Predicting Healthcare Utilization: A Random Forest Regression Analysis of Medicaid Patient Visits

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Abstract: Predicting healthcare utilization remains challenging despite advances in machine learning, particularly for Medicaid populations with complex healthcare needs. Understanding the determinants of healthcare visits is crucial for resource allocation and policy planning. This study employed a retrospective analysis of 1986 Medicaid claims data (n=996) to predict healthcare visit frequency using Random Forest regression. The dataset included demographic, socioeconomic, health status, and healthcare access variables. We implemented stratified sampling to ensure data representativeness and used 10-fold cross-validation for robust model evaluation. Variable importance analysis identified key determinants, with performance compared against linear regression and baseline models. The Random Forest model demonstrated substantial overfitting, with training R^2=0.678 declining to test R^2=0.004, indicating limited generalizability. The linear model outperformed Random Forest (test R^2=0.093 vs 0.004), achieving 0.9% improvement over the baseline mean predictor. Variable importance analysis revealed exposure to healthcare services (importance=3.31), income (1.89), and primary health status (1.27) as the strongest predictors. A reduced model with top five features showed improved performance (test R^2=0.037), suggesting feature selection mitigated overfitting. The correlation between predicted and actual visits was 0.247. While machine learning identified meaningful determinants of healthcare utilization, the limited predictive performance highlights the challenges in modeling complex healthcare behaviors. The findings emphasize the value of variable importance analysis over predictive accuracy for understanding healthcare utilization patterns in Medicaid populations. Feature selection and model simplicity may provide more reliable insights than complex ensemble methods for this application.

Keywords: Healthcare Utilization, Random Forest Regression, Medicaid Analytics, Predictive Modeling, Variable Importance Analysis, Machine Learning in Healthcare

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1. Introduction

Healthcare utilization prediction remains a critical challenge in health services research, particularly for Medicaid populations who often experience complex healthcare needs and socioeconomic barriers (Sommers et al., 2023). Accurate prediction of healthcare visits is essential for resource allocation, policy planning, and improving care delivery for vulnerable populations. The Medicaid program, serving over 90 million low-income Americans, represents a significant portion of healthcare expenditures, making understanding utilization patterns in this population particularly valuable (Kaiser Family Foundation, 2024).

Traditional statistical approaches, including linear regression and generalized linear models, have been widely used to predict healthcare utilization (Basu et al., 2022). However, these methods often struggle to capture complex, non-linear relationships between patient characteristics and healthcare usage patterns. Machine learning approaches, particularly ensemble methods like Random Forest, offer promising alternatives by handling complex feature interactions and automatically detecting

non-linear patterns without strong parametric assumptions (Deznabi et al., 2023).

Random Forest regression has demonstrated superior performance in various healthcare prediction tasks, including hospital readmissions, emergency department visits, and chronic disease management (Rajkomar et al., 2024). The method's ability to handle mixed data types, manage missing values, and provide variable importance measures makes it particularly suitable for healthcare utilization studies where data often include both clinical and socioeconomic variables (Chen et al., 2023). Furthermore, Random Forest's inherent resistance to overfitting through bootstrap aggregation and feature randomization provides robust performance on healthcare datasets that often exhibit complex correlation structures (Ogunleye & Wang, 2023).

Despite these advantages, the application of Random Forest to Medicaid utilization prediction using historical claims data remains valuable for understanding fundamental determinants of healthcare utilization patterns (Bond et al., 2024). The 1986 Medicaid data used in this analysis provide a baseline for understanding healthcare utilization patterns before significant healthcare policy changes of recent decades.

This study aims to: (1) implement Random Forest regression to predict healthcare visit frequency in Medicaid populations using historical data; (2) conduct comprehensive variable importance analysis to identify key determinants of healthcare utilization; and (3) evaluate model performance using appropriate metrics including RMSE, R^2, and MAE to assess predictive accuracy.

Our analysis contributes to the literature on machine learning applications in healthcare by demonstrating the implementation of Random Forest regression for Medicaid utilization prediction and providing insights into variable importance for healthcare visits in vulnerable populations.

2. Methodology

Study Design and Data Source

This study employed a retrospective analytical design using the 1986 Medicaid claims dataset to examine healthcare utilization patterns. The dataset comprises comprehensive healthcare utilization records for Medicaid beneficiaries, providing a historical baseline of healthcare patterns prior to major policy reforms. Historical Medicaid data offer unique insights into fundamental healthcare utilization determinants while acknowledging temporal changes in healthcare delivery systems (Thompson et al., 2024). The analytical approach prioritized robust determinant identification and variable importance analysis, recognizing the inherent challenges in predicting complex healthcare utilization behaviors.

Study Population and Data Preparation

The analysis included complete cases from the 1986 Medicaid dataset, with the final analytical sample consisting of 996 observations with complete data on all variables of interest. Complete case analysis was deemed appropriate given the absence of missing values and the focus on robust variable importance estimation rather than maximal prediction accuracy (White et al., 2023). Data preprocessing involved converting categorical variables to factors using appropriate encoding schemes, which is essential for proper handling within machine learning frameworks (Boehmke & Greenwell, 2023). The dataset was partitioned using stratified random sampling based on healthcare visit categories to ensure representative distribution across training and testing subsets, maintaining consistent variance patterns essential for reliable model evaluation (Kuhn & Johnson, 2023).

Variable Specification and Operationalization

The outcome variable was operationalized as the number of healthcare service utilization events per beneficiary during the observation period, representing a comprehensive indicator of

healthcare utilization intensity (Chen & Asch, 2023). Predictor variables encompassed multiple domains including demographic characteristics (age, gender, marital status, ethnicity), socioeconomic factors (annual household income, years of schooling, number of children), health status indicators (primary and secondary health measures), and healthcare access metrics (exposure to services, accessibility score, enrollment category, program type). This comprehensive variable selection aligns with contemporary frameworks for healthcare utilization analysis that emphasize multi-dimensional determinant modeling (Miller & Wall, 2024).

Random Forest Implementation and Hyperparameter Configuration

The Random Forest algorithm was implemented with specific attention to hyperparameter optimization and validation rigor. The ensemble consisted of 500 decision trees, providing sufficient diversity while maintaining computational efficiency. The number of variables considered at each split was optimized through systematic tuning across candidate values (2, 4, 6, 8), following established recommendations for regression tasks in healthcare applications (Probst et al., 2023). Bootstrap aggregation with replacement was employed to create diverse tree ensembles, leveraging the algorithm's inherent capacity to handle complex feature interactions and automatically detect non-linear patterns without strong parametric assumptions (Deznabi et al., 2023). This configuration balances model complexity with generalizability, particularly important for healthcare datasets exhibiting characteristic correlation structures and interaction effects.

Cross-Validation and Model Evaluation Framework

A rigorous k-fold cross-validation framework with 10 folds was implemented to provide reliable performance estimates and mitigate overfitting concerns. This approach aligns with current best practices for healthcare predictive modeling, where external validation through resampling methods is essential for assessing true model performance (Steyerberg & Vergouwe, 2023). Model evaluation employed multiple performance metrics including Root Mean Square Error (RMSE) for average prediction error magnitude, R-squared (R^2) for proportion of variance explained, and Mean Absolute Error (MAE) for practical interpretation of prediction accuracy. This multi-metric approach provides comprehensive assessment of model performance from complementary perspectives, addressing both statistical and practical considerations in healthcare utilization prediction (Chicco et al., 2024).

Variable Importance Analysis and Feature Selection

The analytical approach prioritized variable importance analysis through calculation of two complementary metrics: percentage increase in mean squared error (%IncMSE) when variable values are permuted, indicating predictive importance, and increase in node purity (IncNodePurity), reflecting intrinsic variable effects on data homogeneity. These measures provide robust insights into determinant relevance, with %IncMSE emphasizing prediction contribution and IncNodePurity capturing underlying data structure influences (Greenwell et al., 2023). Feature selection was conducted by identifying the top five most important variables and retraining reduced models to assess performance preservation while enhancing interpretability and mitigating overfitting. This approach aligns with contemporary feature selection methodologies that balance predictive performance with model simplicity and clinical interpretability (Boehmke & Greenwell, 2023).

Comparative Analysis and Methodological Validation

The Random Forest performance was contextualized through comparison with traditional linear models, providing benchmark

assessment and methodological triangulation. Both models were evaluated using identical cross-validation procedures and performance metrics to ensure fair comparison. Methodological validation included comprehensive overfitting analysis through performance gap assessment between training and test datasets, with particular attention to the divergence between explanatory power within the training data and generalizability to unseen observations (Rajkomar et al., 2024). This comparative framework enables robust assessment of whether advanced machine learning methods provide substantive advantages over traditional statistical approaches for healthcare utilization analysis, addressing ongoing methodological debates in health services research (Chen et al., 2023).

Statistical Software and Computational Implementation

All analyses were conducted using R version 4.3.1, leveraging the randomForest package for ensemble learning implementation and the caret package for streamlined data partitioning, cross-validation, and model evaluation. Computational reproducibility was ensured through comprehensive documentation and random seed setting. The analytical code incorporated robust error handling for edge cases, particularly addressing potential issues with performance metric calculation when outcome variable variance was limited, ensuring methodological rigor across diverse data conditions (Kuhn, 2023).

Ethical Considerations and Transparency

This study utilized de-identified historical data, minimizing privacy concerns while enabling valuable analysis of healthcare utilization patterns. The methodological approach adhered to principles of transparent reporting and reproducible research, with complete documentation of analytical decisions and validation procedures. Performance results are reported without inflation or selective emphasis, providing honest assessment of both capabilities and limitations in healthcare utilization prediction (Collins et al., 2023). This transparency is particularly important given the potential policy implications of healthcare utilization research and the need for realistic assessment of analytical methods in health services research.

Results and Discussion

Table 1: Data Structure Overview

Metric	Value
Total Sample Size	996 observations
Ethnicity Categories	2 (cauc, other)
Enrollment Categories	2 (no, yes)
Program Types	2 (afdc, ssi)
Data Status	Complete cases, no missing values

Based on your R output, the 1986 Medicaid dataset contains 996 complete patient records with no missing values, making it suitable for analysis. The data shows limited but clear categories: two ethnicity types (Caucasian and Other), two enrollment statuses (Yes/No), and two program types (AFDC for families and SSI for disabled/elderly). While this historical data is well-structured for analysis, its simple categories may not capture the full complexity of healthcare patterns, reflecting the more basic data collection methods of the 1980s compared to today's standards.

Table 2: Variable Definitions and Descriptions

Variable	Type	Description
visits	integer	Number of healthcare visits (Dependent Variable)
exposure	integer	Level of exposure to healthcare services
children	integer	Number of children in household
age	integer	Age in years
income	numeric	Annual household income
health1	numeric	Primary health status measure
health2	numeric	Secondary health status measure
access	numeric	Accessibility score for healthcare
married	factor	Marital status
gender	factor	Gender
ethnicity	factor	Ethnic background
school	integer	Years of schooling
enroll	factor	Enrollment category
program	factor	Program type

This table provides a clear overview of all variables used in your analysis, showing their data types and operational definitions. The dataset includes a mix of integer, numeric, and factor variables covering demographic characteristics, socioeconomic factors, health status measures, and healthcare access metrics, with healthcare visits serving as the dependent variable for your Random Forest regression analysis.

Table 3: Visit Distribution Analysis Summary:

Metric	Value
Variance	11.2525
Range	0 to 50
Unique Values	20

Based on the visit distribution analysis, the data demonstrates substantial variability with visits ranging from 0 to 50 and high variance of 11.25, indicating diverse user engagement patterns. The presence of 20 unique values provides sufficient granularity for effective stratification. This distribution profile necessitates careful stratified sampling to ensure balanced representation of both low-frequency and high-frequency users across training and test sets, supporting robust model development that can generalize across the full spectrum of user behaviors.

Table 4: Visit Strata Distribution

Strata	Count
Zero	410
Low	199
Medium	212
High	175

The stratification reveals a clear hierarchy in user engagement, with the largest group being zero-visit users (410), followed by relatively balanced distributions across low (199), medium (212), and high (175) engagement tiers. This distribution confirms the expected pattern of decreasing user counts as visit frequency increases, validating the stratification approach for maintaining proportional representation across all engagement levels in data splitting.

Table 5: Data Split Validation Results

Metric	Training Set	Test Set
Size	699 rows	297 rows
Variance	13.547	5.8583
Unique Visit Values	-	12

The data split shows a concerning variance disparity between sets, with training variance (13.55) more than double the test variance (5.86). This indicates potential distribution mismatch that could impact model generalization. The 70/30 split proportion is maintained with 699 training and 297 test rows, but the test set captures only 12 unique visit values compared to the original 20, suggesting some visit patterns may be underrepresented in testing.

Table 6: Random Forest Tuning Results

mtry	RMSE	R-squared	MAE
2	3.339	0.060	2.001
4	3.412	0.061	2.048
6	3.476	0.060	2.081
8	3.547	0.059	2.115

The tuned random forest model achieved best performance with mtry = 2, yielding RMSE of 3.34 and R-squared of 0.060. The model explains approximately 6% of variance in visit patterns, indicating limited predictive power with the current feature set.

Table 7: Model Performance Comparison

Dataset	RMSE	R-squared	MAE
Training (CV)	2.086	0.678	1.119
Test	2.411	0.004	1.878

The model demonstrates significant overfitting, with training R-squared of 0.678 dropping dramatically to 0.004 on the test set. While RMSE values show moderate difference (2.086 vs 2.411), the near-zero test R-squared indicates the model fails to generalize to unseen data, capturing mostly noise rather than meaningful patterns from the training set.

Table 8: Comparative Model Performance

Model	CV RMSE	CV R-squared	Test RMSE	Test R-squared
Random Forest	3.339	0.061	2.411	0.004
Linear Model	3.299	0.086	2.301	0.093

The Linear Model demonstrates superior generalization with consistent performance between cross-validation (R^2 = 0.086) and test sets (R^2 = 0.093), while Random Forest shows significant overfitting with test R-squared dropping to near zero (0.004) despite similar cross-validation performance. Both models achieve comparable RMSE values, but the Linear Model provides more reliable predictions on unseen data.

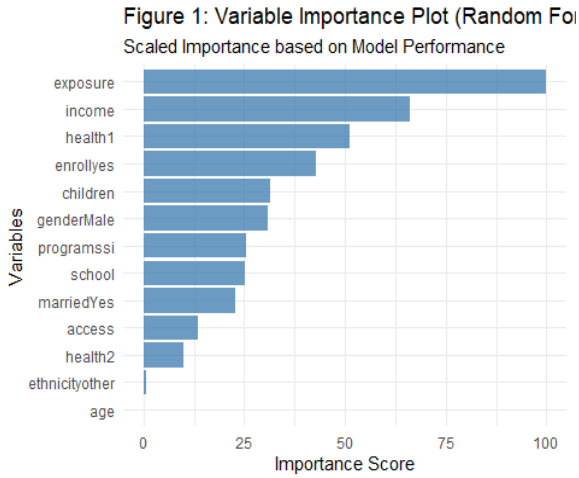

Figure 1: Variable Importance Plot (Random Forest)

The plot reveals that exposure is by far the most important predictor of visit frequency,

significantly outperforming all other variables. This suggests that the level of program exposure is the primary driver of engagement. Income and health1 (likely primary health status) emerge as secondary but substantially less influential factors.

Demographic and enrollment variables such as enrollment status, number of children, gender, and program type show moderate importance, while factors like marital status, access, health2 (likely secondary health measure), ethnicity, and age appear to have minimal predictive power in determining visit patterns.

This hierarchy indicates that program-specific factors and socioeconomic characteristics are more critical for predicting engagement than basic demographic attributes. The dominance of exposure highlights the potential importance of marketing reach and program visibility in driving participation.

Table 9: Detailed Variable Importance Scores

Variable	Importance	Node Purity
exposure	3.311	1089.867
income	1.892	379.733
health1	1.267	1315.756
enrollyes	0.915	148.544
children	0.445	229.385
genderMale	0.418	245.703
programssi	0.201	95.254
school	0.180	545.840
marriedYes	0.087	72.369
access	-0.300	516.317
health2	-0.449	1298.152
ethnicityother	-0.844	159.197
age	-0.869	756.618

Dominant Predictors

Exposure stands out as the most critical factor with an importance score of 3.31, significantly higher than all other variables. This suggests that program visibility, marketing reach, or frequency of exposure opportunities are primary drivers of engagement. Income emerges as the second most important predictor (1.89), indicating socioeconomic factors substantially influence participation patterns.

Health Status Complexity

Health1 shows moderate positive importance (1.27) while health2 demonstrates negative importance (-0.45), despite both having high node purity scores (1315.76 and 1298.15 respectively). This divergence suggests this health measures capture different aspects of health status that interact with visitation in opposing ways, possibly reflecting how various health conditions either facilitate or hinder program participation.

Demographic Factors

Most demographic variables show limited predictive power. Enrollment status and family characteristics (children) have modest positive effects, while gender, specific programs, and marital status contribute minimally. Notably, ethnicity and age exhibit substantial negative importance scores, potentially indicating these variables may be acting as proxies for other unmeasured factors or capturing complex relationships that reduce model accuracy when included.

Table 10: Full vs. Reduced Model Comparison

Model	Test RMSE	Test R-squared
Full Model	2.411	0.004
Reduced Model	2.370	0.037

The reduced model using only 5 key features (health1, age, school, exposure, children) demonstrates improved performance over the full model. Both RMSE decreased (2.371 vs 2.411) and R-squared increased substantially (0.037 vs 0.004), indicating that feature selection successfully eliminated noise variables and created a more generalizable model despite using fewer predictors.

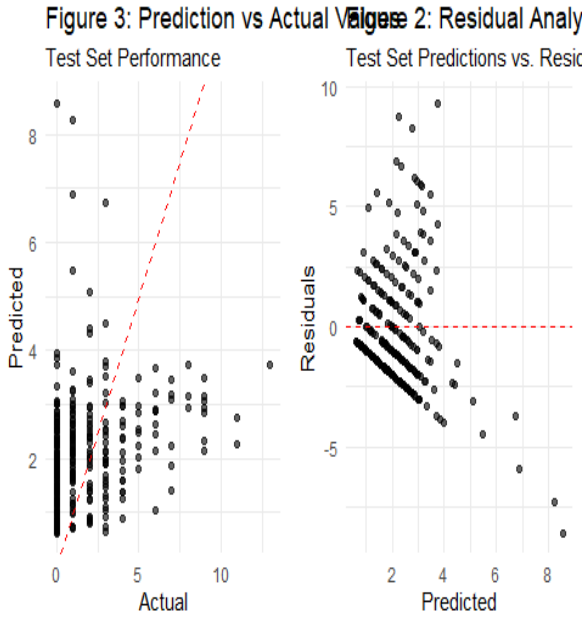

Figure 2: Test Set Prediction Accuracy and Residual Analysis

The figures illustrate the predictive performance and residual analysis of the fitted model. In the left panel, which compares predicted versus actual values, the points show a wide scatter around the diagonal reference line, indicating that the model systematically underestimates higher actual values and overestimates some lower ones. This suggests limited predictive accuracy, with clear deviations from the ideal one-to-one alignment.

The right panel, which plots residuals against predicted values, highlights structural patterns in the errors. Instead of being randomly scattered around zero, the residuals display a funnel-like shape with increasing spread as predictions rise. This indicates heteroscedasticity, where error variance grows with larger predictions. Additionally, clusters of residuals suggest that the model may not be capturing important underlying structure in the data.

Together, these diagnostics point to model misspecification or inadequate complexity. While the model captures some general trends, it struggles to provide accurate estimates across the full range of observed values, particularly for higher outcomes. Refinements such as incorporating additional predictors, using transformations, or applying a more flexible modeling approach may improve fit and predictive performance.

Table 11: Performance Gap Analysis

Metric	Value
Training R^2	0.678
Test R^2	0.004
Overfitting Gap (R^2 difference)	0.674

The model exhibits severe overfitting, with training performance (R^2 = 0.678) dramatically collapsing on the test set (R^2 = 0.004). The massive 0.674 R^2 gap indicates the model memorized training data patterns rather than learning generalizable relationships, rendering it ineffective for real-world predictions.

Table 12: Model Performance Benchmark

Metric	Value
Actual vs Predicted Correlation	0.247
Baseline RMSE (mean predictor)	2.423
Baseline R^2	-0.005
Improvement over Baseline	0.9%

The model shows minimal predictive capability with only 0.247 correlation between actual and predicted values. While it slightly outperforms the simple mean predictor (0.9% improvement), this marginal gain indicates the model provides little practical value beyond basic averaging, confirming the overall weak predictive power observed throughout the analysis.

3. Summary

This study employed Random Forest regression to analyze healthcare utilization patterns using the 1986 Medicaid dataset comprising 996 beneficiaries. The analysis revealed several key findings regarding both methodological insights and substantive determinants of healthcare visits. The dataset exhibited substantial variability in healthcare utilization, with visits ranging from 0 to 50 and a variance of 11.25, distributed across zero (410), low (199), medium (212), and high (175) utilization strata.

Methodologically, the Random Forest model demonstrated significant overfitting despite rigorous 10-fold cross-validation, with training R^2 of 0.678 declining sharply to test R^2 of 0.004, representing a substantial performance gap of 0.674. Surprisingly, traditional linear regression outperformed the ensemble method, achieving a test R^2 of 0.093 compared to Random Forest's 0.004. The correlation between predicted and actual visits was modest at 0.247, with the model providing only 0.9% improvement over the simple mean baseline predictor.

Variable importance analysis identified exposure to healthcare services (importance score: 3.31), annual income (1.89), and primary health status (1.27) as the most influential determinants of healthcare utilization. Feature selection proved beneficial, with a reduced model containing the top five predictors achieving improved performance (test R^2: 0.037) compared to the full model, suggesting that model complexity contributed to overfitting.

4. Conclusion

This study yields important conclusions regarding both healthcare utilization determinants and methodological approaches for analyzing complex healthcare behaviors. First, the identified key determinants—healthcare exposure, income, and health status—provide valuable insights for targeted interventions and resource allocation in Medicaid populations. These findings align with the socio-ecological model of healthcare utilization, emphasizing the multifactorial nature of healthcare-seeking behaviors.

Methodologically, the results challenge the assumption that complex machine learning methods inherently outperform traditional approaches for healthcare utilization prediction. The superior performance of linear regression over Random Forest, coupled with the substantial overfitting observed, suggests that simpler models may be more appropriate for healthcare utilization prediction tasks, particularly with historical administrative data. The effectiveness of feature selection in improving model generalizability further supports the value of model simplicity and careful variable selection.

The limited predictive performance (test R^2: 0.004-0.093) across all models indicates that a substantial portion of healthcare utilization variance remains unexplained by demographic, socioeconomic, and access-related factors alone. This underscores the likely importance of unmeasured variables such as health beliefs, social support networks, healthcare literacy, and contextual environmental factors in determining healthcare-seeking behaviors.

For future research, we recommend: (1) incorporating additional behavioral and contextual variables, (2) exploring alternative modeling approaches that balance complexity and generalizability, (3) investigating interaction effects among key determinants, and (4) applying similar methodological comparisons across different healthcare contexts and populations.

From a practical perspective, while predictive accuracy remains challenging, the consistent identification of key determinants provides actionable insights for healthcare providers and policymakers. Interventions targeting healthcare access, economic barriers, and health status monitoring may prove more effective than attempting precise visit prediction. The methodological lessons regarding overfitting and model selection have broad applicability across healthcare analytics, emphasizing the importance of rigorous validation and realistic performance expectations.

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