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The nexus between quality of customer relationship management systems and customers' satisfaction: Evidence from online customers' reviews

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ABSTRACT

Customer Relationship Management (CRM) is a method of management that aims to establish, develop, and improve relationships with targeted customers in order to maximize corporate profitability and customer value. There have been many CRM systems in the market. These systems are developed based on the combination of business requirements, customer needs, and industry best practices. The impact of CRM systems on the customers' satisfaction and competitive advantages as well as tangible and intangible benefits are widely investigated in the previous studies. However, there is a lack of studies to assess the quality dimensions of these systems to meet an organization's CRM strategy. This study aims to investigate customers' satisfaction with CRM systems through online reviews. We collected 5172 online customers' reviews from 8 CRM systems in the Google play store platform. The satisfaction factors were extracted using Latent Dirichlet Allocation (LDA) and grouped into three dimensions; information quality, system quality, and service quality. Data segmentation is performed using Learning Vector Quantization (LVQ). In addition, feature selection is performed by the entropy-weight approach. We then used the Adaptive Neuro Fuzzy Inference System (ANFIS), the hybrid of fuzzy logic and neural networks, to assess the relationship between these dimensions and customer satisfaction. The results are discussed and research implications are provided.

1. Introduction

The focus on building relationships with customers rather than just focusing on transactions is changing how businesses interact with their customers [1,2]. The number of available choices to customers has grown in recent years. Customer Relationship

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Management [3,4], also known as CRM, is a method of management that aims to establish, develop, and improve relationships with targeted customers in order to maximize corporate profitability and customer value [5,6]. In order to increase the value of the customer asset over time, CRM places an emphasis on two-way communication between suppliers and customers [7]. In fact, the concept of relationship marketing serves as the foundation for CRM [8]. CRM is frequently associated with implementing relationship marketing strategies through the use of information technology. To produce profitable and long-term relationships, CRM combines the potential of new technologies and new marketing concepts. The necessity of managing customer relationships in a multichannel environment in a more efficient manner lies at the core of a successful CRM strategy. The majority of the events that cover the customer experience occur within this channel environment.

Many CRM systems are available in the market. The enterprise applications software market had a value of 241 billion U.S. dollars in 2020 [9]. SAP emerged as the dominant player, with Salesforce and Oracle also holding significant market shares. Projections indicate that the market will experience substantial growth and is expected to expand to 334 billion U.S. dollars by 2025. In the Netherlands in 2019 [10], Microsoft had the largest market share (23 %) among CRM software vendors for medium-sized businesses. SAP Software ranked fourth with a market share of 10 % in the same category. As of September 2023 [11], Zoho was the leading software as a service (SaaS) CRM and related software company, with over 500 million U.S. dollars in revenue. It was followed by Talkdesk (229.5 million U.S. dollars) and Odoo (178 million U.S. dollars). CRM software revenue in the US software market is expected to grow steadily from 2023 to 2028 [12], reaching a total increase of $23.6 billion (+57.91 %). Revenue is expected to reach $64.31 billion by 2028, marking the fifth year of growth. It is worth noting that the revenue of this software segment has consistently increased in recent years. The CRM systems are created by combining business needs, customer needs, and industry best practices. Previous research has extensively investigated the impact of CRM systems on customer satisfaction [13,14] and competitive advantages [15,16], as well as tangible and intangible benefits [17,18]. However, studies assessing the quality dimensions of these systems to meet an organization's CRM strategy are scarce [19]. In addition, although there have been several studies on the assessment of CRM systems using conventional approaches [19,20], online product reviews are increasingly being recognized as a valuable source of user research data for product evaluation [21–23]. As a result, the traditional approach of relying on limited data to uncover patterns in unexplored domains is gradually being replaced by large-scale dataset analysis.

Big-data-driven methods for user research are more effective [24–27], affordable, and have a wider scope than traditional methods [28,29]. Online reviews [30,31] in different formats are also generated freely by users on social networking sites, making them more accurate and reliable representations of user needs [32,33]. With online reviews, product designers can explore the potential value of user data proactively rather than reacting passively to user feedback. Textual data analysis in the realm of CRM is pivotal for gathering actionable insights from unstructured customer feedback, reviews, and interactions. Beyond understanding current sentiments, it facilitates predictive analytics which can contribute to more effective CRM strategies and service improvements. By establishing a continuous feedback loop and visualizing results, textual data analysis ensures that CRM systems remain agile, adaptive, and customer-centric, ultimately strengthening customer relationships and enhancing overall satisfaction. Thus, the purpose of this study is to look into customers' satisfaction with CRM systems via online reviews. Using Latent Dirichlet Allocation (LDA) [34], the satisfaction factors are aimed to be extracted from online customers' reviews. Learning Vector Quantization (LVQ) [35] is used to segment the data. In addition, feature selection is performed by the entropy-weight approach [36]. We then used ANFIS [37] to examine the relationship between these dimensions and customer satisfaction. Based on the above discussion, the potential research questions that this study aims to investigate are.

(1) *What are the key quality dimensions of CRM systems that drive customer satisfaction?*
(2) *How do online reviews provide valuable insights into user needs for CRM systems?*
(3) *What is the relationship between the identified dimensions of CRM systems and customer satisfaction?*

The rest of this paper is structured as follows. Section 2 presents the literature review of related studies. In Section 3, we present the method and the techniques used for the method development. In Section 4, data collection and analysis are presented. In Section 5, the research implications are provided. In Section 6, we conclude this study and provide the limitations and future studies.

2. Literature review

The advancements in CRM have gone through different stages, reflecting the ongoing development and evolution of this field. Initially, relationship marketing was expanded in the 1990s to create CRM [38]. It has been emphasized that CRM goes beyond the purview of advertising to cover areas interacting directly with clients, such as client service, sales, and management of human resources [39]. To improve the interaction with clients through the lenses of online services, the operational structure of online businesses requires an improved CRM strategy. In previous literature, the effectiveness of a business's CRM was based on its employees' capabilities to recognize and meet client requirements as well as to interact, bargain, and build positive connections with clients [40,41]. However, relying on employees' capabilities alone could not meet the emerging requirements of the clients and the growth in the business environment, which requires the integration of several innovations to enhance the performance of the classical CRM. Accordingly, a range of terms has emerged to reflect the innovative approaches implemented to enhance CRM performance [42]. These include E-CRM [43], AI-CRM [44], and social-CRM [42], each highlighting specific advancements in the field.

The core idea behind CRM is the distinction of each individual client in order to offer him/her individualized service and value that is tailored to his/her unique demands [45]. Recruiting prospective clients, increasing client value, and retaining current clients are the three steps of CRM, which is based on the principle that not all clients are treated similarly [46]. In addition to acquiring new customers, CRM should place a strong emphasis on fostering client loyalty. Businesses must concentrate on the top 20 % of their current clients in order to prioritize client retention over acquisition because it is 5–10 times more expensive to acquire a new client than to keep an existing one.

According to numerous studies, both businesses and clients need to cooperate to gain great value from the development of CRM. The requirement for an organization's strategies to win the value of CRM is what spurred the transition from classical CRM to more advanced CRM. CRM can relieve businesses from the financial burdens required for dealing directly with clients. In addition, customer interaction quality can be enhanced directly, overcoming space or time restrictions, since communication can be conducted 24 h a day without a requirement for direct engagement with business representatives, saving labor and time, and lowering managerial and business expenses that directly affect business performance [47]. Therefore, it is crucial for businesses to assess how the innovation is being applied from the standpoint of their customers [48]. Competence is crucial for a business to succeed given the current competitive environment for preserving client relationships. It is crucial to establish an ongoing connection with clients by ensuring customer happiness and customer retention.

E-CRM is another name for converting a CRM into an internet platform. In order to deliver the ideal shopping experience, e-CRM is digitally governed through the hosting website. Additionally, e-CRM has the advantage of being a cost-effective way for a firm to build its intangible resources [49] due to the fact that this technique was mostly conducted virtually by the establishment of websites or applications. E-CRM builds upon the concepts of client cultivation and retention from traditional CRM, specifically targeting online shopping environments. Instead of replacing CRM, the goal is to use the internet and innovations to improve it. A portal that integrates CRM may make it easier for clients to access a business's goods and services, manage and provide more personalized and focused contacts with prospective clients, and strengthen long-term client relationships through quicker online interactions [50]. With the correct advanced tools, analyzing client data to determine the value for clients and business owners allows rapid enhancements to service and the delivery of focused and personalized advertising strategies for every client, which encourages client loyalty, draws in and keeps profitable clients, and increases business profitability [51].

Social CRM is concerned with the creation of strategies, methods, and capabilities to incorporate social media into CRM processes. The dissemination of pertinent information from a business to its consumers is made easier by the integration of social media into the client database through social CRM. Social CRM offers a channel for the online dissemination of knowledge, particularly that pertaining to current events and points of view. Social CRM users create and circulate their own material in addition to receiving and disseminating such information [52]. Social CRM has opened the way for revolutionary methods of sharing, collaboration, and communication. Using the 'many-many' method of interaction rather than the more traditional 'one-many' setting, enables clients to create content and spread it to others. Social networks, blogs, podcasts, wikis, RSS feeds, forums, media sharing, and social bookmarking are just a few of the numerous services, tools, and applications that are usually associated with social CRM [53].

Focusing on the AI-CRM, it is necessary to boost the CRM initiatives of businesses by integrating AI with the current CRM system [44]. The processes of delivering clients individualized services and real-time customer segmentation are made easier with the integration of AI with older CRM systems. Focusing on the technical standpoint, CRM entails the gathering and storing of client data, studying clients' sustainable profits, and maintaining ongoing valuable strategies for managing clients. From a tactical standpoint where companies use client information to manage customer relationships, CRM has developed into a broader strategic vision, in which CRM fundamental operations in charge of creating and managing a network of stakeholder relationships are accountable [54]. Hence, integrating AI in the development, management, and operation of CRM systems offers a multitude of benefits and opportunities for businesses in today's fast-paced and data-driven world [55].

The existing landscape of CRM systems has seen extensive exploration regarding their impact on customer satisfaction, competitive advantages, and associated benefits. However, a notable gap exists in the assessment of the quality dimensions that align these systems with an organization's CRM strategy. Moreover, traditional approaches have been predominantly used for CRM system evaluation, and the growing recognition of online product reviews as a valuable source of user research data has prompted a shift toward large-scale dataset analysis. Leveraging big-data-driven methods for user research, this study seeks to investigate customer satisfaction with CRM systems through online reviews.

3. Method

This study aims to discover the quality dimension of CRM systems from online customers' reviews. LDA was used for textual data analysis from the collected online reviews in the Google play store platform [56]. Then, LVQ was used for data segmentation [57,58]. Finally, ANFIS was used to reveal the relationships between the quality factors and customers' satisfaction with the CRM systems [59,60]. The incorporated techniques are introduced in the following sections.

3.1. LDA Model

As a text mining technique, LDA [34] has been widely used as a probabilistic model in the analysis of a corpus of documents [61]. During the modeling process in LDA, this technique assigns high probabilities to similar documents and members within the corpus [62]. The LDA model allows for documents to exhibit multiple topics simultaneously. This flexibility of LDA enables a more nuanced representation of the underlying topics within the corpus. In the following, the fundamental concept of LDA is summarized.

- Each topic is defined by a probability distribution over words in the corpus.
- Each document is represented as a random combination or mixture of latent topics.

In LDA, the following terms are defined.

- **Word:** A word is an element or item from a vocabulary (e.g. Ref. [63]) In the context of LDA, words represent the basic units of textual data.
- **Document:** A document refers to a sequence of words. It is denoted by d and can be represented as a sequence of N words, such as $= (w_1, w_2, \ldots, w_n)$, where w_i represents the ith word in the document.
- **Corpus:** A corpus is a collection or dataset consisting of multiple documents. It is denoted by C and can be represented as $= (d_1, d_2, \ldots, d_M)$, where d_i represents the ith document in the corpus. The corpus encompasses the entire textual data under consideration.

In the LDA model, it is assumed that each document is created from a combination of K components. The probability θ_d of each component in this mixture is determined by means of a Dirichlet distribution with parameter α. Consequently, each word w_{di} in the document (the ith word of document d) is produced through a repetitive process. First, z_{di} which is a mixture of components sampled from θ_d, representing the topic associated with the word. Then, the word itself is sampled from a multinomial distribution of the vocabulary $\beta_{z_{di}}$, which is specific to the chosen mixture component. Each component in this model is referred to as a topic, and there are K topics in total. The ith topic generated by LDA is denoted by z_i. LDA's generative process can be summarized as shown in Algorithm 1 [34].

Algorithm 1: LDA's generative process
→ For each document $d = 1, \ldots, M$ in the corpus C:
1. Sample mixing probability $\theta_d \tilde{} \mathrm{Dir}(\alpha)$
2. For each of V words w_{di}:
   a) Select a topic $z_{di} \in \{1, \ldots, K\} \tilde{}$ Multinomial (θ_d)
   b) Select a word $w_{di} \in \{1, .., V\} \tilde{}$ Multinomial $(\beta_{z_{di}})$

During the generative process of LDA, several components play essential roles. V represents the vocabulary size, indicating the total number of distinct words in the corpus. K refers to the number of topics, a user-defined parameter specified for the LDA model. The parameter α, provided as input to LDA, represents the symmetric Dirichlet parameter. It influences the distribution of mixture proportions θ_d for each document d, determining the concentration of topics within the document. The multinomial topic parameters $\{\beta_1, .., \beta_K\}$ are associated with K multinomial distributions, where each β_i corresponds to a specific topic. These distributions assign probabilities to words in the vocabulary. Notably, each β_i places a high probability on a specific set of words that exhibit semantic consistency. These distributions, representing distinct thematic clusters, are commonly known as topics.

3.2. LVQ

Kohonen initially introduced the Learning Vector Quantization (LVQ) algorithm as a heuristic classification method [64,65]. Other variations of LVQ algorithms in literature can be classified based on their learning rules. LVQ methods can generally be categorized into three branches: heuristic methods (Kohonen LVQs), margin maximization, and likelihood ratio maximization methods. LVQ is utilized to generate Kohonen codebook vectors that represent the classes in an input space [64]. The LVQ network topology comprises three layers [66]: an input layer, a Kohonen layer, and an output layer. Each neuron in the output layer corresponds to a class in the input space, and the classes are associated with specific vectors in the Kohonen layer. LVQ, much like k-means, does not fall under the category of Self-Organizing Maps (SOMs). However, it is a straightforward method similar to standard SOM techniques and can provide valuable insights. As a preliminary step, the training set T is divided into separate training sets T_c, where each T_c contains instances $\overrightarrow{x}$ from T that belong to a specific class (class $(\overrightarrow{x}) = c$). For each T_c (the training set for a specific class), a separate k-means clustering algorithm is applied. This results in a collection of cluster centers, C_c, represented by $C_c = \{\overrightarrow{m_{c1}}, \ldots, \overrightarrow{m_{ck}}\}$. In each C_c, the output value y_{ci} is assigned to the corresponding center m_i, indicating the class label c. When presented with an input pattern $\overrightarrow{x}$, the output value y_b of the best matching center $(\overrightarrow{m_b})$ is selected as the network's output, where b is obtained by minimizing the Euclidean distance between $\overrightarrow{x}$ and $\overrightarrow{m}_i$, $b = \arg\min_i \left\| \overrightarrow{x} - \overrightarrow{m}_i \right\|$. It is crucial to emphasize that the clustering or quantization process is carried out independently for each class, treating the data from different classes (c_i and c_j, where $i \neq j$) as separate entities. If two distinct classes have closely situated regions with a high density of data, two separate cluster centers will be assigned to them. If the entire training set had not been divided, only a single cluster could have been formed.

3.3. Feature selection by entropy-weight

This study uses the entropy-weight approach to find the important features in each segment. Entropy-weight, which is rooted in Shannon entropy theory, was first introduced by Shannon and Weaver in 1949 [36]. Entropy-weight measures the degree of uncertainty in information using Shannon's concept of entropy. Entropy, a measure of uncertainty used in information theory, is determined by the distribution of a specific probability P_i. This particular approach is primarily employed to assess the disparity between criteria. Shannon's formula for quantifying this uncertainty is defined in Equation (1) and Equation (2).

$$E_i = S(P_1, P_2, \dots, P_n) = -k \sum_{i=1}^{n} [P_i - Ln\ P_i] \tag{1}$$

where

$$-k \sum_{i=1}^{n} [P_i - Ln\ P_i] = -k\left\{\frac{1}{n} Ln \frac{1}{n} + \frac{1}{n} Ln \frac{1}{n} + \dots + \frac{1}{n} Ln \frac{1}{n}\right\} = -k\left\{Ln \frac{1}{n}\left(\frac{n}{n}\right)\right\} = -k \times Ln \frac{1}{n} \tag{2}$$

A constant value, denoted as k is utilized to calculate the values of E_i, which range between zero and one. The specific value of k can be derived using Equation (3).

$$k = \frac{1}{Ln\ (m)} \tag{3}$$

The response matrix depicted in Fig. 1 incorporates data that can be evaluated using entropy as a criterion. It represents a matrix that encompasses n criteria and m respondents.

The calculation of P_{ij} in accordance with the given equation is performed using the provided decision-making matrix (see Equation (4)).

$$P_{ij} = \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}} \tag{4}$$

The entropy of the j^{th} index, denoted as E_j, is computed using Equation (5).

$$E_j = -k \sum_{i=1}^{m} \left[P_{ij}\ Ln\ P_{ij}\right] \tag{5}$$

The degree of uncertainty or deviation, represented as d_j, signifies the importance of the j th criterion for the decision maker. The value of d_j is obtained using Equation (6).

$$d_j = 1 - E_j \tag{6}$$

Consequently, the weight of each criterion can be determined using Equation (7).

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{7}$$

3.4. ANFIS

This study aims to reveal the importance levels of factors for customers' satisfaction with CRM systems. This study used the ANFIS technique [37] to assess the importance level of security satisfaction dimensions. ANFIS, which takes advantage of neural networks and fuzzy logic, has been shown to be effective in modeling systems based on inputs and outputs. Fuzzy logic represents inference techniques that can reason and pattern in a manner similar to human reasoning algorithms when applied to knowledge-based systems. Using ANFIS, prediction issues can be solved with a high degree of accuracy through the use of human knowledge and experience in modeling and eliciting rules from data without prior assumptions. To implement ANFIS for the assessment of customers' satisfaction with CRM systems, several steps were performed which are shown in Fig. 2. As seen from this figure, a five-layer ANFIS is considered for predicting customers' satisfaction (see Fig. 3).

	C_1	C_2	…	C_n
N_1	a_{11}	a_{12}	…	a_{1n}
N_2	a_{21}	a_{22}	…	a_{2n}
.	.	.	⋱	.
.	.	.		.
.	.	.		.
N_m	a_{m1}	a_{m2}	…	a_{mn}
W_j	W_1	W_2	…	W_n

Fig. 1. Response matrix.

4. Data collection and data analysis

This study aims to investigate customers' satisfaction with CRM systems through online reviews. We collected 6432 online customers' reviews from 8 CRM systems in the Google play store platform. The textual data as well as numerical ratings which indicate the customers' satisfaction were collected. Examples of users' reviews on CRM apps are presented in Table 1 in Appendix A. Determining the number of topics (*K*) in LDA is a critical step in topic modeling, and selecting an appropriate value for *K* requires careful consideration [67–69]. The data were pre-processed (e.g., text cleaning, stemming, stop-word removal) [70]. In our study, we utilized perplexity as a key metric to determine the most suitable number of topics for our LDA model. By comparing perplexity scores across LDA models with varying topic numbers, we identified the configuration that provided the best fit to our dataset, ensuring a balanced representation of the underlying topics within the text data. In addition, short reviews were excluded from the collected data. Furthermore, the reviews for the English language were kept in the dataset. After data cleaning, 5172 reviews remained in the dataset for further analysis by the proposed method.

The method was executed on a Windows 10 operating system with an Intel Core i7-6700HQ CPU. To assess the model's performance, 5-fold cross-validation was employed. This technique involves dividing the training sample into five equal portions, with the entire sample being used. The model is trained on four of these portions and then tested on each individual portion in the fifth fold. Cross-validation is a widely recognized technique for the evaluation of a machine learning model's performance [71,72].

LDA was applied to the online customers' reviews to discover the main topics. The results are shown in Table 1. As seen from this table, 31 factors were detected from the textual data which are accuracy, completeness, timeliness, data visualization, data export and reporting, data privacy, data analytics, data accessibility, consistency, relevance, reliability, performance, user permissions and security, usability, compatibility, offline access, system updates and maintenance, backup and recovery, integration capabilities, scalability, user interface, ease of use, adaptability, responsiveness, user training and support, customization and personalization, continuous improvement and updates, collaboration and communication features, user satisfaction and feedback, collaboration and community, and documentation and help resources. These factors were categorized into three dimensions: information quality, system quality, and service quality.

The data for customers' satisfaction was segmented using LVQ. The data included five classes: "Very Low", "Low", "Moderate", "High" and "Very High". In this case, the number of clusters per dataset class was chosen to be 3. To facilitate the learning process, a learning rate of 0.005 was set in the LVQ algorithm. Distance normalization was performed using variance as a metric. As a result, a total of 15 clusters were generated from the data based on the predefined number of clusters. These clusters are represented by their centroids, and you can find the details of these centroids in Table 2 in Appendix A. Note that the cluster sizes are 671, 209, 169, 251, 355, 395, 479, 250, 158, 85, 407, 539, 655, 168, and 381 for Segments 1–15. The results of clustering are visualized in Fig. 4a and b. Customers' satisfaction levels in 15 segments are presented in Table 4 of Appendix A.

The feature selection was performed by entropy-weight in 15 segments. The results of the feature selection are shown in Table 2. The higher values for entropy-weight indicate the importance of the features in each segment. For example, in Segment 1, in the information quality dimension, Timeliness, Consistency, and Data Analytics; in Segment 2, in the system quality dimension, Backup and Recovery, Integration Capabilities, and User Interface; and in Segment 3, in the service quality dimension, User Training and Support, User Satisfaction and Feedback and Collaboration and Communication Features are the most important factors which have influenced customers' satisfaction with CRM systems. In Segment 15, in information quality dimension, Consistency, Accuracy, and Data Accessibility; in Segment 2, in system quality dimension, System Updates and Maintenance, Reliability and Backup and Recovery; and in Segment 3, in service quality dimension, Customization, and Personalization, Collaboration, and Communication Features and Responsiveness are the most important factors which have influenced customers' satisfaction with CRM systems.

ANFIS was developed for 15 segments. The most important factors (top-5) in each group were used in ANFIS. The ANFIS models were trained by Gaussian membership functions. This type of membership function is widely used in decision-making systems [73,74].

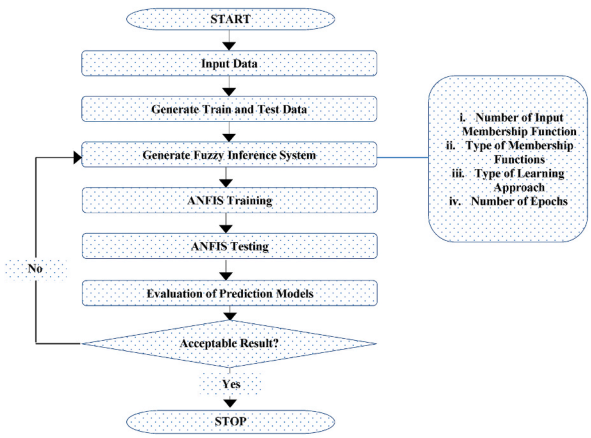

Fig. 2. Flowchart of ANFIS procedure.

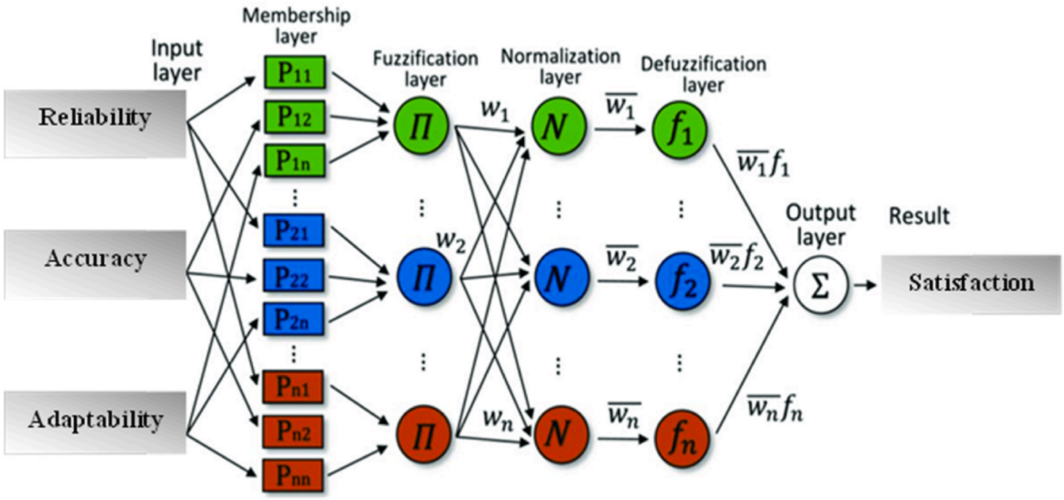

Fig. 3. Five-layer ANFIS model.

Table 1
Topics and factors discovered from online customers' reviews.

Dimensions	Indicators
Information Quality	→ Accuracy
	→ Completeness
	→ Timeliness
	→ Data Visualization
	→ Data Export and Reporting
	→ Data Privacy
	→ Data Analytics
	→ Data Accessibility
	→ Consistency
	→ Relevance
System Quality	→ Reliability
	→ Performance
	→ User Permissions and Security
	→ Usability
	→ Compatibility
	→ Offline Access
	→ System Updates and Maintenance
	→ Backup and Recovery
	→ Integration Capabilities
	→ Scalability
	→ User Interface
	→ Ease of Use
	→ Adaptability
Service Quality	→ Responsiveness
	→ User Training and Support
	→ Customization and Personalization
	→ Continuous Improvement and Updates
	→ Collaboration and Communication Features
	→ User Satisfaction and Feedback
	→ Collaboration and Community
	→ Documentation and Help Resources

In addition, 200 epochs were used to develop the prediction models. The ANFIS models are evaluated using RMSE and R^2 evaluation metrics [69] (see Equation (8) and Equation (9)).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \left(\mathbf{Actual\ Sf_i} - \widehat{\mathbf{Predicted\ Sf_i}}\right)^2}{\mathbf{N}}} \tag{8}$$

Table 2
The importance of factors in each segment.

Factors	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5	Segment 6	Segment 7	Segment 8	Segment 9	Segment 10	Segment 11	Segment 12	Segment 13	Segment 14	Segment 15
Accuracy	0.910	0.942	0.740	0.444	0.685	0.063	0.117	0.037	0.739	0.155	0.244	0.802	0.230	0.516	0.871
Completeness	0.895	0.541	0.550	0.103	0.914	0.237	0.674	0.588	0.883	0.957	0.597	0.838	0.725	0.476	0.467
Timeliness	0.992	0.829	0.601	0.537	0.850	0.580	0.814	0.532	0.471	0.280	0.142	0.841	0.613	0.592	0.759
Data Visualization	0.381	0.394	0.757	0.247	0.189	0.996	0.015	0.322	0.767	0.853	0.557	0.955	0.187	0.669	0.400
Data Export and Reporting	0.250	0.905	0.828	0.028	0.628	0.820	0.596	0.843	0.637	0.460	0.933	0.510	0.094	0.051	0.305
Data Privacy	0.789	0.171	0.318	0.661	0.166	0.223	0.459	0.419	0.235	0.403	0.907	0.888	0.543	0.549	0.276
Data Analytics	0.946	0.876	0.344	0.481	0.675	0.859	0.056	0.670	0.097	0.669	0.224	0.908	0.475	0.239	0.606
Data Accessibility	0.451	0.435	0.330	0.191	0.469	0.018	0.934	0.638	0.863	0.719	0.326	0.011	0.598	0.625	0.763
Consistency	0.959	0.314	0.635	0.818	0.879	0.736	0.249	0.968	0.925	0.345	0.124	0.128	0.386	0.654	0.935
Relevance	0.595	0.389	0.764	0.056	0.039	0.349	0.158	0.276	0.301	0.747	0.656	0.684	0.575	0.788	0.569
Factors	**Segment 1**	**Segment 2**	**Segment 3**	**Segment 4**	**Segment 5**	**Segment 6**	**Segment 7**	**Segment 8**	**Segment 9**	**Segment 10**	**Segment 11**	**Segment 12**	**Segment 13**	**Segment 14**	**Segment 15**
Reliability	0.017	0.476	0.090	0.920	0.276	0.657	0.287	0.345	0.546	0.563	0.138	0.500	0.037	0.240	0.946
Performance	0.389	0.473	0.573	0.648	0.333	0.088	0.018	0.813	0.683	0.016	0.848	0.468	0.583	0.195	0.719
User Permissions and Security	0.149	0.743	0.520	0.118	0.519	0.234	0.990	0.870	0.239	0.443	0.053	0.057	0.741	0.228	0.175
Usability	0.474	0.501	0.497	0.961	0.736	0.376	0.336	0.667	0.430	0.387	0.632	0.419	0.830	0.761	0.222
Compatibility	0.002	0.334	0.817	0.827	0.439	0.724	0.505	0.553	0.097	0.242	0.780	0.366	0.178	0.687	0.310
Offline Access	0.352	0.759	0.658	0.544	0.942	0.719	0.318	0.131	0.269	0.593	0.906	0.896	0.236	0.291	0.455
System Updates and Maintenance	0.542	0.430	0.144	0.175	0.093	0.965	0.881	0.389	0.039	0.540	0.848	0.138	0.427	0.615	0.992
Backup and Recovery	0.949	0.018	0.588	0.509	0.523	0.363	0.637	0.920	0.114	0.549	0.241	0.635	0.731	0.984	0.824
Integration Capabilities	0.907	0.254	0.786	0.616	0.233	0.933	0.286	0.983	0.692	0.381	0.423	0.545	0.489	0.525	0.262
Scalability	0.613	0.669	0.113	0.936	0.302	0.828	0.998	0.521	0.240	0.308	0.021	0.150	0.232	0.310	0.390
User Interface	0.900	0.600	0.323	0.659	0.544	0.523	0.289	0.847	0.105	0.577	0.940	0.931	0.053	0.186	0.716
Ease of Use	0.742	0.249	0.150	0.888	0.164	0.609	0.267	0.147	0.116	0.993	0.827	0.743	0.923	0.763	0.136
Adaptability	0.277	0.529	0.450	0.183	0.132	0.290	0.544	0.343	0.327	0.127	0.233	0.855	0.426	0.327	0.054
Factors	**Segment 1**	**Segment 2**	**Segment 3**	**Segment 4**	**Segment 5**	**Segment 6**	**Segment 7**	**Segment 8**	**Segment 9**	**Segment 10**	**Segment 11**	**Segment 12**	**Segment 13**	**Segment 14**	**Segment 15**
Responsiveness	0.394	0.969	0.883	0.989	0.878	0.688	0.801	0.587	0.675	0.661	0.270	0.752	0.945	0.540	0.557
User Training and Support	0.589	0.572	0.004	0.434	0.998	0.956	0.080	0.137	0.054	0.791	0.219	0.400	0.316	0.915	0.518
Customization and Personalization	0.493	0.219	0.446	0.936	0.701	0.829	0.440	0.923	0.830	0.915	0.974	0.531	0.221	0.549	0.974
Continuous Improvement and Updates	0.231	0.612	0.922	0.077	0.977	0.553	0.385	0.892	0.113	0.272	0.356	0.689	0.768	0.767	0.541
Collaboration and Communication Features	0.541	0.909	0.341	0.867	0.089	0.229	0.649	0.430	0.776	0.612	0.633	0.685	0.135	0.078	0.963
User Satisfaction and Feedback	0.565	0.138	0.003	0.480	0.670	0.929	0.253	0.705	0.038	0.079	0.340	0.415	0.412	0.309	0.530
Collaboration and Community	0.367	0.532	0.399	0.231	0.613	0.402	0.272	0.399	0.127	0.752	0.989	0.759	0.620	0.835	0.326
Documentation and Help Resources	0.045	0.809	0.546	0.473	0.272	0.613	0.960	0.950	0.894	0.129	0.747	0.302	0.109	0.979	0.030

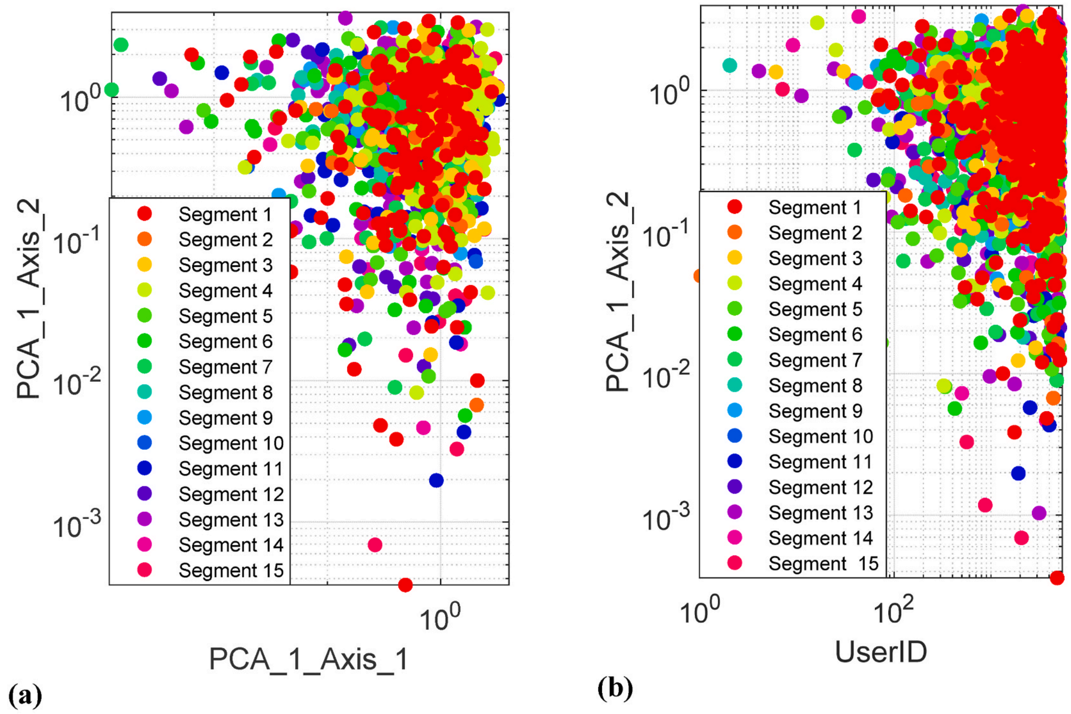

Fig. 4. The results for (a) 15 segments and (b) user and the segments.

$$\mathbf{R}^2 = \mathbf{1} - \frac{\sum_{\mathbf{i=1}}^{\mathbf{N}} (\mathbf{Actual\ Sf_i} - \widehat{\mathbf{Predicted\ Sf_i}})^2}{\sum_{\mathbf{i=1}}^{\mathbf{N}} (\mathbf{Actual\ Sf_i} - \overline{\mathbf{Actual\ Sf_i}})^2} \tag{9}$$

where **N** is the number of samples at each cluster, $\mathbf{Actual\ Sf_i}$ denotes the real satisfaction level, $\widehat{\mathbf{Predicted\ Sf}}_i$ denotes the predicted satisfaction level, $\overline{\mathbf{Actual\ Sf_i}}$ is the mean value of **Actual Sf**.'

In Fig. 5, the RMSE results for 15 segments in ANFIS models are presented. The results are obtained for 150 epochs in ANFIS using the hybrid learning algorithm. According to the results, the minimum RMSE is about 0.135 for Segment 5 and the maximum RMSE is about 0.242 for Segment 2, indicating that ANFIS models are well-trained using the data in each segment. The average result for the

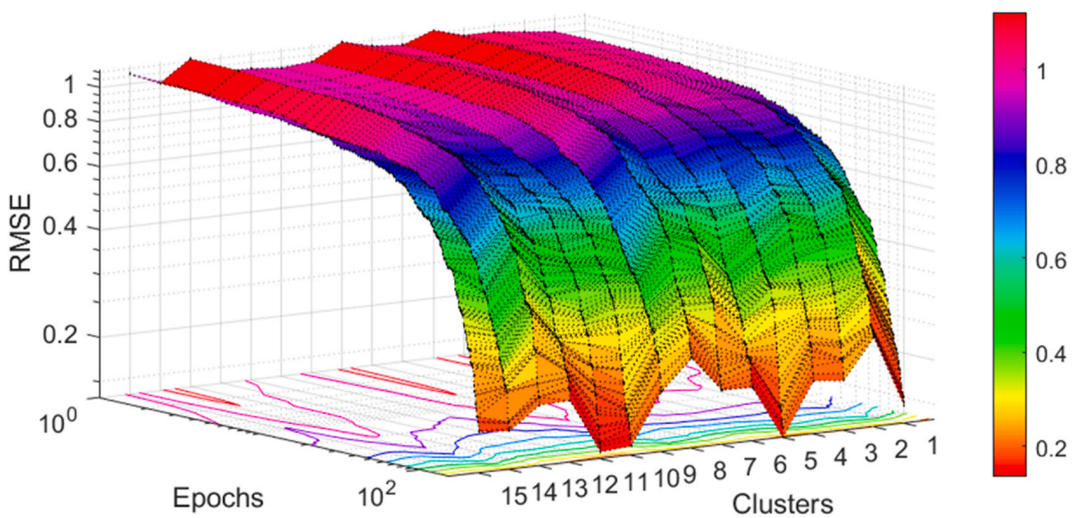

Fig. 5. RMSE for 15 segments in ANFIS models.

proposed method is presented in Table 3. In this table, the results of RMSE and R^2 are compared with the other learning techniques. For the comparisons, different membership functions are considered in ANFIS models. In addition, those methods are trained for two types of learning algorithms (Hybrid and Backpropagation) with different membership functions in ANFIS.

As seen from Table 3, LVQ + ANFIS (Hybrid) with Gaussian MFs, LVQ + ANFIS (Hybrid) with Triangular MFs, LVQ + ANFIS (Hybrid) with Trapezoidal MFs, ANFIS (Backpropagation) with Gaussian MFs, ANFIS (Backpropagation) with Triangular MFs, and ANFIS (Backpropagation) with Trapezoidal MFs were assessed using the collected data. According to the results, LVQ + ANFIS (Hybrid) with Gaussian MFs provide the best results for RMSE and R^2 (RMSE = 0.1932; R^2 = 0.9911), followed by LVQ + ANFIS (Hybrid) with Triangular MFs, LVQ + ANFIS (Hybrid) with Trapezoidal MFs, ANFIS (Backpropagation) with Gaussian MFs, ANFIS (Backpropagation) with Triangular MFs, and ANFIS (Backpropagation) with Trapezoidal MFs. This outcome indicated that the methods which use Hybrid, as well as Gaussian MFs, can better predict customers' satisfaction. Further, the Hybrid algorithm in ANFIS is more reliable in constructing the prediction models compared with the Backpropagation algorithm.

We also performed sensitivity analysis in ANFIS [75,76] which helps in understanding how variations in input data or model parameters affect the model's output. This will provide valuable insights into the model's reliability, its sensitivity to different inputs, and its generalizability. Specifically, we used variance-based global sensitivity analysis in ANFIS. The sensitivity analysis showed that Accuracy has the greatest impact on customers' satisfaction and Scalability was the least sensitive input.

5. Research implications

Based on the three dimensions of information quality, system quality, and service quality discovered from online reviews of CRM systems, the following research implications are derived for managers.

The first implication of this research is regarding the information quality dimensions in CRM systems. Our research results reveal the following key insights. In Segment 1, attributes such as Timeliness, Consistency, and Data Analytics within the information quality dimension held the most substantial influence. In Segment 2, focusing on system quality, crucial factors included Backup and Recovery, Integration Capabilities, and User Interface. Similarly, Segment 3, centered around service quality, highlighted the pivotal roles of User Training and Support, User Satisfaction and Feedback, along with Collaboration and Communication Features in shaping customer satisfaction with CRM systems. These trends were consistently observed in Segment 15, emphasizing the importance of attributes like Consistency, Accuracy, Data Accessibility, System Updates and Maintenance, Reliability, Backup and Recovery, Customization, Personalization, Collaboration and Communication Features, and Responsiveness in influencing overall customer satisfaction with CRM systems. The importance of the information provided by CRM systems, which is both accurate and relevant, is emphasized by the information quality dimensions [77,78]. Clients and businesses both will be impacted if employees utilizing a CRM system fail to exchange meaningful, on-time, or reliable customer information [79]. Previous research has widely emphasized the impact of different information quality dimensions on customers' satisfaction in online business systems. For example, the absence of a suitable infrastructure can lead to several integration and operational issues that hinder the CRM system from improving the quality of client information [79]. CRM systems can obtain timely, up-to-date, correct, accurate, complete, and relevant data or information from numerous inner and outer sources thanks to a firm's benevolent infrastructure abilities and in agreement with those systems. This facilitates the CRM systems' efficient integration and processing of the data or information. These quality dimensions also include several indicators in which reliability and accuracy have been the focus of a large number of researches. The reliability and accuracy of the data that is communicated via the CRM system should be the primary focus of the managers of the organization. In CRM systems, several critical steps must be taken into account to ensure the accuracy of the data, including the reduction of the number of errors or inconsistencies and the implementation of efficient processes for validating the data. In order to accurately extract valuable insights from customer data, it is crucial for managers to invest in reliable data analytics tools and techniques. By doing so, they can improve their decision-making processes and offer customers through CRM systems more individualized experiences.

The second implication of this research is regarding the optimization of system quality in CRM systems. System quality in information systems is mainly referred to as the system's overall functionality, performance, and usability [78,80]. This dimension can have a significant impact on customer satisfaction in CRM systems. As seen from the results of our study, critical indicators such as reliability, performance, user permissions, security, usability, and compatibility have been discovered for this dimension from online customers' reviews using the text mining technique. In order to optimize the CRM system's performance, managers should prioritize the continual enhancement of the CRM system's technical aspects, such as the user interface, responsiveness, and usability. The CRM system must be simple to use and effective for users, requiring less time and effort to access and use customer information. Therefore, it is essential to perform routine monitoring, maintenance, and updates on the system in order to address any performance issues and

Table 3
RMSE and for R^2 the method comparisons.

Method	RMSE	R^2
LVQ + ANFIS (Hybrid) + Gaussian MFs	0.1932	0.9911
LVQ + ANFIS (Hybrid) + Triangular MFs	0.2893	0.9821
LVQ + ANFIS (Hybrid) + Trapezoidal MFs	0.2974	0.9742
ANFIS (Backpropagation) + Gaussian MFs	0.4353	0.9598
ANFIS (Backpropagation) + Triangular MFs	0.4621	0.9521
ANFIS (Backpropagation) + Trapezoidal MFs	0.4832	0.9438

guarantee that operations run smoothly.

The third implication of this research is regarding the enhancement of service quality [81] in CRM systems. Previous literature has endorsed the connection between service quality, client satisfaction, client retention, and client commitment. Although the variables affecting service quality may vary depending on the type of service, the relationship between service quality and these desirable outcomes is constant. Client satisfaction is influenced by service quality, while client retention is influenced by client satisfaction. Numerous researches have discovered that client satisfaction also functions as a mediating factor in the relationship between service quality and client commitment [82]. Thus, the literature demonstrates that long-standing relationships with clients and service quality are directly related. Service quality is defined as the clients' full comprehension of how they feel when obtaining services involving information and the value of the outcomes of those services [83]. It also relates to the client's assessment of the procedure for receiving information services as well as the results of those services. The level of support, assistance, and responsiveness that is provided to customers through the CRM system is referred to as the service quality which is an important aspect of the overall quality of information systems. As a result, the primary goal of managers ought to be focused on improving customer service procedures, such as providing prompt responses to inquiries or problems, engaging in personalized interactions, and engaging in practices that effectively manage customer relationships. By incorporating feedback mechanisms into the CRM systems, managers are better able to address customer concerns and maintain high-quality service.

The fourth implication of this study stresses the effectiveness of user-generated content in understanding clients' experiences. The integration of the internet into an individual's daily life, which has been fueled by the advancement of digital technologies, has drastically changed the behaviors of internet users and increased their reliance on online review sites in particular. Under the pretext of online review venues, virtual settings enabled users to create and consume User-Generated Content (UGC). Customers who are driven by the desire to assist other customers can express their ideas and assessments of goods and services by creating UGC. Customers can learn more about business performance and product value by reading online reviews, which also help them feel more confident about their assessment of the product or service quality. Numerous academics have noticed the value of online reviews and have researched how the quantity and quality of online reviews affect product sales [84]. In order to help consumers successfully and precisely extract pertinent information from a large number of data, numerous resources have been utilized to address the issues of information overload and to aid customers reach the right decision. Online reviews are among these resources with primarily cover the sentimental tendencies of other clients and reflect product characteristics to help the user to reach the right decision based on other clients' views and perceptions [85]. This study revealed that online reviews offer valuable insights into user needs for CRM systems by presenting a rich source of feedback and opinions from real users, helping organizations gain a deeper understanding of customer preferences, pain points, and expectations. The study also highlights the necessity of using various analytics approaches on UGC to derive practical insights into customers' experiences. Although text mining techniques have been widely applied in a variety of contexts to understand users' experiences [30,86], their implementation in CRM apps has been rather rare. CRM apps have the power to unearth valuable insights concealed within customer comments, reviews, and social media posts by employing text-mining algorithms on UGC. These techniques enable the extraction and examination of textual data, endowing organizations with a deeper comprehension of their clients' sentiments, inclinations, and perspectives. Despite the proven effectiveness of text mining in various domains, its utilization within the realm of CRM apps has been constrained. Recognizing the untapped potential of these strategies can propel the industry forward, empowering CRM apps to harness the robustness of UGC analysis and generate invaluable customer revelations.

6. Conclusion and future study

Previous studies have extensively investigated the impact of CRM systems on customer satisfaction [13,87,88]. However, there is a gap in the research when it comes to assessing the quality dimensions of these systems in alignment with an organization's CRM strategy. To address this gap, we investigated customer satisfaction with CRM systems by the analysis of 5172 online customer reviews from 8 CRM systems. Using LDA, the satisfaction factors were extracted and categorized into three dimensions: information quality, system quality, and service quality. Then we used LVQ for data segmentation. The feature selection was conducted through the entropy-weight approach to select the most important features in each segment. To predict the customers' satisfaction in each segment through the selected features, ANFIS was utilized to assess the relationship between these dimensions and customer satisfaction. The proposed method (LVQ + ANFIS (Hybrid) + Gaussian MFs) was compared with different ANFIS models with or without LVQ. This outcome indicated that the methods which use Hybrid, as well as Gaussian MFs, could better predict customers' satisfaction. Further, the Hybrid algorithm in ANFIS was more reliable in constructing the prediction models compared with the Backpropagation algorithm. The findings of this study shed light on the levels of customer satisfaction connected to various CRM systems and offer insightful information about the elements that influence customer satisfaction in terms of information quality, system quality, and service quality. These findings have implications for businesses looking to enhance customer satisfaction and CRM strategies. By being aware of specific factors that influence customer satisfaction, businesses can better adapt their CRM systems to meet customer needs. This will accordingly lead to better customer relationships, increased profitability, and increased customer value. It is important to recognize the limitations of this study even though it has offered insightful information about customers' satisfaction with CRM systems through online reviews. It is important to take into account these limitations in order to fully comprehend the research results and to identify potential research directions. First, the data collection process solely relied on user reviews from the Google Play Store platform. The collected reviews might not be representative of all customers or might be influenced by a particular group of users. Therefore, the generalizability of the findings to the broader customer base could be limited. In addition, data segmentation plays an important role in identifying customers' preferences. Thus, developing sophisticated segmentation methods through the analysis of online customers' reviews is important. Therefore, the method for data segmentation can be improved with optimization machine techniques [89–92] to better cluster the customers' reviews based on their similarities. Another limitation is that individual learning approaches were used in this study in segmentation and prediction tasks which can be extended for ensemble learning approaches. Ensemble learning can reduce errors, enhance predictive performance, and provide stability and robustness to the learning process compared to a single model. In light of these limitations, future research endeavors may focus on broadening data sources, refining segmentation methods, and exploring ensemble learning approaches to further enhance our understanding of customer satisfaction with CRM systems. Addressing these limitations will undoubtedly contribute to more comprehensive and reliable insights in the field.

Data availability statement

Sharing research data helps other researchers evaluate your findings, build on your work and to increase trust in your article. We encourage all our authors to make as much of their data publicly available as reasonably possible. Please note that your response to the following questions regarding the public data availability and the reasons for potentially not making data available will be available alongside your article upon publication.

Has data associated with your study been deposited into a publicly available repository? No.

Please select why. Please note that this statement will be available alongside your article upon publication.

Data will be made available on request.

CRediT authorship contribution statement

Mehrbakhsh Nilashi: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rabab Ali Abumalloh:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hossein Ahmadi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Investigation, Conceptualization. **Sarminah Samad:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Conceptualization. **Mesfer Alrizq:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Investigation, Conceptualization. **Hamad Abosaq:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Investigation, Conceptualization. **Abdullah Alghamdi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. A

Table 1
Examples of Users' Reviews on CRM apps

Online customers' reviews
→ Great app, great design, simple to understand and use, and the support is amazing. Being the head of a real estate brand, and having to sign up for the professional package is great, and then getting the team leaders into the same package, great. But, now they expect everyone in the company to sign up for the same package even though they don't need all the bells and whistles … Practically and economically makes no sense …. Surely they can allow their clients to alternate between users.
→ I have been using pipedrive since about February (6 months) it is definitely helping me with my work, organizing connecting with customers, and trying to find them. In the last couple months i have lost the ability with the phone app to delete tasks, and discard does nothing, this may be an administrative thing but all of my managers made no changes and don't know how to fix it. therefore I'm giving 4 stars, not 5. It is still functional but I have to work around it. edit Aug 12: the fix worked!
→ Excellent Business game changer but Calendar Sync Leaves App as Untrustworthy. I have massively reduced my time and the complications arisen from my original setup for my business due to easy autonomous integration of this with AutoEntry and Quickbooks. However I can't trust the calendar

(*continued on next page*)

Table 1 (*continued*)

as it doesn’t seem to sync everything from my Google Business calander so it’s made it a bad choice for peace of mind task tracking which if it wasn’t for this would of recieved 5 stars as its an amazing app!

→ This is hands down the best CRM I’ve ever used. Highly recommend it for small business that need to manage their clientele. As long as you honor this price packages I guarantee Salesmate group will succeed in knocking out the competition. Love the chatbot function and the fact I can add my own HTML templates. The most impressive part is that it tracks my email links and it tells me where my customer click, and my open rates are 40 %. I’m 100 % SOLD.

→ This CRM does it all, and it has the best price. I’ve looked at them all. I use it every single day in the insurance biz. The support is also phenomenal. I use this app to make calls, send text messages, track my emails, and much more. This is a unicorn when it comes to price and functionality.

→ Best CRM on the market! We tried a few different CRMs before Salesmate and non of them were quite right for our work flow. Salesmate was a perfect match. Really customizable, easy to use and the customer support is 10/10. Would highly recommend giving them a go.

→ Excellent App. Customer care service is very quick. Best app on play store to keep in touch with your customers on a stipulated time period. Different strategies can be formed to deal with customers. Very innovative ideas built in this app. And most important, the developers of the app continue adding lot of new features. Many congratulations to all team if 3 sigma CRM.

→ Salesforce is great. It’s app for Android is awful though. It’s slow, bloated, lacks user-friendly UI, and some of the most basic things like a back button. Even using the back button on my Galaxy phone does nothing. SFDC, if you’re reading this, please redesign from the ground up.

→ I’ve tried multiple times to install this app. Installation works, and I attempt to login. After entering the verification code I get a white screen that never goes away. It’s totally blank. I close it and get the white screen. I restart the device and try again to get the white screen again. I use a Samsung Notr 9. It’s absurd that a company this size can’t get it’s act together and provide a working mobile app.

→ All reports can easily be accessed on one platform and saves time especially when one is looking for the right information regarding a client. The platform also allows for updates for example changes in personal care, medication, reports For one to be familiar with sales force the platform gives instruction manuals that are easy to follow especially on how to go about the tasks like recording shift reports, appointments, incidences among other tasks required. Salesforce is a one stop shop.

→ App auto-updated itself with the permission to do so turned off. This makes me question what else this spyware app is doing without my explicit permission.

→ This app did not work on my Galaxy 22 and it does not work on my Galaxy S23 Ultra. Please update for Samsung devices.

Table 2
Cluster centroids

Attribute	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5	Segment 6	Segment 7	Segment 8	Segment 9	Segment 10	Segment 11	Segment 12	Segment 13	Segment 14	Segment 15
C1	0.639628	0.5510	0.3771	0.3669	0.5309	0.6328	0.4013	0.3787	0.5230	0.3566	0.5912	0.4792	0.5515	0.3257	0.3931
C2	0.5168	0.3609	0.3548	0.3900	0.4868	0.5739	0.5994	0.6712	0.6487	0.5758	0.5336	0.5151	0.3639	0.4580	0.3951
C3	0.6024	0.3657	0.6341	0.3368	0.4268	0.3820	0.4444	0.5350	0.4211	0.3158	0.5463	0.4071	0.6115	0.3825	0.6717
C4	0.4655	0.3273	0.3629	0.5322	0.6179	0.5161	0.6130	0.6237	0.3528	0.2857	0.4740	0.4593	0.4371	0.6145	0.4743
C5	0.5006	0.5515	0.4013	0.4889	0.4645	0.4036	0.6496	0.5618	0.6955	0.5234	0.5498	0.3790	0.5410	0.5602	0.4473
C6	0.5408	0.6203	0.3471	0.3487	0.3355	0.5802	0.4311	0.5552	0.3638	0.3713	0.3321	0.6153	0.5537	0.6197	0.5768
C7	0.5252	0.6672	0.3627	0.4825	0.4234	0.5777	0.4791	0.5109	0.5181	0.3350	0.5209	0.4704	0.4607	0.3671	0.6278
C8	0.5256	0.5343	0.5822	0.3808	0.3447	0.5323	0.6469	0.4888	0.4029	0.5214	0.5611	0.6883	0.4001	0.3333	0.3644
C9	0.4389	0.5048	0.3405	0.4157	0.6299	0.4738	0.6045	0.4808	0.3753	0.3053	0.4862	0.5424	0.5923	0.3484	0.4140
C10	0.5668	0.5715	0.5980	0.3322	0.5897	0.6283	0.5021	0.3876	0.6112	0.4143	0.3417	0.4456	0.5150	0.5888	0.4006
C11	0.4248	0.6360	0.5104	0.5411	0.4705	0.6624	0.6658	0.3714	0.5525	0.6149	0.3914	0.4229	0.3875	0.6772	0.5893
C12	0.5141	0.6095	0.3989	0.3995	0.5601	0.4281	0.4638	0.5632	0.5680	0.4818	0.4733	0.5529	0.5085	0.5351	0.3555
C13	0.4505	0.3675	0.6970	0.4525	0.5907	0.5644	0.4069	0.6447	0.5976	0.3864	0.4176	0.6189	0.4959	0.3543	0.4649
C14	0.6026	0.6663	0.6124	0.5521	0.3912	0.4228	0.5098	0.4559	0.3865	0.3648	0.5794	0.6148	0.4809	0.4178	0.3528
C15	0.3857	0.6302	0.4435	0.6366	0.4876	0.3873	0.5685	0.4019	0.4984	0.6538	0.4144	0.5654	0.6285	0.3889	0.5561
C16	0.5592	0.5808	0.5015	0.5962	0.3941	0.3659	0.6311	0.3376	0.4996	0.3458	0.4937	0.5589	0.4984	0.4907	0.4569
C17	0.4955	0.6857	0.6327	0.4912	0.3603	0.4335	0.5860	0.4779	0.6168	0.5793	0.3776	0.3865	0.5443	0.4296	0.6067
C18	0.6095	0.5675	0.3147	0.5589	0.5621	0.5559	0.5872	0.4077	0.2979	0.3971	0.3649	0.5124	0.4547	0.4083	0.6062
C19	0.5392	0.4785	0.6131	0.3879	0.4712	0.5846	0.4978	0.3963	0.5423	0.4012	0.6135	0.3628	0.5828	0.4690	0.4746
C20	0.5470	0.5907	0.4421	0.3460	0.6680	0.4951	0.4948	0.3681	0.6003	0.5176	0.5299	0.4614	0.3986	0.4107	0.6626
C21	0.3345	0.6566	0.6156	0.5223	0.4948	0.6204	0.5354	0.6075	0.6595	0.6399	0.5755	0.5131	0.3885	0.4413	0.5643
C22	0.6258	0.5450	0.6081	0.6138	0.4956	0.5811	0.5748	0.2960	0.5316	0.3533	0.5171	0.4524	0.3788	0.3113	0.5024
C23	0.5245	0.4519	0.5050	0.4585	0.6927	0.5052	0.4227	0.6188	0.6174	0.5707	0.4014	0.4038	0.5036	0.6841	0.5268
C24	0.5147	0.3365	0.6539	0.6182	0.4489	0.4986	0.4811	0.5248	0.4886	0.6542	0.6278	0.4115	0.4525	0.4247	0.5363
C25	0.3489	0.4814	0.6298	0.6120	0.4525	0.6471	0.3793	0.4879	0.2826	0.5066	0.5428	0.6470	0.4849	0.4461	0.5722
C26	0.4744	0.3553	0.4704	0.5371	0.5237	0.4125	0.5042	0.5045	0.5122	0.2879	0.6243	0.4975	0.6027	0.4879	0.4493
C27	0.4140	0.5979	0.5782	0.6516	0.3984	0.4403	0.5087	0.6662	0.4400	0.3593	0.6501	0.4545	0.4601	0.4382	0.5625
C28	0.4931	0.5502	0.4293	0.5643	0.5338	0.5690	0.4525	0.3733	0.5377	0.4041	0.6532	0.4641	0.3903	0.5784	0.5527
C29	0.4746	0.6168	0.4936	0.4578	0.5703	0.3670	0.4077	0.5046	0.3493	0.6218	0.5729	0.5473	0.4937	0.4154	0.5884
C30	0.4417	0.4770	0.5046	0.5690	0.5578	0.5510	0.4895	0.6094	0.5917	0.3182	0.3965	0.4814	0.5463	0.5747	0.3948
C31	0.3895	0.4229	0.3528	0.3252	0.5380	0.5087	0.6529	0.5863	0.3420	0.5861	0.5403	0.4404	0.6451	0.3677	0.4994

Note: Accuracy = C1; Completeness = C2; Timeliness = C3; Data Visualization = C4; Data Export and Reporting = C5; Data Privacy = C6; Data Analytics = C7; Data Accessibility = C8; Consistency = C9; Relevance = C10; Reliability = C11; Performance = C12; User Permissions and Security =

C13; Usability = C14; Compatibility = C15; Offline Access = C16; System Updates and Maintenance = C17; Backup and Recovery = C18; Integration Capabilities = C19; Scalability = C20; User Interface = C21; Ease of Use = C22; Adaptability = C23; Responsiveness = C24; User Training and Support = C25; Customization and Personalization = C26; Continuous Improvement and Updates = C27; Collaboration and Communication Features = C28; User Satisfaction and Feedback = C29; Collaboration and Community = C30; Documentation and Help Resources = C31.

Table 3
Customers' satisfaction levels in 15 segments

		Customer Satisfaction Level				
		Very Low	Low	Moderate	High	Very High
		Frequency	Frequency	Frequency	Frequency	Frequency
Segment	c_lvq_1_1	125	144	138	139	125
	c_lvq_1_2	44	38	42	43	42
	c_lvq_1_3	30	34	34	43	28
	c_lvq_2_1	39	61	52	43	56
	c_lvq_2_2	61	83	74	65	72
	c_lvq_2_3	62	94	80	85	74
	c_lvq_3_1	90	115	98	86	90
	c_lvq_3_2	56	66	54	41	33
	c_lvq_3_3	33	33	32	32	28
	c_lvq_4_1	16	19	16	18	16
	c_lvq_4_2	82	85	83	75	82
	c_lvq_4_3	116	112	102	102	107
	c_lvq_5_1	138	147	119	128	123
	c_lvq_5_2	39	36	30	32	31
	c_lvq_5_3	84	62	78	82	75

Table 4
Feature selection results

Factors	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5	Segment 6	Segment 7	Segment 8	Segment 9	Segment 10	Segment 11	Segment 12	Segment 13	Segment 14	Segment 15
The Weights for Information Quality Factors															
C1	0.909	0.942	0.739	0.444	0.685	0.063	0.117	0.037	0.739	0.155	0.244	0.802	0.230	0.516	0.871
C2	0.895	0.541	0.550	0.103	0.913	0.237	0.674	0.588	0.883	0.957	0.597	0.838	0.725	0.476	0.467
C3	0.992	0.829	0.601	0.537	0.850	0.580	0.814	0.532	0.471	0.280	0.142	0.841	0.613	0.592	0.759
C4	0.381	0.394	0.757	0.247	0.189	0.996	0.015	0.322	0.767	0.853	0.557	0.955	0.187	0.669	0.400
C5	0.250	0.905	0.828	0.028	0.628	0.820	0.596	0.843	0.637	0.460	0.933	0.510	0.094	0.051	0.305
C6	0.789	0.171	0.318	0.661	0.166	0.223	0.459	0.419	0.235	0.403	0.907	0.888	0.543	0.549	0.276
C7	0.946	0.876	0.344	0.481	0.675	0.859	0.056	0.670	0.097	0.669	0.223	0.908	0.475	0.239	0.606
C8	0.451	0.435	0.330	0.191	0.469	0.018	0.934	0.638	0.863	0.719	0.326	0.011	0.598	0.625	0.763
C9	0.959	0.314	0.635	0.818	0.879	0.736	0.249	0.968	0.925	0.345	0.124	0.128	0.385	0.654	0.935
C10	0.595	0.389	0.764	0.056	0.039	0.349	0.158	0.276	0.301	0.747	0.656	0.684	0.575	0.788	0.569
The Weights for System Quality Factors															
C11	0.017	0.476	0.090	0.920	0.276	0.657	0.286	0.344	0.546	0.563	0.138	0.500	0.037	0.240	0.946
C12	0.389	0.473	0.573	0.648	0.333	0.088	0.018	0.813	0.683	0.016	0.848	0.468	0.583	0.195	0.719
C13	0.149	0.743	0.520	0.118	0.519	0.234	0.990	0.870	0.239	0.443	0.053	0.057	0.740	0.228	0.174
C14	0.474	0.501	0.497	0.961	0.736	0.376	0.336	0.667	0.430	0.387	0.632	0.419	0.830	0.761	0.222
C15	0.002	0.334	0.817	0.827	0.439	0.724	0.505	0.553	0.097	0.242	0.780	0.366	0.178	0.687	0.310
C16	0.352	0.759	0.658	0.544	0.942	0.719	0.318	0.131	0.269	0.593	0.906	0.896	0.236	0.291	0.455
C17	0.541	0.430	0.144	0.175	0.093	0.965	0.881	0.389	0.039	0.540	0.848	0.138	0.427	0.614	0.992
C18	0.949	0.018	0.588	0.509	0.523	0.363	0.637	0.920	0.114	0.549	0.241	0.635	0.731	0.984	0.824
C19	0.907	0.254	0.786	0.616	0.233	0.933	0.286	0.983	0.692	0.381	0.423	0.545	0.489	0.525	0.262
C20	0.613	0.669	0.113	0.935	0.302	0.828	0.998	0.521	0.240	0.308	0.021	0.150	0.232	0.310	0.390
C21	0.900	0.600	0.323	0.659	0.544	0.523	0.289	0.846	0.105	0.577	0.940	0.931	0.053	0.186	0.716
C22	0.742	0.249	0.150	0.887	0.164	0.609	0.267	0.147	0.116	0.993	0.827	0.743	0.923	0.762	0.136
C23	0.277	0.529	0.450	0.183	0.132	0.290	0.544	0.343	0.327	0.127	0.233	0.854	0.426	0.327	0.053
The Weights for Service Quality Factors															
C24	0.394	0.969	0.883	0.989	0.878	0.688	0.801	0.587	0.675	0.661	0.270	0.752	0.945	0.540	0.557
C25	0.589	0.572	0.004	0.434	0.998	0.956	0.080	0.137	0.054	0.791	0.219	0.400	0.316	0.915	0.518
C26	0.493	0.219	0.446	0.936	0.701	0.829	0.440	0.923	0.830	0.915	0.974	0.531	0.221	0.549	0.974
C27	0.231	0.612	0.922	0.077	0.977	0.553	0.385	0.892	0.113	0.272	0.356	0.689	0.768	0.767	0.541
C28	0.541	0.909	0.341	0.867	0.089	0.229	0.649	0.430	0.776	0.612	0.633	0.685	0.135	0.078	0.963
C29	0.565	0.138	0.003	0.480	0.670	0.929	0.253	0.705	0.038	0.079	0.340	0.415	0.412	0.309	0.530
C30	0.367	0.532	0.399	0.231	0.613	0.402	0.272	0.399	0.127	0.752	0.989	0.759	0.620	0.835	0.326
C31	0.045	0.809	0.546	0.473	0.272	0.613	0.960	0.950	0.894	0.129	0.747	0.302	0.109	0.979	0.030

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