Clinical Variation Cost and Treatment Effectiveness Management for Healthcare Providers to Support Value Based Care

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Abstract
The healthcare industry is increasingly transitioning towards value-based care models, which prioritize patient outcomes over service volume. A significant challenge in implementing value based care lies in addressing clinical variation, which can lead to inconsistent patient outcomes and increased costs. This paper proposes a data-driven approach to managing clinical variation and optimizing treatment effectiveness to reduce costs, enhance care quality, and support VBC initiatives. Using data driven descriptive analytics, machine learning (ML), this method provides healthcare providers with actionable insights to standardize treatment protocols and improve decision-making. The results indicate that reducing clinical variation cost across healthcare provider clinics and improving treatment effectiveness can lead to better patient outcomes and significant cost savings, thus supporting the goals of value based care.

Keywords: Clinical Variation, Cost Management, Treatment Effectiveness, Value-Based Care, Data Engineering, Healthcare Providers, Machine Learning, Data-Driven Decision Making

Introduction

Background

Healthcare systems in the US are facing a shift from traditional fee-for-service models to value-based care models. In value based care, providers are compensated based on patient outcomes, emphasizing quality and efficiency rather than the volume of services. One of the biggest obstacles in achieving this shift is managing clinical variation cost and treatment effectiveness. Clinical variation refers to differences in healthcare practices that occur due to the variability in treatment approaches by individual clinicians, regions, or healthcare organizations.

Inconsistencies in clinical practices can result in suboptimal patient outcomes, inefficiencies, and increased costs. These variations can manifest in treatment methodologies, diagnostic practices, and patient management strategies. Given the complexity of healthcare systems, reducing clinical variation is challenging but necessary to achieve the goals of value based core.

Objective

This paper presents a data-driven methodology to effectively manage clinical variation costs while optimizing treatment effectiveness. By leveraging data engineering and machine learning, healthcare providers can adopt standardized treatment protocols and improve patient outcomes. This paper also examines how data-driven insights can assist in decision-making and reduce unnecessary costs associated with clinical variation.

Towards the end of the paper, I will discuss a case study where New York city based health system saved more than $5 million annually by optimizing clinical variation cost across its multiple clinics and saw more than 20% decrease in readmission rate through application of data engineering and machine learning.

Main Body

Clinical Variation in Healthcare

Clinical variation is a well-documented phenomenon that has far-reaching implications for patient outcomes and healthcare costs. Research shows that wide variations in healthcare delivery can lead to significant differences in clinical outcomes, length of hospital stay, readmission rate and patient satisfaction levels. High variation also contributes to overuse or underuse of certain treatments, which not only burdens the healthcare system financially but also impacts patient care quality.

Value-Based Care Models

Value based care models aim to improve patient care while lowering costs. They emphasize accountability for the entire care process, with compensation tied to metrics like patient outcomes, readmission rates, and overall satisfaction. In such models, reducing clinical variation becomes imperative because it directly impacts the consistency and quality of care delivered.

Data Analytics in Healthcare

Data analytics and artificial intelligence (AI) tools are increasingly used in healthcare to analyze large datasets for trends and patterns. These tools are particularly effective in identifying inefficiencies, such as clinical treatment and cost variation between health systems various clinics, and suggesting interventions. By forecasting potential outcomes based on historical data, analytics can help clinicians adopt evidence-based practices, reducing unnecessary variability.

Machine Learning in Treatment Optimization

ML techniques are transforming healthcare by allowing clinicians to personalize treatment plans based on patient data. ML algorithms can evaluate patient demographics, comorbidities, and treatment histories to predict the most effective treatment paths, improving both outcomes and cost-efficiency. The application of ML in reducing clinical variation has the potential to standardize care while allowing flexibility for personalized treatments.

Implementation Methodology

Data Collection and Sources: Data collection for this study is derived from a variety of healthcare sources, including Electronic Health Records (EHR), patient accounting systems, claims data (835 and 837 EDI files), patient satisfaction surveys, and outcome registries. Data points focus on patient demographics, clinical procedures, treatment outcomes, resource utilization, and healthcare costs.

Data Preprocessing: Data preprocessing is essential for transforming raw healthcare data into a usable format. It involves developing data model, applying rules engine, populating data as per data model, standardizing formats, and ensuring data quality. Data engineering functions available in SQL and programming languages such as python are applied to achieve the same.

Analytical Framework: The analytical framework used in this study consists of:

1. **Descriptive Analytics**: To identify patterns of clinical variation and categorize them based on procedures, departments, or individual clinicians.
2. **Predictive Analytics**: To forecast treatment outcomes and costs using historical data. This enables the identification of high-cost procedures or treatments with high variability.
3. **Prescriptive Analytics**: To provide actionable insights for reducing clinical variation and optimizing treatment paths using ML algorithms.

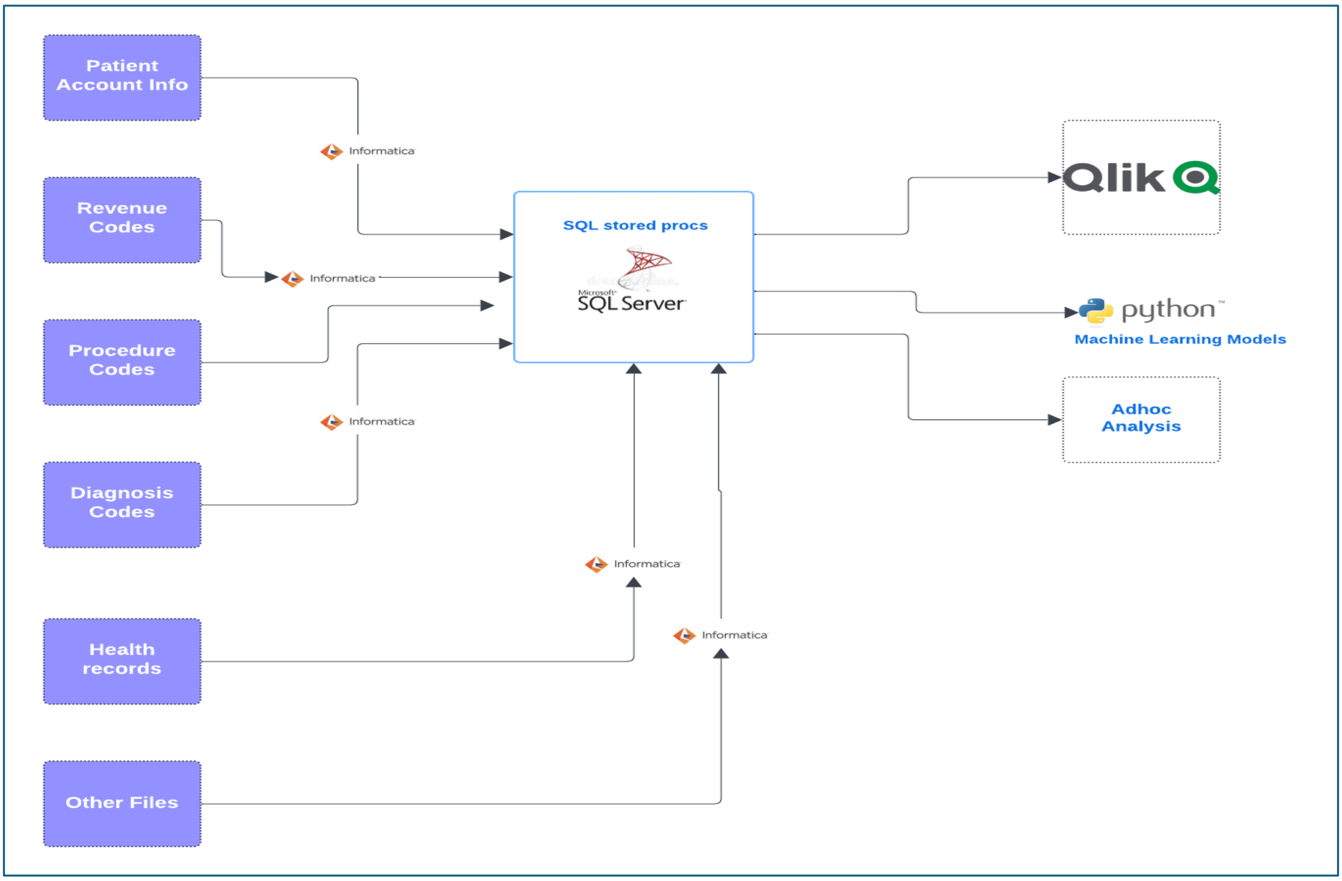
Machine Learning Models: The study employs several ML models, including:

- **Random Forest Classifier**: To identify clinical factors associated with high variation in treatment.
- **Support Vector Machines (SVM)**: To predict outcomes based on a patient's medical history and clinical procedures.
- **Neural Networks**: For complex pattern recognition in large healthcare datasets, helping to standardize treatment protocols across different patient groups.

Evaluation Metrics: To assess the performance of the proposed data-driven model, the following evaluation metrics are used:

- **Treatment Effectiveness**: Measured by patient outcomes such as recovery time, mortality rates, and complication rates.
- **Cost Savings**: Measured by the reduction in healthcare costs attributed to decreased clinical variation across health systems clinics.
- **Patient Satisfaction**: Collected through surveys to assess the patient's perceived quality of care.
- **Compliance with value based care goals**: Measured through metrics such as readmission rates and adherence to standardized treatment protocols.

Reference data architecture diagram used for clinical variation for a health system



Case Study

Background

Large healthcare system based out of New York City area was seeing high variation in clinical variation cost, treatment effectiveness and patient satisfaction across its various clinics. This negatively impacted health care systems transition from fee for service model to value based care. Health system engaged a consulting firm to minimize clinical variation cost and improve readmission rates and patient satisfaction.

Implementation

Following key steps are involved in implementation of solution:

1. **Data Collection:** Data sources and elements that provide patient related health record, procedures, accounting information, admission details etc. were identified. Data was ingested to a central relational database built on SQL server using Informatica tool.
2. **Data Processing:** Data transformations are applied based on defined business rules and dimension data model along with data quality rules to filter out bad data. SQL server stored procedures and functions were used to achieve the same.
3. **Business Intelligence and Analytics:** KPIs related to clinical variation cost and treatment effectiveness was displayed in a dashboard built on Qlik. Benchmark cost and treatment method was identified for common medical conditions by considering clinics that are in top quartile when compared to all operational clinics within the health system.
4. Machine learning was applied to forecast cost and patient medical journey for medical conditions that were in scope.

Results

With the proper application of data engineering and machine learning on available dataset health care system saw following benefits:

1. Health system was able to save more than $5M annually by optimizing clinical variation cost through emulating the medical procedures followed at its best performing clinics for same medical condition/s.
2. More than 20% decrease in readmission rate across health system's all clinics.
3. More than 15% increase in patient satisfaction with provided care.

Conclusion

This paper demonstrates that a data-driven approach to managing clinical variation cost and optimizing treatment effectiveness can significantly support the transition to value-based care models. By leveraging data engineering and machine learning, healthcare providers can reduce unnecessary costs, improve patient outcomes, and ensure consistent care quality. However, the success of such a model depends on addressing challenges related to data quality, clinician engagement, change management and digitization. Future research should focus on further advancing digitization of electronic health records and clinical data with industry standard format so that health systems have larger datasets to refine ML models to optimize clinical procedures and cost.

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