3)
Environment	0.111***	0.045	0.187***	0.105
	(8.25)	(0.68)	(10.01)	(1.11)
Tangible assets	0.260***	0.232***	0.146***	0.337***
	(20.3)	(3.39)	(8.14)	(4.07)
Control Variables				
Price	Yes	Yes	Yes	Yes
Review Length	Yes	Yes	Yes	Yes
Destination Country	Yes	Yes	Yes	Yes
Country of the reviewer	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Intercept-1	-0.057***	-0.030***	-0.032***	0.008
	(-26.77)	(-2.72)	(-8.45)	(0.37)
Intercept-2	-0.065***	-0.063***	-0.030***	-0.035**
	(-36.03)	(-6.58)	(-9.63)	(-2.22)
Intercept-3	-0.020***	-0.005	-0.032***	-0.015
	(-6.39)	(-0.31)	(-6.91)	(-0.67)
Intercept-4	-0.043***	-0.043***	-0.024***	-0.070***
	(-14.47)	(-2.72)	(-5.41)	(-3.60)
Constant	-1.622**	0.915*	-0.102	0.022
	(-2.32)	-1.66	(-0.11)	(0.02)
Observations	114365	4228	28470	1355
adj. R2	0.35	0.215	0.268	0.213
AIC	3.10E+05	1.10E+04	7.70E+04	3450.702

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Econometric Modeling Results of the Impact of TripAdvisor Platform Reviews on Ratings.

	English	Spanish	French	Dutch
	Rating	Rating	Rating	Rating
Deliverables	0.441***	0.900***	0.924***	0.524***
	(22.52)	(30.01)	(24.08)	(11.14)
Location	0.129***	0.246***	0.247***	0.146***
	(10.57)	(12.12)	(10.32)	(5.25)
Service	0.202***	0.494***	0.450***	0.379***
	(21.3)	(34.55)	(23.99)	(18.02)
Environment	0.136***	0.137***	0.202***	0.092**
	(7.57)	(5.15)	(5.77)	(2.34)
Tangible assets	0.174***	0.255***	0.253***	0.098***
	(9.72)	(9.05)	(8.21)	(2.63)
Control Variables				
Price	Yes	Yes	Yes	Yes
Review Length	Yes	Yes	Yes	Yes
Destination Country	Yes	Yes	Yes	Yes
Country of the reviewer	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Intercept-1	-0.017***	-0.043***	-0.041***	-0.020***
	(-5.77)	(-9.44)	(-7.28)	(-2.95)
Intercept-2	-0.007***	-0.081***	-0.070***	-0.060***
	(-3.14)	(-24.31)	(-15.41)	(-11.44)
Intercept-3	-0.021***	-0.023***	-0.036***	-0.008
	(-5.26)	(-3.86)	(-4.49)	(-0.82)
Intercept-4	-0.024***	-0.043***	-0.045***	-0.015
	(-5.85)	(-6.65)	(-6.33)	(-1.59)
Constant	-1.127***	0.883	0.361	0.715
	(-3.54)	(1.09)	(0.46)	(0.89)
Observations	28344	26349	10560	12688
adj. R2	0.697	0.264	0.428	0.277
AIC	5.70E+04	6.10E+04	2.30E+04	2.90E+04

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5. Discussion

In the field of research on external factors affecting marketing and product word-of-mouth, studies on the impact of product attributes on ratings and cross-cultural differences are popular, Zhang et al. (Zhang et al., 2022) analyzed the differences between English and Chinese review texts and concluded that there are significant differences between English- and Chinese-speaking customers in terms of establishing host-guest relationships Jahandideh et al. (Jahandideh et al., 2014) also revealed through an empirical study that Arab and Chinese customers have significant differences in terms of complaint behavior. Zhang et al. (Zhang et al., 2022) concluded the same in our results, as there are differences in consumer perceptions across language groups, which may stem from language barriers and differences in access to offline consumer information.

In terms of Question 2, in the case of the restaurant we used, the customer group reviewing in English differed significantly between Deliverables and those reviewing in other languages, and the same results were seen in Dutch, while the customer groups reviewing in Spanish and French performed similarly on each attribute. The results calculated from the multiple linear explain well the reasons for the differences in the impact on the satisfaction of customer groups with different linguistic backgrounds, compared to traditional marketing science research methods.

This study makes a multifaceted research and practical contribution. First, based on the Customer based Discrepancy Theory, it explores the differences in the influence of customer groups with different language backgrounds on restaurant satisfaction among the language-based user groups of online review platforms. Based on this study, we argue that this online review community exerts a heterogeneous influence on the product knowledge and characteristics of customers with different linguistic backgrounds, which has not been emphasized in previous studies (Zhao & Guan, 2022). Second, this paper utilizes the quantitative strength and timeliness of eWOM, and the aspect terms and related polarity extracted from eWOM provide interpretable results that can guide companies to improve their operations. Third, through multiple linear modeling analysis at the attribute level, the results of the study show that the affective scores of the five attributes, including deliverables, positively affect consumer satisfaction to varying degrees, and that the affective polarity of the restaurant attributes is a key factor in the process of establishing satisfaction anchors and forming perceptions of customers, which extends the Customer based Discrepancy Theory in the field of customer satisfaction. Fourth, this paper provides a case study of linguistic analysis, which analyzes the similarities and differences between four languages, also from Europe, at the level of restaurant reviews from the perspective of linguistic expression, which well helps us to interpret the empirical study.

5.1. Theoretical implications

Our research makes some contributions to the theoretical aspect, and the results of this study prove the necessity of research based on multilingual eWOM and other business environments. First, in previous studies, multilingual environments have been a popular area in international political disciplines such as ideology, for example in the European Union, a working organization in multilingual environments, where Lovrits et al. argued that language choice should be considered as a cross-cultural dimension (Lovrits et al., 2024). Whereas in consumer behavior and marketing science, language appears in research only as a moderating or controlling variable, the focal variable in cross-documentary research often comes from country-oriented cross-cultural theories such as Hofstede's theory of cultural dimensions (Nakayama & Wan, 2021; Jia, 2020).

In consumer behavior and marketing, language only appears as a moderating or controlling variable in research, whereas in cross-cultural dedication research, the focal variable often comes from country-based cross-cultural theories such as Hofstede's theory of cultural dimensions, and this cross-cultural research paradigm of comparing countries with each other has a number of limitations in the current new scenarios of the research, whereas this study's findings with a multilingual eWOM environment of the findings can be useful in the following scenarios.

Firstly, when studying dozens of national markets in a global context, the goal of simplifying the research object can be achieved by combining these dozens of countries in terms of language type, e.g. the markets of the United Kingdom, the United States, Australia, and New Zealand, where English is the official language, can be regarded as a single entity.

Secondly, with the global economic downturn, more and more countries have begun to implement anti-globalization economic policies, which has led to more and more market research to delve into different regions within countries, and many studies use questionnaires and other methods to delineate the scores of cultural dimensions in different regions, which greatly reduces the credibility of the research findings. In contrast, in multilingual countries such as Singapore, the Netherlands, and France, and even in immigrant countries such as the United States, Canada, and Australia, our findings can be directly applied or extended to studies analyzing differences in consumer groups in these countries.

Researchers have not focused on the characteristics of the language itself when studying cross-language model performance, and the amounts of data in many languages are very similar to ensure statistical significance when studying cultural differences, which in turn deviates from the actual situation (Schuckert et al., 2015). In practice, English, as the most widely spoken language, has a higher proportion of all the same review subjects in the dataset, with the amount of data for other languages gradually decreasing based on local languages, dialects, and foreign languages. In this study, the application of different relocatable cross-linguistic models in data processing, and model training theoretically achieves relocatable learning of language reviews from a large English training set with a small amount of data, and the combination of these methods ensures that the data of the local study fits with the distribution of multi-lingual data in the real business environment while two online review platforms: Yelp and TripAdvisor. even with differences in reviewer identity characteristics, restaurant characteristics, time characteristics, and language ratios, more practical and generalizable research results are obtained.

5.2. Managerial implications

Our findings show that all five attributes, Deliverables, Location, Service, Environment, and Tangible assets, have a positive impact on satisfaction even across different language groups, with Deliverables having the greatest impact. Therefore, restaurants need to pay attention to the quality of Deliverables. In addition, our findings can help to develop effective restaurant services and policies, especially in countries and regions with a high level of international travel, to provide a more responsive experience for customers with different linguistic backgrounds. Consumption patterns of offline experiences are shifting from immediate feedback to word-of-mouth communication based on online platforms. With the end of the epidemic, more and more companies in the travel services industry are seeking to reach out to more travelers from different countries, and acquiring customers in a competitive business environment remains a constant battle. In this context, it is crucial to study the impact of product attributes on customer satisfaction and identify the key factors. Studies such as ours can provide new business marketing strategies for restaurant companies to prioritize the need to consider the differences in restaurant attributes of consumer groups from other language backgrounds in a multilingual environment and develop more careful marketing strategies; and to take the lead in marketing by promoting their restaurant brand to new customers who share a common language background with their main consumer group, which can minimize the risk of consumer satisfaction.

6. Conclusions, Limitations, and Future Research Prospects

Electronic word-of-mouth (eWOM) is gaining popularity among customers in an increasing number of countries, as these customers choose products or services based on past historical reviews. This situation poses a challenge for customer markets in multilingual environments, such as shops in popular international destinations and multinational chains. To address this issue, this paper is based on a dataset of reviews in four languages, including English and Spanish, on two platforms, Yelp and TripAdvisor, and selects the ratings of the reviews as a numerical variable to measure customer satisfaction and as an explanatory variable, considering different attributes that a restaurant can offer to the customer experience, including Deliverables, Location, Service, Environment, and Tangible assets, and a multiple linear model was developed by taking into account the heterogeneity of factors such as time characteristics, reviewer identity characteristics, and restaurant characteristics. Our statistical analyses show that users with different linguistic backgrounds differ in the extent to which attributes such as service, location and have an impact on satisfaction. This study also provides a theoretical contribution to the group of companies targeted in this study. At the same time, this paper has some limitations. Firstly, the research area is focused on Europe, and the next step should be to conduct market research on multilingual environments in densely populated areas such as Asia. Secondly, endogeneity issues between attributes and satisfaction have not been considered, such as cultural tolerance, local economic level, destination popularity, and policies. Finally, the analysis of the restaurant data was conducted statistically, yet the subsequent step should be to consider including hotels and cars in the study. In the discussion section, we discuss the relationship and differences between this study and Hofstede's cultural dimensions theory, where phonological information can be used to distinguish slang and accents in the future and where English-speaking countries (Canada, the United States, Australia, and the United Kingdom) have similar dimension scores and cultural beliefs (Michon & Chebat, 2004). In studying cultural differences in these countries, it is possible to use phonetic data to differentiate and conduct cross-linguistic studies, which is a very worthwhile next step.

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