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Predictive modeling of customer satisfaction in community pharmacies using machine learning

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Abstract
Customer satisfaction is a critical determinant of success in community pharmacies, influencing customer loyalty and overall business performance. This study aims to predict customer satisfaction scores in pharmacies by leveraging machine learning techniques on a comprehensive dataset of pharmacy operational metrics. Key factors examined include prescription accuracy and safety, service efficiency and accessibility, product availability, cost management, customer engagement, and the quality of pharmacy staff interactions. Using a Random Forest Regressor, the study evaluates model performance through cross-validation and test set results, employing metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The findings highlight the significant operational factors impacting customer satisfaction and demonstrate the potential of machine learning models in accurately predicting customer satisfaction scores. The results offer valuable insights for pharmacies to enhance their operational practices, ultimately leading to improved customer satisfaction and retention.

Keywords: Customer satisfaction, machine learning, operational metrics, community pharmacies

1. Introduction
Customer satisfaction is a vital measure of success for community pharmacies, directly impacting customer retention and overall business performance. Understanding and predicting customer satisfaction can help pharmacies improve their services and operational efficiency (Ung *et al*., 2016; Aldhwaihi *et al*., 2016) [1, 13]. This study leverages a comprehensive dataset of pharmacy operational metrics to develop a machine learning model that predicts customer satisfaction scores. The goal is to identify key operational factors that influence customer satisfaction and to evaluate the predictive accuracy of the model (Gopalakrishnan *et al*., 2017) [3].

Operational factors influencing customer satisfaction in community pharmacies encompass various aspects related to service delivery, product availability, staff interaction, and overall pharmacy environment. Based on research and industry practices, some key operational factors (Konyak *et al*., 2018) [15] include prescription accuracy and safety (Panesar *et al*., 2016) [8]. Higher rates of medication adherence, where patients follow their prescribed medication regimens, indicate better service and customer satisfaction (Brown *et al*., 2016) [12]. Additionally, lower medication error rates in prescriptions and dispensing enhance trust and satisfaction, while the efficiency and accuracy of filling prescriptions timely also impact customer experience (Pervanas *et al*., 2016) [11].

Service efficiency and accessibility are crucial, with shorter patient wait times for prescriptions and consultations significantly improving customer satisfaction (Aldhwaihi *et al*., 2016) [13]. The ability to handle a large volume of prescriptions efficiently reflects the pharmacy's capacity and reliability. Product availability and management, including efficient inventory turnover (Dwivedi *et al*., 2012) [4], ensure that essential medications are always available, avoiding stockouts (Ung *et al*., 2016) [1]. Sales revenue and average transaction value (ATV) can indicate the variety and availability of products and services that meet customer needs (Dwivedi *et al*., 2012) [4].

Cost and financial factors, such as labor costs, impact operational costs and can influence service delivery quality. Sustainable profit margins allow reinvestment in service quality improvements (Gregório *et al*., 2016) [6]. Customer engagement and retention are also important, with higher customer retention rates signifying consistent satisfaction and loyalty (Brown *et al*., 2016) [12]. Effective Medication Therapy Management (MTM) services can improve patient outcomes and satisfaction (Viswanathan *et al*., 2015) [9].

Pharmacy staff and service quality play a significant role, with friendly, knowledgeable, and approachable staff greatly enhancing customer satisfaction (Van Eikenhorst *et al*., 2017) [10]. The availability of pharmacists for consultations and health advice is a significant factor. Operational and financial performance, measured by ROI (Return on Investment), indicates effective resource utilization, which can translate into better services for customers (Gregório *et al*., 2016) [6]. Regulatory compliance and reporting, including prompt and accurate reporting of Adverse Drug Events (ADEs), demonstrate a pharmacy's commitment to patient safety (Gonzalez-Gonzalez *et al*., 2013) [7].

Technology and innovation (Olkhovska *et al*., 2017) [14], such as the implementation of modern technologies for prescription processing, inventory management, and customer interaction, can improve efficiency and satisfaction (Odukoya *et al*., 2013) [2]. The availability of online prescription refills, consultations, and delivery services enhances convenience for customers (Nabelsi *et al*., 2017) [5]. The pharmacy environment, including cleanliness and organization, contributes to a positive customer experience. Accessibility, with convenient location and hours of operation, is critical for customer satisfaction (Aldhwaihi *et al*., 2016) [13].

Additional considerations include regularly seeking and acting on customer feedback to identify areas for improvement and enhance satisfaction (Brown *et al*., 2016) [12]. Pharmacies that actively engage with their community through health camps, awareness programs, and other initiatives can build stronger customer relationships and trust (Gonzalez-Gonzalez *et al*., 2013) [7]. Focusing on these operational factors can help community pharmacies improve their customer satisfaction scores. By leveraging data and machine learning techniques, pharmacies can better understand the impact of these factors and continuously optimize their operations to meet customer needs and expectations (Gopalakrishnan *et al*., 2017; Odukoya *et al*., 2013) [3, 2].

2. Materials and Methods

The dataset used in this study was generated synthetically to correlate closely with real-world data. It was designed to reflect a comprehensive collection of operational metrics from community pharmacies. This synthetic dataset was loaded from a CSV file. To focus on relevant features and prevent potential data leakage, several columns, such as 'Pharmacy Name' and 'Date', were excluded from the analysis.

The study focused on a range of operational metrics that potentially influence customer satisfaction. The features selected for analysis included Sales Revenue (INR), Prescription Volume, Medication Adherence Rate (%), Inventory Turnover, Labor Costs (INR), Average Transaction Value (ATV) (INR), Profit Margin (%), Prescription Fill Rate (%), Generic Dispensing Rate (GDR) (%), Patient Wait Times (min), Medication Error Rate (%), Return on Investment (ROI) (%), Customer Retention Rate (%), MTM (Medication Therapy Management) Utilization (%), ADE (Adverse Drug Event) Reporting Rate (%), Staff Professionalism and Communication, Consultation Services, Use of Technology, Online Services, Cleanliness and Organization, Accessibility, and Community Engagement. The target variable was the 'Customer Satisfaction Score'.

The dataset was split into training and testing sets, with 80% of the data allocated to training and 20% to testing. This ensures that the model is trained on a substantial portion of the data while its performance is evaluated on unseen data. To enhance model performance and ensure uniformity among the features, standardization was applied. This process scales the features so they have a mean of zero and a standard deviation of one.

A Random Forest Regressor was chosen for its robustness and ability to handle complex, non-linear relationships. The model was initialized with 100 estimators and a random state of 42 to ensure reproducibility.

To ensure the robustness of the model, 5-fold cross-validation was performed. This method splits the training data into five subsets, training the model on four subsets and validating it on the fifth, rotating through all subsets. This process was repeated for both Mean Absolute Error (MAE) and Mean Squared Error (MSE) metrics.

The model was trained on the full training set to capture all the patterns and relationships within the data. Predictions were made on the test set, and the model's performance was evaluated using MAE, MSE, and Root Mean Squared Error (RMSE).

Results Reporting: The cross-validation and test set results were reported to assess the model's predictive accuracy and consistency.

3. Results and Discussion

The pre-processing steps involved selecting relevant features and standardizing them to ensure uniformity in the dataset. The features included various operational metrics such as Sales Revenue, Prescription Volume, Medication Adherence Rate, and others that potentially influence customer satisfaction. The data was then split into training and testing sets with an 80-20 ratio to ensure a substantial portion for training while preserving unseen data for testing. The dataset consisted of a total of 100,010 examples, providing a robust sample size for model training and evaluation.

A Random Forest Regressor model was chosen for its robustness in handling complex, non-linear relationships. The model was initialized with 100 estimators and a random state of 42 to ensure reproducibility. Cross-validation was performed using 5-fold cross-validation to assess the model's performance during training. This method helps in understanding the model's stability and generalization by evaluating it on different subsets of the training data.

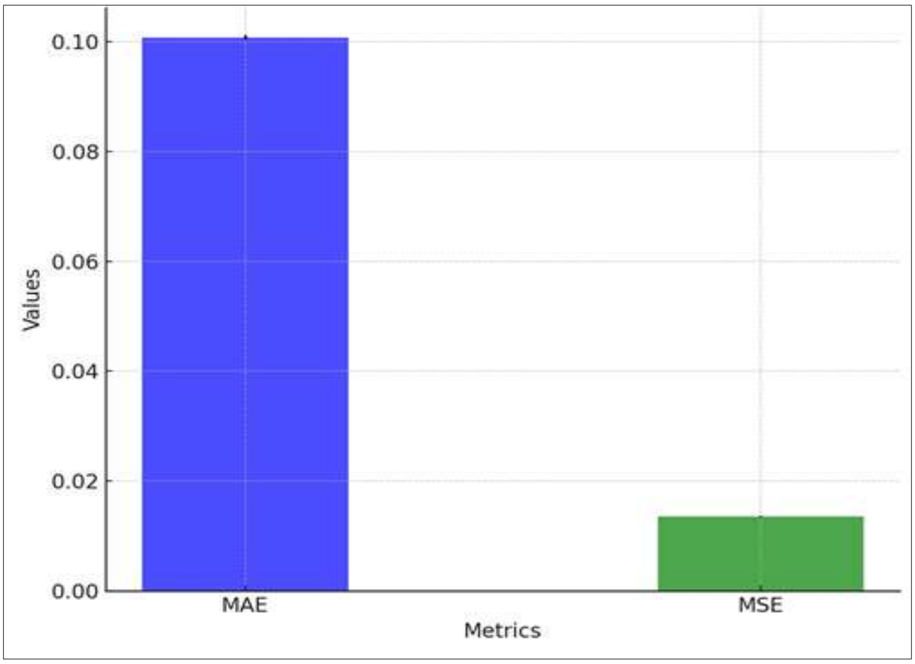

Fig 1: Cross-Validation Results

The cross-validation results - Average MAE: 0.1007 ± 0.0004 and Average MSE: 0.0136 ± 8.45e-05 are shown in Fig 1. These metrics indicate that the model had a consistent performance across different folds of the training data. The low standard deviations suggest that the model is stable and does not significantly vary across different subsets.

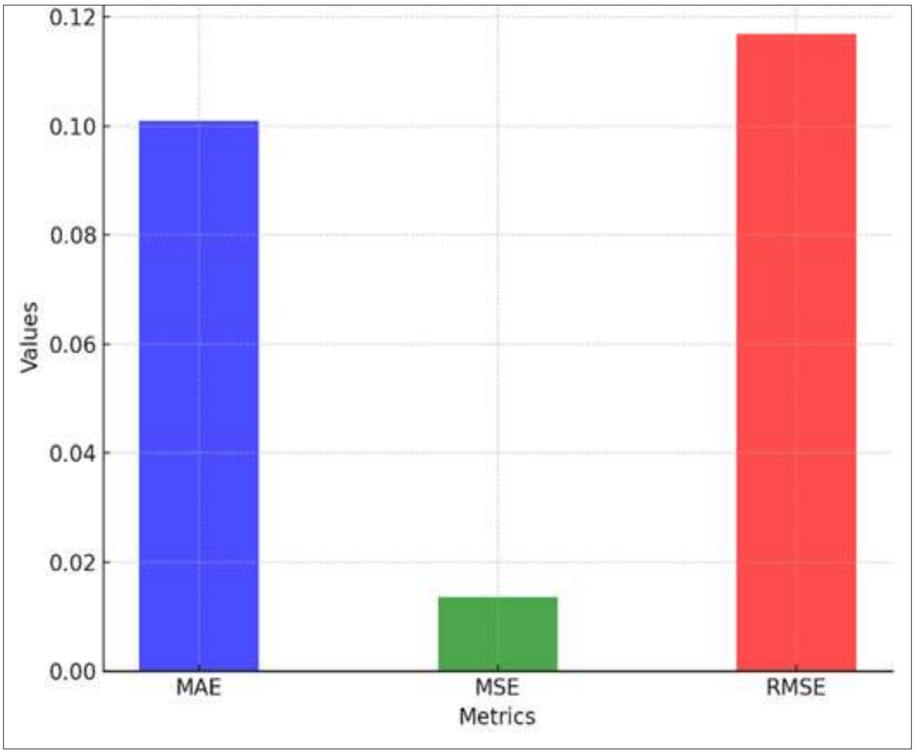

Fig 2: Test Set Results

The model was trained on the full training set to capture all possible patterns and relationships within the data. Predictions were then made on the test set, and the model's performance was evaluated using MAE, MSE, and RMSE: The test set results - MAE: 0.1009, MSE: 0.0136 and RMSE: 0.1168 are shown in Fig 2.

These results are consistent with the cross-validation findings, confirming the model's ability to generalize well to unseen data. The low MAE indicates that the average prediction error is small, which is crucial for practical applications where accuracy in predicting customer satisfaction scores is important. The MSE and RMSE values further support the model's performance, with RMSE providing an interpretable measure of average prediction error magnitude.

The consistent performance across both cross-validation and test set evaluations demonstrates the effectiveness of the Random Forest Regressor in predicting customer satisfaction scores based on operational metrics. The selected features, representing various aspects of pharmacy operations, appear to provide a comprehensive view of the factors influencing customer satisfaction.

The inclusion of diverse features such as Sales Revenue, Prescription Volume, and Staff Professionalism suggests that customer satisfaction is influenced by a blend of financial performance, service efficiency, and staff interaction.

The low standard deviations in cross-validation results indicate that the model is robust and not overly sensitive to variations in the training data. This stability is essential for reliable performance in real-world scenarios.

The model's ability to predict customer satisfaction can guide community pharmacies in optimizing their operations. By focusing on key operational metrics, pharmacies can make targeted improvements to enhance customer satisfaction, such as reducing wait times, ensuring medication availability, and improving staff training.

Leveraging a comprehensive dataset of operational metrics and a robust machine learning model like the Random Forest Regressor provides valuable insights into the factors influencing customer satisfaction in community pharmacies. This approach not only aids in accurate predictions but also helps identify areas for operational improvements, ultimately leading to better customer experiences and business performance.

4. Conclusion

This study demonstrates the effectiveness of using machine learning techniques, specifically a Random Forest Regressor, to predict customer satisfaction in community pharmacies based on a comprehensive dataset of operational metrics. Key operational factors influencing customer satisfaction were identified, including prescription accuracy, service efficiency, product availability, cost management, customer engagement, and staff interactions. The model exhibited consistent performance across both cross-validation and test set evaluations, with low MAE, MSE, and RMSE, indicating robust and reliable predictions. These results highlight the model's ability to generalize well to unseen data, making it a valuable tool for practical applications in the pharmacy industry. By focusing on these key operational metrics, pharmacies can make targeted improvements, such as reducing wait times, ensuring medication availability, and enhancing staff professionalism and communication. Leveraging machine learning the model provides actionable insights for optimizing operations, ultimately leading to better customer experiences and improved business performance. Future research could further explore the importance of individual features and develop more sophisticated models for customer satisfaction predictions.

5. References

1. Ung COL, Chao CK, Hu Y, Zhao J, Li P, Wang Y, *et al*. Community pharmacists' understanding, attitudes, practice and perceived barriers related to providing pharmaceutical care: A questionnaire-based survey in Macao. Tropical Journal of Pharmaceutical Research. 2016;15(4):847-854.
2. Odukoya OK, Chui MA. E-prescribing: A focused review and new approach to addressing safety in pharmacies and primary care. Research in Social and Administrative Pharmacy. 2013;9(6):996-1003.
3. Gopalakrishnan V, Ramaswamy C. Patient opinion mining to analyze drugs satisfaction using supervised learning. Journal of applied research and technology. 2017;15(4):311-319.
4. Dwivedi S, Kothiyal P. Inventory management: A tool of identifying items that need greater attention for control. The Pharma Innovation. 2012;1(7, Part A):125.
5. Nabelsi V, Gagnon S. Information technology strategy for a patient-oriented, lean, and agile integration of hospital pharmacy and medical equipment supply chains. International Journal of Production Research. 2017;55(14):3929-3945.
6. Gregório J, Russo G, Lapão LV. Pharmaceutical services cost analysis using time-driven activity-based costing: A contribution to improve community pharmacies' management. Research in Social and Administrative Pharmacy. 2016;12(3):475-485.
7. Gonzalez-Gonzalez C, Lopez-Gonzalez E, Herdeiro MT, Figueiras A. Strategies to improve adverse drug reaction reporting: A critical and systematic review. Drug safety. 2013;36:317-328.
8. Panesar SS, Desilva D, Carson-Stevens A, Cresswell KM, Salvilla SA, Slight SP, *et al*. How safe is primary care? A systematic review. BMJ quality and safety. 2016;25(7):544-553.
9. Viswanathan M, Kahwati LC, Golin CE, Blalock SJ, Coker-Schwimmer E, Posey R, *et al*. Medication therapy management interventions in outpatient settings: a systematic review and meta-analysis. JAMA internal medicine. 2015;175(1):76-87.
10. Van Eikenhorst L, Salema NE, Anderson C. A systematic review in select countries of the role of the pharmacist in consultations and sales of non-prescription medicines in community pharmacy. Research in Social and Administrative Pharmacy. 2017;13(1):17-38.
11. Pervanas HC, Revell N, Alotaibi AF. Evaluation of medication errors in community pharmacy settings: a retrospective report. Journal of Pharmacy Technology. 2016;32(2):71-74.
12. Brown MT, Bussell J, Dutta S, Davis K, Strong S, Mathew S, *et al*. Medication adherence: truth and consequences. The American journal of the medical sciences. 2016;351(4):387-399.
13. Aldhwaihi K, Schifano F, Pezzolesi C, Umaru N. A systematic review of the nature of dispensing errors in hospital pharmacies. Integrated Pharmacy Research and Practice. 2016;5:1-10.
14. Olkhovska A, Olkhovska AB. Marketing communication and digital technology innovative instruments in promoting pharmaceutical brands in Ukraine and their efficiency estimation. The Pharma Innovation. 2016;5(9, Part A):38.
15. Konyak CY, Vidyarthi VK. Optimizing community pharmacy performance: Key performance indicators and strategic insights. Pharma Innovation. 2018;7(12):463-466.