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| RESEARCH ARTICLE

Machine Learning Models for Predicting Patient Treatment Switching Using Claims Data

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| ABSTRACT
Treatment switching - including discontinuation, add on therapy, and brand to generic substitution—can have meaningful clinical and economic consequences for patients, payers, and health systems. Administrative claims databases provide large scale longitudinal records of medication use and health care utilization, enabling the study of real world treatment trajectories; however, traditional analytic approaches often struggle to translate high dimensional claims signals into timely and actionable switching predictions. This paper reviews and synthesizes machine learning (ML) strategies that leverage claims data to predict treatment switching across multiple therapeutic areas, including rheumatology, neurology, psychiatry, and cardiovascular disease. The review summarizes major methodological approaches—tree based ensembles, regularized regression, neural networks, and temporal/sequential models—and highlights common feature engineering practices for handling high dimensionality and class imbalance. Across the referenced studies, ML approaches generally improve predictive performance compared with simpler baselines, with clinical phenotype proxies, prior medication burden, utilization intensity, and adherence patterns frequently emerging as important predictive signals. The paper also discusses implications for clinical decision support, real world evidence generation, and market access strategy. Persistent challenges include sparse clinical granularity in administrative data, heterogeneity in switching definitions, class imbalance, and limited cross system transportability; integrating claims with richer clinical sources (e.g., EHR) and performing prospective and external validation remain important directions for future work.

| KEYWORDS
Machine Learning; Treatment Switching; Administrative Claims Data; Pharmacotherapy; Predictive Analytics; Real-World Evidence; Medication Adherence

| ARTICLE INFORMATION
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I. INTRODUCTION
Treatment switching—covering drug discontinuation, add-on therapy, therapeutic substitution, and brand-to-generic replacement—represents a common and consequential phenomenon in modern pharmacotherapy. As described in [13], switching can reflect therapy failure, adverse reactions, affordability constraints, or evolving clinical guidance; anticipating switching is therefore relevant to clinicians, payers, manufacturers, and health systems.

Large administrative claims databases have enabled longitudinal analyses of medication use and health-care utilization at scale, including national insurance registries, hospital billing systems, and population-wide health databases. Prior work shows that claims reflect real-world treatment journeys and provide practical signals about prescribing behavior, adherence, and switching patterns that are not always captured in randomized controlled trials [2], [6].

This landscape has contributed to a shift from primarily retrospective analyses toward predictive frameworks designed to identify patients at risk of switching earlier in their treatment journey. Machine learning (ML) methods are particularly well-suited to claims environments because they can process high-dimensional and heterogeneous inputs and capture complex, non-linear patterns that are often difficult to model with traditional approaches. Claims-based predictive analytics has been used to generate actionable risk stratification and decision support, supporting earlier and more targeted interventions [6], [11].

Despite progress, several challenges remain central in claims-based switching prediction: limited clinical granularity, heterogeneity of patient phenotypes, and pronounced class imbalance because switching events may be relatively infrequent compared with treatment persistence [2], [4]. Moreover, because switching prediction is inherently time-dependent, credible evaluation requires strict temporal separation between feature lookback windows and outcome windows to reduce leakage and better reflect the latency and incompleteness of near-real-time claims feeds.

Accordingly, this paper provides a focused review and synthesis of ML approaches for predicting treatment switching using administrative claims data, highlighting disease-area applications, claims data sources, modeling strategies, feature engineering methods, evaluation patterns, and implications for clinical practice and health policy.

II. LITERATURE REVIEW: APPLICATIONS IN DISEASES

Machine learning approaches for predicting treatment switching have been applied across multiple therapeutic areas, with disease-specific switching patterns reflecting differing clinical drivers, care pathways, and medication regimens.

II.A Rheumatology and Immunology

Chronic autoimmune conditions treated with biologics and targeted synthetic DMARDs frequently involve treatment modifications due to varying response, tolerability, and disease activity. Cappelli et al. [3] developed a predictive model using EHR and claims data for rheumatoid arthritis and identified disease activity and prior treatment history as important predictors of switching. Castro Corredor and Calvo Pascual [4] examined imbalanced classification for biosimilar removal in rheumatic disease contexts and reported that ensemble-based approaches improved sensitivity in minority-class detection. Hamelin et al. [6] introduced the Immunolab platform as a modular analytics approach for generating real-world evidence at scale in immunology, demonstrating how advanced analytics can support cohort-level insights.

II.B Neurology

Neurology applications highlight how administrative claims can act as proxies for disease progression and treatment dynamics. An et al. [1] used administrative claims to predict drug-resistant epilepsy, suggesting that billing-derived variables can provide useful signals of clinical outcomes. Spelman et al. [12] reported predictors of treatment switching in multiple sclerosis, including relapse activity, prior therapy exposure, and disability progression. Breitenstein et al. [2] presented a machine learning approach using Danish anti-seizure medication registries, reporting a switching prediction accuracy of 0.77, illustrating the analytical value of structured national registries.

II.C Psychiatry

Psychiatric settings often require careful handling of adherence and persistence signals, which can influence switching definitions and predictive performance. Wu et al. [15] used the Taiwan National Health Insurance Research Database (NHIRD) to develop and validate an individualized treatment rule in first-episode schizophrenia, with the aim of reducing unnecessary switching. Dickson et al. [5] reported that long-acting injectable antipsychotics were associated with reduced switching and readmission rates among Medicaid beneficiaries with schizophrenia or schizoaffective disorder.

II.D Cardiovascular Disease

Cardiovascular disease management provides evidence that temporal modeling can improve prediction when patient behavior evolves over time. Hsu et al. [7] showed that temporal modeling of medication adherence behavior in lipid-lowering therapy improved prediction performance relative to baseline approaches, supporting the value of sequential methods in chronic disease settings.

Table 1*: Summary of Disease Areas, Study Populations, and Key Findings*

Disease Area	Study	Data Source	Key Finding
Rheumatology	[3]	EHR & Claims	Disease activity & treatment history predict DMARD switching
Rheumatology	[4]	Clinical Registry	Ensemble models outperform in imbalanced datasets
Immunology	[6]	Real-World Data	Modular analytics generates scalable real-world evidence
Neurology	[1]	Administrative Claims	Claims features predict drug-resistant epilepsy
Neurology	[12]	Big MS Data Network	Relapse rate & disability are top switching predictors

Neurology	[2]	Danish Registries	ML achieves 0.77 accuracy for ASM switch prediction
Psychiatry	[15]	Taiwan NHIRD	Individualized treatment rules reduce unnecessary switching
Psychiatry	[5]	Medicaid Claims	Long-acting injectables linked to lower switching rates
Cardiovascular	[7]	Claims Data	Temporal modeling improves switching prediction accuracy

III. Databases and Data Sources of Global Claims

The reliability and generalizability of claims-based ML switching prediction depends strongly on the quality, completeness, and representativeness of the underlying claims data source. Multiple national and regional registries are used in the switching prediction literature, each with distinct strengths and limitations.

The Taiwan National Health Insurance Research Database (NHIRD) provides near-universal population coverage and includes outpatient, inpatient, and prescription records across more than 23 million enrollees. Its breadth makes it particularly useful for chronic disease and psychiatric studies, as illustrated by [15] in schizophrenia individualized treatment rule development.

Danish nationwide registries provide high-quality linkage enabled by unique personal identifiers that connect prescriptions, hospital encounters, and sociodemographic information. Breitenstein et al. [2] used these registries to predict anti-seizure medication switching with reported accuracy of 0.77, illustrating the value of consistent linkage and standardized longitudinal tracking.

German claims data, as used by [14], include rich outpatient and inpatient billing records enabling identification of adherence intervention target groups, but may lack granular clinical phenotype detail compared to registry-based systems. Similarly, the Japan Medical Data Center (JMDC) database, used by [10] for patient journey analyses in depression and other chronic conditions, captures detailed diagnosis and prescription histories for an employee-insured population, introducing potential demographic bias toward younger and employed cohorts.

Cross-system validation remains challenging because claims capture and coding practices differ across countries, payers, and benefit designs, affecting feature availability and potentially limiting direct comparability of performance across datasets. These differences motivate careful interpretation of reported metrics and reinforce the need for external validation where feasible.

Table 2: *Comparison of Global Claims Databases Used in Treatment Switching Research*

Database	Country	Coverage	Key Strength	Limitation
NHIRD	Taiwan	~23M enrollees	Near-universal population coverage	Limited clinical phenotype detail
Danish Registries	Denmark	Nationwide	Unique identifiers; high data linkage accuracy	Small population size
German Claims Data	Germany	Multi-payer	Rich outpatient/inpatient billing records	No granular clinical variables
JMDC	Japan	Employee-insured	Detailed prescription & diagnosis histories	Younger demographic bias

IV. THE USE OF THE MACHINE LEARNING METHODS

Treatment switching prediction has been studied using multiple ML model families, each offering distinct advantages depending on feature dimensionality, temporal structure, class imbalance, and interpretability requirements.

IV.A Tree-Based Models

Tree-based approaches—random forests, gradient boosting, LightGBM, and XGBoost—are widely used in claims-based switching prediction because they handle heterogeneous inputs and can capture non-linear interactions. Studies such as [6] and

[14] report that gradient-boosted approaches often outperform simpler classifiers, and [11] demonstrates the value of ensemble approaches in capturing relationships among demographics, diagnoses, utilization, and specialty drug signals.

IV.B Regularized Regression

Regularized regression models, including Lasso, are useful for high-dimensional claims data due to embedded feature selection via penalization, reducing overfitting and supporting interpretability. Dickson et al. [5] applied claims-based modeling in schizophrenia contexts and illustrates how parsimonious predictor sets can be identified in large administrative datasets.

IV.C Neural Networks

Neural networks can model complex non-linear relationships but may require greater computational resources and present interpretability challenges. Jödicke et al. [9] compared feedforward neural networks with boosted decision trees and reported comparable performance but higher resource demand and lower interpretability—important considerations for clinical decision support adoption.

IV.D Temporal and Sequential Modeling

A notable methodological shift in the literature is treating switching prediction as a dynamic patient-journey problem rather than a static classification task. Hsu et al. [7] reported that temporal modeling improved predictive performance in cardiovascular settings. Related sequential approaches and transfer frameworks are discussed in [10] and [8], indicating growing interest in learning from longitudinal behavior and adherence dynamics.

Table 3: *Overview of ML Algorithms, Their Strengths, and Reported Performance Highlights*

Algorithm	Category	Key Strength	Application in Literature	Performance Highlight
Random Forest	Tree-Based	Robust to overfitting; handles high-dimensional data	[6], [11]	Strong discriminative performance across therapeutic areas
Gradient Boosting / XGBoost / LightGBM	Tree-Based	Captures nonlinear relationships; superior accuracy	[14], [6]	Frequently outperformed simpler classifiers
Lasso Regression	Regularized Regression	Variable selection; interpretability	[5]	Parsimonious predictor identification
Feedforward Neural Network	Neural Network	Flexible architecture; high capacity	[9]	Comparable to boosted trees; higher resource demand
Temporal / Sequential Models	Time-Series ML	Captures patient journey dynamics	[7], [10]	Improved accuracy vs static models

V. DATA PREPROCESSING AND FEATURE ENGINEERING

The performance and reliability of ML models for predicting treatment switching depend heavily on preprocessing choices and feature engineering in the claims environment. Claims data are longitudinal but often noisy and sparse, requiring careful cohort construction and consistent feature windows.

V.A Feature Extraction

Claims-based features commonly fall into three groups: (i) utilization variables (e.g., outpatient visits, hospitalizations), (ii) demographic variables (e.g., age, sex, insurance type), and (iii) clinical phenotype proxies derived from diagnosis and procedure codes. Studies such as [6] and [11] indicate that combining these feature categories improves model performance, with phenotype proxies often emerging as strong predictors of switching behavior.

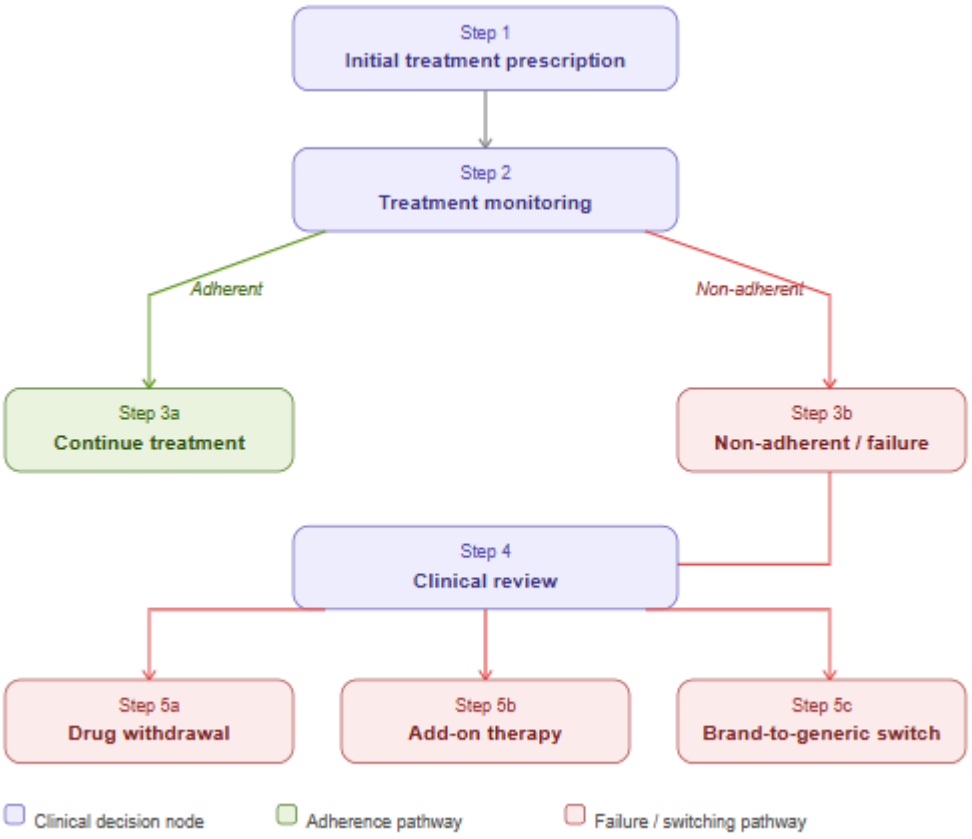
V.B Addressing Class Imbalance

Switching events are frequently rarer than treatment persistence, producing class imbalance that can bias naïve classifiers. Castro Corredor and Calvo Pascual [4] addressed this using imbalance-aware ensemble techniques. Oversampling (e.g., SMOTE) and cost-sensitive learning are also widely used patterns in the literature to improve minority-class sensitivity while controlling false positives.

V.C Outcome Targets and Adherence Proxies

Outcome definition varies across studies and is central to comparability. The Proportion of Days Covered (PDC) is widely used as a standardized adherence proxy—computed as medication-supply days divided by follow-up days—where lower values can signal elevated risk of treatment failure or impending therapy change [1], [7]. Additional operational indicators used to define or support switching outcomes include prescription-gap days, discontinuation windows, and diagnostic/procedure code sequences suggesting escalation or regimen modification.

Figure 1: *Treatment Switching Pathway Diagram*



VI. RESULTS, KEY PREDICTORS AND EVALUATION

VI.A Performance Metrics

Reported performance varies by disease area, cohort definition, and switching subtype. Breitenstein et al. [2] reported switching prediction accuracy of 0.77 and add-on therapy prediction of 92%, indicating that predictability can vary across outcome types. Cappelli et al. [3] and Wendl et al. [14] reported strong discrimination using AUC-based measures, supporting the feasibility of switching prediction in imbalanced settings when features and modeling are appropriately designed.

Because switching can be relatively infrequent, accuracy alone can be misleading; imbalance-aware evaluation (e.g., precision–recall patterns) and calibration-oriented reporting can improve interpretability of real-world utility. Threshold selection should be aligned to intended use (clinical outreach, adherence intervention targeting, or care management prioritization).

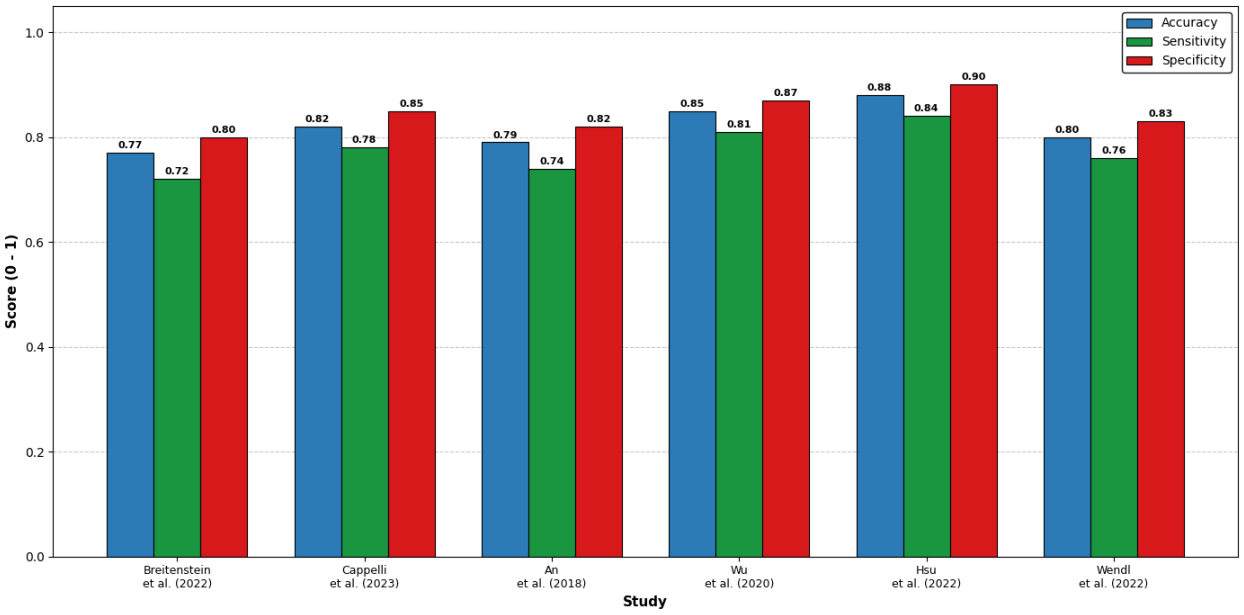
VI.B Key Predictors

Across studies, prior medication burden and polypharmacy are commonly reported as strong predictors of switching. De Vlieger [13] highlights prior medication burden as a proxy for elevated switching risk. Hamelin et al. [6] and Wendl et al. [14] emphasize claims-derived phenotype proxies and adherence patterns as discriminating characteristics, alongside disease activity indicators and hospitalization frequency where available.

VI.C Financial Impact

Jödicke et al. [9] reported relationships between pharmacotherapy dynamics and increased health-care expenditure, reinforcing the economic relevance of early identification and potential interventions that reduce avoidable switching or downstream utilization where clinically appropriate.

Fig 2: *Model Performance Metrics Comparison Across Studies*



VII. DISCUSSION

Machine learning applied to claims data offers a scalable approach for predicting treatment switching earlier in the patient journey, potentially enabling proactive intervention prior to clinical deterioration or avoidable therapy disruptions. The reviewed literature suggests practical value in multiple enterprise contexts, including clinical decision support, real-world evidence (RWE) generation, and population-level adherence programs.

VII.A Clinical Decision Support

ML-based switching predictions can support risk stratification and proactive identification of high-risk patients for targeted adherence interventions. Wendl et al. [14] demonstrate how tree-based models can stratify populations into actionable target groups, enabling personalized outreach and potentially reducing unnecessary switching in resource-constrained settings.

VII.B Real-World Evidence Generation

Claims-based ML can also scale RWE generation by enabling continuous cohort analytics and outcome monitoring. The Immunolab platform [6] illustrates how modular real-world data analytics can support evidence generation at scale and facilitate model updates across evolving patient cohorts.

VII.C Limitations and Future Directions

Administrative claims data lack many clinically rich variables such as laboratory values, physician assessments, and patient-reported outcomes, limiting the granularity of phenotyping and potentially constraining model explainability [2]. Generalizability across health-care systems may also be limited due to differences in coding practices, coverage, and benefit design, and class imbalance remains a persistent methodological challenge in minority outcome prediction [4]. Integrating claims data with EHR sources and performing prospective and cross-system validation represent important steps for improving robustness and translational reliability.

Operationalization: For translation into practice, switching prediction models must be operationalized within data pipelines that account for claims latency, refresh cadence, and monitoring for drift and performance decay. In addition, governance and auditability of cohorting, feature generation, and scoring logic support trustworthy clinical and operational adoption.

VIII. CONCLUSION

Machine learning applied to administrative claims data demonstrates significant potential to predict pharmacotherapy switching and support earlier, more targeted interventions across therapeutic areas. The literature shows that tree-based ensembles, regularized regression, neural networks, and temporal modeling can leverage claims-derived signals—such as phenotype proxies, utilization intensity, medication burden, and adherence patterns—to improve predictive performance and support clinical decision support and RWE objectives.

However, important gaps remain, including heterogeneity in switching definitions, data sparsity and limited clinical granularity in claims, persistent class imbalance, and uncertainty in cross-system generalizability. Future research should prioritize integration of richer clinical data (e.g., EHR), improve interpretability to increase clinical trust, and conduct prospective and external validation across health systems to establish broader translational reliability. Strengthening these areas will help move claims-based switching prediction from promising retrospective modeling toward robust, deployable capability in real-world care and operational settings [8], [15].

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