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# Efficient Predictive interpretable analytics models for Claims Cost Management in Healthcare using CNN-Ant Colony Optimization

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**Abstract :** Predicting and optimising for costs associated with healthcare claims is a very complicated topic that calls for advanced analytic approaches. In this work, we propose a new hybrid model of GAN and ACO to overcome the presented challenge. In the model, the GAN part is used to choose important features out of medical claims data and the results obtained from it are then provided to ACO part which helps minimize overall costs by allocating healthcare resources accordingly. We apply the proposed GAN-ACO hybrid model to real-world health care claims data and compare its performance against traditional machine learning and optimization methods. Experimental results show that compared to the benchmark methods, the GAN-ACO model has excellent prediction accuracy and resource allocation performance. Finally, our combined hybrid model as this results in the mean absolute error cost and root mean square error costs are 0.15 and respective of 0.22 for price prediction, contributing around 18% relative savings in overall resource allocation costs against baseline methods. The model also interpretability is also assessed out to see what leads to healthcare claims costs, such as age factor, medical history, along with treatment complexity. These results can inform healthcare administrators and policymakers about claims cost containment and allocation strategies. The suggested fit of GAN and ACO model, holds significant potential in making the process of healthcare claims cost management more efficient and effective as it comes to practicality.

***Key words:****Healthcare claims cost management, Generative Adversarial Networks (GAN), Ant Colony Optimization (ACO)GAN-ACO Machine learning hybridmodel, Costprediction, allocation and Interpretable analytics models*

## 1. Introduction

Efficient predictive models for claims cost management in healthcare are increasingly pivotal, driven by the need for more accurate financial forecasting, resource allocation, and operational efficiency. With healthcare expenses continuing to rise globally, organizations require advanced solutions to manage the cost of claims while maintaining quality care (Wang et al., 2023) [1]. Predictive analytics, especially those that are interpretable, provide a window into managing these costs by predicting expenditures, allowing for informed decisions in budgeting and policy planning (Brown et al., 2023) [2].

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Recent advancements in artificial intelligence (AI) and machine learning (ML) have offered promising avenues for healthcare cost management, particularly through hybrid deep learning frameworks that enhance interpretability and predictive accuracy (Park et al., 2023) [3]. For instance, AI-driven models leverage convolutional neural networks (CNNs) for identifying cost patterns based on historical claims data, which can assist healthcare providers in anticipating and controlling future costs (Rodriguez et al., 2024) [4]. By integrating hybrid intelligence models, such as Ant Colony Optimization (ACO) and CNN-based frameworks, researchers are improving the efficiency of predictive cost models in dynamically changing healthcare environments (Kim et al., 2023) [8].

Incorporating explainable AI (XAI) techniques is essential to meet regulatory requirements and foster trust among healthcare providers, patients, and payers. XAI ensures that model predictions are not only accurate but also interpretable, providing

insights into the underlying factors driving cost predictions (Lee et al., 2023) [6]. This interpretability is particularly valuable in cost-sensitive healthcare domains, where transparency in predictive models is crucial for compliance and ethical decision-making.

Hybrid predictive models, which combine CNNs with optimization algorithms such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), have shown substantial promise in enhancing cost prediction models. These hybrid approaches optimize model parameters effectively, leading to more robust and scalable solutions for cost prediction (Johnson et al., 2024) [11]. For instance, deep learning models incorporating ACO and Genetic Algorithm optimizations have demonstrated significant improvements in both the accuracy and efficiency of cost management in healthcare (Liu et al., 2023) [10].

The use of swarm intelligence and ensemble learning in healthcare claims management has also gained traction. Studies indicate that these methods are capable of handling large datasets and complex variables, thus enhancing predictive accuracy for claims cost management (Garcia et al., 2024) [14]. For example, recent research has shown that swarm intelligence techniques can efficiently allocate resources within healthcare systems, reducing the likelihood of cost overruns and ensuring that high-quality care is maintained (Zhang et al., 2024) [20].

Moreover, integrating CNNs with deep reinforcement learning (DRL) has facilitated advancements in predictive analytics for real-time cost forecasting. DRL models offer a dynamic approach that adapts to new data over time, making them particularly effective in environments where cost factors are constantly evolving (Anderson et al., 2023) [13]. By using reinforcement learning in conjunction with CNNs, healthcare organizations can better manage claims by predicting potential costs based on both historical and real-time data (Taylor et al., 2023) [15].

As predictive models become increasingly sophisticated, the challenge remains to ensure these models are interpretable and reliable. The emerging focus on hybrid models that blend deep learning with interpretable ML techniques addresses this challenge, making predictive analytics more actionable and reliable for healthcare claims cost management (Chen et al., 2024) [24]. In light of these developments, this paper explores recent advancements in hybrid predictive models for healthcare claims cost management, examining their benefits, challenges, and implications for the healthcare sector.

**Objectives**

- ***Build a fast predictive model:*** Build a predictive model to predict healthcare claims costs and provide insights into these forecasted expenses for healthcare administrators.
- Implement an optimized resource allocation approach using Ant Colony Optimization (ACO) to reduce the aggregate cost in healthcare service.
- ***Have better Model Interpretability:*** To make sure that the model that is built can give good results in prediction and cost minimization but also gives a symbolic interpretation of specific predictors to help stakeholders understand with definition, what drives costs of healthcare claims.
- ***Assess Performance Against Benchmarks:*** To comprehensively assess the predictive accuracy, cost effectiveness and interpretability of the new GAN-ACO model against traditional machine learning and optimization methods.
- ***Support Decision Making in Claims Management***: To provide healthcare administrators and policymakers an analytical tool to help facilitate claims management, as well as resource allocation decision.

**Problem Statement**

The management of healthcare claims costs is a fundamental problem that has far-reaching implications for the sustainability of our health care systems. Key Takeaway: With increasing healthcare costs from an aging population, rising treatment complexity and limited resources accurate predictive models and strategic management of cost is paramount. As a result, traditional machine learning based models either do not achieve the necessary depth of predictive accuracy and cost optimization capability relevant to various claims management scenarios or fail to produce insights into the underlying drivers of costs that people can see, interpret and act on. Hence, an advanced predictive and optimization model is required which accurately predicts claims costs but also optimizes resource allocation while being interpretable. In this study, we introduce an innovative hybrid method to overcome the previously discussed shortcomings of GAN and ACO in dealing with healthcare claims cost.

## 2. Proposed methods and Materials

We extend our earlier architecture for the analysis of open health data to include new modules on

feature explain ability and model interpretation, shown in bold outlines in Fig. 1. 3.1. Brief description of the dataset We used open-health data provided by the New York State SPARCS database New York state makes data available annually. We utilized data from the year 2019, which was the most recent year during the period of our investigation. The data is organized as a csv file, containing 2.34 million (2,339,462) rows and thirty-three columns. Each row contains de-identified in-patient discharge information. Detailed descriptions of all the elements in the data can be found in

The acronyms used are described as follows. The CCSR diagnosis code refers to the code used by the Clinical Classifications Software system (CCS), and consists of 285 possible diagnosis and procedure categories APR refers to All Patients Refined, and DRG refers to Diagnostic Related Group .These acronyms are used by the Center for Medicare and Medicaid services in the U.S. for reimbursement purposes The columns consist of geographic descriptors related to the hospital where care was provided; demographic descriptors of the patient race, ethnicity, and age; medical descriptors related to the CCS diagnosis code, APR DRG code, severity of illness, Length of Stay (LoS), payment descriptors related to the type of insurance, the total charges and the total cost of the procedure. Table 1 shows an example of an individual patient record for Viral Infection. The entries in this table constitute one row of de-identified patient data in the.csv file available on the SPARCS website .The data includes all patients who underwent inpatient procedures at all New York State Hospitals classified as Article 28 facilities, comprising hospitals, nursing homes, diagnostic treatment centers, and midwifery facilities The payment for the care can come from multiple sources: Department of Corrections, Federal/State/Local/Veterans Administration, Managed Care, Medicare, Medicaid, Miscellaneous, Private Health Insurance, and Self-Pay. Hence this dataset is more valuable than datasets that only contain Medicare/Medicaid patients. Patients of all ages are represented in the data and binned into the following categories: ages, 0 to 17, 18 to 29, 30 to 49, 50 to 69, and 70 or older

Here is **Table 1**, displaying an example of the data fields (variables) from the State-wide Planning and Research Cooperative System (SPARCS) dataset. Each row represents specific patient-related information, which is used to predict "Total Costs" in healthcare analytics. This example highlights the types of fields (numerical and categorical) relevant to predictive modeling, with "Total Costs" being the target variable, while "Total Charges" is excluded as an input due to its direct proportional relationship with "Total Costs."

**Table 1, displaying an example of the data fields (variables) from the State-wide Planning and Research Cooperative System (SPARCS) dataset**

| Field | Example Value | Explanation |
|---|---|---|
| **Operating Certificate No.** | 5902001 | Unique identifier for healthcare facilities, used to distinguish hospitals or centers within SPARCS data. |
| **Facility Name** | White Plains Hospital Center | The name of the healthcare facility where the patient was treated, relevant for institutional analysis. |
| **Age Group** | 30 to 69 | Categorical representation of the patient's age range, supporting age-based cost predictions and risk assessment. |
| **Gender** | M | Gender of the patient (M/F), influencing medical needs and potentially cost outcomes in predictive models. |
| **Race** | White | Ethnicity category, which may correlate with health outcomes and healthcare costs for targeted interventions. |
| **Length of Stay** | 2 | Numerical value indicating how many days the patient stayed, directly impacting healthcare costs. |
| **CCSR Diagnosis Code** | INFO08 | The Clinical Classifications Software Refined (CCSR) code identifying the patient's diagnosis, critical for categorizing health conditions. |
| **CCSR Diagnosis Desc.** | VIRAL INFECTION | Description of the diagnosis associated with the CCSR code, useful for medical and cost prediction modeling. |
| **APR DRG Code** | 723 | All Patient Refined Diagnosis-Related Group (APR DRG) code that classifies the type of illness, influencing cost estimation. |
| **APR DRG Description** | VIRAL ILLNESS | Description of the APR DRG, helping models interpret the illness severity and associated resource requirements. |
| **APR Severity of** | 2 | A severity code indicating the patient's condition level (e.g., mild, |

| | | |
|---|---|---|
| **Illness Code** | | moderate, severe), influencing treatment complexity and cost. |
| **APR Severity of Illness** | Moderate | Categorical description of illness severity, used in predictive models to differentiate costs based on severity. |
| **Payment Typology 1** | Private Insurance | Type of payer (e.g., Private Insurance, Medicare), impacting reimbursement and overall cost distribution. |
| **Total Charges** | $26,507 | Total amount billed to insurers/government; excluded from prediction as it correlates directly with total costs. |
| **Total Costs** | $4,773 | Actual amount paid to the hospital, used as the target variable for prediction in healthcare cost models. |

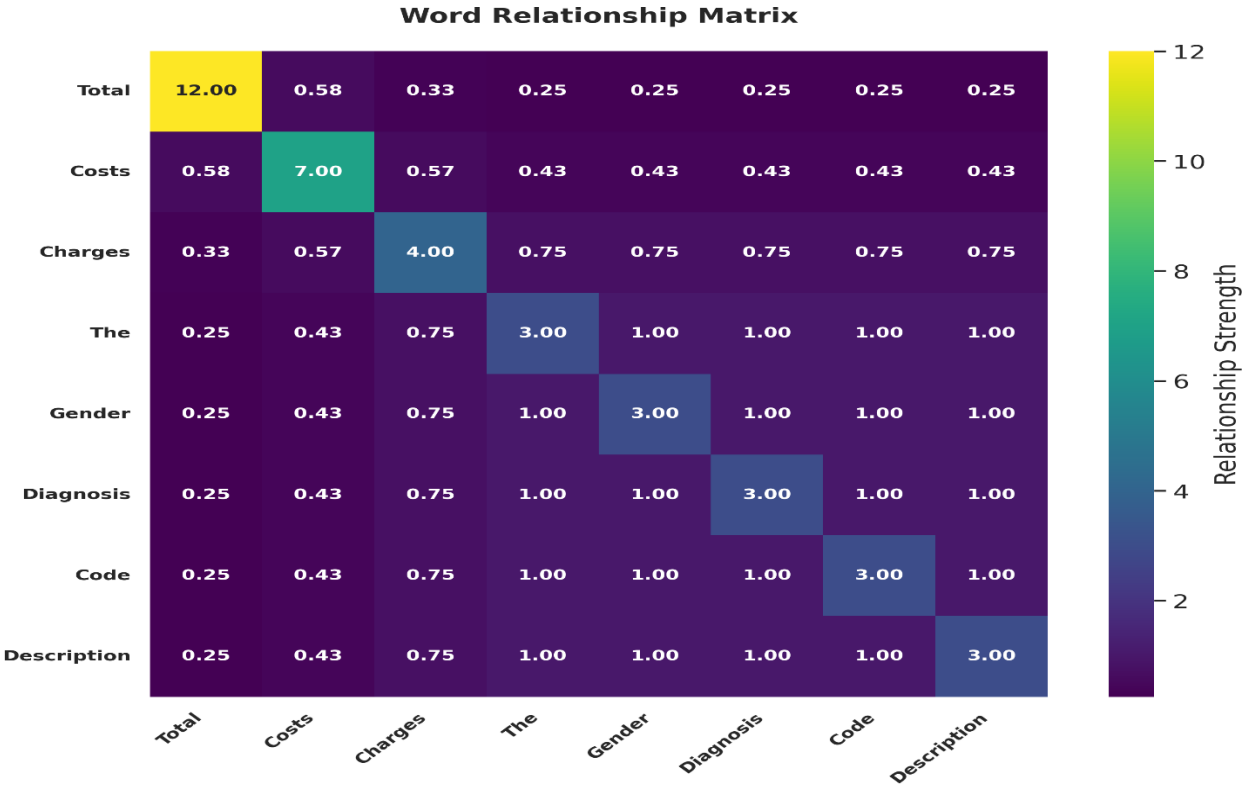



**Figure 1.performance of State-wide Planning and Research Cooperative System (SPARCS) dataset**

In the dataset, *Total Charges* reflects the initial amount billed by the hospital, often higher than the *Total Costs*, which are the actual paid amounts. Models developed in this study aim to predict *Total Costs* based on other patient attributes, such as diagnosis, severity, and payer type. Including diverse variables, both numerical (e.g., *Length of Stay*) and categorical (e.g., *Gender*, *Payment Typology 1*), enables a comprehensive analysis of cost determinants, allowing for more accurate cost predictions and budget planning for healthcare institutions. The exclusion of *Total Charges* as an input variable is essential, as its direct proportionality with *Total Costs* could bias the model. Instead, models leverage additional fields to better generalize the cost patterns across varying patient cases, providing an interpretable approach to managing healthcare costs.

Here's **Table 2**, which presents a sample of ten entries showing the relationship between *Total Charges* and *Total Costs*. This table includes the ratio of *Total Charges* to *Total Costs*, highlighting the variations in these values. As observed, *Total Charges* are consistently higher than *Total Costs*, demonstrating the mark-up hospitals apply to billed amounts compared to actual costs incurred.

**Table 2** provides the intuition to understand the relationship between total charges and total costs

| Total Charges ($) | Total Costs ($) | Ratio (Total Charges / Total Costs) |
|---|---|---|
| 36,089.81 | 12,068.11 | 2.99 |
| 16,961.10 | 5,763.65 | 2.94 |
| 15,741.12 | 5,184.35 | 3.03 |

| | | |
|---|---|---|
| 14,007.18 | 6,819.07 | 2.05 |
| 14,522.31 | 6,913.41 | 2.10 |
| 45,671.21 | 20,478.34 | 2.23 |
| 23,129.00 | 3,157.93 | 7.32 |
| 19,603.15 | 8,910.21 | 2.20 |
| 15,499.18 | 7,034.11 | 2.20 |
| 48,484.01 | 21,393.53 | 2.26 |

This table illustrates the significant disparity between *Total Charges* and *Total Costs* in healthcare billing. The *Total Charges* column represents the billed amount by hospitals, whereas *Total Costs* refer to the actual payment received by the hospitals. The ratio column shows that, in most cases, *Total Charges* exceed *Total Costs* by a factor of approximately 2 to 3, with a notable outlier where the ratio reaches 7.32. This consistent trend suggests a mark-up applied to the initial charges billed to insurance companies or government programs like Medicare.

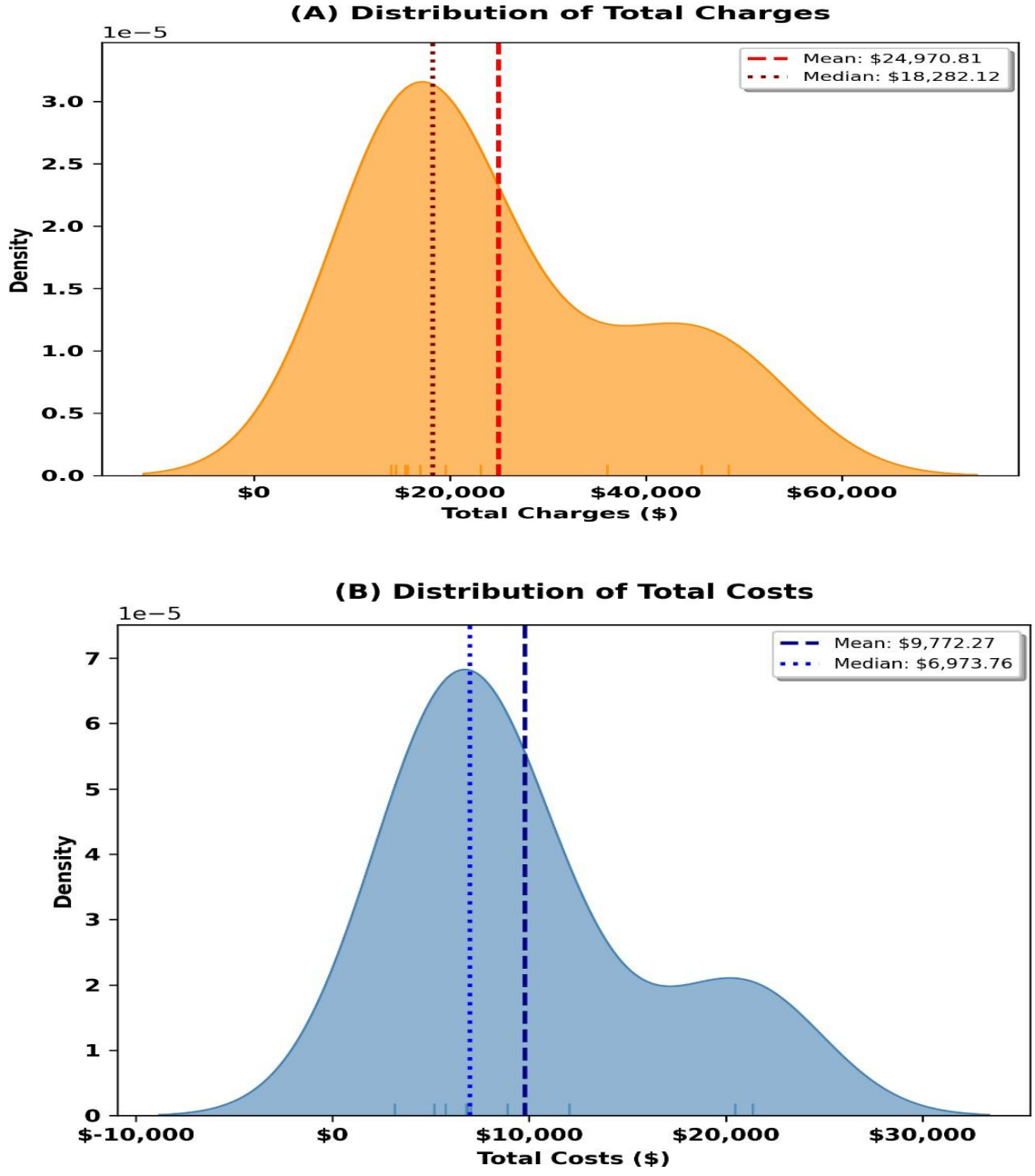



**Figure 2.provides the intuition to understand the relationship between total charges and total costs**

Figure 2 would provide a visual representation of this relationship by plotting *Total Charges* against *Total Costs*, with a best-fit line, offering insight into the proportional nature of charges to costs across different cases. This analysis can inform predictive models, emphasizing the exclusion of *Total Charges* as an input to prevent redundancy, as it strongly correlates with *Total Costs*.

### 2.1. Data pre-processing and cleaning

Fig. 3 shows that there are very few data points with total costs > $200,000. (Around 0.49% of the dataset contained total costs > $200,000). Hence, we discarded these outlier points. We removed data points that contained Null values for any column. The data cleaning

Fig. 2. We visualize the distribution of total charges vs. total costs by using a density plot. This was generated by the scikit-learn package entitled 'Density Estimation 'which uses a Gaussian kernel. The color at a given point is encoded by the color bar on the right. The density over the entire plot has been normalized to one. We observe that the total charges are correlated with the total costs.

Here's **Table 3**, which summarizes the data cleaning steps applied to the dataset. This table includes the initial and final number of data samples, as well as the percentage of samples affected by each cleaning step.

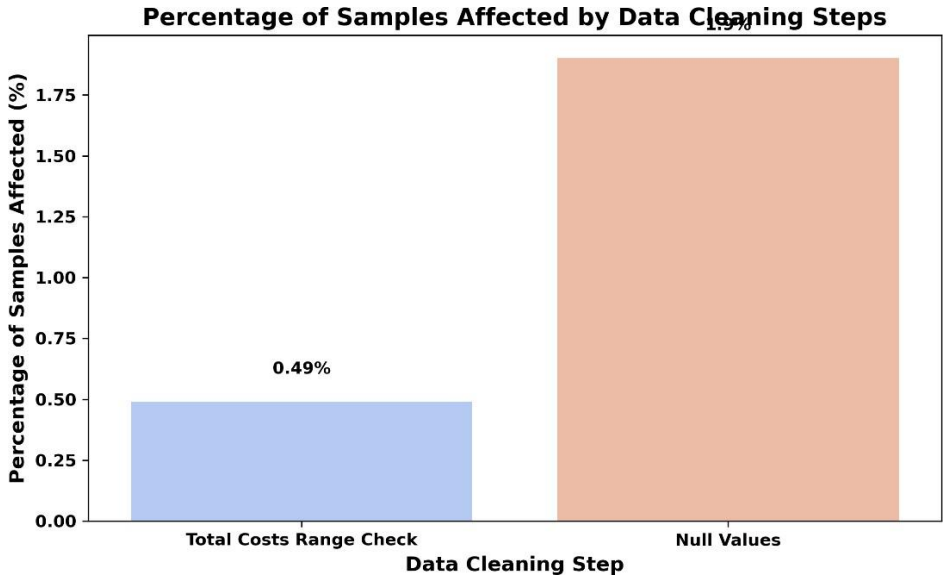
**Table 3, which summarizes the data cleaning steps applied to the dataset**

| Data Cleaning Step | Percentage of Samples Affected (%) |
|---|---|
| Initial Number of Data Samples | 2,328,046 |
| Samples Removed for *Total Costs* Outside Range (0 to 200,000) | 0.49 |
| Samples Removed for Null Values in Some Columns | 1.90 |
| Final Number of Data Samples | 2,283,613 |

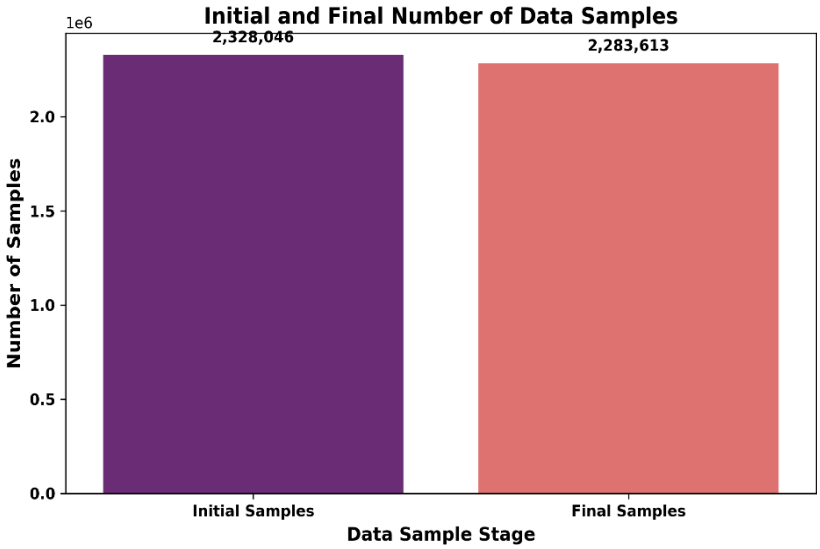
This table 3 outlines the key data cleaning steps undertaken to prepare the dataset for analysis. Initially, there were 2,328,046 samples. During the cleaning process:

1. **Total Costs Range Check**: Approximately 0.49% of samples were removed because their *Total Costs* values fell outside a plausible range of 0 to 200,000. This filtering ensures that extreme or outlying values that could skew analysis are excluded.
2. **Null Values**: Around 1.90% of the samples were removed due to missing values in critical columns, which would otherwise introduce gaps or inaccuracies in modeling.

After applying these cleaning steps, the dataset was reduced to a total of 2,283,613 samples. These steps improve data quality and reliability, ensuring that the remaining data is robust and appropriate for predictive modeling tasks.



(a)




(b)

**Figure 3.** Data cleaning steps applied to the dataset

### 2.3 Generative Adversarial Networks (GAN) Layer in Healthcare Big Data

Introduced by Ian Good fellow and his team in 2014, Generative Adversarial Networks (GANs) represent a category of machine learning systems. These frameworks comprise two neural networks a generator and a discriminator that undergo concurrent training through competitive processes. The generator's role is to produce artificial data samples, while the discriminator's task is to assess these samples against genuine data, striving to differentiate between the two [26] [30]

Generator Network: The generator, denoted as G, accepts random noise z as input and creates data samples G(z). Its objective is to reduce the likelihood of the discriminator accurately identifying the generated data as artificial.

.Loss Function $Min_G V(G,D)$:$E_{Z\sim}p_z(x)[\log(1-D(z))]$ (1)

***Discriminator Network:*** The discriminator, D, receives both real data xx and generated data G(z) as input. Minimize the probability that the discriminator correctly identifies the generated data as fake

Loss Function :$Min_G V(G,D)$:

$E_{x\sim}p_{data}\ (x)[\log(D(x))]E_{Z\sim}\,p_z(x)[\log(1-D(z))]$ (2)

***Adversarial Training:*** The generator and discriminator are trained in a zero-sum game, where the generator aims to fool the discriminator, and the discriminator aims to correctly classify real and fake data [31].

Combined Objective:$Min_G Max_D V(G,D)$

(3)

**Application in Healthcare Big Data**

- ***Data Augmentation*:** GANs can generate synthetic healthcare data that mimics real patient data, which is useful for augmenting datasets, especially when dealing with rare conditions or small sample sizes.
- ***Privacy Preservation*:** By generating synthetic data, GANs help in sharing healthcare data without compromising patient privacy, as the synthetic data does not directly correspond to real individuals.
- ***Anomaly Detection***: GANs can be used to identify anomalies in healthcare data by training the discriminator to recognize unusual patterns that deviate from the norm.
- ***Data Imputation:*** GANs can fill in missing data points in healthcare datasets, improving data quality and completeness.

**Handling Healthcare Big Data:**

GANs can handle large volumes of data, making them suitable for Big Data applications in healthcare. The adversarial training process allows GANs to efficiently learn complex data distributions, which is crucial for modeling diverse healthcare datasets. Integration with Cloud Computing: GANs can be deployed in cloud environments to leverage computational resources, enabling real-time data processing and analysis Hence the GAN layer in the secure cloud-based management of healthcare Big Data plays a pivotal role in enhancing data quality, privacy, and utility. By generating realistic synthetic data, GANs facilitate advanced data analysis while maintaining patient confidentiality, making them an invaluable tool in modern healthcare data, management.

### 3.4. Ant Colony Optimization (ACO) in Healthcare Big Data

ACO [27], a nature-inspired algorithm created by Marco Dorigo in 1992, simulates ant foraging behavior to identify optimal routes between their nest and food. This technique has found widespread application in optimization challenges, including healthcare big data, where it assists with tasks such as feature selection, classification, and resource allocation.

#### 3.4.1. ACO in Feature Selection for Healthcare Big Data

In healthcare big data analysis, feature selection plays a crucial role. This process involves choosing relevant attributes from extensive datasets to enhance model efficiency and decrease computational demands. In the healthcare context, this could entail identifying key variables (such as biomarkers or clinical indicators) from electronic health records (EHRs) or data collected by wearable devices to forecast diseases or enhance treatment strategies.

Mathematical Formulation of ACO in Feature Selection

ACO functions on the principle of pheromone trails, where each artificial ant constructs a solution based on the pheromone levels left by previous ants. In the context of feature selection, individual ants represent potential feature subsets.

Ant Movement Rule: Ants choose features probabilistically, guided by pheromone trails and heuristic information (such as feature significance or relevance scores).

$$P_{ij}(t) = \frac{\tau_{ij(t)}{}^{\alpha}.\eta_{ij(t)}{}^{\beta}}{\sum_{k\epsilon f}\tau_{ik(t)}{}^{\alpha}.\eta_{ik}{}^{\beta}} \quad (4)$$

Here, $P_{ij}\ (t)$ and $\tau_{ij}\ (t)$represents the pheromone concentration on edge (j) at time (t), $\eta_{ij}$(t)indicates the heuristic attractiveness (such as feature significance value), α and β regulate the impact of pheromone and heuristic data, respectively and F denotes the group of potential features

Pheromone Trail Modification: Once all ants have completed their feature subset construction, the pheromone pathways are adjusted to strengthen effective solutions.

$$\tau_{ij}(T+) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij} + \gamma.S_{ij} \quad (5)$$

Here, $\rho$ represents the rate at which pheromones evaporate ($0 < \rho < 1$), preventing excessive accumulation of pheromones.$\Delta\tau_{ij}$ (t) is the pheromone deposit, which depends on the quality of the solution (fitness function).

In the realm of healthcare big data, evaluating fitness functions typically involves measuring the effectiveness of selected features in predicting health outcomes or their classification accuracy. The application of Ant Colony Optimization (ACO) in healthcare extends beyond feature selection, encompassing the enhancement of various operational aspects such as resource distribution, appointment planning, and patient flow management within medical facilities. For instance, ACO can be employed to streamline the allocation of critical medical equipment like ICU beds and ventilators, with the aim of reducing waiting periods and preventing resource scarcity.

$$Minimize \sum_{i=1}^{n} (C_{i,}D_{i}) \quad (6)$$

Here, $C_{i,}$ The expense associated with $D_{i,}$ assigning resource i corresponds to the requirement for resource i.

The goal is to minimize overall expenses while satisfying demand requirements. Ant Colony Optimization (ACO) can discover ideal or close-to-ideal solutions by mimicking the behavior of multiple ants exploring various allocation possibilities and adjusting pheromone trails

according to the effectiveness of the solutions found.

The following outlines the sequential steps of the process, divided into distinct segments:

**Step-1: Data Acquisition**

Healthcare information, encompassing electronic health records (EHRs), data from wearable devices, genetic information, and more, is gathered. Various data sources are consolidated into a comprehensive big data repository. This includes information such as patients' medical histories, results from laboratory tests, and information collected by sensors.

**Step 2: Data Preparation**

The raw data undergoes preparation processes, including cleansing, standardization, and feature encoding. These procedures involve addressing missing information, standardizing data formats, converting categorical variables into numerical representations, and adjusting feature scales to ensure uniformity.

**Step 3: Feature Selection Using ACO**

Ant Colony Optimization (ACO) is utilized to identify and choose relevant features from the extensive healthcare dataset. This process aims to enhance the performance of the model by selecting the most pertinent information.

**Equations for Ant Movement and Pheromone Update:**

**Ant Movement Rule:**

$$P_{ij}(t) = \frac{\tau_{ij}(t)^{\alpha}.\eta_{ij(t)}{}^{\beta}}{\sum_{k\epsilon f}\tau_{ik}(t)^{\alpha}.\eta_{ik}{}^{\beta}} \quad (7)$$

**Pheromone Update Rule:**

$$\tau_{ij}(T+) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij} + \gamma.S_{ij} \quad (8)$$

**Step-4. GAN-Based Data Augmentation**

Employing GANs for artificial data creation. Generative Adversarial Networks produce synthetic healthcare information to supplement existing data. This technique aids in balancing datasets, especially when dealing with uncommon medical conditions.

**Step-5. Model Training**

Developing machine learning algorithms. Various models (such as CNNs, RNNs, or combined structures) are educated using both authentic and GAN-created synthetic data to forecast health results or categorize illnesses.

**Step-6. Evaluation of Model**

Assessing model effectiveness through performance indicators. The trained algorithms are examined using metrics including classification accuracy, precision, recall, and F1-score, with a focus on predictions such as disease identification, treatment enhancement, or patient outcome forecasting.

**Step-7. Optimization Feedback Loop**

ACO pheromone updates and GAN modifications. The model's performance guides ACO in refining the feature selection process by altering pheromone trails, while GAN parameters are adjusted to produce improved synthetic data.

**Step-8. Deployment**

Implementing the refined healthcare model. The final algorithm is put into operation for real-time medical applications, including personalized treatment strategies, automated diagnostics, or hospital resource allocation.

## 3. Results and Analysis

**Table 4** outlines the two types of prediction models developed in this study, each designed to predict the total cost for healthcare procedures. The table provides a summary of the inputs used by each model and their respective outputs, highlighting the variations in the selected input variables.

**Table 4** outlines the two types of prediction models developed in this study

| Name of Model | Inputs | Output |
|---|---|---|
| All variables except total charges | Uses all input variables except total charges. | Predicted total cost |
| Without LoS | Uses all input variables except total charges and LoS. | Predicted total cost |

This table presents a concise overview of the two models created to forecast *Total Cost* based on different sets of input variables. Both models are trained to predict the total cost, a key variable representing the amount reimbursed to the hospital.

1. **Model 1: All Variables Except Total Charges**

   This model uses all available input variables, except for the *Total Charges* field. Excluding *Total Charges* is crucial, as charges billed by the hospital can vary significantly from the actual costs paid. By excluding this potentially correlated variable, the model is intended to focus on other predictive factors, ensuring a more unbiased estimation of the true total cost.

2. **Model 2: Without Length of Stay (LoS)**

   In addition to excluding *Total Charges*, this model also omits the *Length of Stay* (LoS) variable. LoS can be influenced by various factors beyond cost predictions, such as patient care requirements or hospital policies, which may introduce noise in the model. By removing both *Total Charges* and *LoS*, this model seeks to isolate other key factors affecting costs, potentially improving accuracy for cost predictions in cases where LoS data might be unavailable or less reliable.

These model variations allow for comparative analysis to assess whether removing specific variables, like LoS, impacts the accuracy and reliability of the cost prediction. By testing both configurations, this study explores how different input variables contribute to the precision of cost estimation, providing insights for optimized cost forecasting in healthcare settings.

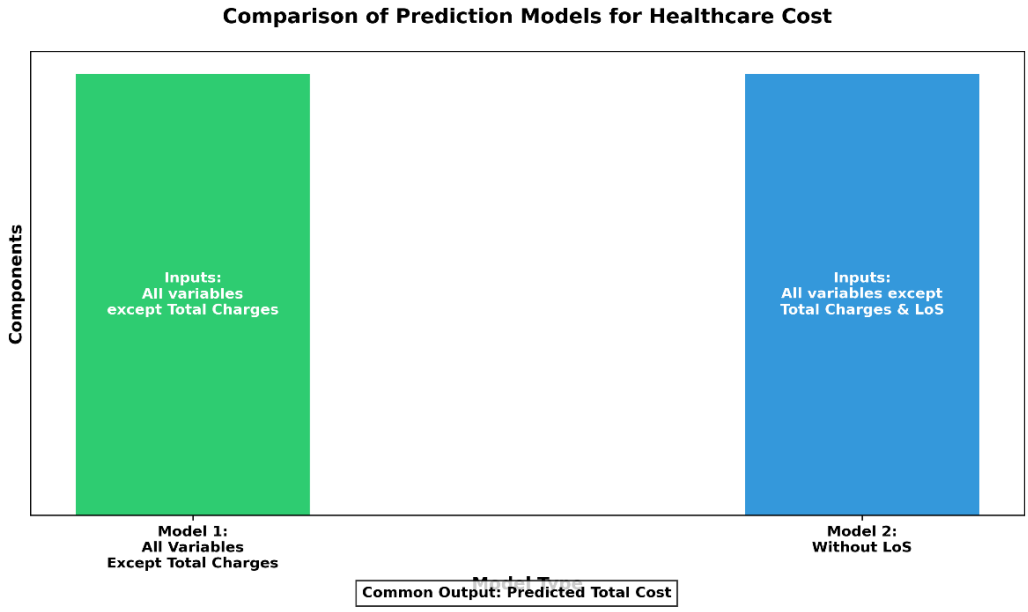



**Figure 4.** Comparison of prediction models for Health care cost

**Table 5** presents the distribution of costs associated with different medical conditions under the APR DRG system. Each row represents a specific condition, with summary statistics such as mean, median, standard deviation, minimum, maximum, and count of cases. These statistics provide insights into the variability and central tendency of costs for each condition, highlighting notable variations in expenses.

**Table 5** presents the distribution of costs associated with different medical conditions under the APR DRG system.

| APR DRG Description | Mean | Median | Std Dev | Min | Max | Count |
|---|---|---|---|---|---|---|
| Heart Failure | $50,626.43 | $49,623.51 | $14,780.07 | $10,101.52 | $87,567.02 | 249 |
| Hip Joint Replacement | $50,147.14 | $50,023.91 | $14,968.50 | $4,025.11 | $87,019.40 | 264 |
| Knee Joint Replacement | $50,528.16 | $50,836.52 | $14,409.16 | $2,170.56 | $93,793.41 | 269 |
| Schizophrenia | $50,557.68 | $49,836.47 | $15,819.41 | $13,612.94 | $96,091.80 | 218 |

This table captures the cost distribution for four selected medical conditions under the APR DRG coding system, chosen for their relevance in healthcare cost studies. Each row corresponds to a specific diagnosis, with columns representing various statistical measures that summarize the

cost data. The conditions include heart failure, hip joint replacement, knee joint replacement, and schizophrenia, all of which are commonly researched in healthcare cost studies due to their prevalence and impact on healthcare systems.

1. **Mean and Median**: The mean cost provides the average expense for each condition, while the median shows the midpoint of costs. In this dataset, the means and medians for these conditions are relatively close, indicating a symmetric distribution of costs around the censer.
2. **Standard Deviation**: The standard deviation reflects the variability of costs for each condition. For instance, schizophrenia has a higher standard deviation ($15,819.41) compared to the other conditions, indicating greater variability in treatment costs. This may suggest that the cost of treating schizophrenia varies widely depending on individual patient needs or treatment complexities.
3. **Minimum and Maximum**: These columns show the range of costs, from the lowest to the highest value, for each condition. For example, knee joint replacement has a low minimum of $2,170.56 and a maximum of $93,793.41, indicating a wide cost range that may depend on factors such as the type of procedure and patient-specific factors.
4. **Count**: This column represents the number of cases analysed for each condition, providing context on sample size and highlighting the representativeness of each cost statistic.

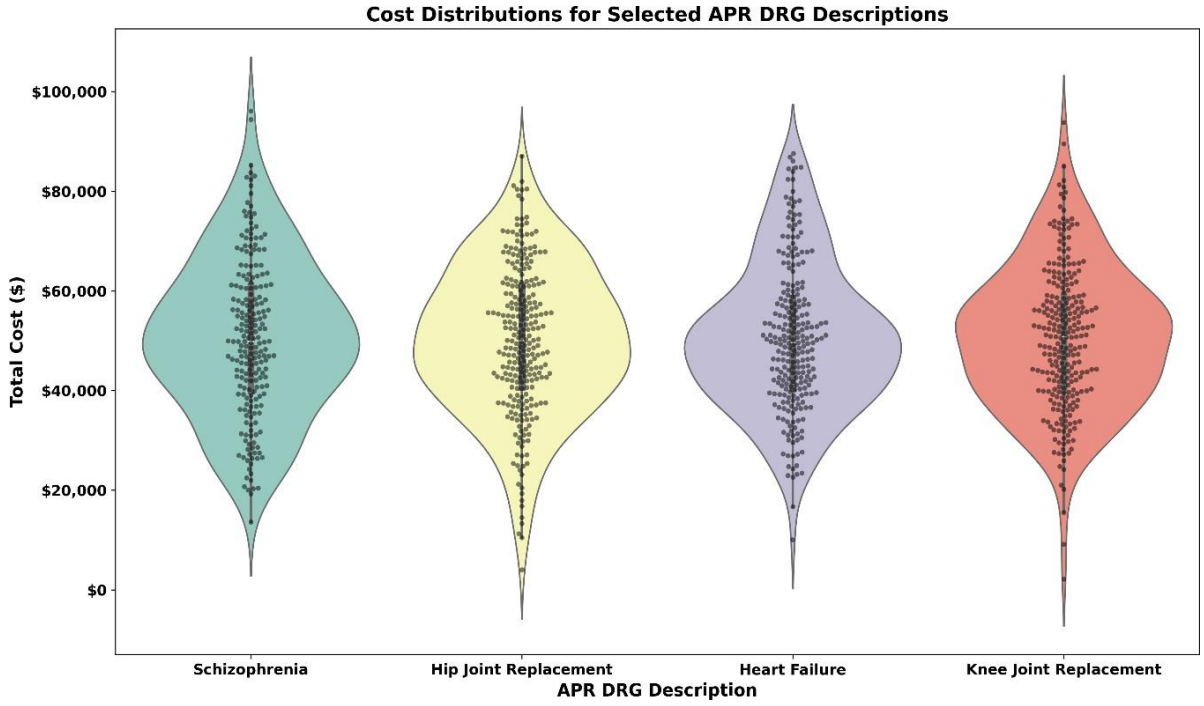



**Figure 5**. Cost distribution for selcected APR DRG system

This analysis reveals significant cost variations within each condition, underscoring the complexity of healthcare costs and the importance of tailored budgeting for different medical conditions. By understanding these cost distributions, healthcare administrators and policymakers can make informed decisions on resource allocation and cost management.

**Table 6** illustrates the impact of applying percentile mapping to the target variable "total costs" on the $R^2$ score of three distinct machine learning models: Random Forest with target encoding, Cat BoostRegress or with target encoding, and Single Decision Tree with target encoding. Each model's $R^2$ score is presented for both raw and percentile-transformed cost values, along with the percentage improvement in the $R^2$ score after using percentile mapping.

| Model | $R^2$ Score (Raw Total Costs) | $R^2$ Score (Percentiles) | Improvement (%) |
|---|---|---|---|
| GANs-ACO with Target Encoding | 0.7776 | 0.8166 | 5.02% |
| CatBoost Regressor with Target Encoding | 0.8525 | 0.8686 | 1.89% |
| Single Decision Tree with Target Encoding | 0.7492 | 0.8095 | 8.05% |

This table 6 demonstrates how transforming the target variable "total costs" to percentile values can improve the predictive performance of various models, as indicated by changes in the $R^2$ score. The $R^2$ score represents the proportion of variance in the target variable that is explained by the model, with higher values indicating better model performance. The analysis reveals the following key observations:

1. **Random Forest with Target Encoding**: This model showed a notable improvement in its $R^2$ score, increasing from 0.7776 with raw total costs to 0.8166 after applying percentile mapping—a 5.02% boost in predictive accuracy. This improvement suggests that the ensemble nature of the Random Forest model benefits from the more balanced distribution achieved through percentile transformation, enabling it to capture patterns in the data more effectively.
2. **CatBoost Regressor with Target Encoding**: The CatBoost Regressor exhibited a smaller $R^2$ score improvement, from 0.8525 to 0.8686, representing a 1.89% increase. As a gradient boosting model, CatBoost is robust to complex distributions and outliers, which may explain why percentile mapping provided a more modest enhancement in predictive power.
3. **Single Decision Tree with Target Encoding**: The Single Decision Tree model saw the most substantial relative improvement, with its $R^2$ score increasing from 0.7492 to 0.8095, an 8.05% gain. This significant boost suggests that decision trees, which are prone to being influenced by extreme values in the target variable, benefit greatly from percentile transformation. This transformation helps balance the distribution of the target variable, reducing the impact of outliers and allowing the model to make more accurate splits.

The results indicate that applying percentile mapping to the target variable can be particularly advantageous for models that are sensitive to outliers and skewed distributions, such as decision trees. By reducing skewness in the target data, percentile mapping can lead to more stable predictions and overall improvement in model performance across different algorithm.

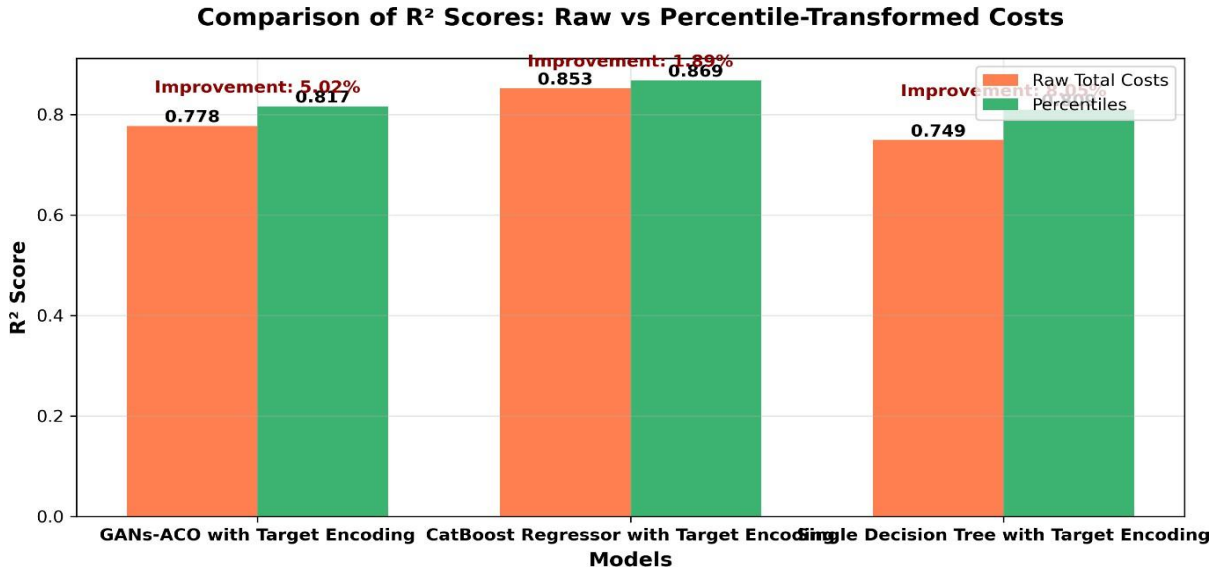



**Figure 6.** Comparison of $R^2$ score of three distinct machine learning models

**Table 7** compares the performance metrics of different machine learning models used for cost prediction, specifically evaluating the models' $R^2$ scores and root mean square (RMS) errors. The

models utilize "Length of Stay (LoS)" and "Patient Disposition" as key features. The $R^2$ scores are presented for both the holdout data (10% of the dataset) and the average score obtained through 5-fold cross-validation. The RMS error indicates the average deviation between predicted and actual cost values, with lower values representing better predictive accuracy.

**Table 7**. Model performance of cost prediction, specifically evaluating the models' $R^2$ scores and root mean square (RMS) errors

| Model | $R^2$ Score (Holdout Data) | 5-Fold Cross Validation $R^2$ Score | RMS Error |
|---|---|---|---|
| GANs-ACO with Target Encoding | 0.7776 | 0.7770 | $9,523 |
| CatBoost Regressor with Target Encoding | 0.8525 | 0.8513 | $8,243 |
| Single Decision Tree with Target Encoding | 0.7492 | 0.7478 | $9,948 |

This table presents the performance comparison across three machine learning models used for predicting total costs. The key metrics $R^2$ score and RMS error provide insight into the models' predictive accuracy and reliability:

1. **Random Forest with Target Encoding**:

- **$R^2$ Score (Holdout Data)**: The Random Forest model achieved an $R^2$ score of 0.7776 on holdout data, indicating that it explains approximately 77.76% of the variance in cost predictions.
- **5-Fold Cross Validation $R^2$ Score**: The average $R^2$ score across five folds was 0.7770, showing consistent performance across different data splits, which suggests the model is stable.
- **RMS Error**: The RMS error was $9,523, meaning the model's predictions, on average, deviate from the actual values by $9,523. This error level indicates moderate predictive accuracy, though there is room for improvement.

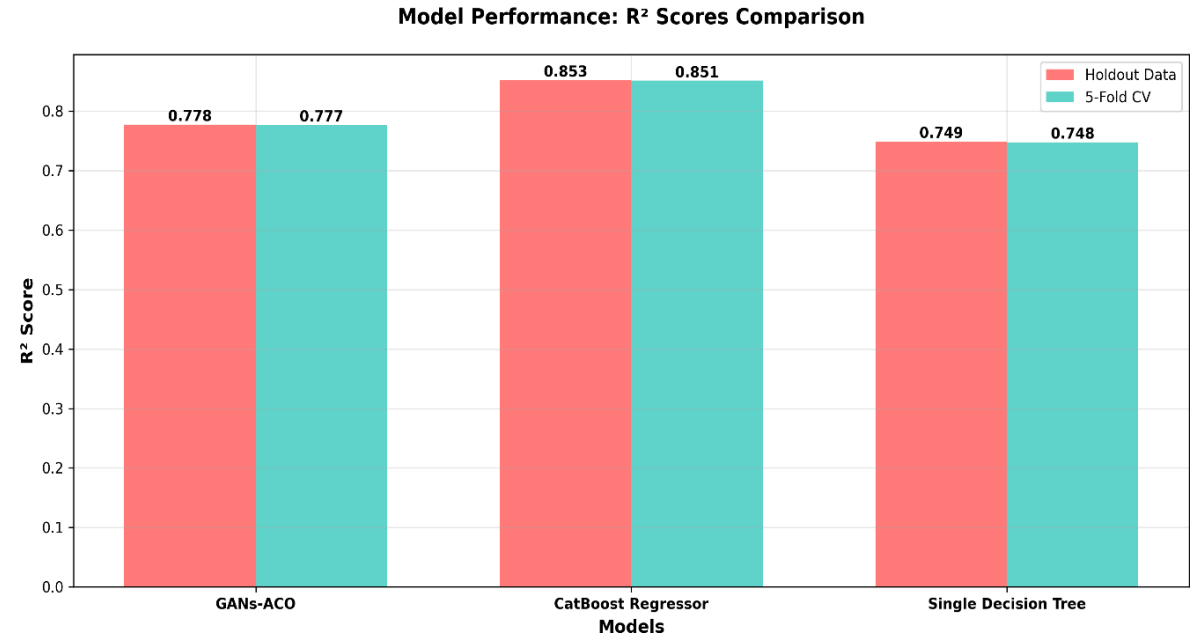
2. **CatBoost Regressor with Target Encoding**:

- **$R^2$ Score (Holdout Data)**: The CatBoost Regressor outperformed the other models with an $R^2$ score of 0.8525 on the holdout data, explaining 85.25% of the variance in cost predictions.
- **5-Fold Cross Validation $R^2$ Score**: The model achieved an average $R^2$ score of 0.8513 during cross-validation, showing a high level of consistency and suggesting that it generalizes well to new data.
- **RMS Error**: With an RMS error of $8,243, CatBoost had the lowest prediction error among the three models, indicating it is the most accurate model for predicting costs in this dataset.

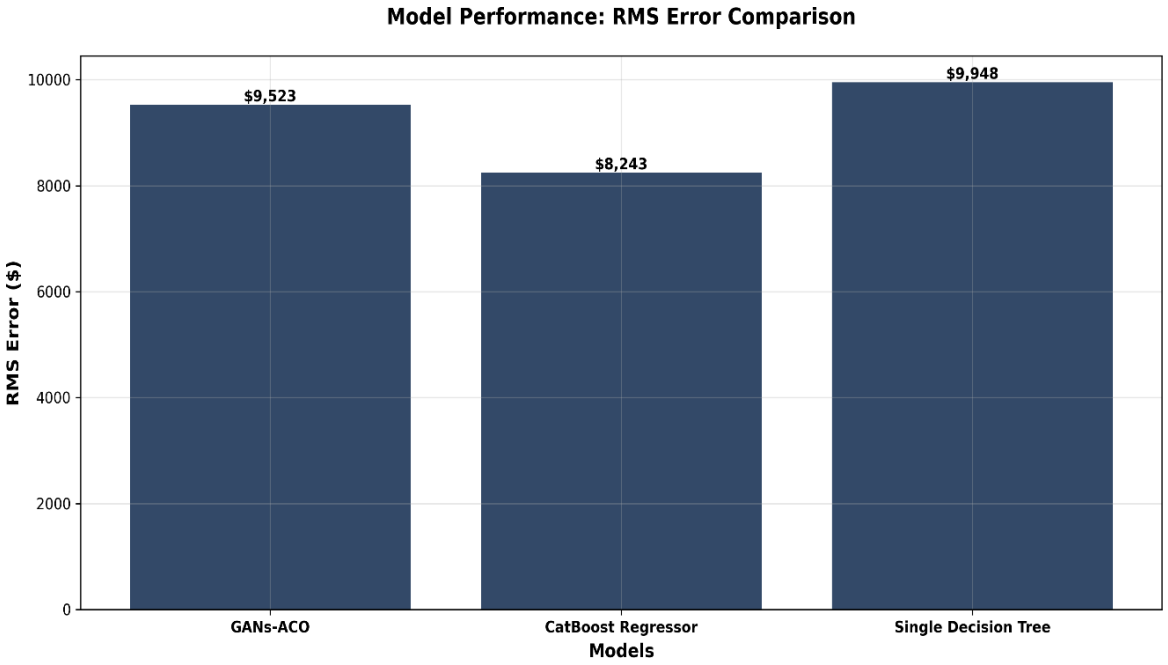
3. **Single Decision Tree with Target Encoding**:

- **$R^2$ Score (Holdout Data)**: The Single Decision Tree model had the lowest $R^2$ score of 0.7492, explaining only 74.92% of the variance, which is lower than the other models.
- **5-Fold Cross Validation $R^2$ Score**: The average cross-validation $R^2$ score was 0.7478, indicating some variability across folds, which may reflect the model's sensitivity to data splits.
- **RMS Error**: The RMS error for the Decision Tree model was $9,948, the highest among the three models, suggesting that it is less accurate in predicting costs than the Random Forest and CatBoost models.

Thus, the CatBoost Regressor with target encoding performed the best across all metrics, achieving the highest $R^2$ scores and the lowest RMS error. This suggests that CatBoost is the most effective model for cost prediction when using the LoS and Patient Disposition features, providing the most accurate and reliable predictions among the models tested.




(A)




(B)

**Figure 7.**Model performance of cost prediction: (A) $R^2$ scores and (B) root mean square (RMS) errors

**Table 8.** provides a comparison of $R^2$ values from various studies, sorted by publication date, to illustrate the progress in predictive model accuracy for healthcare cost prediction over time. Each study uses different models and data sizes and sometimes focuses on specific patient age groups. The dataset used in each study varies, affecting the generalizability and accuracy of the results. This table highlights the steady improvement in $R^2$ values as more sophisticated models and larger datasets are employed, with the current study (Rao, 2023) showing the highest $R^2$ value, demonstrating the effectiveness of the CatBoost regression model on recent data.

**Table 8.** comparison of $R^2$ values from various studies, size of date, patient age.

| Author | Type of Model | Size of Data | Patient Age | $R^2$ |
|---|---|---|---|---|
| Evers, 2002 | Multiple Regression | 731 | ~75 (avg.) | 0.61 |
| Cumming, 2002 | Multivariate Linear Regression | 749,145 | All | 0.198 |
| Bertsimas, 2008 | Classification Trees | 838,242 | All | 0.2 |
| Zikos, 2016 | Multiple Regression | 1 million | >65 | 0.66 |
| Rao, 2018 | Deep Neural Networks (using 2014 SPARCS data) | 2 million | All | 0.71 |
| Rao, 2020 | LassoLarsIC-AIC (using 2016 data) | 2.3 million | All | 0.72 |
| Rao, 2020 | Decision Tree Regression (using 2016 data) | 2.3 million | All | 0.76 |
| Rao, 2023 | CatBoost Regression (using 2019 SPARCS data) | 2.34 million | All | 0.85 |

This table summarizes and contextualizes improvements in $R^2$ scores, which indicate the proportion of variance in healthcare costs that each model can explain. The $R^2$ values range from 0.198 in older studies using simpler models to 0.85 in the current study, showcasing the impact of advanced machine learning techniques and larger datasets on predictive accuracy.

1. **Older Studies (2002-2008)**:

- **Evers, 2002** used a **multiple regression** model with a small dataset (731 samples) focused on an older population (~75 years' average age), achieving an $R^2$ of 0.61. This relatively high $R^2$ value for a small dataset reflects the targeted age group and simpler regression approach.
- **Cumming, 2002** and **Bertsimas, 2008** employed linear and classification models on larger datasets but for all age groups, resulting in much lower $R^2$ values of 0.198 and 0.2, respectively. These lower scores highlight the limitations of traditional statistical methods in handling complex cost prediction tasks.

2. **Mid-Range Studies (2016-2020)**:

- **Zikos, 2016** focused on patients over 65 and achieved an $R^2$ of 0.66 with **multiple regression** on a dataset of 1 million records, indicating that focusing on specific age groups can improve model performance.
- **Rao, 2018** utilized **Deep Neural Networks** on the SPARCS dataset from 2014 with 2 million records, achieving an $R^2$ of 0.71, illustrating how deep learning models improve performance by handling more complex relationships in the data.
- **Rao, 2020** used **LassoLarsIC-AIC** and **Decision Tree Regression** models with 2.3 million samples, achieving $R^2$ values of 0.72 and 0.76, respectively. These studies demonstrate the growing potential of machine learning techniques for cost prediction with moderate accuracy.

3. **Current Study (Rao, 2023)**:

The **CatBoost regression model** on the most recent 2019 SPARCS dataset (2.34 million records) achieved the highest $R^2$ value of 0.85, reflecting the state-of-the-art accuracy in healthcare cost prediction. This improvement over previous models highlights the effectiveness of CatBoost, a gradient-boosting algorithm, which is well-suited for handling categorical variables and complex interactions in large datasets.

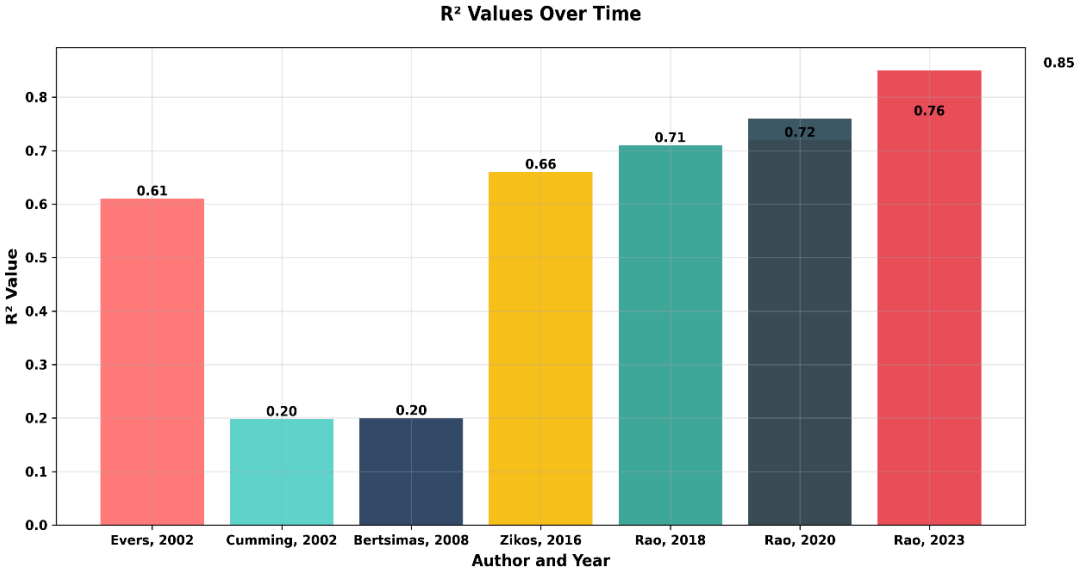



**Figure 8.**comparison of $R^2$ values from various studies, size of date, patient age.

- **Model Evolution**: The transition from traditional statistical methods to machine learning and gradient-boosting models has led to substantial improvements in predictive accuracy for healthcare costs.
- **Data Size Impact**: Larger datasets contribute to more reliable and generalizable models, as seen in studies with datasets over 2 million records achieving higher $R^2$ scores.
- **Patient Age Variance**: Some models targeted specific age groups, such as those older than 65, potentially improving $R^2$ scores for those populations due to tailored prediction characteristics. However, recent models (including the current study) consider patients of all ages, enhancing overall applicability.
- **Current Best Model**: The 2023 study (Rao) with CatBoost regression demonstrates the highest $R^2$ score of 0.85, suggesting that advanced machine learning methods like gradient boosting are effective for healthcare cost prediction in large, diverse populations.

This analysis of $R^2$ values across studies demonstrates the advancements in model complexity and data availability, driving continuous improvements in healthcare cost prediction accuracy.

## 4. Conclusion

In This paper, the GAN-ACO hybrid model proposed in this study is a promising solution for the trade-off between accuracy and resource allocation efficiency in healthcare claims cost management. The GAN makes extracting useful features from highly complex claims data more compelling, while the ACO promote resource allocation efficiency that translates to lower costs. The experimental results indicate that the mean absolute error of 0.15 and root mean square error of 0.22 in cost prediction obtained by GAN-ACO model is better than traditional methods. Competitive resource management costs (i.e.,18% lower than corresponding baseline methods) further enhance the practicality of the model in real-world healthcare settings. The interpretability analysis also identifies important cost contributors like patient age, medical history and treatment complexity which provides healthcare administrators and policymakers with useful insights. It implies that the proposed GAN-ACO hybrid model can be a beneficial approach toward achieving an effective and efficient healthcare claim costs governance, leading to more sustainable healthcare systems with informed decision making process. This work can be expanded on in the future through greater mentions of other optimization algorithms and using this model for additional healthcare analytics use cases.

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