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Customer Electronic Word of Mouth Management Strategies Based on Computing with Words: The Case of Spanish Luxury Hotel Reviews on TripAdvisor

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Abstract: The rapid growth of the internet and social media has made electronic word of mouth (eWOM) a key element of modern marketing. In the hospitality industry, nowadays, effective eWOM management is essential for developing impactful strategies and fostering customer satisfaction. This paper introduces an enhanced approach to strategic customer base management based on online reviews by extending the Recency, Frequency, and Monetary (RFM) model with three novel dimensions, the Helpfulness, Promoter Score, and Stability of the customer, thereby forming the RFHPS model. It also includes the 2-tuple linguistic model, one of the most popular computing with words models, to improve precision in the RFHPS score's computation and the findings' interpretability. Using K-means clustering, customers are segmented across these five dimensions. The data on luxury hotels in Spain gathered from TripAdvisor demonstrate the model's applicability. By integrating this framework into customer relationship management systems, managers can tailor marketing strategies for distinct segments, facilitating deeper customer understanding and bolstering eWOM generation.

Keywords: electronic word of mouth; customer segmentation; marketing strategies; 2-tuple linguistic model; analytical hierarchy process method; customer relationship management; decision-making

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1. Introduction

The rapid advancement of emerging technologies, such as Artificial Intelligence (AI), Virtual Reality, Blockchain, and the Internet of Things, has profoundly reshaped customer–brand dynamics, enabling more complex and personalized customer journeys in an omnichannel landscape. This digital disruption has expanded customer choices and heightened competition, making customer retention more critical and challenging than ever before. In response, marketing strategies nowadays increasingly prioritize the identification and retention of high-value customer segments. By leveraging data-driven insights, these strategies enable targeted communication, promotions, pricing, and other tailored activities to optimize customer engagement and profitability in an evolving marketplace.

Around the year 2000, the emergence of Web 2.0 revolutionized online interactions by enabling the widespread creation and sharing of user-generated content (UGC). This shift was particularly evident on platforms serving as recommender systems, such as social networks and various internet platforms, including Online Travel Agencies (OTAs) (e.g., Expedia, Booking, Lastminute.com), major retailers (e.g., Amazon, AliExpress), and review websites (e.g., TripAdvisor, Filmaffinity). These platforms allow customers to share their opinions and experiences with goods and services, facilitating electronic word-of-mouth (eWOM) communication. eWOM is defined by Hennig-Thurau et al. [1] as "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet".

In the technological age, eWOM impacts customers' attitudes toward brands and companies [2]. Bore et al. [3] identify eWOM as the primary driver influencing customers' hotel purchasing decisions. The contemporary customer's information-gathering process heavily relies on internet content, including ratings (e.g., hotel stars and overall scores), satisfaction questionnaire responses, textual comments, and uploaded images. This highlights the important role of eWOM in the customer decision-making process [4]. Within this context, online reviews, a representative form of eWOM, have become essential information sources to support customers' decision-making [5], gaining prominence, especially in the hospitality and tourism industry, because of the experiential nature of travel [6,7]. Travelers increasingly rely on eWOM, such as online reviews, to reduce uncertainty [8].

Customer segmentation, an important aspect of customer relationship management (CRM), helps companies understand and target nuanced customer groups based on shared characteristics and behaviors. For example, eWOM providers (i.e., social media users) can be grouped by the nuances in their behavior to develop related strategies [1]. By analyzing the nuances of customer behavior and preferences, businesses (e.g., hotels) can craft personalized marketing strategies that improve customer engagement and satisfaction [9]. The K-means clustering technique, combined with the Recency, Frequency, and Monetary (RFM) model, is globally recognized as a powerful partitioning clustering technique that has proven highly efficient in various business settings [10]. The enduring popularity of the RFM model in marketing arises from its simplicity and the capacity to make interpretable decisions, either as a standalone model or in conjunction with others [11]. However, the RFM model needs to be adapted to incorporate additional dimensions to enhance its applicability and effectiveness, considering the characteristics of different industries. To the best of our knowledge, the traditional RFM model is not nuanced enough to effectively segment customers in the context of eWOM.

Therefore, this paper aims to offer strategic management guidelines for practitioners through the application of clustering techniques to discern customer profiles based on their online reviews. Specifically, it introduces a novel model, RFHPS, built upon the widely adopted RFM model [12,13]. The RFHPS model incorporates five dimensions derived from customer reviews: Recency, Frequency, Helpfulness, Promoter Score, and Stability. By introducing RFHPS, this paper contributes to addressing the limitations of traditional RFM customer segmentation dimensions in capturing customer profiles within the context of eWOM, emphasizing the need for a more nuanced approach. Moreover, this novel model integrates the 2-tuple linguistic model [14] to enhance accuracy and linguistic interpretation, representing a general advancement over the traditional RFM model [15]. The efficacy of K-means clustering on a 2-tuple model for achieving more explicable segmentation using RFM models was previously validated by Martínez et al. [16] in a study involving a furniture retailer. Moreover, the proposed model integrates the analytical hierarchy process (AHP) for intra-cluster segmentation, enhancing detailed customer prioritization via quartiles. Experts' criteria guide the creation of pairwise comparison matrices for the model's dimensions, establishing weights for the following two constructs: customer engagement value and customer sentiment value.

The proposed model has been applied to a business use case involving TripAdvisor's reviews of luxury hotels in Spain. The model identified and characterized seven customer segments, each associated with distinct marketing strategies. By leveraging eWOM data collected from TripAdvisor, the model integrates valuable insights from online reviews to enhance customer segmentation and supports the implementation of more effective marketing strategies through CRM systems. Notably, the inclusion of the "Stability" dimension introduces a novel nuance, capturing customers who exhibit inconsistent behaviors in their reviews—those who praise in one instance but criticize in another. While prior research, such as Lin and Kalwani [17], has explored cultural differences in review patterns at a regional level, our approach is unique in addressing such variability at the individual customer level, offering a finer granularity to segmentation efforts.

The remainder of this paper is structured as follows. Section 2 provides an overview of studies on CRM, customer segmentation, eWOM, and the RFM model. Section 3 introduces the fundamental concepts on which the proposed model is based. Section 4 describes the application of the proposed model to the dataset of luxury hotel reviews in Spain collected through web scraping on TripAdvisor. It also presents the results of the customer segmentation achieved by the proposed model. Then, the obtained results are discussed in Section 5. Section 6 presents the conclusions of this study and possible directions for future research.

2. Literature Review

This section presents an overview of the main concepts that have led to the development of a new model for strategic customer management. It starts with CRM and customer segmentation, followed by eWOM, and concludes with the RFM model.

2.1. CRM and Customer Segmentation

Customer retention and management have long been focal points in business and are extensively examined in the academic literature. The importance of customer management increases as industry becomes more competitive [18] and leads to a critical need for the customization of marketing strategies and efficient resource allocation to address diverse customer needs. The concept of CRM emerged in the 1990s, gaining traction in academic research during the early 2000s. Scholars began exploring its theoretical underpinnings and practical applications across various disciplines, including marketing, management, and information systems [19].

The primary goal of CRM is to personalize customer interactions and boost loyalty through the strategic use of advanced information systems. This involves identifying and understanding diverse customer needs, interests, and preferences. Leveraging information systems for personalized customer handling, as suggested by Li et al. [20], enables businesses to build stronger relationships and drives customer retention and loyalty. By employing CRM strategies and technologies, companies can gather and analyze customer data to tailor offerings and communication, enhancing customer experience and cultivating long-term loyalty [21].

The evolution of CRM aligns with the growing emphasis on customer-centric strategies and advances in information technologies. Radical transformations in organizational CRM deployment stem from the Internet and computing technology advancements [22]. The Internet facilitates seamless communication via social media, online forums, and review platforms (e.g., TripAdvisor), while computing technologies enable the processing of extensive customer data, applying advanced analytics, and utilizing AI for predictive modeling and segmentation. Social media, the fastest-growing platform, empowers its users and motivates firms to adopt new technologies to align their business operations with this shift [23].

This integration has reshaped CRM implementation, fostering more efficient, personalized interactions, improved insights, and enhanced relationship management strategies [24]. Van Nguyen et al. [25] suggest that effective segmentation is crucial, as different customer groups interact uniquely with channels, necessitating tailored experiences, especially amid the growing complexity of omnichannel retailing. This supports the need for advanced segmentation models, such as the five-dimensional framework proposed in this paper for the luxury hotel context.

The evolution of digital technologies significantly impacts the design, implementation, and use of CRM systems in businesses, expanding capabilities for enhanced customer data collection, analysis, and personalized interactions [19,22]. Digital disruption generates substantial customer data in different formats (i.e., Big Data), adding complexity to business decision-making [9]. Adapting to the dynamic environment and making informed decisions requires the crucial role of data mining-based CRM (DCRM) or Analytical CRM [24]. The integration of AI introduces powerful data mining techniques to CRM, enabling the use of unstructured data for extracting valuable insights from large datasets [26,27]. This empowers businesses to understand customers better, make data-driven decisions, and enhance relationships to achieve CRM objectives. Lampropoulos et al. [28] conducted a review and found that the use of AI, Blockchain, Big Data Analytics, Data Mining, and Machine Learning (ML) in CRM helps businesses stay competitive, offer personalized products and services, and improve customer satisfaction, acquisition, loyalty, and retention.

Analytical CRM focuses on improving decision-making through data analysis, employing various ML techniques, such as classification, to categorize customers based on their characteristics and behaviors [29–31]; clustering techniques to group customers with similar traits [32–35]; regression analysis to understand the relationship between customer attributes and specific outcomes [36–38]; association techniques to identify patterns and relationships among customer attributes [39,40]; and prediction techniques to forecast future customer behavior [41–43]. The application of ML techniques allows for the analysis of customers' personal and behavioral data to create targeted offers, predict preferences, and enhance loyalty, thereby fostering long-term relationships [44].

In reality, DCRM or Analytical CRM does not operate in isolation but works alongside two other CRM subsystems: Social CRM and Operational CRM. Figure 1 illustrates the relationship among these three CRM subsystems. Operational CRM automates and enhances customer-facing processes in sales, marketing, and service, while Social CRM focuses on managing interactions and relationships on social media platforms and review websites, collecting social data to improve customer satisfaction. The abundance of data from online platforms and applications enables the data-driven personalization of marketing strategies. This approach facilitates audience segmentation and allows marketing decisions based on individual characteristics rather than just historical behaviors [45]. Using data from various sources (i.e., Social CRM), including web-scraping techniques, for customer segmentation enables companies to identify valuable customers based on their behavior patterns.

Customer segmentation, a vital aspect of Analytical CRM, helps companies effectively understand and target diverse customer groups based on shared characteristics and behaviors. This approach empowers companies to nurture and enhance relationships, fostering greater customer loyalty [47]. Recognized as a highly effective strategy for managing customer bases, customer segmentation acknowledges the diverse preferences among customers [48]. It entails grouping customers with similar characteristics from larger, heterogeneous populations, serving as a pivotal driver for personalized marketing strategies and the cultivation of meaningful customer relationships.

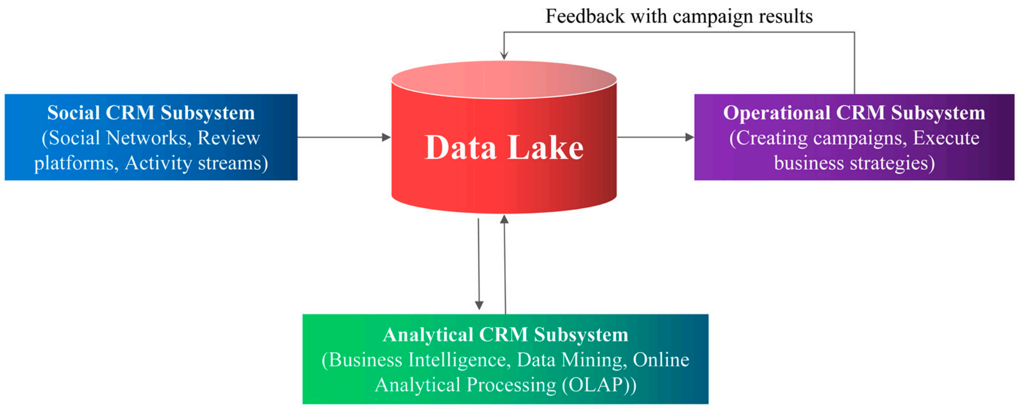


Figure 1. CRM data information flow (adapted from He et al. [46]).

Analyzing customer value through segmentation is fundamental in marketing research [49]. Marketers strive to efficiently and accurately segment and select the best customers, employing different techniques for detecting behavior patterns. Leveraging behavior pattern detection models empowers marketers to optimize customer targeting and engagement strategies for enhanced business outcomes. The widely used models to perform customer segmentation include the RFM model [50], ML-based clustering techniques such as K-means and decision trees [51,52], as well as models like Latent Class Analysis [53] and Self-Organizing Maps [54]. The K-means clustering technique, combined with the RFM model, is globally recognized as a powerful partitioning clustering technique that has proven highly efficient in various business settings [10]. However, the RFM model needs to be adapted to incorporate additional dimensions to enhance its applicability and effectiveness, considering the characteristics of different industries, which will be detailed in Section 2.3.

The current wealth of data from online platforms and applications enables the data-driven personalization of marketing strategies. This approach allows audiences to be segmented and marketing decisions to be made based on information about individuals rather than on their historical choices [45]. Using data from various sources (i.e., Social CRM), including web-scraping techniques, for customer segmentation enables companies to identify valuable customers based on their behavior patterns.

2.2. eWOM

In the current hotel industry, customers typically encounter offerings first through websites and online platforms. The fact that potential customers cannot physically assess the features of a hotel makes them seek reliable information and cues about the quality of alternative options, including images of the hotel, reviews, and their membership to some quality club or platform with an independent ranking [55]. A growing body of scientific research underscores the impact of OTAs (e.g., Booking) and review platforms (e.g., TripAdvisor) on hotel bookings, with eWOM being a key determinant in booking decisions [3]. Along the same lines, Fan et al. [56] consider that eWOM has become one of the primary channels customers rely on to make their booking decisions. The anonymity of eWOM often suggests lower credibility compared to traditional word-of-mouth (WOM) communication [57], as a source's credibility may be the most influential factor [58]. Gellerstedt and Arvemo [59] studied the differences in the impact of traditional WOM (a single review by a good friend or family member) compared to the impact given by eWOM by an online majority, and they suggest that a good friend's word of mouth could outweigh the online majority. Nevertheless, this personal advice may not always be available, hence the importance of eWOM.

The use of eWOM within CRM is reviewed in some studies in the context of customer experience and satisfaction [60,61]. Studies explore eWOM's impact on hotel booking decisions [56,62], the influence of positive reviews on consumer trust and attitudes [63,64], and measuring tourist satisfaction with sentiment analysis and review scores in Marketing Campaigns [65]. The online environment's significance is underscored, with studies indicating that hotels lacking online reviews face reduced consideration and selection [62,66]. Limited knowledge about actual product features and the inability to physically evaluate them emphasizes eWOM as a primary channel for informed booking decisions [56]. Additionally, due to the perceived risks linked to unfamiliar destinations and accommodations, eWOM serves as a valuable tool for building trust and fostering the uptake of online information [67]. Reimer and Benkenstein [68] assert that e-WOM's credibility and accessibility surpass traditional advertising, recognizing potential drawbacks like loss of credibility and customer skepticism. Therefore, this paper utilizes online reviews from TripAdvisor (i.e., eWOM) as a data source for the CRM system (i.e., Social CRM). It introduces a new customer segmentation model based on the classic RFM model that is manageable within CRM systems.

2.3. The RFM Model

The RFM model offers a simple and helpful method for understanding and classifying customers based on their behavior. It plays a crucial role in evaluating Customer Lifetime Value (CLV), helping to predict future profitability. By facilitating data-driven decision-making within CRM strategies, the RFM model is widely used for customer segmentation, enabling businesses to design targeted and impactful marketing strategies.

The original RFM model, introduced by Hughes [69], segments a customer database based on three dimensions of shopping behavior: Recency, Frequency, and Monetary value. Its widespread adoption in customer segmentation for decades is attributed to its effectiveness in identifying valuable customers [70]. Additional reasons include cost-effectiveness in customer behavior analysis and the facilitation of behavior quantification [71,72]. The model's simplicity aids decision-makers in understanding its application [70]. Wei et al. [73] elaborated on more reasons and noted some drawbacks, particularly concerning customers with short sales histories who only purchased once and placed small orders. This segment embodies significant untapped potential, representing 80% of the customer base [72]. Most companies often find that 80% of their sales come from 20% of their customers [70]. Consequently, RFM proves valuable in concentrating efforts on a specific customer group, enhancing overall profitability.

As businesses evolve and customer preferences change, it becomes necessary to adapt the original RFM dimensions [74] to consider the characteristics of each industry and additional factors. For example, Zhang et al. [75] enhanced the traditional RFM model by introducing "Clumpiness" to capture temporal patterns in customer behavior and propose further extensions to better assess customer value. Peker et al. [76] introduced a new RFM model called Length, Recency, Frequency, Monetary, and Periodicity (LRFMP) to classify customers in the grocery retail industry. Zhou et al. [77] introduced a new dimension, Interpurchase Time (T), to propose an enhanced RFMT model for analyzing customers' online purchase patterns over an extended period, facilitating customer segmentation on a retailer's website. Ho et al. [78] also proposed an expanded RFMD model incorporating D for demographics, with a combination of behavioral and demographic variables to perform customer segmentation in retail. The study by Chen et al. [79] enhances the conventional RFM model applied in the airline industry by introducing an additional dimension, the "likelihood of purchasing ancillary services," to more accurately assess traveler value and forecast future behavior. Obviously, conventional RFM models often fail to address the diverse requirements of all industries, highlighting the need for businesses to customize models to suit their specific needs [80,81].

In particular, online reviews, a representative form of eWOM, do not include information about customers' expenditures in hotels. In this case (e.g., TripAdvisor's hotel reviews), the traditional RFM model is not applicable. To address this and consider the unique features of eWOM (such as online reviews), this paper proposes an extension of the traditional RFM model by incorporating additional dimensions: Helpfulness, Promoter Score, and Customer Stability, resulting in a new RFHPS model. This paper substitutes the Monetary dimension with the Helpfulness value (i.e., the number of "likes") of the customer review, as voted by the community. The inclusion of "Helpfulness" reflects a response to the changing landscape and the recognition of value as a significant aspect of customer behavior.

Social support can take many forms, including emotional, informational, and tangible support. In the context of customer service, "Helpfulness" can be seen as a form of informational support, which has been found to be particularly important for customer satisfaction and loyalty [82]. The introduction of "Helpfulness" as a component of reviews was first proposed by Sussman and Siegal [83]. A study by Yang et al. [84] examined the role of customer reviews in shaping customer behavior and found that the "Helpfulness" ratings of customer reviews had a significant positive effect on customer trust and purchase likelihood. The "Helpfulness" of reviews is a key aspect of eWOM that can strongly influence customers' booking decisions [85]. Platforms like TripAdvisor incorporate an evaluation system where users can vote on the usefulness of a post, enabling the filtering of reviews based on their utility [86]. Travelers perceive the most valuable reviews as the most reliable and, therefore, useful [87]. Bueno et al. [88] already proposed the Recency, Frequency, Helpfulness model to obtain a ranking of hotels through the opinions of their past clients and posited that the "Helpfulness" of the reviews is an eWOM attribute that can contribute to influencing customers' booking intentions. The model proposed in this paper is an evolution of that one, where two new dimensions have also been added, Promoter Score and Stability, which reflect customer behavior by incorporating sentiments and opinions. The Promoter Score dimension reflects the value of customer ratings, while the Stability dimension measures the variation among different ratings. To the best of our knowledge, the current literature lacks studies that consider these additional dimensions.

The Promoter Score dimension goes beyond transactional data, as it can capture the level of customer satisfaction, loyalty, and advocacy. It indicates the customers' level of satisfaction and their likelihood of promoting the brand, providing valuable insights into the overall customer experience and sentiment towards the hotel. Including the Promoter Score also improves the predictive power of the model. The Promoter Score can serve as a powerful predictor of future customer behavior. Customers who provide high ratings and positive reviews are more likely to exhibit desirable RFM characteristics, such as a higher repeat purchase Frequency and increased Monetary value. The RFM model gains predictive power by including the Promoter Score, allowing hotels to identify customers who are more likely to become loyal and valuable brand advocates.

Adding the Customer Stability dimension to the RFM model offers insight into how consistent customer sentiment and satisfaction are over time. This dimension allows businesses to identify customers who consistently rate hotels positively or negatively, indicating their stable preferences and loyalty patterns. It helps capture customers' long-term behavior and sentiment toward different hotels, going beyond the transactional aspect of RFM by considering the temporal consistency or variability in the ratings given. This information can aid in understanding customers' evolving preferences and loyalty toward specific hotels. Analyzing variations in ratings enables businesses to identify areas for service improvement, address inconsistencies in customer experiences, and take necessary actions to enhance satisfaction and loyalty. This can lead to higher customer retention and improved overall service quality. Further details of this proposal are outlined in Section 3.2.

3. Theoretical Framework

This section presents the essential concepts on which this proposal is based: the AHP method, the RFM model, the 2-tuple linguistic model, and the 2T-RFHPS model.

3.1. The AHP Method

The AHP method was introduced by Thomas Saaty [89,90], which uses hierarchical decomposition to manage complicated information in Multi-Criteria Decision-Making (MCDM) problems [91]. It allows experts to measure the importance of qualitative and quantifiable criteria, which have become essential for addressing MCDM and prioritization problems [92].

The AHP method has gained renown and has been applied in many fields, such as business and financial management [93–96], logistics and supply chain management [97–99], CRM [100,101], healthcare [102–104], etc. This method derives from determining a goal, setting criteria used to evaluate the goal, and employing sub-criteria to evaluate the criteria. The pairwise comparison matrix is employed to determine the weights of each criterion and sub-criterion. This allows decision-makers to systematically evaluate different criteria and sub-criteria. Table 1 presents Saaty's 9-point scale, a commonly used scale for pairwise comparison in the AHP method.

Table 1. Saaty's 9-point scale, adapted from Saaty [89] and Shu et al. [105].

Intensity of Importance	Definition	Explanation
1	Equal importance	Judgment favors both criteria equally.
3	Moderate importance	Judgment slightly favors one criterion.
5	Strong importance	Judgment strongly favors one criterion.
7	Very strong importance	One criterion is favored strongly over another.
9	Extreme importance	There is evidence affirming that one criterion is favored over another.
2, 4, 6, 8	Immediate values between above-scale values	Absolute judgment cannot be given, and a compromise is needed.
Reciprocals of the above non-zero numbers	Reciprocals for inverse comparison	If criterion A is assigned one of the above non-zero numbers when compared to criterion B, then criterion B has the reciprocal value when compared to A.

The consistency of the pairwise comparison matrix should be checked using the Consistency Ratio (CR) since these judgments of decision-makers are subjective and sometimes could be inconsistent. The CR is calculated by dividing the Consistency Index (CI) by the Random Index (RI), where CI $= (\lambda_{max} - \chi)/(\chi - 1)$, with λ_{max} being the maximum eigenvalue of the pairwise comparison matrix, χ being the number of criteria or sub-criteria compared, and RI as the consistency of a randomly generated pairwise comparison matrix. If CR > 0.1, it is necessary to revise the pairwise comparison matrix until it is consistent (i.e., CR ≤ 0.1). On the contrary, the pairwise comparison matrix is consistent and can continue to calculate the weights of each criterion or sub-criterion. Further steps in the AHP method are described in the work of Saaty and Vargas [106].

3.2. RFM and Its Extension

The RFM model, originally implemented to segment customers based on their purchasing behavior in sales analysis, can also be applied to address customer comments with the development of eWOM in industries like tourism and entertainment. As discussed in Section 2.3, to fill the gap in the literature, this paper introduces RFHPS, an extended RFM model with the following five dimensions: Recency (R) is the number of days between the date of the most recent review left by the customer and the date of data extraction; Frequency (F) is the number of reviews that the customer left during the analysis period; Helpfulness (H) is the total number of "likes" given by other customers who found his or her review(s) to be helpful during the analysis period; Promoter Score (P) is the average of the overall rating given by the customer to different hotels on TripAdvisor during the analysis period; and Stability (S) is the standard deviation of the overall rating given by the customer to different hotels during the analysis period. These five dimensions are divided into two categories: the customer engagement value, which includes the dimensions of RFH to show the quality of customer reviews, and the customer sentiment value, which includes the last two dimensions (PS) to reflect the level of customer satisfaction. Figure 2 shows the structure of RFHPS dimensions, designed following the principles of the AHP method.

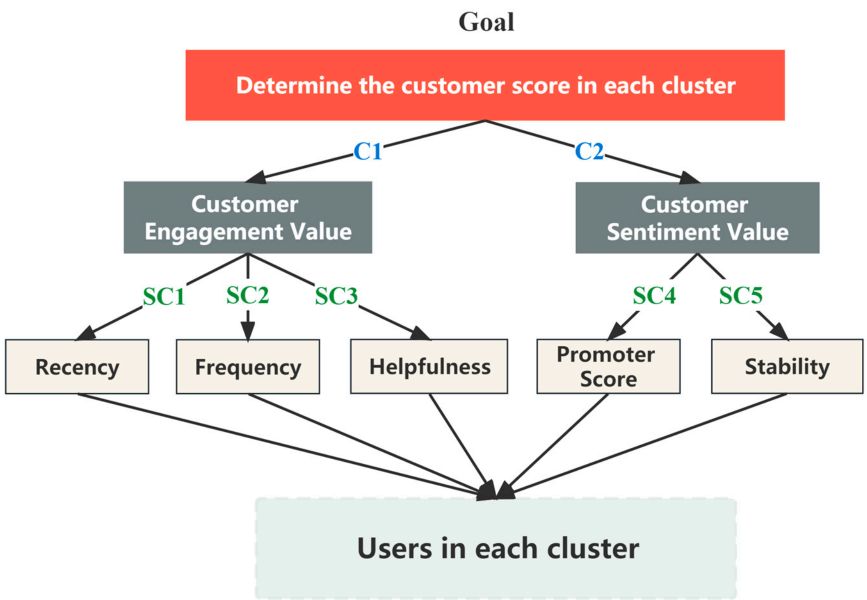


Figure 2. RFHPS dimensions for customer value calculations.

To the best of our knowledge, the dimensions P and S are correlated, as the Stability dimension is calculated as the standard deviation of the ratings of the Promoter Score. The proposed interpretation of these two dimensions is shown as a matrix in Figure 3, and their definitions are given as follows:

- **Consistent Positive Behavior** refers to a pattern of behavior where individuals consistently exhibit positive feedback and tend to influence others around them positively. In this context, the Promoter Score tends to be consistently very high.
- **Consistent Negative Behavior** refers to a pattern of behavior where individuals consistently exhibit negative feedback and tend to influence others around them negatively. In this context, the Promoter Score tends to be consistently very low.
- **Inconsistent Negative Behavior** refers to a pattern of behavior where individuals occasionally express dissatisfaction but are more likely to change their sentiment than someone who consistently gives low scores (i.e., consistent negative behavior).

- **Inconsistent Positive Behavior** refers to a pattern of behavior where individuals occasionally express positive feedback and provide valuable insights and information due to their varied opinions. In this context, despite the high Promoter Score, there is an instability in their opinions, and attention should be paid if they change into giving inconsistent negative behavior.

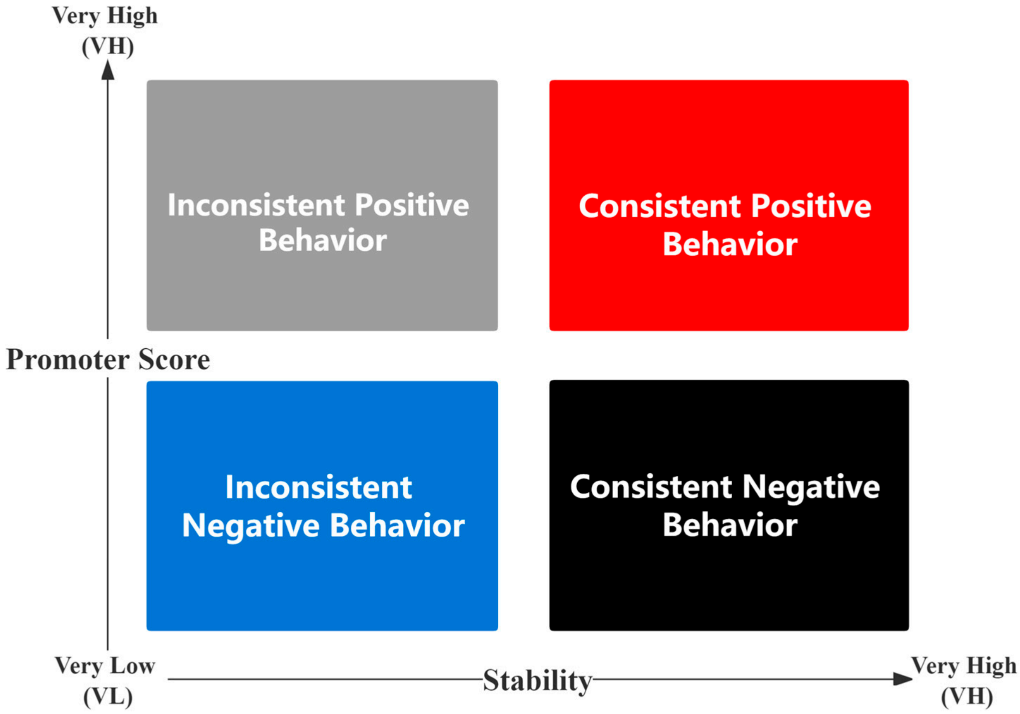


Figure 3. Customer sentiment matrix: combinations of the dimensions P and S.

3.3. The 2-Tuple Linguistic Model

The 2-tuple linguistic model was developed by Herrera and Martínez to address the problem of information loss in linguistic information fusion [14]. This model is better than the other symbolic fuzzy-based models in precision and interpretability [107]. It has been used by many authors to model customer reviews, offering decision-makers more understandable results than using only numerical scales [108–110]. In the context of eWOM, the 2-tuple linguistic model has been widely applied in numerous studies [4,88,110,111], highlighting its advantages in enhancing precision and interpretability when analyzing linguistic assessments, such as customer online reviews.

The 2-tuple linguistic model expresses linguistic information through a pair of values called the 2-tuple value (s_i, α), where $s_i \in S$ is a linguistic term, and $\alpha \in [-0.5,\ 0.5)$ represents the distance to the central value of s_i. The definition is given as follows.

Definition 1. *Let $S = \{s_0, \ldots, s_g\}$ be the linguistic term set, and $\beta \in [0,\ g]$ be a value that represents the result of an operation of symbolic aggregation. The function $\Delta : [0,\ g] \rightarrow \langle S \rangle = S\ x\ [-0.5,\ 0.5)$ is used to convert β to the 2-tuple value (s_i, α) as shown in Equation (1):*

$$\Delta(\beta) = (s_i, \alpha), with \begin{cases} i = round(\beta) \\ \alpha = \beta - i,\ \alpha \in [-0.5,\ 0.5) \end{cases} \tag{1}$$

where $round(\cdot)$ is the rounding operation; s_i has the nearest index label to β; and α represents the numerical value of the symbolic translation. The function Δ is bijective, whose inverse function $\Delta^{-1} : \langle S \rangle = Sx[-0.5,\ 0.5) \rightarrow [0, g]$ can convert the 2-tuple value into its equivalent numerical value as $\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta$.

The negation operator of a 2-tuple value is used to handle inverse dimensions (e.g., the smaller the Recency, the better). The definition is given as follows. The comparison and aggregation operators for 2-tuple linguistic computation can be consulted in [112].

Definition 2. *The negation operator of a 2-tuple value* (s_i, α) *is defined as shown in Equation (2):*

$$neg((s_i, \alpha)) = \Delta\left(g - (\Delta^{-1}(s_i, \alpha))\right) = \Delta(g - \beta) \quad (2)$$

3.4. The 2T-RFHPS Model

The 2T-RFHPS model is a combination of the 2-tuple linguistic model and the improved RFM model that considers the structure of the hotel reviews.

The 2-tuple linguistic model has been added to the RFHPS model to increase the precision of the RFHPS score's computation and easier comprehension of the findings. Let *Very Low (VL)*, *Low (L)*, *Average (A)*, *High (H)*, and *Very High (VH)* be the linguistic terms to demonstrate customer reviews, so $S = \{s_0, \ldots, s_g\}$ with $g = 4$: $s_0 = VL$, $s_1 = L$, $s_2 = A$, $s_3 = H$, $s_4 = VH$, as shown in Figure 4.

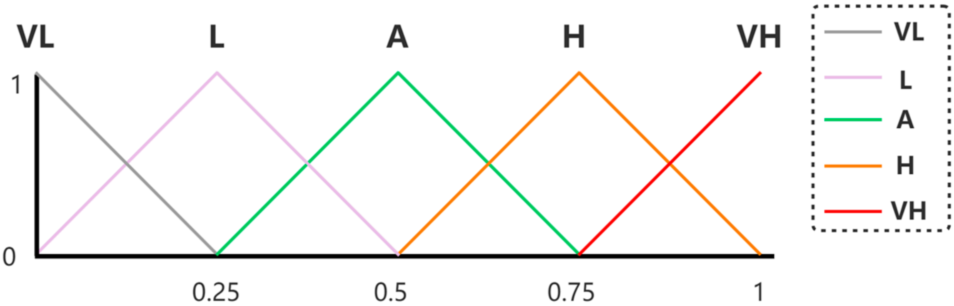


Figure 4. Linguistic term set S.

Therefore, the RFHPS scores of each customer l are R_l, F_l, H_l, P_l, S_l $\in [-0.5,\ 0.5)$. Customers should be arranged in ascending order according to each RFHPS dimension. Let C_{lj} be a set of values corresponding to the RFHPS scores of the customer l, with $C_{l1} = R_l$, $C_{l2} = F_l$, $C_{l3} = H_l$, $C_{l4} = P_l$, $C_{l5} = S_l$. For each element in C_{lj}, its 2-tuple value is calculated using Equation (3):

$$C_{lj}^{2T} = \Delta(C_{lj}) = \begin{cases} \Delta\left(percent\_rank(C_{lj})\right), if\ j \neq 1\ and\ j \neq 5 \\ neg\left(\Delta(percent\_rank(C_{lj}))\right), if\ j = 1\ or\ j = 5 \end{cases} \quad (3)$$

where $percent\_rank(\cdot) = \frac{rank_{lj}(\cdot)-1}{n-1}$ is a function that scales data in the range [0, 1]; $rank_{lj}(\cdot)$ represents the ranking corresponding to each RFHPS dimension of the customer l, $l = 1, \ldots,\ n$ and $j = \{1,\ 2,\ 3,\ 4,\ 5\}$; and $\Delta(\cdot)$ and $neg(\cdot)$ are defined in Equations (1) and (2), respectively. The negative operator is applied to inverse dimensions R and S, because Recency is better when it is smaller; Stability is calculated by the standard deviation, which is less stable when the standard deviation is greater.

4. Proposed Model and Its Application

This section delineates the development process of the proposed model and its application in customer segmentation for luxury hotels. Figure 5 illustrates each step of the model and its relationship with three CRM subsystems.

As depicted in Figure 5, data sourced from eWOM via TripAdvisor feeds into Social CRM. Subsequently, these data flows into the Analytical CRM, where techniques like K-means clustering and the AHP method are employed to identify customer traits. Finally, Operational CRM utilizes the information obtained from Analytical CRM to establish personalized communication with customers on an individual basis. Salesforce, renowned as the world's leading cloud-based CRM software, is recognized for its comprehensive capabilities in managing and organizing customer data, sales processes, and customer interactions. This paper utilizes Salesforce to present customer 2-tuple-RFHPS scores and the results of customer segmentation. It clarifies the clusters to which each customer belongs, thereby facilitating the formulation of specific strategies.

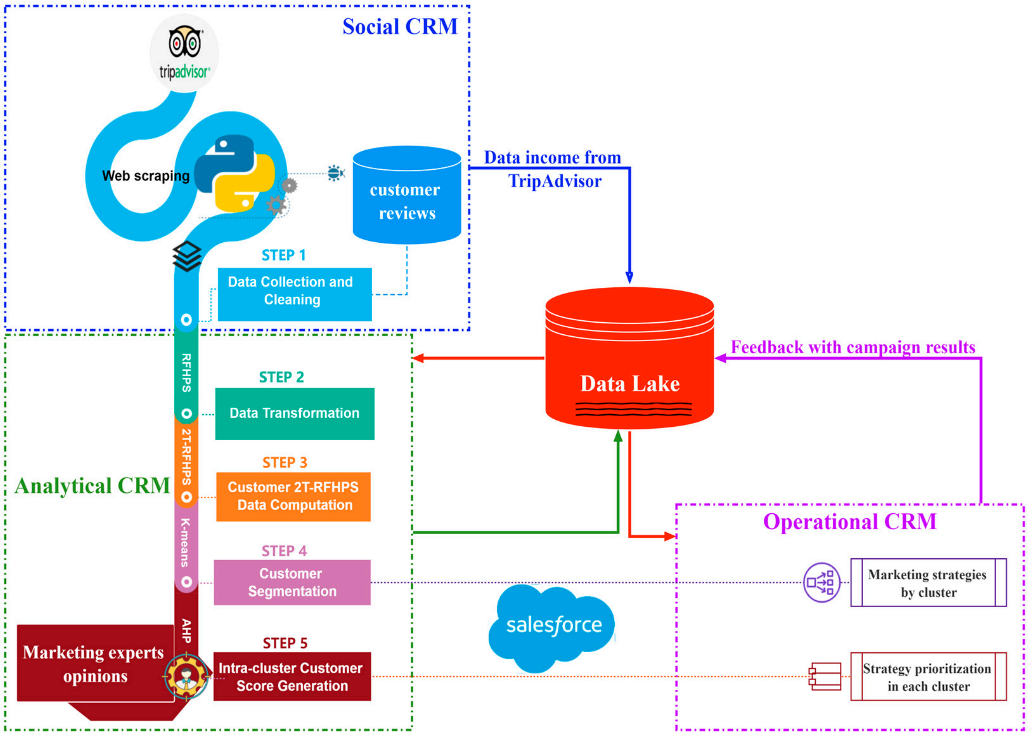


Figure 5. Steps used to create the proposed model.

4.1. Data Collection and Cleaning

Hotel reviews for luxury hotels in Spain were collected from TripAdvisor in December 2022 using web crawlers written in the Python programming language. Spain was selected because it is the top travel destination [113], and its hospitality and tourism industry are highly developed, offering a wide variety of hotels with different service levels and types, including business, boutiques, and leisure hotels. TripAdvisor was chosen as the data source due to its widespread use among travelers [114,115], its increasing global influence in recent years [116], and its recognition as a reliable data source in the hospitality and tourism industry. This paper selected luxury hotels for study due to their relevance in the hospitality industry and their high level of interest in the investigation [117–119].

The dataset collected in this paper includes 447,180 reviews (user ID, user comment date, overall rating of the hotel, and the number of "Helpfulness" votes given by other users to the comment) from 422 luxury hotels in Spain. However, there are 522 reviews from anonymous IDs whose "Helpfulness" is a missing value. To ensure the quality of the study, they were regarded as non-significant customers and were removed from the dataset. Furthermore, although the dataset's oldest review dates back to 2002, the study period was set to the last ten years, as older reviews lose their timeliness and relevance, and considering only the most recent one or two years of reviews would result in a less comprehensive analysis. After data cleaning, 401,007 comments left by 338,361 customers on TripAdvisor between 19 December 2012 and 19 December 2022 were studied for the proposed model. Table 2 shows some examples of customer reviews.

Table 2. Examples of customer reviews.

User ID	Comment Date	Overall Rating	Comment's Helpfulness
045AF74F139E39C3A508E84A71E62CCB	15 December 2013	5	33
0AF15852C62CBC621FBC86E491D9C942	21 August 2015	4	37
00008ADCC6A0590E793779976BDC7FF6	5 January 2016	5	2
057B5646A068F84FD61B33C81F4F3447	27 June 2016	5	16
41E7DA33C376CBC15DF83E637FFF1138	31 August 2016	3	25
0114793522C8AF8B901820CB68304AC0	26 February 2017	5	32
057B5646A068F84FD61B33C81F4F3447	6 June 2017	5	16
045AF74F139E39C3A508E84A71E62CCB	8 March 2018	4	33
00615CF9C5830F58DEC9C33ED6C8F048	22 June 2018	3	2
057B5646A068F84FD61B33C81F4F3447	30 July 2018	5	16
0AAC9240E77A931856141B9BAEFA69E3	2 December 2019	5	1
0AED5DC791F503FC43DEDBCEF1D81CAC	17 May 2021	5	1
0AF15852C62CBC621FBC86E491D9C942	10 December 2021	5	37
0AF15852C62CBC621FBC86E491D9C942	18 December 2022	5	37
3FE45D05AD59323A0DC4E07ECE19E941	18 December 2022	4	16

4.2. Data Transformation

The five-dimensional values for each customer—Recency, Frequency, Helpfulness, Promoter Score, and Stability—were derived by transforming the data collected in the previous step based on their definitions in the 2T-RFHPS model (see Section 3.4). Table 3 shows the results of data transformation for some customers.

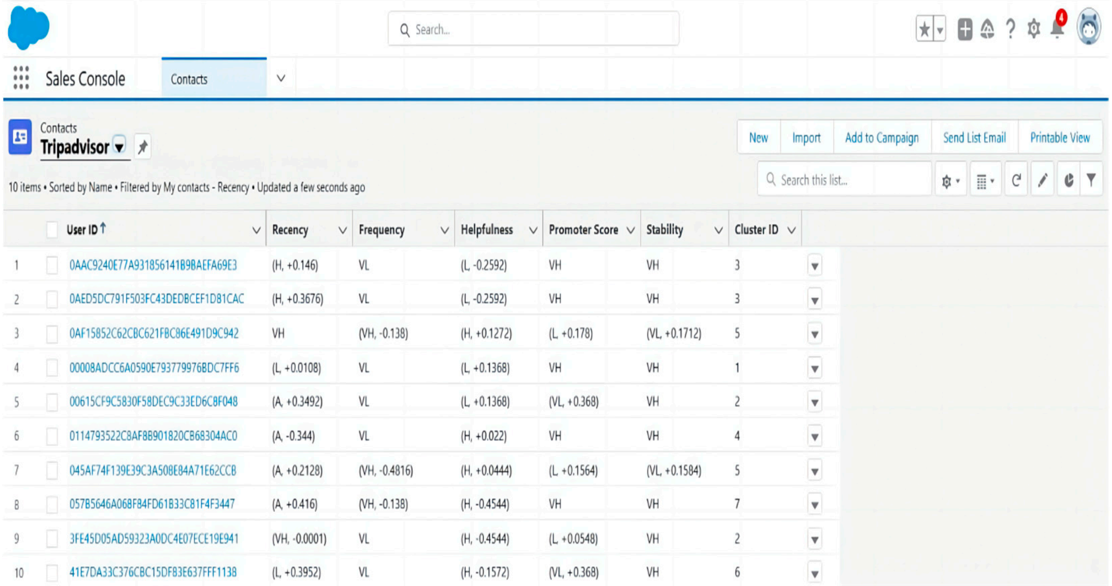
Table 3. Data transformation results for some customers.

User ID	Recency [1]	Frequency	Helpfulness	Promoter Score	Stability [1]
045AF74F139E39C3A508E84A71E62CCB	1747	2	33	4.5	0.7071
00008ADCC6A0590E793779976BDC7FF6	2540	1	2	5	0
41E7DA33C376CBC15DF83E637FFF1138	2301	1	25	3	0
0114793522C8AF8B901820CB68304AC0	2122	1	32	5	0
00615CF9C5830F58DEC9C33ED6C8F048	1641	1	2	3	0
057B5646A068F84FD61B33C81F4F3447	1603	3	16	5	0
0AAC9240E77A931856141B9BAEFA69E3	1113	1	1	5	0
0AED5DC791F503FC43DEDBCEF1D81CAC	581	1	1	5	0
0AF15852C62CBC621FBC86E491D9C942	1	3	37	4.6667	0.5774
3FE45D05AD59323A0DC4E07ECE19E941	1	1	16	4	0

[1] This dimension is better when it is smaller. For example, "Stability" measures the variability among scores given by the same customer, calculated by the standard deviation. A standard deviation of 0 means the customer gave the same score each time or has only given one review. "Stability" decreases as the standard deviation increases.

4.3. Customer 2T-RFHPS Data Computation

To be consistent with the linguistic terms shown in Figure 4, the customers' five-dimensional values were scaled to the range from 0 to 1 before being converted into the 2-tuple values. Their corresponding 2-tuple values were obtained using Equation (3), whose results are shown in Figure 6, which provides a screenshot of Salesforce CRM software, also showing the cluster IDs to which these customers belong. Section 5 provides more information on each cluster's characteristics.


Sales Console
Contacts
Contacts
Tripadvisor
New | Import | Add to Campaign | Send List Email | Printable View
10 items • Sorted by Name • Filtered by My contacts - Recency • Updated a few seconds ago

	User ID	Recency	Frequency	Helpfulness	Promoter Score	Stability	Cluster ID
1	0AAC9240E77A931856141B9BAEFA69E3	(H, +0.146)	VL	(L, -0.2592)	VH	VH	3
2	0AED5DC791F503FC43DEDBCEF1D81CAC	(H, +0.3676)	VL	(L, -0.2592)	VH	VH	3
3	0AF15852C62CBC621FBC86E491D9C942	VH	(VH, -0.138)	(H, +0.1272)	(L, +0.178)	(VL, +0.1712)	5
4	00008ADCC6A0590E793779976BDC7FF6	(L, +0.0108)	VL	(L, +0.1368)	VH	VH	1
5	00615CF9C5830F58DEC9C33ED6C8F048	(A, +0.3492)	VL	(L, +0.1368)	(VL, +0.368)	VH	2
6	0114793522C8AF8B901820CB68304AC0	(A, -0.344)	VL	(H, +0.022)	VH	VH	4
7	045AF74F139E39C3A508E84A71E62CCB	(A, +0.2128)	(VH, -0.4816)	(H, +0.0444)	(L, +0.1564)	(VL, +0.1584)	5
8	057B5646A068F84FD61B33C81F4F3447	(A, +0.416)	(VH, -0.138)	(H, -0.4544)	VH	VH	7
9	3FE45D05AD59323A0DC4E07ECE19E941	(VH, -0.0001)	VL	(H, -0.4544)	(L, +0.0548)	VH	2
10	41E7DA33C376CBC15DF83E637FFF1138	(L, +0.3952)	VL	(H, -0.1572)	(VL, +0.368)	VH	6

Figure 6. The 2-tuple-RFHPS scores for some customers and their cluster ID.

4.4. Customer Segmentation

Customer segmentation was performed using K-means clustering, an unsupervised ML technique. First, the function Δ^{-1} was used to convert the 2-tuple values generated in the previous step into numbers. Second, the *KElbowVisualizer* function in the Python package *Yellowbrick* was applied to select the optimal number of clusters between 2 and 20. As shown in Figure 7, the elbow point was achieved with seven clusters, indicating the optimal number of clusters.

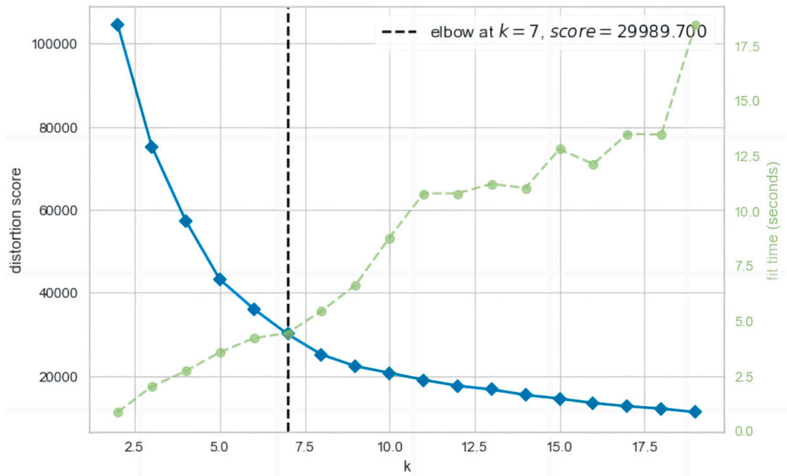


Figure 7. Distortion score elbow for K-means clustering.

Therefore, customers were divided into seven groups. Table 4 shows the centroids of each cluster expressed in 2-tuple values and the number of customers in the dataset. A centroid represents the average of a variable for the observations in a cluster. As shown in Table 4, the linguistic terms combined with some signs (positive or negative) indicate whether the customers in that cluster are above or below that linguistic term (i.e., *VL*, *L*, *A*, *H*, *VH*). For instance, cluster 1 has a Recency value that is slightly below "*Low*", its Frequency is "*Very Low*", and its Helpfulness is slightly above "*Low*", although it has "*Very High*" Promoter and Stability values.

Table 4. Cluster centroids expressed in 2-tuple values.

Cluster ID	Recency	Frequency	Helpfulness	Promoter Score	Stability	Number of Customers
1	(L, −0.0091)	VL	(L, +0.0591)	VH	VH	60,651
2	(A, +0.3491)	(VL, +0.0082)	(L, −0.1255)	(L, −0.2741)	VH	32,783
3	(H, +0.1396)	VL	(L, −0.318)	VH	VH	75,202
4	(A, −0.217)	VL	(H, −0.0046)	VH	VH	81,082
5	(A, +0.2302)	(VH, −0.3309)	(H, +0.0437)	(L, −0.0304)	(VL, +0.1265)	17,600
6	(L, +0.3744)	(VL, +0.0053)	(H, −0.1351)	(L, −0.2123)	VH	48,051
7	(A, +0.3446)	(VH, −0.4022)	(H, −0.4203)	(VH, −0.2874)	VH	22,992

Figure 8 displays a radar map for each cluster centroid. The gradation of each chart goes from "*Very Low*" to "*Very High*" in relation to each of the five dimensions of the RFHPS model. The shape of the dark area demonstrates the intuition of the different customer profiles in each segment (cluster). According to Figure 8, cluster 7 could be the most attractive customer segment for platform managers to keep engaged and nurture long-term relationships. Further analysis of the different segments and tailored strategies is carried out in Section 5.

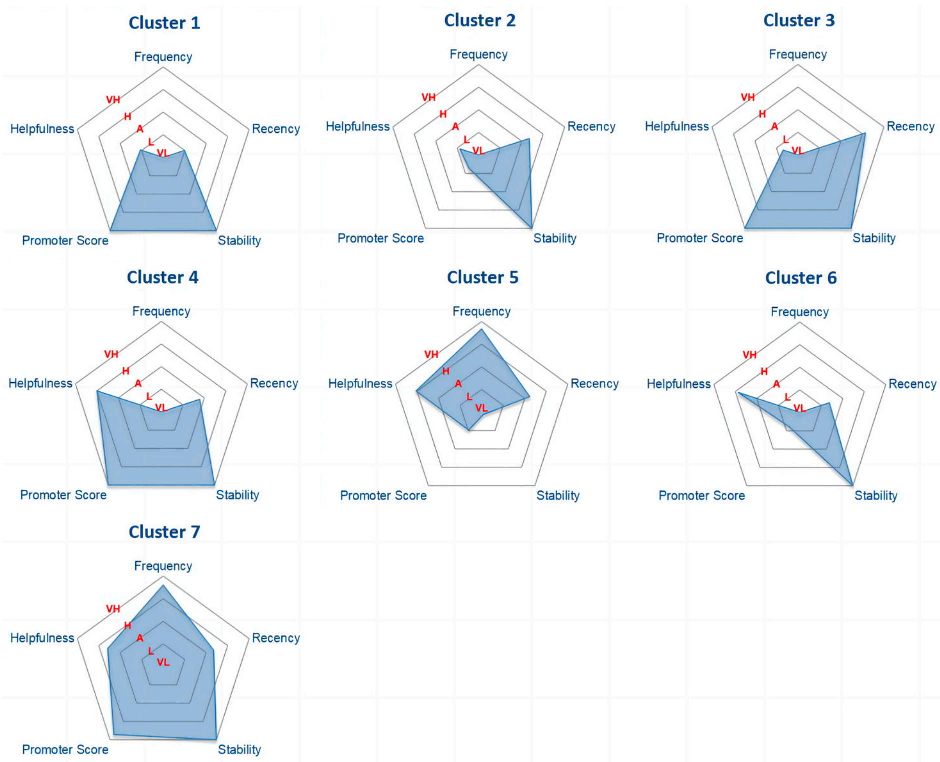


Figure 8. Radar map for each cluster centroid.

4.5. Intra-Cluster Customer Score Generation

The AHP method was applied to establish a framework for making judgments regarding intra-cluster customer scores. This method measures the importance of qualitative and quantifiable criteria and has grown into an essential tool for addressing MCDM and prioritization problems [92].

According to the structure shown in Figure 2, the experts created pairwise comparison matrices between the dimensions R, F, H, and P, S to determine their weights for customer engagement value and customer sentiment value, respectively. Table 5(a),(b) show the pairwise comparison matrices and the corresponding weights for each dimension.

Table 5. (a). Pairwise comparison matrix of the dimensions (R, F, H) included in the customer engagement value and the corresponding weights calculated for each dimension. (b). Pairwise comparison matrix of the dimensions (P, S) included in the customer sentiment value and the corresponding weights calculated for each dimension.

(a)

	Recency	**Frequency**	**Helpfulness**	**Weight**
Recency	1	2	1/3	0.249
Frequency	1/2	1	1/3	0.157
Helpfulness	3	3	1	0.594

(b)

	Promoter Score	**Stability**	**Weight**
Promoter Score	1	2	0.667
Stability	1/2	1	0.333

Similarly, experts compared the importance of the customer engagement value and customer sentiment value in generating the intra-cluster customer score. Customer engagement value weights were 0.667, while customer sentiment value weights were 0.333. Given that all CR values were less than 0.1, experts' judgments were accurate, and pairwise comparison matrices were consistent.

Based on Figure 2, the intra-cluster customer score was obtained by combining customer engagement and sentiment values with their respective weights. When calculating the customer sentiment value for cluster 5, where both the Stability and Promoter Scores tend to be "*Very Low*" (i.e., inconsistent negative behavior, see Figure 3), the negative operator defined in Equation (2) should be employed to correct the calculation of their customer sentiment value, akin to the principle of two negatives resulting in a positive in mathematics. The calculation of customer sentiment value for other clusters is multiplying the corresponding value of dimensions P and S with their corresponding weight.

Table 6 shows the intra-cluster customer scores for some customers and their respective rankings within their cluster. The highest and lowest intra-cluster customer scores are also presented in Table 6 to compare scores within each cluster. The higher the intra-cluster customer score ranking, the higher the priority that should be given to that customer. Even though the strategies applied to customers within the same cluster are almost identical, adjustments should be made based on their prioritization ranking within that cluster. The utility of intra-cluster customer scores is explored in Section 5.

Table 6. Intra-cluster customer scores for some customers and their corresponding ranking in their cluster.

User ID	**Cluster ID**	**Intra-Cluster Customer Scores**	**Intra-Cluster Ranking (Quartile)**	**Lowest Intra-Cluster Customer Scores**	**Highest Intra-Cluster Customer Scores**
045AF74F139E39C3A508E84A71E62CCB	5	(H, −0.0003)	10,852/17,600 (Q3)	(L, +0.45)	(VH, −0.0808)
00008ADCC6A0590E793779976BDC7FF6	1	(A, −0.0497)	29,977/60,651 (Q2)	(L, +0.3321)	(A, +0.3683)
41E7DA33C376CBC15DF83E637FFF1138	6	(A, −0.1167)	29,396/48,051(Q3)	(L, −0.0841)	(H, −0.0806)
0114793522C8AF8B901820CB68304AC0	4	(H, −0.1957)	40,037/81,082 (Q2)	(A, +0.3609)	(VH, −0.4225)
00615CF9C5830F58DEC9C33ED6C8F048	2	(L, +0.3659)	14,392/32,783 (Q2)	(VL, +0.4778)	(A, +0.4879)
057B5646A068F84FD61B33C81F4F3447	7	(H, +0.1463)	10,744/22,992 (Q2)	(L, +0.3845)	(VH, −0.0135)
0AAC9240E77A931856141B9BAEFA69E3	3	(A, +0.1481)	32,766/75,202 (Q2)	(A, −0.3504)	(H, +0.076)
0AED5DC791F503FC43DEDBCEF1D81CAC	3	(A, +0.1849)	30,306/75,202 (Q2)	(A, −0.3504)	(H, +0.076)
0AF15852C62CBC621FBC86E491D9C942	5	(H, +0.3591)	4474/17,600 (Q2)	(L, +0.45)	(VH, −0.0808)
3FE45D05AD59323A0DC4E07ECE19E941	2	(A, +0.2507)	80/32,783 (Q1)	(VL, +0.4778)	(A, +0.4879)

5. Results and Discussion

This section discusses the customer profiles uncovered by the proposed model and suggests differentiated strategies for them. Table 7 provides descriptions for each of the identified customer segments, along with brief outlines of the corresponding marketing strategies used. Within each cluster, attention should be paid to the position of customers in relation to the quartiles seen in the intra-cluster customer scores, giving preference to Q1 and Q2 customers above the rest in terms of the rewards and perks offered to them.

Table 7. Customer segment description and strategy.

Cluster ID	Cluster Name	Description	Strategy
1	Low Recency and high promoters	Tend to give high ratings in the hotels where they stay. They have not written recently and are considered little help by the community. They are sleeping customers.	Send an email with a price discount or Non-Fungible Tokens (NFTs) to remind this group of customers of the importance of their reviews in assisting other users and to encourage them to write again.
2	Average Recency and low promoters	Tend to give low ratings with average Recency. They are considered little help by the community.	Email to show genuine interest in their feedback and demonstrate that the community values their opinion. Try to engage in further dialog to build trust.
3	High Recency and high promoters	Tend to give high ratings, and their reviews are more recent than those of other clusters. The community does not find them very useful. This could be because they are new users, or their reviews are so recent that few people have read them.	A thank-you email with an invitation to gain a badge for the most helpful customers in the community. Offer exclusive discounts or bonus points for their support.
4	Average Recency and helpful promoters	Tend to give high ratings and have posted reviews recently. They are considered helpful by the community.	Email to show appreciation for their positive contributions and helpfulness within the community. Send personalized thank-you messages and offer exclusive perks or rewards for their continued support.
5	Frequent and helpful low promoters	Post frequently and are deemed helpful by the community. However, they have low Promoter Scores and little Stability in their evaluations. They are very informative, as they have varied opinions.	An acknowledgment email with a scheme to obtain badges according to their usefulness to the community, incentivizing them to give higher ratings in the future.
6	Helpful low promoters	Are perceived as helpful by the community and tend to give low ratings. They have low Recency and low Frequency.	In-time emails to show concern about their negative experience and offer special incentives to recover their trust in the brand.
7	Frequent and helpful high promoters	Write frequently and tend to give high ratings, are considered highly helpful by the community, very stable, and have average Recency. They are the ideal customers.	Email to acknowledge and recognize these customers for their helpful contributions to the community. Outline a badge scheme and give access to exclusive promotions to foster a sense of belonging and appreciation for their continued support.

Some authors [120] have studied the importance of online platforms as value co-creators for hotels. The traffic ranking for 2022 in the Travel and Tourism industry [121] featured Booking.com and TripAdvisor as the top thematic platforms. The case of TripAdvisor is unique as the top platform for reviews and ratings of hotels, restaurants, sights, and activities across the world. However, unlike other online platforms on TripAdvisor, hotel room sales are facilitated through third-party entities known as OTAs, such as Booking.com, Expedia, Hotels.com, and more. Therefore, the primary business objective of TripAdvisor is not transactional but the collection of reviews as eWOM. In this context, the actionability of customer segmentation is different from that which could be performed in a hotel chain or in an OTA itself, where campaigns could be aimed at strengthening and rewarding customer loyalty or providing discounts for new transactions (bookings). On TripAdvisor, the campaigns should be aimed at incentivizing customers to provide eWOM to maintain the brand's value as an independent reference for travelers.

The customers with the highest value to the brand should receive unique treatment, including perks for loyalty (e.g., discounts on transactions through third-party platforms) and a customer badge as proof of their value to the community. The most valuable customers are the ones who have been active in the last 5 years and who are considered helpful by their peers (i.e., community). These customers are found in clusters 4, 5, and 7, with variations among them in terms of Frequency, Promoter value, and Stability. Customers in cluster 3 are mostly new users, and the goal is to keep them engaged regularly and progress them toward cluster 7. Furthermore, the computation of intra-cluster customer scores enables the prioritization of strategies within each cluster. As illustrated in Table 6, certain customers within the same cluster may fall into different quartiles. For instance, in the case of cluster 5, out of two customers, one in Q3 and the other in Q2, higher priority should be given to the customer in Q2.

Specific marketing strategies should be designed for active and helpful customers to increase their Frequency rate and maintain their loyalty to the brand with some incentives such as loyalty programs or direct discounts with a coupon system to redeem on third-party platforms, for instance. A different marketing strategy should be devised for those customers who have not been active in the last 5 years (i.e., sleepers) to bring them back to provide eWOM on the platform. The Recency percentiles are specific to the dataset used (10-year range), as they could vary for other data and companies. A usual consideration for business analysis could be labeling active customers as those who performed transactions (i.e., writing reviews in the case of TripAdvisor) in the last 12 months or even 24 months. However, in the case of TripAdvisor, keeping reviews from further back in time offers advantages for comprehensive analysis.

To summarize, the proposed RFHPS model significantly enhances the traditional RFM framework by introducing three innovative dimensions that address critical gaps in the customer segmentation literature, particularly in the eWOM context. Most notably, the "Stability" dimension introduces a novel element by quantifying the variability in customer ratings, enabling the identification of inconsistent reviewers. This addresses the limitation of classic segmentation approaches that overlook individual behavioral fluctuations, offering a more nuanced understanding of customer profiles. By incorporating these dimensions, RFHPS enhances the granularity of segmentation and strengthens the connection between segmentation insights and actionable CRM strategies. The model's ability to identify nuanced patterns in customer behavior makes it a powerful tool for tailoring marketing efforts and improving decision-making in the hospitality sector.

6. Conclusions and Future Work

This paper introduces an innovative model for segmenting hotel customers based on their online reviews. Building on the widely used RFM model, the new RFHPS model substitutes the Monetary value with Helpfulness and adds two new dimensions from customer satisfaction in their online hotel reviews: Promoter Score and Stability. The inclusion of the 2-tuple linguistic model enhances the precision and interpretability of the RFHPS score. By applying K-means clustering to segment customers and the AHP method to establish intra-cluster customer scores, this model offers a comprehensive framework for customer segmentation. In this way, this paper contributes to a more nuanced approach for effectively segmenting customers in the context of eWOM, providing a refined CRM method to better understand and engage with customers based on their reviews and behaviors.

An empirical study using over 400,000 customer online reviews from TripAdvisor validates the effectiveness of the proposed model. The results show that the proposed model enhances the accuracy and linguistic interpretability of customer segmentation compared to previous RFM models. This enhanced clarity allows for the detailed characterization of customer segments, facilitating the design of targeted marketing strategies for each segment. The use of the 2-tuple linguistic model enables the direct interpretation of results through intuitive expressions, eliminating the need for reference numbers. Additionally, intra-cluster customer scores prioritize customers within each segment, allowing for tailored marketing strategies and promotions, such as rewards and perks for high-priority customers. The main contributions of the proposed model are summarized as follows:

- From a theoretical perspective, this research is original in its innovative extension of the traditional RFM model to include dimensions derived from online customer reviews—specifically Helpfulness, Promoter Score, and Customer Stability—thereby bridging a gap in the existing literature. It adds a level of granularity to understanding customer behavior that traditional RFM dimensions cannot capture, offering a new perspective for calculating CLV. Monetary value is excluded in this refined framework because, in the context of eWOM, it may not fully capture a customer's overall contribution to the business, and this dimension is not available on most occasions. Non-monetary dimensions such as Helpfulness, Promoter Score, and Stability provide deeper insight into customer loyalty and influence. This introduces a theoretical shift from viewing customers solely as transaction generators to recognizing their broader roles in promoting brand value, influencing other potential customers, and enhancing the company's reputation. This novel approach also integrates the 2-tuple linguistic model and the AHP method, providing a more nuanced and accurate framework for customer segmentation. The RFHPS model's ability to incorporate eWOM data from TripAdvisor reviews represents a significant advancement in utilizing online reviews for customer segmentation. This research also pioneers the application of the 2-tuple linguistic model in the context of customer segmentation, offering a unique contribution to the field. By combining these novel dimensions with established clustering techniques, this study broadens the theoretical foundation of customer segmentation models. The integration of the 2-tuple linguistic model and the AHP method into the RFHPS model enhances the precision and interpretability of customer profiles. These new suggested dimensions reflect the shift towards customer-centric marketing strategies, integrating an enhanced model that theoretically updates customer segmentation by recognizing that customers who advocate for the brand (even if they spend less) contribute to customer acquisition and retention. By shifting to dimensions like Helpfulness, Promoter Score, and Stability, this new model aligns better with contemporary theories that emphasize customer advocacy, engagement, and brand loyalty, particularly in industries where customer experience and reputation are key drivers of business success.
- From a practical perspective, the applicability of the proposed model goes beyond the use case and holds substantial potential for strategic customer segmentation in the hotel industry. By leveraging online reviews, hotel chains, and OTAs can better understand customer preferences and behaviors and develop differentiated marketing strategies tailored to specific customer segments. The RFHPS model enables the extraction of valuable insights from eWOM data, enhancing CRM systems and improving the effectiveness of marketing strategies. The application of the model to

a real-world dataset demonstrates its practical utility, providing a blueprint for its implementation in various contexts within the hospitality sector. Each of the seven customer segments may represent a unique combination of behaviors and engagement levels. For example, a segment with high Promoter Scores but a low Frequency of visits may be targeted with loyalty or referral programs to maximize advocacy. Conversely, a segment with high Recency but lower Helpfulness might benefit from incentives to encourage them to contribute more reviews or engage in social media activity, enhancing their impact on the brand's reputation and visibility through eWOM. Finally, while this paper focuses on the hotel industry, the RFHPS model can also be applied to other sectors that rely on online reviews, such as restaurants, car rentals, cruises, and e-commerce platforms like Amazon or FilmAffinity, where Helpfulness, Promoter, and Stability data can be collected.

Despite its strengths, this work has certain limitations. The dataset used in this work only contains reviews of a fixed set of hotels (i.e., luxury) in one country, and the Frequency of reviews provided by each customer is low. Additionally, the dataset is missing other reviews of the same customers for other types of hotels in the same country as well as in other countries, which would provide more Frequency and a better chance to measure the Stability of the customer (i.e., lack of dispersion). Therefore, in future work, reviews from the same customers across different types of hotels (e.g., budget, mid-range, business, boutique, leisure hotels, etc.) will be examined to increase Frequency, as well as reviews from various geographic regions to enhance the sample's diversity. Web crawlers could be used to acquire more far-reaching customer data, including reviews from different product sectors on TripAdvisor (e.g., restaurants, hotels, car rentals, cruises).

New research could explore the factors influencing customer segmentation outcomes, such as altering the time frame or considering customer demographics like nationality or gender. It could also investigate other factors impacting customer decision-making, such as the emotional tone of reviews or the effect of visual content on customer perceptions. Moreover, incorporating a qualitative approach (e.g., in-depth interviews) could help evaluate customer feedback, providing a deeper understanding of customers' feelings and motivations. Finally, future research could explore the integration of network centrality as an additional dimension in customer segmentation models, especially within the context of eWOM. A customer's connectedness online—such as their role as an influencer or prominence on social media—could reflect the impact of their reviews and recommendations. For instance, a review from a highly connected customer may generate much more visibility and influence than one from an average user. Incorporating network centrality can allow future studies to better capture the multiplier effect that influencers or well-connected customers have on brand perception, customer acquisition, and the effectiveness of eWOM strategies.

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