Fuzzy System for Perception Level Estimation in E-Commerce Web Sites

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Abstract **– Customer reviews on e-commerce platforms significantly impact the acceptance of products offered by companies. In this paper we propose a software system based on fuzzy logic for estimating the level of perception of users of e-commerce portals regarding a product or service. The constructed system receives as its first input the level of perception of opinion, determined through sentiment analysis, while the second input is the star rating provided by each user for the product or service. For the development of the proposed fuzzy system, the RAD (Rapid Application Development) methodology was used. The fuzzy system presented in this paper aims to support decision making in the marketing divisions of companies with respect to the products and services offered.**

Keywords **– E-commerce, fuzzy logic, fuzzy system, perception, polarity sentiment analysis.**

1. Introduction

With the accelerated growth of technological media and the evolution of social networks, customers of e-commerce companies have found in online reviews of products and services by other customers a fundamental input to support their decision-making before making a purchase, harnessing the wisdom of the crowd [1], [2], [3].

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In a similar way, e-commerce companies can make use of reviews made by their customers on technological media to characterize purchasing habits and study their preferences based on opinions, aiming to formulate and adjust marketing strategies regarding products and services [1], [4].

One of the techniques belonging to affective computing is sentiment analysis, which allows for a quantitative analysis of qualitative data such as user opinions posted on digital media, obtaining relevant insights regarding the polarity of customer opinions for decision-making and competitiveness within companies [5], [6], [7]. Similarly, opinion mining tools allow decision makers to monitor possible changes in opinions about products and services on social networks, making them an important input in marketing divisions [8], [9], [10].

Sentiment analysis can be defined as a technique that makes use of machine learning (ML) and natural language processing (NLP) models for the determination of the polarity value (negative, neutral or positive) of a text or opinion regarding a product, service, organization or person [11], [12], [13]. In different application contexts, sentiment analysis techniques have been used to analyze the polarity of customer opinions concerning the products and services offered by companies [14], [15], [16], [17]. However, challenges remain in determining intelligible perception levels based on polarity and combining them with traditional methods of perception identification (quantitative perception surveys, star ratings).

The main contribution of this paper is the proposal of a new approach based on fuzzy logic and opinion mining to obtain the degree or level of perception of users with respect to the products and services offered by e-commerce companies. Specifically, the fuzzy system receives as input both the perception level of the opinions expressed about a product or service and the star rating given by the user as a complement to the opinion. The level of perception corresponding to user opinions is determined from the polarities calculated using sentiment analysis techniques.

Similarly, the fuzzy system outputs a perception level per user in numerical and linguistic terms, which is calculated through the logical operation of the fuzzy sets of the mentioned input variables, considering 12 logical inference rules that relate the inputs with the output of the system. The proposed fuzzy logic based system aims to enrich traditional methods of perception determination, which do not take into account the quantitative perception associated with user opinions regarding a product or service.

The fuzzy system was implemented using the jFuzzyLogic library, which enables the specification of fuzzy sets, the definition of inference rules, and the execution of input fuzzification and output defuzzification processes. Similarly, for the calculation of the perception level of the opinion, the advantages provided by the VaderSentiment library for sentiment analysis were utilized. Finally, the fuzzy system was evaluated through a proof of concept carried out using comments and star ratings obtained through web scraping techniques from the Ebay website. The fuzzy system presented in this article can be used as a reference to support the marketing divisions of companies in conducting customer perception studies, so that companies can obtain not only quantitative but also qualitative feedback about the products and services offered, in order to define marketing strategies.

The rest of the article was organized as follows: in section 2, the methodology considered in this work was presented. In section 3, the results obtained were described, in such a way that both the graphical interface of the system and the results of the proof of concept conducted were presented. Finally, in section 4 the conclusions and future work obtained in this work are presented.

2. Methodology

To develop the research presented in this paper, an adaptation of the Rapid Application Development (RAD) methodology was carried out. The RAD methodology follows an iterative and incremental approach and consists of four phases: requirements planning, prototype design, iterative construction, and evaluation (Figure 1) [18], [19], [20].

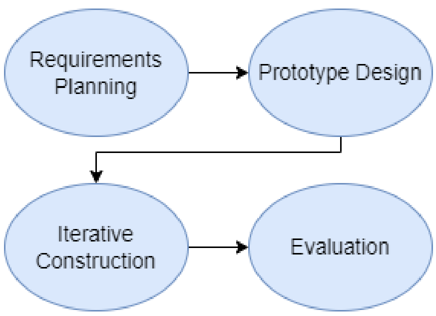

Figure 1. Methodology considered

In the requirements planning phase, the variables identified for the inputs and output were specified, as shown in Table 1.

Table 1. Input and output variables of the system

Variable	Description	Ranges
rating	It is the first input to the system and corresponds to the star rating assigned by users or customers to a product or service published on an e-commerce portal.	1-5
sent_perc	The second input to the system is the perception determined from polarities (positive, negative, and neutral) obtained through the application of sentiment analysis techniques on user opinions regarding a product or service. If the value of this variable is closer to 1, the perception tends to be positive, while if the value is close to 0, the perception tends to be negative. Finally, if this value is close to 0.5, perception tends to be neutral.	0-1
perc_level	The output of the system corresponds to the estimated percentage perception level based on the values of the inputs and the defined inference rules.	0-100

While the rating variable can be directly obtained through web scraping techniques from the reviews made by users on the products and services, the sent_perc variable is calculated based on the polarities (negative, neutral and positive) belonging to the user's opinion regarding a specific product or service. Thus, for the calculation of the sent_perc variable, Equation (1) [21] is used.

$$sent\_perc = \left(\frac{p}{\sqrt{p^2 + a}} + \frac{\sqrt{a+1} - 1}{\sqrt{a+1}} \right) \quad (1)$$

In Equation (1), p corresponds to the difference between the positive and negative polarity values (Equation (2)), while “a” is an arbitrary value that ensures that the three roots of the equation are exact. Therefore, possible values for “a” can be 3, 8, 15, etc.

$$p = pol_{pos} - pol_{neg} \quad (2)$$

In the prototype design phase, the inference rules were specified for the rating and sent_perc variables (inputs), as well as for the perc_level variable (output), taking into consideration the associated ranges for each of them. In the case of the input variable rating, 4 fuzzy sets were defined: poor, fair, good, and excellent, with their membership degree functions (Figure 2).

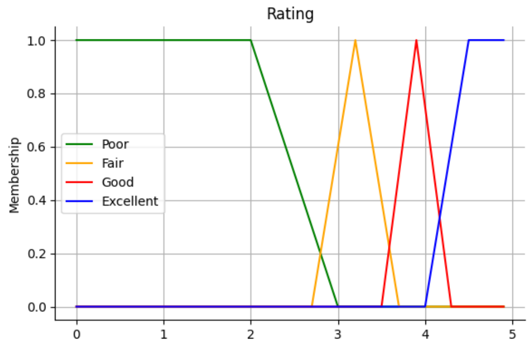

Figure 2. Membership degree function of the rating variable

Similarly, regarding the sent_perc input variable, 3 fuzzy sets were defined: negative, neutral, and positive, which are associated with the three polarities obtained through sentiment analysis techniques. In Figure 3 it is possible to appreciate the membership degree functions belonging to the variable sent_perc.

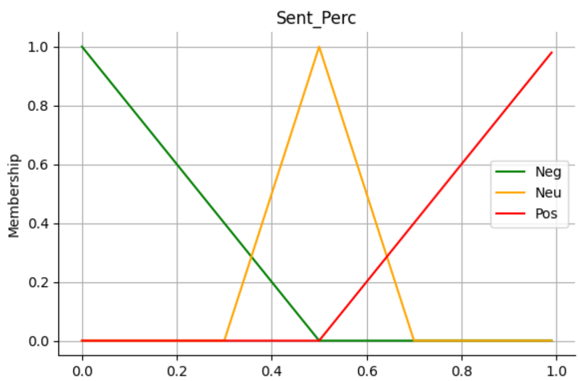

Figure 3. Membership degree function of the sent_perc variable

On the other hand, regarding the perc_level output variable, four fuzzy sets were defined: poor, fair, good, and excellent, each addressing different percentages covering the percentage range from 0% to 100%. The membership degree functions corresponding to the variable perc_level are presented in Figure 4.

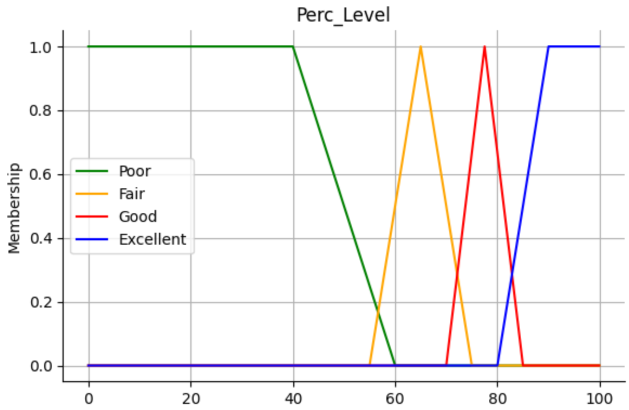

Figure 4. Membership degree function of the perc_level variable

Similarly, in this phase, the 12 inference rules were defined (Table 2), which allow to logically relate the fuzzy sets of inputs and output of the system, for the estimation of the level of perception in both numerical and linguistic terms. The defined rules consist of an antecedent and a consequent. In the antecedent, the fuzzy sets of the rating and sent_perc variables are related by means of a logical operator, while the consequent refers to the conclusion obtained in the perc_level variable, according to the result of the operation of the antecedent.

Table 2. Inference rules of the fuzzy system

Id	Antecedent	Consequent
1	rating = poor AND perc_level = negative	perc_level = poor
2	rating = poor AND perc_level = neutral	perc_level = poor
3	rating = poor AND perc_level = positive	perc_level = fair
4	rating = fair AND perc_level = negative	perc_level = poor
5	rating = fair AND perc_level = neutral	perc_level = fair
6	rating = fair AND perc_level = positive	perc_level = good
7	rating = good AND perc_level = negative	perc_level = poor
8	rating = good AND perc_level = neutral	perc_level = fair
9	rating = good AND perc_level = positive	perc_level = good
10	rating = excellent AND perc_level = negative	perc_level = fair
11	rating = excellent AND perc_level = neutral	perc_level = good
12	rating = excellent AND perc_level = positive	perc_level = excellent

In the prototype construction phase, the fuzzy system was implemented, taking into account the 4 functional modules that compose the system: fuzzification, inference system, defuzzification, and knowledge base (Figure 5).

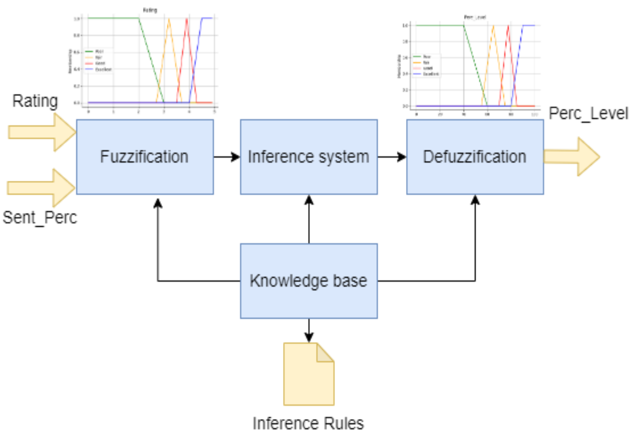

Figure 5. System functional modules

The fuzzification module takes the rating and sent_perc variables as input to obtain the fuzzy sets associated with the inputs (in numerical and linguistic terms), considering the membership functions presented in Figures 2 and 3. From the sets defined for the two inputs of the system, the inference system makes use of the knowledge base (inference rules) to determine, through the defuzzification module, the output value or perception level (perc_level).

For the implementation of the functional modules of fuzzification, defuzzification, as well as the configuration of the inference rules in the knowledge base, the JFuzzyLogic library in the Java language was selected. This library allows the specification of the fuzzy sets corresponding to the input and output variables, in addition to the specification of the inference rules in FCL (Fuzzy Control Language) in a plain text configuration file. In terms of obtaining the opinions and star ratings (input variable rating) from e-commerce portals, the Beautiful Soup library in Python was used for web scraping. Additionally, the VaderSentiment Python library was chosen to determine the polarities associated with users' opinions about products and services, to obtain the sent_perc variable. The graphical interface of the system was developed using the components provided by the Java Swing library.

Finally, in the evaluation phase, a proof of concept was conducted on the implemented fuzzy system, in which comments and star ratings of a technological product from the eBay store were collected to determine the output perception level of users or customers using fuzzy logic.

As mentioned previously, web scraping techniques were used to obtain the reviews and star ratings from the e-commerce portal.

3. Results

The fuzzy system, based on the functional modules shown in Figure 5, was implemented in the Java programming language. The graphical user interface (GUI) of the system consists of four tabs: "Rating per User," "Sentiment Analysis," "Fuzzy Perception Analysis," and "Membership Functions", as shown in Figure 6.

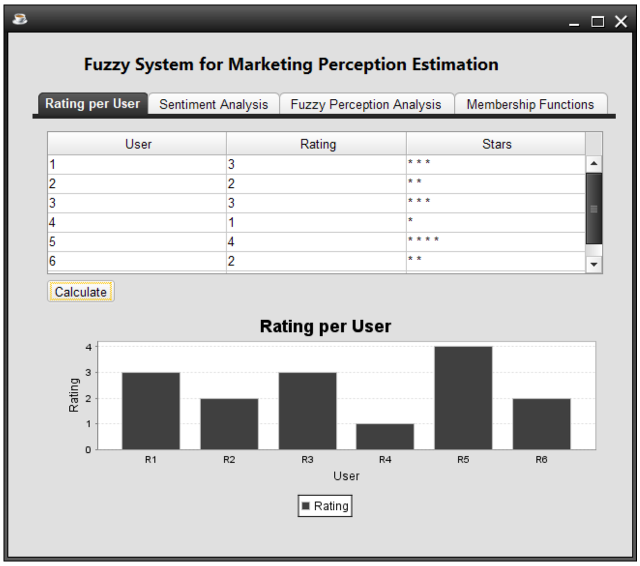

Figure 6. Main graphical interface of the system

In the "Rating per User" tab, the star rating made by customers for a specific product is loaded into the system from a .csv file (variable input: rating). These ratings are displayed in a table with three columns: user, rating, and stars. Additionally, when the "Calculate" button is pressed, a bar chart showing the star ratings assigned by each user is created and displayed in this tab. As an example, in the sample data shown in Figure 6, out of the 6 total ratings, the highest rating is given by user 5 with 4 stars, while the lowest rating is given by user 2 with 2 stars. On the other hand, Figure 7 depicts the graphical interface of the "Sentiment Analysis" tab in the fuzzy system.

In the "Sentiment Analysis" tab of Figure 7, the system loads the opinions of a set of users from a .csv file corresponding to the example star ratings presented in Figure 6. When the "Calculate" button is pressed, the system obtains the polarities of each opinion and the value of the sent_perc input variable using equation (1). It is worth mentioning that the value of this variable ranges from 0 to 1, so as it approaches 1, the polarity tends to be more positive.

Additionally, in the "Sentiment Analysis" tab, the fuzzy system displays a bar chart that shows the calculated values of the sent_perc variable for each opinion based on the polarities. For the calculation of polarities, the fuzzy system invokes a Python script in the background that utilizes the VaderSentiment library. The opinions, polarities, and corresponding values of the sent_perc variable for each opinion are displayed in a table with 6 columns: user, opinion, pos, neutral, neg, sent_perc. As an example, it can be observed that for the sample opinions in Figure 7, the highest value of the sent_perc variable is found in the opinion of user 6 with a value of 0.5, while the lowest value of the sent_perc variable is observed for user 1 with a value of 0.252.

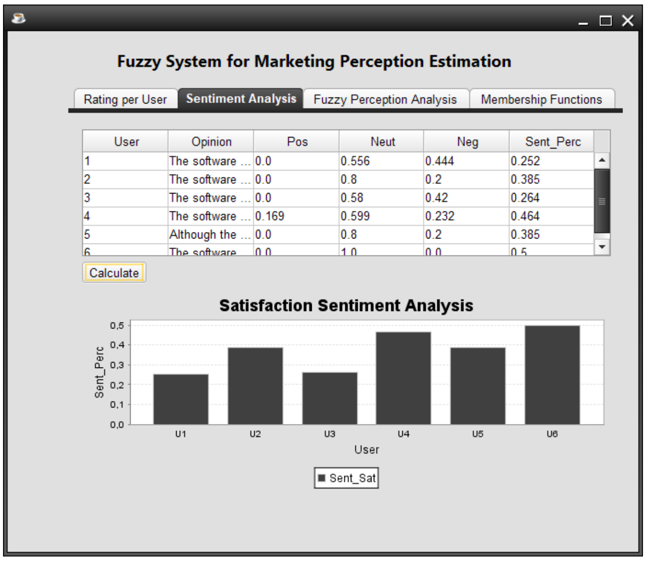

Figure 7. Interface of the "Sentiment Analysis" tab

Additionally, Figure 8 presents the graphical interface of the "Fuzzy Perception Analysis" tab.

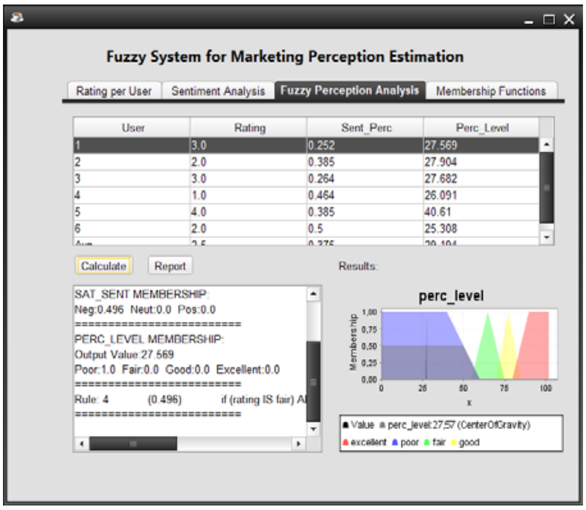

Figure 8. Interface of the "Fuzzy Perception Analysis" tab

In the "Fuzzy Perception Analysis" tab, the system loads the values of the rating variable and the sent_perc variable for each user or client who provided feedback on a product or service from the previous two tabs. Once the "Calculate" button is pressed, the system determines the output perception level (perc_level) in linguistic and numeric terms using the defined inference rules presented in Table 2. These data are presented within the interface in a table with 4 columns: user, rating, sent_perc, and perc_level. Furthermore, upon pressing the "Calculate" button, the fuzzy system displays the inference rules that are activated in the calculation of the output variable and membership degree functions associated to the output variable, which shows the location of the estimated value determined by the system. Similarly, in this tab it is possible to obtain a report that contains the results calculated by the system for each record of the table, that is, for the two inputs of each user loaded from the .csv file containing the study data. As an example, Figure 8 illustrates how, for the given test values, specifically for user 1 with a rating value of 3 and a sent_perc value of 0.252, the fuzzy system infers a value of 27.569 for the perc_level variable. In this inference, the system activates rule 4 presented in Table 1 and displays the position of that level in the "poor" fuzzy set within the membership function.

Continuing with the system description, the "Membership Functions" tab of the system is presented in Figure 9. In this tab, the system allows selecting a specific client from the perception study. Once the "Consult" button is pressed, the membership grade functions are displayed for the rating and sent_perc variables with their fuzzified values, as well the membership degree function of the perc_level variable with its defuzzified value. Similarly, the system presents the activated inference rules and the inferred value in both numerical and linguistic terms. For instance, in Figure 9, when user 3 is selected from the test data, the system performs fuzzification on the input variable rating (3.0) and assigns it to the fuzzy set "fair." Similarly, the input variable sent_perc (0.264) is fuzzified to the fuzzy set "negative." As a result, rule 3 from Table 2 is activated, and the output variable perc_level is inferred to have a value of 27.682, which corresponds to the fuzzy set "poor."

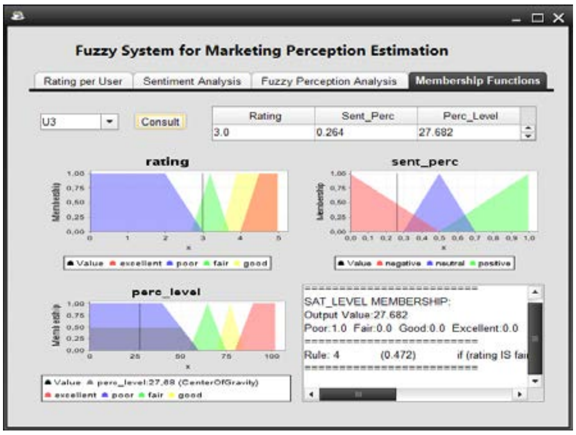

Figure 9. Interface of the "Membership Functions" tab

As mentioned in the methodology section, a proof of concept was conducted with the purpose to verify the functionality of the fuzzy system. Through web scraping techniques, data corresponding to the reviews and star ratings of a technological product from the Ebay portal were collected. Table 3 presents the 10 reviews and star ratings given to the mentioned product, extracted from the Ebay website.

Table 3. Opinions and ratings for a product from the Ebay portal

User	Opinion	Rating
1	Very easy to set up and use. Love the face ID feature and is really quick to sign in. The phone is a good size and fits safely in a pocket or a small bag and is not heavy. I have not got any negative points to share. So glad I managed to finally upgrade to the IPhone X - it' been worth it.	5
2	Product is what I expected as I had same. Delivered as promised, eBay for me is a reliable platform with good deals and also secured.	4
3	Great design, good quality, ease of use.	5
4	Really pleased with this phone so far. Works perfectly, great condition & battery life. 12 months warranty too.	5
5	Good phone very fast only issue I have is battery barely last a day.	5
6	My husband got me this iPhone X to replace my 6s. This upgrade is perfect for my needs It is so much faster.	4
7	Just as it was said	5
8	Just what I wanted	5
9	A nice phone, shame it did not come with the accessories, when bought as new.	4
10	All ok.	4

Utilizing the opinions and star ratings provided by users or customers for the technological product on the Ebay website, as presented in Table 3, the fuzzy system estimated the value of the perc_level variable. This estimation involved determining the input variable sent_perc by analyzing the polarities (positive, negative, neutral) of the 10 user or customer opinions (Table 4). Likewise, Table 4 includes the average value calculated for the perc_level variable, providing an indication of the overall perception of the customers regarding the product.

Table 4. Estimated results by the fuzzy system

User	Sent_perc	Rating	Perc_level
1	0.677	5	82.362 Good
2	0.653	4	70.992 Fair
3	0.877	5	86.66 Excellent
4	0.746	5	85.956 Excellent
5	0.605	5	74.964 Good
6	0.58	4	67.326 Fair
7	0.5	5	70.271 Fair
8	0.5	5	70.271 Fair
9	0.491	4	61.61 Fair
10	0.5	4	65 Fair
Prom	0.613	4.6	73.534 Good

From Table 4, it was possible to observe that the highest level of perception corresponds to user 3, with a value in the perc_level variable of 86.66 (linguistic level: Excellent), while the lowest perception level was obtained for user 9 with a perc_level value of 61.61 (linguistic level: Fair). Furthermore, the average perception level was 73.534, corresponding to a linguistic level of good. The above can be better appreciated in Figure 10, where the membership degree functions determined by the system for the average values of the rating variable and the sent_perc variable are displayed. It can be observed in Figure 10 that, in the case of the average perception level, 4 inference rules (8,9,11,12) were activated, being rule 11 the one with the highest degree of membership.

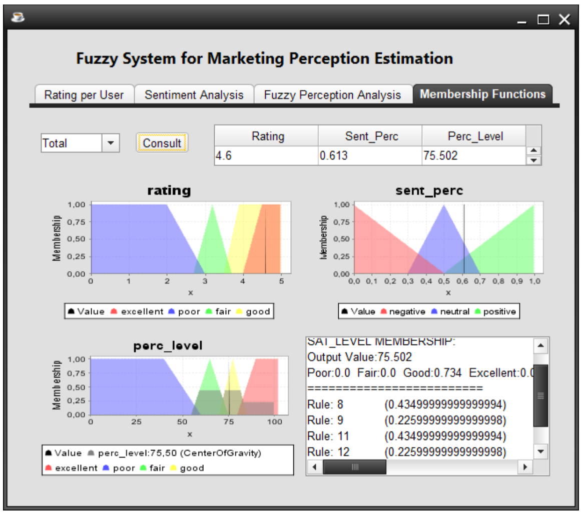

Figure 10. Membership functions for the average values of sent_perc and rating variables

Based on the analysis performed by the fuzzy system on proof-of-concept data, it can be concluded that the system presents, as an added value, the combination of the traditional star rating method with the quantitative value associated with user opinions. This represents a key contribution for the marketing divisions of companies in making decisions with respect to the products and services they offer to their customers.

4. Conclusions and Future Work

Regarding traditional methods for estimating perception in the context of marketing, which rely on quantitative perception surveys or user ratings of products and/or services, this article proposes a new hybrid approach. In this approach, fuzzy logic is used to combine the quantitative value encapsulated in opinions through sentiment analysis techniques, and the quantitative value derived from user star ratings given to products and services on e-commerce platforms. The proposed approach allows for harnessing the quantitative value inherent in user opinions on corporate platforms to support decision-making within marketing divisions of companies.

The present research made use of different open-source tools for the implementation of a fuzzy system supported by sentiment analysis techniques. This allows for the extrapolation of this research to different contexts where there is a desire to leverage the quantitative value of opinions along with other variables for user satisfaction estimation. As a tool for implementing the fuzzification and defuzzification modules, the system employed the jFuzzyLogic library, while sentiment analysis and/or opinion mining techniques were implemented through the benefits provided by the VaderSentiment library.

The proposed fuzzy system demonstrated proper functionality and proved to be useful in conducting brand perception studies in the context of marketing. In this regard, the fuzzy system was designed and built to be extensible, allowing for the loading of a .csv file containing opinions and ratings provided by users for products and services published on an e-commerce portal. It is worth mentioning that while the fuzzy system does not directly employ web scraping techniques for obtaining opinions and ratings from an e-commerce portal, the Beautiful Soup library was utilized to obtain data for the proof of concept. Thus, this library can be employed to retrieve data from different portals, provided a prior study of their website structures.

The results obtained in the proof of concept demonstrated the feasibility of the fuzzy system in combining star ratings with the perception derived from sentiment analysis techniques.

In this regard, it was observed that when analyzing the average results of the proof of concept, the perception level obtained for a technological product sold on the Ebay platform was 73.534, corresponding to the linguistic level of "Good."

As future work obtained from this research, it is intended to enhance the fuzzy system by including other input variables, such as the perception of users or customers on social media regarding the products or services offered by companies. This would involve adjusting the inference rules of the proposed system to accommodate this additional input.

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References:

[1]. Lin, H.-C. K., Wang, T.-H., Lin, G.-C., Cheng, S.-C., Chen, H.-R., & Huang, Y.-M. (2020). Applying sentiment analysis to automatically classify consumer comments concerning marketing 4Cs aspects. *Applied Soft Computing*, *97*, 106755. Doi: 10.1016/j.asoc.2020.106755.

[2]. Yang, Z., Xiong, G., Cao, Z., Li, Y., & Huang, L. (2019). A Decision Method for Online Purchases Considering Dynamic Information Preference Based on Sentiment Orientation Classification and Discrete DIFWA Operators. *IEEE Access*, *7*, 77008-77026. Doi: 10.1109/ACCESS.2019.2921403

[3]. Zuheros, C., Martínez-Cámara, E., Herrera-Viedma, E., & Herrera, F. (2023). Crowd Decision Making: Sparse Representation Guided by Sentiment Analysis for Leveraging the Wisdom of the Crowd. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *53*(1), 369-379. Doi: 10.1109/TSMC.2022.3180938

[4]. Chanchí-Golondrino, G. E., Muñoz-Sanabria, L. F., & Sierra-Martínez, L. M. (2022). Determinación del nivel de percepción de usuario a través de estudios de análisis de sentimientos en el contexto del marketing. *Inge CUC*, *18*(22), 238-248.

[5]. Ahmed, A. A. A., Agarwal, S., Kurniawan, Im. G. A., Anantadjaya, S. P. D., & Krishnan, C. (2022). Business boosting through sentiment analysis using Artificial Intelligence approach. *International Journal of System Assurance Engineering and Management*, *13*(1), 699-709. Doi: 10.1007/s13198-021-01594-x

[6]. Pouromid, M., Yekkehkhani, A., Oskoei, M. A., & Aminimehr, A. (2021). ParsBERT Post-Training for Sentiment Analysis of Tweets Concerning Stock Market. *2021 26th International Computer Conference, Computer Society of Iran (CSICC)*, 1-4. Doi: 10.1109/CSICC52343.2021.9420569

[7]. Srivats Athindran, N., Manikandaraj, S., & Kamaleshwar, R. (2018). Comparative Analysis of Customer Sentiments on Competing Brands using Hybrid Model Approach. *2018 3rd International Conference on Inventive Computation Technologies (ICICT)*, 348-353. Doi: 10.1109/ICICT43934.2018.9034283

[8]. Alattar, F., & Shaalan, K. (2021). Using Artificial Intelligence to Understand What Causes Sentiment Changes on Social Media. *IEEE Access*, *9*, 61756-61767. Doi: 10.1109/ACCESS.2021.3073657

[9]. Awajan, I., Mohamad, M., & Al-Quran, A. (2021). Sentiment Analysis Technique and Neutrosophic Set Theory for Mining and Ranking Big Data From Online Reviews. *IEEE Access*, *9*, 47338-47353. Doi: 10.1109/ACCESS.2021.3067844

[10]. Mishev, K., Gjorgjevikj, A., Vodenska, I., Chitkushev, L. T., & Trajanov, D. (2020). Evaluation of Sentiment Analysis in Finance: From Lexicons to Transformers. *IEEE Access*, *8*, 131662-131682. Doi: 10.1109/ACCESS.2020.3009626

[11]. Khan, F. H., Qamar, U., & Bashir, S. (2016). eSAP: A decision support framework for enhanced sentiment analysis and polarity classification. *Information Sciences*, *367-368*, 862-873. Doi: 10.1016/j.ins.2016.07.028

[12]. Moreno-Ortiz, A., & Fernández-Cruz, J. (2015). Identifying Polarity in Financial Texts for Sentiment Analysis: A Corpus-based Approach. *Procedia - Social and Behavioral Sciences*, *198*, 330-338. Doi: 10.1016/j.sbspro.2015.07.451

[13]. Xiang, C., Ren, Y., & Ji, D. (2019). Identifying Implicit Polarity of Events by Using an Attention-Based Neural Network Model. *IEEE Access*, *7*, 133170-133177. Doi: 10.1109/ACCESS.2019.2938966

[14]. Ikoro, V., Sharmina, M., Malik, K., & Batista-Navarro, R. (2018). Analyzing Sentiments Expressed on Twitter by UK Energy Company Consumers. *2018 Fifth International Conference on Social Networks Analysis, Management and Security (SNAMS)*, 95-98. Doi: 10.1109/SNAMS.2018.8554619

[15]. Park, J. (2020). Framework for Sentiment-Driven Evaluation of Customer Satisfaction With Cosmetics Brands. *IEEE Access*, *8*, 98526-98538. Doi: 10.1109/ACCESS.2020.2997522

[16]. Setik, R., Ahmad, R. M. T. R. L., & Marjudi, S. (2021). Exploring Classification For Sentiment Analysis From Halal Based Tweets. *2021 2nd International Conference on Artificial Intelligence and Data Sciences (AiDAS)*, 1-6. Doi: 10.1109/AiDAS53897.2021.9574255

[17]. Xie, S., Cao, J., Wu, Z., Liu, K., Tao, X., & Xie, H. (2020). Sentiment Analysis of Chinese E-commerce Reviews Based on BERT. *2020 IEEE 18th International Conference on Industrial Informatics (INDIN)*, *1*, 713-718. Doi: 10.1109/INDIN45582.2020.9442190

[18]. Ang, S. Y., & Ng, G. W. (2020). A Study on the Effect of the Real-world Backgrounds using Colour Blending Technique on Optical See-through AR User Interface Design. *2020 6th International Conference on Interactive Digital Media (ICIDM)*, 1-4. Doi: 10.1109/ICIDM51048.2020.9339664

[19]. Ardhana, V. Y. P., Sapi'i, M., Hasbullah, H., & Sampetoding, E. A. M. (2022). Web-Based Library Information System Using Rapid Application Development (RAD) Method at Qamarul Huda University. *The IJICS (International Journal of Informatics and Computer Science)*, *6*(1), 1. Doi: 10.30865/ijics.v6i1.4031

[20]. Sasmito, G. W., & Wibowo, D. S. (2020). Implementation of rapid application development method in the development of geographic information systems of industrial centers. *Journal of information and communication convergence engineering, 18*(3), 194-200.

[21]. Chanchí-Golondrino, G. E., Ospina-Alarcón, M., & Sierra-Martínez, L. (2023). Determination of the satisfaction attribute in usability tests using sentiment analysis and fuzzy logic. *International Journal of Computers Communications & Control*, *18*(3), 1-14. Doi: 10.15837/ijccc.2023.3.4901