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Customer Review Sentiment Analysis on Google Maps as a Basis for CRM Strategy Optimization: Evidence from Coffeeshop Z Purwokerto

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Abstract

The rapid growth of digital platforms has encouraged customers to share their experiences and evaluations through online reviews, particularly on Google Maps. These reviews provide valuable insights that can support Customer Relationship Management (CRM) strategies when analyzed systematically. This study aims to analyze customer review sentiment toward Coffee Shop Z in Purwokerto using the Multinomial Naïve Bayes algorithm and to utilize the findings as a basis for CRM strategy formulation through the get, keep, and grow framework. A mixed-method approach was employed, combining quantitative sentiment analysis of 242 Google Maps reviews and qualitative interviews with customers for methodological triangulation. The research process included data collection through web scraping, text preprocessing, TF-IDF feature extraction, sentiment labeling, classification modeling, and performance evaluation. The results indicate that negative sentiment dominated customer reviews (57.02%), followed by neutral sentiment (30.16%) and positive sentiment (12.80%). The classification model achieved an accuracy of 63.27%, with stronger performance in identifying negative sentiment than neutral and positive sentiments. The findings reveal that customer dissatisfaction is primarily associated with service quality and waiting time, while positive perceptions are related to food quality, affordability, and cleanliness. Based on these findings, CRM strategies were developed through customer acquisition (get), retention (keep), and loyalty enhancement (grow) initiatives. This study demonstrates that sentiment analysis can serve not only as a customer perception measurement tool but also as a valuable source of evidence-based recommendations for customer relationship management and digital marketing strategy development.

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INTRODUCTION

The coffee shop industry in Indonesia has experienced rapid growth in recent years, including in education-oriented cities such as Purwokerto. The increasing number of business players has intensified competition, requiring coffee shops to compete not only in terms of product quality but also in their ability to build consistent and memorable customer experiences. In such a competitive environment, business success is strongly influenced by the ability of entrepreneurs to establish and maintain long-term relationships with customers.

Along with the advancement of digital technology, the way customers interact with businesses has also changed. Customers no longer simply visit and make purchases; they also share their experiences through digital platforms such as Google Maps. Customer reviews on Google Maps function as electronic word-of-mouth (e-WOM), which can influence business reputation and potential customers' purchasing decisions (Azhar et al., 2021). Therefore, customer reviews have become an important source of information for understanding consumer perceptions and experiences.

Although the number of customer reviews continues to increase, many business owners have not systematically used them. Reviews are often read in general without structured analysis to identify patterns of customer satisfaction or complaints. As a result, marketing strategies and customer relationship management efforts are frequently not fully data-driven, which may reduce their effectiveness and accuracy.

To address this issue, sentiment analysis can be applied as an approach to classify customer opinions into positive, neutral, and negative categories. As part of Natural Language Processing (NLP), sentiment analysis enables unstructured text data to be transformed into more measurable and meaningful information (Rivaldi & Wismarini, 2024). The Naïve Bayes algorithm is chosen in this study due to its simplicity, efficiency, and suitability for large-scale text classification (Purnamasari et al., 2023). Through sentiment analysis, patterns of customer perception can be identified more objectively.

The identified sentiment results are then linked to Customer Relationship Management (CRM) strategies. CRM is a strategic approach focused on managing customer relationships through three main stages: acquiring customers (get), retaining customers (keep), and developing customer loyalty (grow) (Yahya et al., 2025). In this context, customer sentiment data can serve as a foundation for formulating more targeted relational strategies. Negative sentiment can provide insights for evaluation at the "get" stage, neutral sentiment can support improvement strategies at the "keep" stage, and positive sentiment can be leveraged to strengthen loyalty at the "grow" stage.

Furthermore, CRM implementation in the digital era cannot be separated from digital marketing strategies. Digital marketing is not merely a promotional tool but also a medium for two-way interaction that enables companies to build sustainable engagement with customers (Nugroho & Suryadi, 2023). Therefore, the results of sentiment analysis should not stop at data classification but should be translated into concrete digital marketing strategies, such as actively responding to reviews, strengthening content based on positive testimonials, and designing more relevant loyalty programs.

Previous studies have examined sentiment analysis in the context of digital marketing and Social CRM (Safiesza et al., 2024). However, most of these studies focus primarily on measuring customer perception or marketing segmentation, without directly integrating sentiment analysis results into operational CRM strategies through the get, keep, and grow approach, particularly by utilizing Google Maps reviews in the coffee shop business context.

Previous studies have extensively applied sentiment analysis to evaluate customer perceptions on digital platforms such as Google Reviews, social media, and e-commerce applications. Other studies have investigated Customer Relationship Management (CRM) and digital marketing strategies to improve customer retention and loyalty. However, these studies generally focus on either sentiment classification performance or CRM implementation separately. Limited research has integrated sentiment analysis findings into CRM strategy formulation, particularly through the get, keep, and grow framework. In addition, the utilization of Google Maps reviews as a strategic source for developing CRM recommendations in the coffee shop industry remains underexplored. Therefore, this study addresses this gap by integrating sentiment analysis results from Google Maps reviews with CRM strategy development, enabling customer feedback to be transformed into actionable managerial recommendations for customer acquisition, retention, and loyalty enhancement.

The novelty of this study lies in integrating Google Maps-based sentiment analysis with CRM strategy formulation using the get, keep, and grow framework. Unlike previous studies that primarily emphasize sentiment classification accuracy, this research extends the practical application of sentiment analysis by translating customer sentiment into evidence-based CRM strategies. This approach provides both analytical and managerial contributions by linking customer-generated online reviews with customer relationship development initiatives.

Based on these conditions, this study aims to analyze customer review sentiment of Coffee Shop Z in Purwokerto using the Naïve Bayes algorithm and integrate the results into the formulation of Customer Relationship Management (CRM) strategies through the get, keep, and grow approach within the context of digital marketing. This research is expected to contribute by linking digital review data analysis with more structured, evidence-based customer relationship management strategies

RESEARCH METHODS

This study employs a mixed-method approach. According to Creswell & Clark, (2017), a mixed-methods research design is a procedure for collecting, analyzing, and integrating both qualitative and quantitative methods within a single study or a series of studies to gain a comprehensive understanding of a research problem. In this study, the quantitative approach is used to analyze the sentiment of customer reviews, while the qualitative approach is applied to strengthen and validate the findings through methodological triangulation.

A. Data Collection

The research data were obtained through a web scraping technique to extract 242 customer reviews of Coffee Shop Z from Google Maps. This technique was employed to collect data automatically, systematically, and efficiently.

To enhance the validity of the results, methodological triangulation was conducted through observation of digital marketing activities and interviews with customers. The observation focused on content patterns and interactions on Instagram and Google Maps, while the interviews were conducted to confirm the consistency between the sentiment classification results and customers' actual experiences. This process aimed to validate the sentiment analysis findings, ensuring that the formulated CRM strategy recommendations are aligned with real conditions.

B. Text preprocessing

Text preprocessing is a process of managing and preparing a dataset before it is further analyzed. At this stage, the dataset is processed to improve its quality and optimize it for analysis. Text preprocessing is a filtering and preparation stage applied to each document before it is processed (Nurian et al., 2023). It is also considered one of the techniques in data mining used to transform raw data into a more structured and understandable format, enabling it to be processed more effectively (Agustina et al., 2022).

The purpose of text preprocessing is to obtain structured text data. The stages of text preprocessing generally include the following steps:

1. Cleaning

Cleaning is an essential stage in text preprocessing aimed at removing irrelevant or meaningless elements from the data. This step involves identifying empty or null values and eliminating unnecessary components such as symbols. Cleaning is performed to remove characters that are not part of the alphabet, including emoticons, numbers, hashtags, mentions, and URLs or links found in the reviews (Salsabila et al., 2022).

2. Case Folding

Case folding is the process of converting all uppercase letters into lowercase letters within a review to ensure consistency and facilitate text processing. It is a stage in text preprocessing that aims to transform all characters into lowercase, enabling the system to recognize identical words without distinguishing between uppercase and lowercase usage (Febriyani & Februariyanti, 2022).

3. Normalization

Data normalization is the process of converting informal or abbreviated words into their standard forms, for example, changing "tdk enak" to "tidak enak." Normalization is a stage in text preprocessing that aims to standardize textual data so that it becomes more structured and suitable for further analysis. In addition, this stage may involve removing punctuation marks, numbers, symbols, URLs, and usernames to ensure that the resulting data is cleaner, more consistent, and ready for the subsequent processing steps (Wahyuni, 2022).

4. Tokenizing

Tokenizing is a stage in text preprocessing that aims to remove unnecessary punctuation and split text into smaller units such as words, symbols, characters, or punctuation marks, resulting in tokens that are ready for analysis (Wahyuni, 2022). The tokenizing process involves breaking a sentence into smaller components. For example, the sentence “Sop ayam disini enak” is divided into individual tokens: “Sop”, “ayam”, “disini”, and “enak”.

5. Stopword Removal

Stopwords removal is the process of eliminating words that are considered less important or do not carry significant meaning in the analysis, so they do not affect the results of text processing (Indriyani et al., 2023). Stopword removal is a stage in text preprocessing that removes common words with little analytical value, such as “yang,” “di,” and “ini.” By removing these frequently occurring but less meaningful words, the analysis can focus more on.

C. Feature Extraction

After the preprocessing stage, the textual data were transformed into numerical representations using the Term Frequency–Inverse Document Frequency (TF-IDF) technique. TF-IDF was employed to measure the importance of words within customer reviews by considering both term frequency and inverse document frequency. This approach helps reduce the influence of commonly occurring words while emphasizing more informative terms.

The resulting TF-IDF vectors were used as input features for the Multinomial Naïve Bayes classification model. Through this process, textual review data could be represented in a structured numerical format suitable for sentiment classification.

D. Data Labeling

The collected review data were subsequently labeled as negative, neutral, or positive based on the content of the text. Reviews containing complaints, criticism, or disappointing experiences were categorized as negative sentiment. Conversely, reviews expressing appreciation, praise, or satisfying experiences were classified as positive sentiment. Meanwhile, descriptive reviews without strong emotional tendencies were included in the neutral sentiment category.

To ensure high objectivity and dataset quality, the manual labeling process was not conducted by a single researcher but by a panel of three experts. The selection of three experts was intentional to allow for agreement ranking and minimize individual subjective bias. The experts consisted of: (1) a Data Scientist with over five years of experience in Natural Language Processing (NLP) and text mining; (2) a Senior Digital Marketing Practitioner specializing in the Food and Beverage (F&B) industry; and (3) an Academic Researcher with a focus on Consumer Behavior and Customer Relationship Management (CRM). This combination of technical, practical, and theoretical backgrounds ensured that the labeling criteria were evaluated comprehensively from multiple perspectives.

Before the full labeling process, a structured guideline document detailing the definitions, criteria, and examples for each sentiment class (positive, neutral, negative) was provided to the three experts. Each expert independently labeled the entire dataset of 242 reviews.

To analyze the agreement between the labelers and ensure the quality and validity of the resulting dataset, Aiken’s Validity Index (V) or Shifted Item Technique (SVI) was applied. Aiken’s V was chosen because it is highly effective for measuring content validity among a small panel of experts (Aiken, 1985). A 3-point rating scale was used, where 1 = "Inappropriate/Does not match the sentiment," 2 = "Quite appropriate/Needs revision," and 3 = "Appropriate/Perfectly matches the sentiment." The Aiken’s V coefficient was calculated using the formula:

$$V = \frac{\Sigma s}{n(r-1)} \quad (1)$$

Where s is the score given by the rater minus the minimum score, n is the number of raters, and r is the maximum rating scale. The results of the Aiken's V calculation yielded a coefficient of 0.89 for negative sentiment, 0.85 for neutral sentiment, and 0.92 for positive sentiment. Since all coefficients exceeded the minimum threshold of 0.80 (indicating high validity and agreement), no major revisions to the label definitions were required. For the few reviews where initial disagreements occurred (e.g., one rater labeled "neutral" while another labeled "negative"), a focused group discussion was held among the three experts to reach a final consensus. This rigorous process ensured that the labeled data was highly reliable and served as a robust foundation for training the classification model.

E. Classification Modeling

The sentiment classification process was conducted using the Multinomial Naïve Bayes algorithm. This algorithm was selected due to its simplicity, computational efficiency, and proven effectiveness in text classification tasks. The TF-

IDF feature vectors obtained from the previous stage were used as input for the classification model.

The model was trained to identify patterns associated with positive, neutral, and negative sentiments within customer reviews and subsequently predict the sentiment category of unseen data.

F. Evaluation

The dataset was divided into training and testing sets using an 80:20 ratio, where 80% of the data was used for model training and 20% for testing. To evaluate model robustness and reduce evaluation bias, 10-fold cross-validation was applied during the classification process.

Model performance was assessed using a confusion matrix, from which accuracy, precision, recall, and F1-score were calculated. These metrics were used to evaluate the effectiveness of the Naïve Bayes model in classifying customer review sentiments.

It should be noted that the dataset exhibited class imbalance, with negative sentiment reviews being more dominant than positive and neutral reviews. This condition may influence the classification results and contribute to the model's tendency to predict the majority class more frequently.

G. Implementation of CRM recommendation strategy

Customer Relationship Management (CRM) is a strategy that focuses on selecting and managing customers who provide long-term value to a company through structured and continuous interactions (Kumar & Reinartz, 2018). The primary objective of CRM is to enhance customer satisfaction and loyalty by creating relevant and valuable experiences (rahmaida, 2025)). In this study, the results of sentiment classification are not only used to measure customer perceptions but are also integrated into the formulation of CRM strategies through the get, keep, and grow approach.

The implementation of CRM strategies is based on the dominant sentiment findings identified in customer reviews. Each sentiment category is analyzed to determine the most frequently mentioned aspects, such as price, taste, service quality, and waiting time. These findings are then translated into operational relational strategies supported by digital marketing initiatives.

1. Get Strategy

According to Nashah et al., (2024), attracting new customers can be achieved by providing easy access to information, offering innovations, and delivering appealing services related to the company. In this study, the get strategy focuses on attracting new customers by utilizing insights derived from both positive and negative sentiments.

For instance, negative sentiment related to price, such as perceptions of being "expensive," indicates the need to adjust value communication strategies. Therefore, the get strategy can be implemented through digital campaigns such as bundling promotions, limited-time discounts, and emphasizing value for money across social media platforms and Google Maps. Meanwhile, positive sentiment related to taste can be leveraged as testimonial content to enhance the attractiveness of the coffee shop to potential customers.

2. Keep Strategy

According to Nashah et al., (2024), retaining customers requires companies to build loyalty by listening to customers and striving to fulfill their expectations. In this study, the keep strategy is directed toward maintaining existing customers by improving aspects frequently appearing in negative and neutral sentiments, such as service quality and waiting time.

Service improvements can be carried out through staff training and internal operational evaluations. In the context of digital marketing, the keep strategy is implemented through active responses to customer reviews on Google Maps. The provision of a digital feedback system increases engagement and strengthens customer trust.

3. Grow Strategy

According to Nashah et al., (2024), enhancing customer relationships requires companies to provide special treatment, such as cross-selling complementary products and up-selling higher-quality versions of similar products. In this study, the growth strategy aims to increase loyalty among customers who have expressed satisfaction through positive sentiment.

Dominant positive aspects, such as food taste and comfort, can be utilized to build more personalized relationships through loyalty programs, interactive social media content, and appreciation for customers who provide positive reviews. Through this approach, customers are not only retained but also encouraged to become advocates who strengthen the coffee shop's digital reputation.

RESULT AND DISCUSSION

Out of 242 analyzed review data, 138 reviews (57.02%) were classified as negative sentiment, 73 reviews (30.16%) as neutral sentiment, and 31 reviews (12.80%) as positive sentiment. This distribution indicates that more than half of the customer reviews of Coffee Shop Z on Google Maps are dominated by less satisfactory perceptions. The relatively high proportion of negative sentiment suggests that certain aspects of the customer experience have not fully met expectations. The dominance of negative sentiment suggests that service-related issues have a stronger influence on customer evaluations than product-related aspects. Although customers generally appreciate food quality and affordability, dissatisfaction with service speed and waiting time appears to significantly affect their overall experience. This finding highlights the importance of operational service quality in shaping customer satisfaction and online reputation.

The dominance of negative sentiment not only reflects dissatisfaction with the products but may also relate to service quality, waiting time, and the overall consumption experience. Meanwhile, the presence of 30.16% neutral sentiment indicates a group of customers who do not express strong impressions, meaning there is still an opportunity to shift these perceptions toward a more positive direction. The positive sentiment proportion of 12.80% shows that certain aspects have met customer expectations; however, the percentage remains relatively small compared to negative sentiment.

To provide a clearer overview of the distribution of these three sentiment categories, a visualization in the form of a graph is presented in Figure 1. This visualization illustrates the proportional comparison of sentiments more intuitively, making it easier to interpret customer perception patterns toward Coffee Shop Z.

Figure 1. Positive sentiment visualization

Based on the visualization results in Figure 1, within the positive sentiment category, the most frequently occurring words include "delicious," "food," "affordable," and "clean," along with several other terms representing pleasant experiences. The appearance of these words indicates that customer satisfaction is generally associated with food taste, affordable prices, and cleanliness. These findings align with previous research stating that core product quality (taste) and perceived value (affordability) are primary drivers of positive customer evaluations in the F&B sector (Ryu et al., 2012). Furthermore, the emphasis on "cleanliness" supports the notion that physical environment and hygiene are critical antecedents of customer satisfaction in hospitality settings (Parasuraman et al., 1988). These aspects can be identified as key strengths that should be maintained. In the context of Customer Relationship Management (CRM), these findings can serve as the foundation for get-and-grow strategies by strengthening promotional content based on positive testimonials and reinforcing product-quality branding in digital marketing efforts.

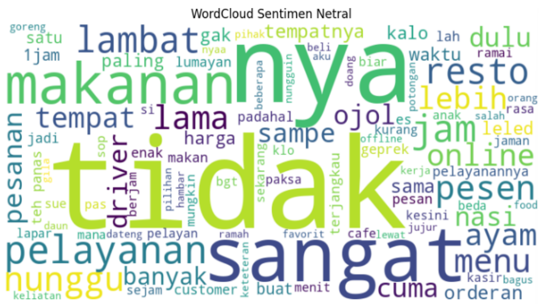

Figure 2. Neutral sentiment visualization

The visualization of the neutral sentiment category shows frequently occurring words such as "slow," "the food," and "order." Neutral sentiment reviews typically contain descriptive experiences without strong expressions of satisfaction or dissatisfaction. The presence of words like "slow" in a neutral context suggests a threshold of tolerance; customers notice the delay but are not yet frustrated enough to express strong negativity. This aligns with the expectation-confirmation theory, where performance slightly below expectations does not immediately trigger dissatisfaction but results in apathy (Oliver, 1980). From a CRM perspective, customers within the neutral sentiment group represent potential opportunities that can be enhanced through keep strategies, such as improving service efficiency and increasing digital interaction to create more memorable experiences.

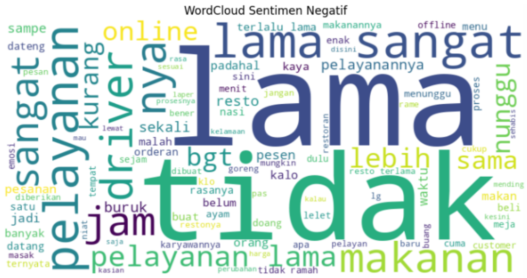

Figure 3 Negative sentiment visualization

Meanwhile, in the negative sentiment category, dominant words include “service,” “long,” “food,” and “staff service.” The presence of these words indicates that customer dissatisfaction mainly relates to service quality, service speed, and waiting time. The dominance of waiting time complaints is consistent with extensive service marketing literature, which identifies "tangibles" and "responsiveness" as key dimensions of service quality that heavily influence customer dissatisfaction when failed (Parasuraman et al., 1988; Kumar & Reinartz, 2018). Additionally, the appearance of the word “food” in a negative context suggests a mismatch between customer expectations and the product quality received. These findings emphasize that service and operational aspects are crucial factors in shaping customer perceptions. Therefore, within the CRM framework, service improvement strategies become a top priority, particularly in the keep strategy to retain customers and prevent loyalty decline due to unsatisfactory experiences.

Table 1 Classification Report

Sentiment	Evaluations			
	Precision	**Recall**	**F1-Score**	**Support**
Negative	0.62	1.00	0.77	28
Neutral	0.67	0.13	0.22	15
Positive	1.00	0.17	0.29	6

Although the overall accuracy reached 63.27%, the model’s performance should be interpreted cautiously. The relatively low recall values for neutral and positive sentiments indicate that the classifier tends to favor the majority class. This behavior is likely influenced by the imbalanced distribution of sentiment categories, where negative reviews dominate the dataset. Consequently, the model learns more characteristics associated with negative sentiment and predicts this class more frequently.

The classification report table 1 shows that the negative sentiment class achieved the highest recall value of 1.00, indicating that the model effectively identified all test data belonging to the negative category. The precision value of 0.62 suggests that although the model successfully detected all negative data, some neutral or positive data were incorrectly predicted as negative. The F1-score of 0.77 indicates that overall performance for the negative class is relatively good.

For the neutral sentiment class, the model produced a precision value of 0.67, meaning that when the model predicted neutral sentiment, the predictions were reasonably accurate. However, the recall value was low at 0.13, indicating that the model was only able to recognize a small portion of the actual neutral data, while most neutral reviews were misclassified into other classes. Consequently, the F1-score for the neutral class was only 0.22, reflecting weak performance in detecting neutral sentiment.

In the positive sentiment class, the model achieved the highest precision value of 1.00, meaning all positive predictions made by the model matched the true labels. However, the recall value was only 0.17, indicating that the model captured only a small portion of the existing positive data, with many positive reviews misclassified into other categories. As a result, the F1-score for the positive class was 0.29. The low recall in the positive class is likely due to the smaller number of positive data compared to the negative and neutral classes, making the model less optimal in predicting positive sentiment.

Overall, the weighted average F1-score of 0.54 indicates that the model’s performance still requires improvement. The imbalance in the number of data instances across sentiment classes significantly affects the evaluation results.

Based on the confusion matrix results in Figure 4, the sentiment classification model using the Naïve Bayes algorithm successfully classified all negative sentiment test data correctly, with 28 data points predicted accurately as negative. There were no misclassifications in the negative class, demonstrating the model’s strong capability in recognizing negative reviews.

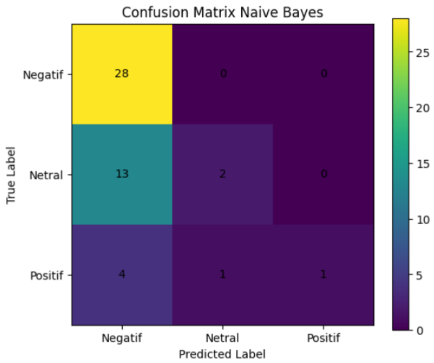

Figure 4 Confusion matrix

In the neutral sentiment class, out of 15 test data instances, only 2 were correctly classified as neutral, while 13 neutral data instances were misclassified as negative. This indicates that the model still struggles to distinguish between neutral and negative sentiment.

For the positive sentiment class, out of 6 test data instances, only 1 was correctly predicted as positive. Four positive data points were misclassified as negative, and 1 was classified as neutral. This finding shows that the model tends to classify positive and neutral sentiments into the negative category.

Overall, the confusion matrix results indicate that the model has a bias toward negative sentiment, this tendency is likely influenced by the imbalanced distribution of sentiment classes, where negative reviews dominate the dataset. Consequently, the model learns more characteristics associated with negative sentiment and tends to classify ambiguous reviews into the majority class. Future studies may address this limitation through data balancing techniques or the application of more advanced classification algorithms. Influenced by the imbalance in the number of data instances across each class. Nevertheless, the model's strong ability to accurately detect negative sentiment remains a key contribution of this study, considering that negative sentiment is directly related to customer complaints and the formulation of Customer Relationship Management (CRM) strategies.

The interview participants were customers of Coffee Shop Z. The results show that customer perceptions of Coffee Shop Z are divided into positive, neutral, and negative sentiments. The interview findings were then compared with the results of the sentiment analysis of Google Maps reviews using the Naïve Bayes algorithm as a form of methodological triangulation. The purpose of this triangulation was to ensure that the sentiment classification results obtained from Google Maps reviews are consistent with the actual experiences of interviewed customers, thereby enhancing the validity of the research findings.

The interview results indicate that positive sentiment generally appears in aspects related to product quality and price, supported by statements such as "the food tastes good," "cheap price," and "affordable price." These findings are consistent with the sentiment analysis of Google Maps reviews, which also shows that positive sentiment is dominated by words related to satisfaction with the taste of food and beverages as well as affordable pricing. Thus, it can be concluded that positive customer perceptions of Coffee Shop Z, both in Google Maps reviews and interviews, share similar tendencies, particularly regarding product taste and price suitability.

In addition, the interviews revealed neutral sentiment largely associated with informative evaluations that do not strongly express satisfaction or dissatisfaction. Neutral sentiment in the interview data is characterized by statements such as "the atmosphere is just ordinary," "a typical experience," or "standard food and drinks." This aligns with the findings from Google Maps reviews, where some customers provide neutral feedback consisting of general descriptions of the place and their visit experience without significant praise or criticism.

The interviews also demonstrate negative sentiment consistently related to service quality and comfort, with statements such as "slow service," "less responsive," "long waiting time," "the place is less clean," and "noisy atmosphere." These findings are in line with the sentiment analysis of Google Maps reviews, which indicates that the main customer complaints are associated with slow or inefficient service. Therefore, the tendency of negative sentiment in the interviews supports the Google Maps sentiment analysis results, highlighting that service quality and overall customer experience are the primary issues that require improvement at Coffee Shop Z.

Based on this comparison, it can be concluded that the interview results are consistent with the sentiment analysis of Google Maps reviews. This consistency is reflected in the recurring keywords and themes, where positive sentiment relates to taste and price, neutral sentiment relates to general evaluations, and negative sentiment relates to slow service and comfort issues. Therefore, the methodological triangulation in this study confirms that the sentiment classification results from Google Maps reviews effectively represent customer perceptions of Coffee Shop Z and can serve as a valid foundation for formulating CRM strategy recommendations.

1. Implementation of Negative Sentiment Findings into CRM Strategy (Get)

Based on the negative sentiment results from Google Maps reviews of Coffee Shop Z, customer complaints are predominantly related to service issues, particularly long serving times and limitations in the service and payment systems. Frequently appearing words in negative sentiment include “slow service,” “long waiting time,” and “waiting too long.” This indicates that negative perceptions are largely driven by service experience. If not properly addressed, this condition may reduce the interest of potential new customers, as negative e-WOM significantly deters prospective buyers (Chevalier et al., 2018).

Goals of CRM (Get) based on negative sentiment are: (1) to improve public perception of Coffee Shop Z’s service quality; (2) to attract new customers by presenting a friendlier and faster service image (Nashah et al., 2024); (3) to transform negative sentiment into promotional opportunities; and (4) to increase the trust of potential new customers. Meanwhile, the recommended CRM (Get) strategies based on negative sentiment are described as follows.

1) Responsive Social Media Content

Coffee Shop Z can openly communicate with customers through Instagram or TikTok content by responding to complaints under themes such as “We listen, we improve.” Transparent communication regarding service recovery has been proven to restore customer trust and attract new users who value corporate accountability (Kumar & Reinartz, 2018).

2) Digital Campaigns

Creating content that emphasizes the coffee shop’s commitment to service speed, including behind-the-scenes cooking processes to help customers estimate preparation time, and providing clear complaint-handling information. Managing customer expectations through digital channels reduces the gap between perceived and actual service quality (Zeithaml et al., 1996).

3) Special Promotions for New Customers

To attract new customers, Coffee Shop Z can offer discounts or free items for first-time visitors under certain conditions, such as following social media accounts and leaving a Google Maps review. Acquisition promotions are a fundamental tactic in the "get" phase of CRM to lower the barrier to trial for new prospects (Nashah et al., 2024).

4) Online Review Optimization

Responding politely to negative reviews on Google Maps and confirming that complaints have been received and evaluated can improve digital image and strengthen prospective customers’ trust. Managerial responses to online reviews signal high responsiveness and mitigate the negative impact of bad reviews on future potential customers (Lee & Cranage, 2014).

By utilizing negative sentiment as the foundation for the CRM get strategy, Coffee Shop Z focuses not only on internal improvements but also on effectively communicating changes to potential customers, thereby enhancing its digital reputation.

2. Implementation of Neutral Sentiment Findings into CRM Strategy (Keep)

Based on neutral sentiment results from Google Maps reviews, some customers perceive their visit as ordinary. Neutral sentiment typically arises when customers experience neither significant satisfaction nor dissatisfaction. Frequently appearing words include “quite okay,” “order,” and “ordinary.” This suggests that customers accept the product and service quality but do not find the experience particularly memorable, placing them at a high risk of switching to competitors (Keaveney, 1995).

Goals of CRM (Keep) based on neutral sentiment are: (1) to increase customer satisfaction and prevent switching to competitors; (2) to transform customer perceptions by enhancing the overall experience; (3) to build long-term relationships with returning customers (Nashah et al., 2024); and (4) to increase repeat visits and repurchases. Meanwhile, the recommended CRM (Keep) strategies based on neutral sentiment are described as follows.

1) Improving Service Consistency

Coffee Shop Z needs to enhance and maintain consistency in service quality, particularly in serving time, friendliness, and taste consistency. Consistency is crucial in the "keep" stage, as inconsistent service is a primary driver of customer churn (Parasuraman et al., 1988).

2) Personalizing Customer Experience

The coffee shop can adopt a more personal approach, such as remembering regular customers' menu preferences, offering tailored recommendations, or greeting customers personally. Personalization is a core CRM mechanism that fosters emotional closeness and transforms ordinary experiences into positive ones (Ngai et al., 2009).

3) Digital Follow-Up Communication

Utilizing social media or creating a WhatsApp Business community to share promotions, new menus, or special events helps maintain continuous communication with customers who may not yet have strong emotional attachment. Continuous engagement prevents customer attrition (Kumar & Reinartz, 2018).

4) Requesting Customer Feedback

Encouraging customers to provide feedback via social media or QR-based feedback forms on tables makes them feel valued and involved in service improvement. Voice-of-the-customer (VoC) programs are essential for identifying operational blind spots that cause neutral experiences (Baker & Cullen, 1993).

5) Interactive Customer Engagement

Conducting social media polls such as "Best Menu of the Week" can increase excitement and engagement. Active two-way interaction strengthens customer bonds and increases switching costs (Nugroho & Suryadi, 2023).

Through a neutral sentiment-based CRM keep strategy, Coffee Shop Z can gradually enhance customer experience and transform neutral perceptions into positive ones, supporting long-term business sustainability.

3. Implementation of Positive Sentiment Findings into CRM Strategy (Grow)

Based on positive sentiment analysis from Google Maps reviews, customers provide favorable evaluations, particularly regarding food and beverage taste, affordable prices, and comfortable atmosphere. Frequently appearing words include "delicious," "affordable," "clean," "comfortable," and "recommended." This indicates that satisfied customers have a strong tendency to revisit and recommend Coffee Shop Z to others, exhibiting characteristics of brand advocates (Hennig-Thurau et al., 2004).

Goals of CRM (Grow) Based on Positive Sentiment are: (1) To increase customer loyalty (Nashah et al., 2024); (2) To encourage repeat visits and repeat purchases; (3) To maximize positive customer evaluations; and (4) To utilize satisfied customers as part of a word-of-mouth (WoM) strategy to recommend the café to others. Meanwhile, the recommended CRM (Grow) strategies based on positive sentiment are described as follows.

1) Utilizing Testimonials

Positive reviews can be repurposed as promotional content on Instagram and TikTok. Leveraging user-generated content (UGC) and electronic WoM (eWOM) enhances trust and reinforces loyalty among existing customers while acting as social proof for new ones (Hennig-Thurau et al., 2004).

2) Upselling and Cross-Selling Favorite Menus.

Based on positive sentiment toward certain menus, Coffee Shop Z can develop bundled packages, complementary menu recommendations, or new variants of popular items to increase transaction value. Upselling and cross-selling are standard "grow" strategies used to maximize Customer Lifetime Value (CLV) (Kumar & Reinartz, 2018).

3) Enhancing Customer Experience.

Creating memorable experiences through live music, special-day promotions, or monthly themes can encourage customers to return and bring others along. Experiential marketing enhances emotional attachment, which is a prerequisite for customer growth (Pine & Gilmore, 1998).

4) Referral Programs

Implementing referral systems, such as discounts for customers who bring friends or family, leverages satisfied customers to indirectly conduct word-of-mouth marketing. Referral programs systematically capitalize on positive sentiment to drive customer acquisition at a low cost (Kumar et al., 2010).

Through the implementation of a positive sentiment-based CRM growth strategy, Coffee Shop Z can strengthen relationships with satisfied customers and enhance long-term customer value. By leveraging positive experiences as a core strength, the coffee shop can not only retain customers but also drive business growth through loyalty and customer recommendations.

CONCLUSION

This study analyzed customer review sentiment on Google Maps as a basis for optimizing Customer Relationship Management (CRM) strategies at Coffee Shop Z in Purwokerto. The sentiment analysis results revealed that negative sentiment dominated customer reviews (57.02%), followed by neutral sentiment (30.16%) and positive sentiment (12.80%). These findings indicate that customer dissatisfaction is primarily associated with service quality and waiting time, while positive perceptions are related to food quality, affordability, and cleanliness.

The Multinomial Naïve Bayes algorithm achieved an accuracy of 63.27%, indicating moderate classification performance. The model demonstrated strong capability in identifying negative sentiment but showed limitations in classifying neutral and positive sentiments, which may be influenced by the imbalanced distribution of sentiment classes within the dataset.

Furthermore, the sentiment analysis results were successfully integrated into CRM strategy formulation through the get, keep, and grow framework. Negative sentiment served as the basis for customer acquisition improvement strategies (get), neutral sentiment supported customer retention strategies (keep), and positive sentiment contributed to customer loyalty enhancement strategies (grow). This integration demonstrates that customer reviews on Google Maps can be utilized not only to measure customer perceptions but also to support evidence-based managerial decision-making.

Future studies are recommended to utilize larger datasets, apply data balancing techniques, and compare the performance of more advanced machine learning or deep learning algorithms to improve sentiment classification accuracy and the effectiveness of CRM strategy recommendations.

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