Humana-Mays Healthcare Analytics 2023 Case Competition

Predicting Therapy Discontinuation Following Adverse Drug Events

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1. Executive Summary

Adverse Drug Events (ADEs) stand as a significant factor leading individuals to discontinue their early-stage lung cancer treatment. These events have a multifaceted impact on patients, infiltrating their social and personal lives, and ultimately diminishing their Quality of Life. Our mission is to leverage Humana's data to target and assist those patients who prematurely halt their treatment, thus preventing them from experiencing these detrimental drug-related complications in their fight against this life-threatening cancer.

To harness the potential of the provided data, we meticulously examined each column and consulted the data dictionary to grasp the meaning behind them. Once we comprehended the data's nuances, we embarked on a data cleaning process, handling null values by imputing with medians, guided by the information contained within the merged dataset. To address data imbalance, we employed SMOTE Tomek techniques. Furthermore, we crafted new features based on our contextual understanding to facilitate the effective modeling of this dataset.

Following the data cleansing, we created a Logistic Regression model with lasso regularization, which emerged as the most effective in predicting patients prone to discontinuing their medication. We gauged the model's performance using primary metrics, such as the AUC score and the False Negative Rate (FNR), while also ensuring fairness by evaluating potential bias in sensitive variables, employing disparity scores as our measure. This model serves as the initial stride in comprehending the problem, with the aim of devising more effective solutions.

ADEs present a multitude of challenges, as their side effects, including blood clots, nausea, and fatigue, complicate the treatment journey, exacerbating the physical and emotional burden on patients. These adverse events can substantially alter an individual's overall well-being and personality. While current approaches serve as an initial step in assisting lung cancer patients, enhancing their coping mechanisms through our three targeted recommendations: a Caregiver Incentive program to enhance caregiver involvement, a Comprehensive Geriatric Assessment for senior patients, and motivational management strategies to improve the patient's Quality of Life, all aimed at addressing adverse effects can offer Humana a multitude of opportunities to provide even more effective support to those battling this disease.

We anticipate potential cost savings of USD 27,651 per capita for the first year and USD 61,670 for five years. This approach not only makes proactive mitigation of adverse effects financially sensible but also improves patient care, aligning with Humana's commitment to enhancing the well-being of individuals fighting lung cancer.

2. Background

2.1 Case Introduction and Business Problem

In oncology, the utilization of Osimertinib, when administered as per prescription, exhibits a potential for extending the life expectancy of patients diagnosed with certain forms of lung cancer. However, a significant challenge arises from the occurrence of treatable side effects, which may lead patients to discontinue their treatment prematurely. This premature discontinuation can have adverse effects on patient outcomes and the healthcare system as a whole, including both clinical and economic consequences. It is, therefore, imperative to address this issue by developing a predictive model utilizing the data provided by Humana that can identify patients who are at risk of prematurely ending their treatment following the occurrence of an adverse drug event (ADE). Such a model will facilitate early intervention, personalized patient care, and optimizing treatment plans, ultimately improving patient outcomes and resource allocation within the healthcare system. This predictive model aligns with Humana's commitment to advancing patient-centric care and enhancing the effectiveness of oncological treatments.

2.2 Definition of Metrics/ Key Performance Indicators

The model we are building should have the capability to predict which patients are most likely to discontinue therapy due to an adverse drug event. To ensure that our model accurately identifies members at risk, we have chosen ROC AUC (Receiver Operating Characteristic Area Under the Curve) as our primary key performance indicator. This choice is based on the expectation that our model's output should rank members at the highest risk at the top, with the ranking decreasing as the likelihood of discontinuation decreases. ROC AUC quantifies how well the rank-ordered results align with true class membership.

In addition to ROC AUC, we are also considering the False Negative Rate of the model as a secondary performance indicator. We aim to minimize misclassifications of members at high risk of discontinuing therapy. Therefore, we strive for a low False Negative Rate in our model. Both of these metrics will be thoroughly explored and discussed in detail in the Modeling Section.

3. Preliminary Research

Non-Small Cell Lung Cancer (NSCLC) and Its Treatment

Lung cancer is a prevalent and serious health concern in the United States. In 2020, there were an estimated 228,820 new cases of lung cancer and 135,720 deaths attributed to the disease. Patients with lung cancer are typically grouped based on the type of lung cancer they have, with the two main categories being non-small cell lung cancer (NSCLC) and small cell lung cancer (SCLC). Early-stage lung cancer, particularly of the non-small cell variety, is a localized form of

the disease, often categorized as stages I and II. At these stages, the tumor remains relatively small and is confined to the lung or nearby lymph nodes. Treatment for early-stage NSCLC is typically more effective and carries a more favorable prognosis.

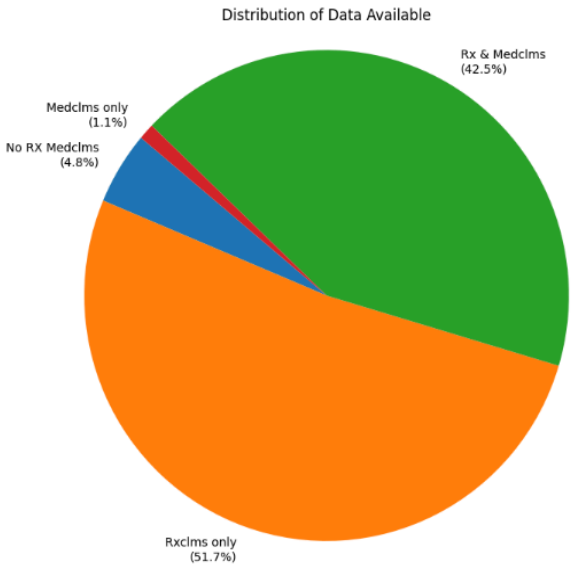
For NSCLC patients, surgical intervention is commonly the primary treatment approach, alongside the use of medication treatments like Osimertinib, an oral tyrosine kinase inhibitor. Osimertinib, when employed as a targeted therapy, has demonstrated remarkable effectiveness in delaying disease progression and enhancing the overall survival of EGFR-positive NSCLC patients. Clinical trials have substantiated its superiority over earlier-generation EGFR inhibitors, particularly in terms of progression-free survival. Common side effects associated with Osimertinib treatment may encompass skin rash, diarrhea, dry skin, fatigue, and alterations in nail color.

The treatment dropout rate in the United States can vary depending on multiple factors, including cancer stage, overall patient health, and access to healthcare. For patients with early-stage lung cancer, the dropout rates are generally lower compared to those with more advanced stages, as early-stage patients typically have a higher completion rate for their treatments. However, it is important to note that even in early-stage cases, some patients may discontinue treatment due to severe side effects or difficulties in tolerating the treatment regimen.

4. The Data

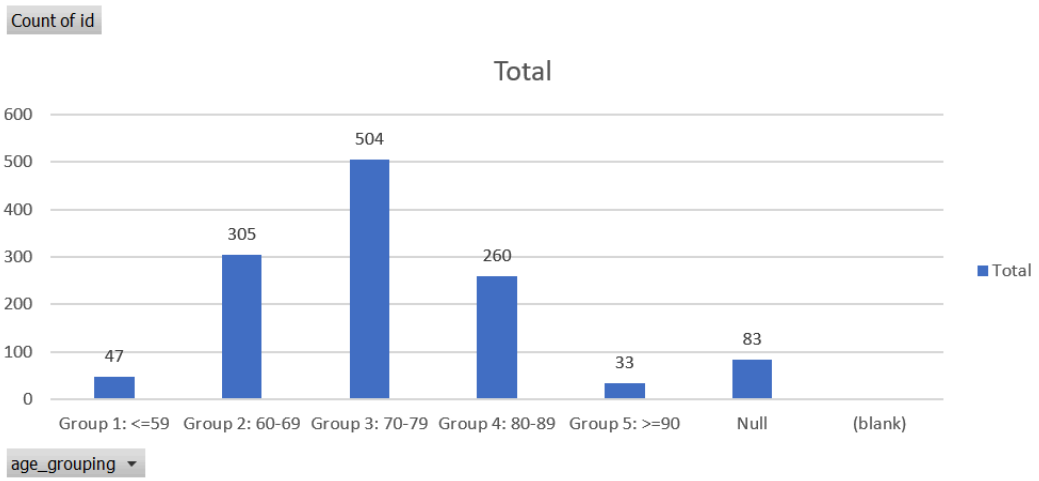
4.1.Data Overview

In our training data, we have a total of 1,232 members for whom we have a binary indicator variable that signifies whether a member discontinued their osimertinib therapy due to an adverse drug event within 6 months of starting the therapy. Out of these 1,232 members, we have pharmacy claims data available for 1,160 members within the time frame spanning 90 days before the commencement of therapy through the end of the therapy. Furthermore, we have medical claims data for only 536 members within the same 90-day window before the start of therapy through the end of the therapy. It's worth noting that among the 1,232 members, 59 (1.1%) do not have either pharmacy or medical claims data available. Our dataset includes essential information such as the start and end dates of therapy, as well as protected attributes like sex, race, age, and disability indicators. Among the members, 637 (51.7%) have pharmacy claims data but lack medical claims data, while 523 (42.5%) have both pharmacy and medical claims data available.



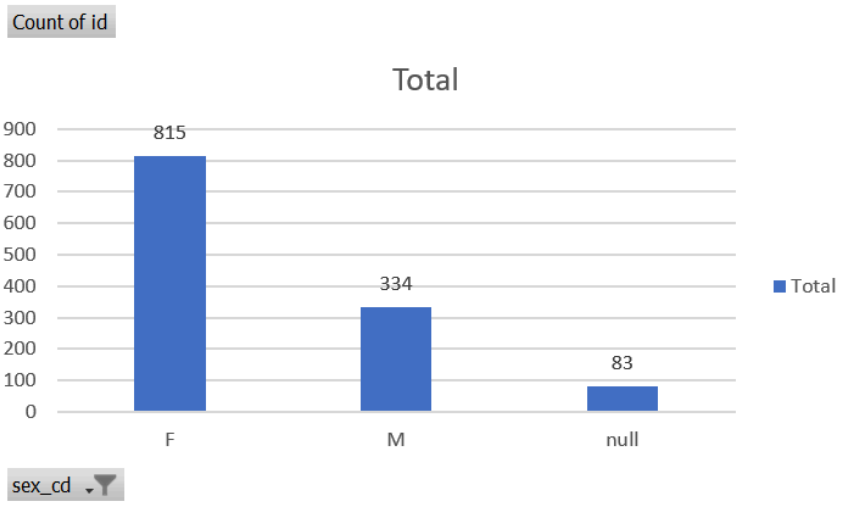
The pie chart above shows the distribution of data available. It indicates that only 42.5% of the population has both Rx claims and Medclms data available.

Distribution of age across the population:



From the bar plot, above, approximately 89.4% of the population (excluding Group 1: <=59 and null values) are above the age of 60.

Distribution of gender across the population:



Our data has approximately 66% Females and 27% males.

4.2 Data Aggregation

Since the available data is limited, we ensured that we extracted most of the features from the available data. Taking a look at pharmacy claims data, we have multiple pharmacy claims for each member 90 days before the start of the therapy through 180 days after. Hence these need to be aggregated and some features need to be extracted out of this data that can represent all the pharmacy claims at aggregated level. These aggregated features can be further used in the modeling to predict our target variable. Similarly, the data aggregation needs to be carried out on medical claims data as well. We preserved all the claims data prior to the start of the therapy too, as we could create features that can compare the type of drugs a member is taking after the start of the therapy to the type of drugs that a member is taking prior to the start of the therapy. An extensive feature engineering is performed to extract as much information from the pharmacy and medical claims as possible.

4.3 Feature Engineering

Pharmacy Claims:

Features, such as the number of unique drugs taken, emphasize the number of unique pills a member has taken. Additionally, the last dates of prescription fills were calculated, which can be utilized to understand the time elapsed between the therapy start date and the last pharmacy prescription date. Considering the perspective of a member undergoing therapy, we created various comparison variables. These enable us to compare the difference in drug consumption patterns before the therapy started to those observed afterward. Indicator variables were created to denote whether each pharmacy prescription was filled before or after the initiation of the therapy. Utilizing these indicators, we generated multiple features to assist in identifying and

comparing drug consumption patterns before the onset of the therapy and following its commencement. For example, a member might be taking a significant number of anticoagulant drugs, especially after beginning therapy, and fewer before starting therapy. We aimed to account for these variations using these types of variables. In addition to capturing differences in drug consumption patterns, we also considered financial aspects by creating variables that indicated the total cost of pharmacy prescriptions both before and after the initiation of therapy. This information could prove valuable, as the cost of pharmacy prescriptions after beginning therapy or the supply count of medications following the start of therapy could serve as useful indicators of whether the patient is adhering to the treatment plan. This data could significantly assist in distinguishing members who have chosen to discontinue therapy from the others.

Medical Claims:

Much like the aggregation process applied to pharmacy claims data, we have generated multiple features using medical claims data. Features such as the last visit date can provide insights into the duration of a patient's interactions with medical professionals. Additionally, the average processing time for all medical claims can offer clues as to whether patients may discontinue treatment due to extended claims processing times. Moreover, the medical claims data includes indicators that signify whether each claim is related to the diagnosis of a specific side effect of osimertinib. We have aggregated these indicator variables both before and after the initiation of therapy. The predictive model we are developing can leverage these variables to make more accurate predictions regarding the likelihood of treatment discontinuation based on the severity of these side effects.

After aggregating the data and generating the necessary features, all of them are combined to create a unified record for each patient, which can then be input into the model.

4.4 Data Cleaning

(Handling Missing values, including missing indicators)

Medclms:
During the data aggregation and feature extraction process, we excluded all the variables in the medical claims data that had null values, this is because out of the whole population, medical claims data is available to only 43% of members. Consequently, utilizing features with additional missing values in the available medical claims data may not represent useful information about the member. Therefore, we chose to exclude them.

Rxclms:
Some of the variables that had missing information in pharmacy claims were not considered for feature extraction. Hence no explicit missing value treatment was done during the process of feature extraction.

Merged data:
However, after merging all the extracted features from medical and pharmacy claims with the target data, we encountered missing values. This was due to the presence of members in our population who had pharmacy claims but not medical claims, as well as members who had medical claims but not pharmacy claims. Since all the data we had post-merge was numerical in nature, we chose to impute all the missing values with the median. Additionally, we considered the possibility of creating missing indicators for each missing column as separate features, in addition to the median-imputed features. This was because sometimes, missing features could potentially reveal hidden information that might enhance the model's predictive capabilities. For instance, the absence of medical claims alongside multiple pharmacy claims could suggest that even if a member experienced an adverse drug event, it might not be severe enough to warrant consultation with a medical professional, indicating a tolerable situation.

4.5 Handling Data Imbalance

Out of a total population of 1,232 members, our dataset includes only 117 members who both discontinued therapy and experienced an adverse drug event, accounting for just 9.5% of the population. Consequently, the dataset is highly imbalanced, and the model will only get an opportunity to see very few records to learn any patterns that can help classify members at risk accurately. To address this, we applied SMOTE Tomek, a combination of two techniques for balancing imbalanced datasets: Synthetic Minority Over-sampling Technique (SMOTE) and Tomek links. SMOTE generates synthetic samples for the minority class, while Tomek links are used to identify and remove potentially noisy or borderline samples. By utilizing a combination of these techniques, we achieved a balanced dataset that better represents the original dataset.

5. Modeling

5.1 Model Creation

First, we split our data into 70% training and 30% validation datasets. Having enough validation data is essential for us, as this can help us identify if our model is overfitting to the small training data instead of learning any patterns as it should.

Once the train and validation partitions are in place, before feeding the training data to the model, we want to ensure that all our features are on the same scale. Machine learning models like lasso or ridge logistic regression can be sensitive to scale and since we wanted to try out different models including linear and tree based models, and pick the best one that suits the given dataset, we scaled all the numerical features in the dataset such that they all have a zero mean and unit variance. By doing so, one feature doesn’t dominate any other feature just because of the scale during the model training process.

5.2 Model Comparison and KPI Evaluation

We have tried three different models, Logistic Regression, Random Forest, XGBoost. We evaluated all these models primarily based on two metrics ie., roc_auc and False Negative Rate. A model with high roc_auc indicates that the model has better discrimination and overall predictive performance in distinguishing between the positive and negative classes in a binary classification problem. In other words, the model is better at ranking the positive class instances higher than the negative class instances across various probability thresholds. As a secondary metric of evaluation, we have used False Negative Rate or Miss Rate. If a member is actually at risk of discontinuing therapy and our model missed to correctly classify them, it is counted as a false negative. False Negative Rate indicates the proportion of such misclassifications out of all the members that actually discontinued the therapy. The best model will be the one which has least False Negative Rate.

The performance of different models based on these two evaluation metrics is as below

Model Name	**Train AUC**	**Validation AUC**	**False Negative Rate (FNR)**	**Recall**
Logistic Regression with lasso	0.971	0.923	17.14%	0.83
Random Forest	1	0.926	22.85%	0.77
XGBoost	1	0.92	31.42%	0.69

Based on the model results, logistic regression had comparable validation AUC with other tree based models, but False Negative Rate is least for logistic regression models. Hence, we chose logistic regression as our final model. Since the difference between train and validation AUC is high, we used lasso penalization and performed hyperparameter tuning to select the optimal penalization coefficient.

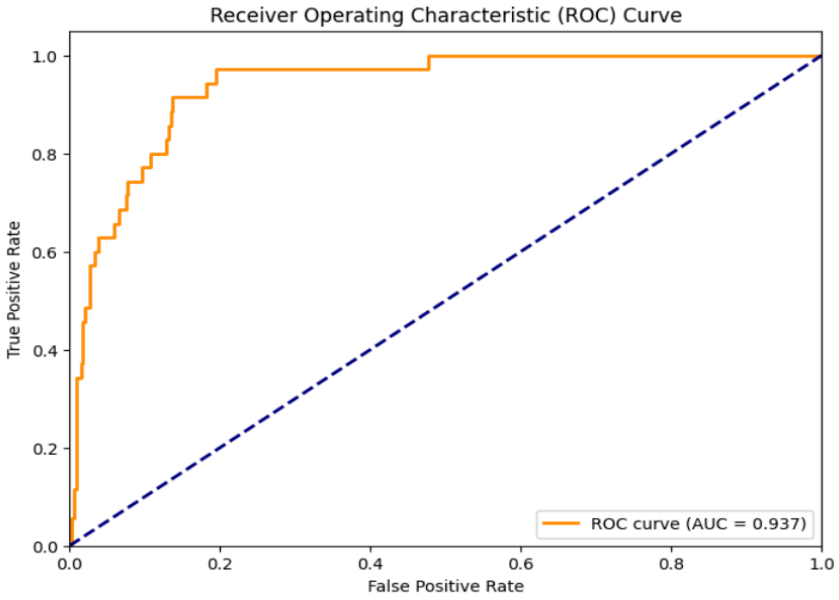
5.3 Final Model Evaluation

After tuning hyperparameters of lasso logistic regression to reduce overfitting in the model, the resultant model had following performance

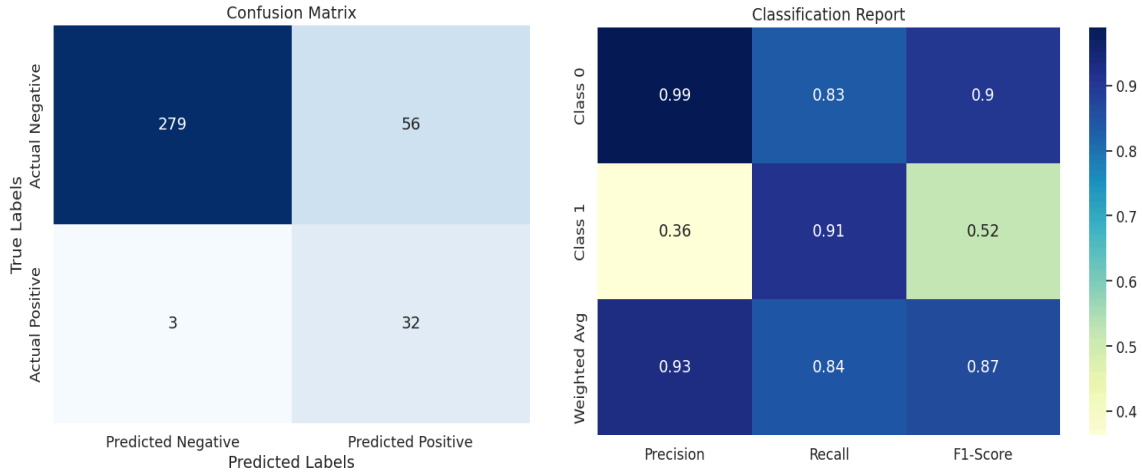
Model Name	**Train AUC**	**Validation AUC**	**False Negative Rate**
Lasso Logistic Regression	0.958	0.937	8.57%

The final model has a holdout AUC of 0.869 as per official case competition leaderboard.

ROC Curve:



Confusion Matrix & Classification Report:



From the confusion matrix on the validation partition, it can be observed that the model predicted very few false negatives which meets our expectations that the model should not miss out on identifying members at risk of discontinuing therapy. From the classification report, it can be seen that our model has a high recall of 0.91, but has precision of around 0.36. However, the overall weighted average yields a precision of 0.93 and recall of 0.84 and an F1 score of 0.87.

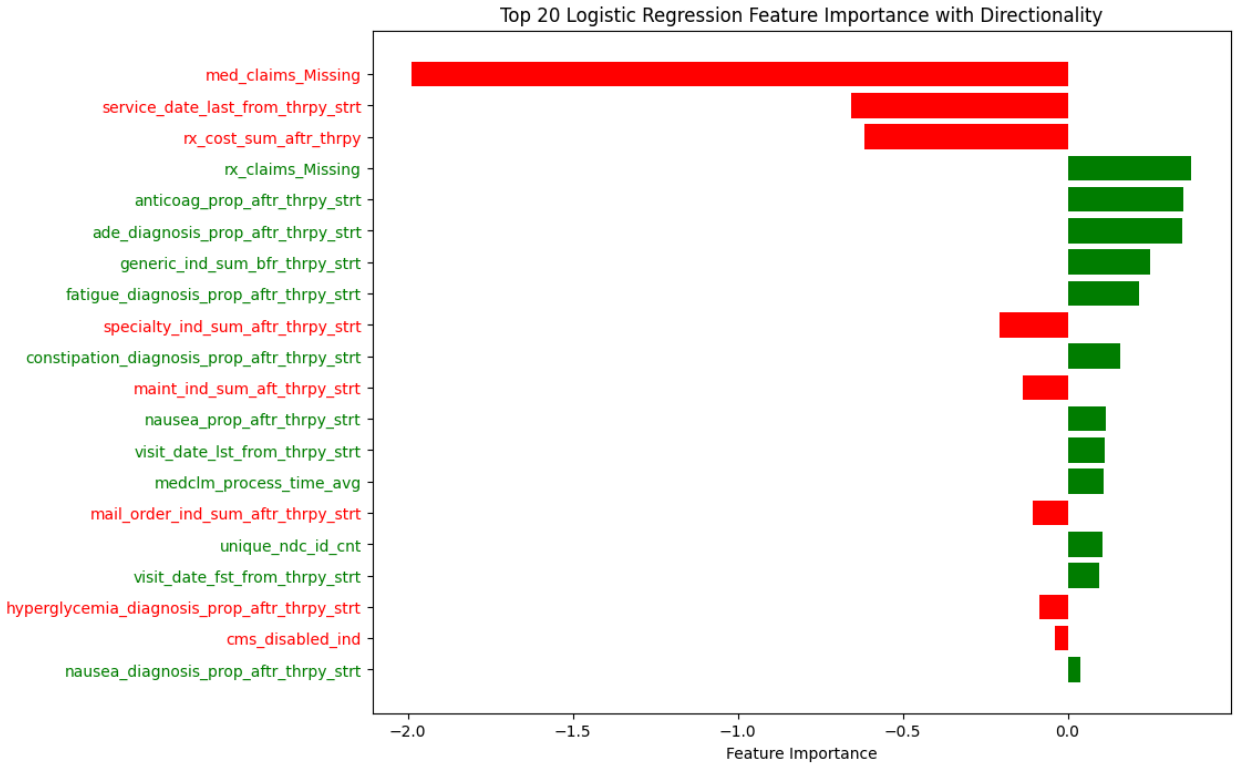
5.4 Fairness Diagnostic

Another important aspect of assessing our model's performance is ensuring that its output remains unbiased with respect to sensitive variables. Even when sensitive features such as race are excluded, it does not guarantee immunity from potential biases that might exist in the data in unexpected ways. Machine learning models trained on such data can inadvertently amplify these biases. In this competition, we utilize a disparity score to evaluate the fairness of our model's predictions. The disparity ratio is determined by comparing the true positive rate of each gender and race group to the true positive rate of the reference privileged group (White, Male). The overall disparity score is then computed as the average of all disparity ratios across all sensitive variables.

$$Disparity\ Score = \frac{\sum_{SV} \sum_{S} \min\left(\frac{S_n}{S_0}, 1\right)}{N}$$

Our model had a disparity score of 99.03%, which means our model is immune to exhibiting any bias in terms of sensitive variables.

5.5 Feature Importance Analysis:

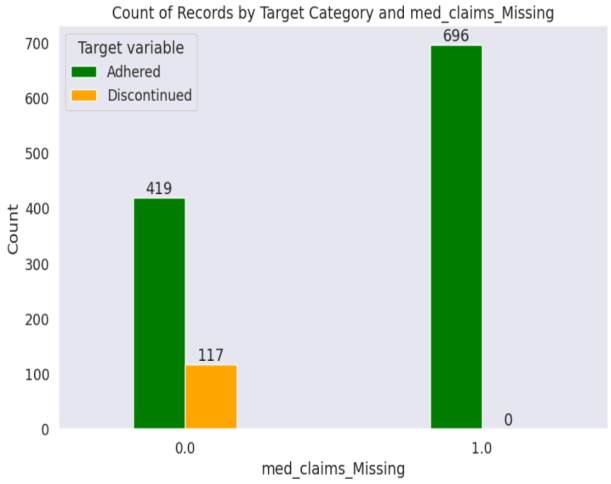


The above feature importance plot displays the top 20 features selected by our model. The length of the bar represents the magnitude of feature importance, while the color indicates the directionality of impact. Features colored in red indicate a negative impact, while those colored

in green have a positive impact on the likelihood of discontinuing therapy. Based on our top 15 features, we can categorize them into three groups based on the business insights they convey.

Category 1: Features representing pharmacy and medical visits

(i) med_claims_Missing: This represents a missing indicator that takes a value of 1 when a patient's medical claims are missing and 0 when they are present. This particular feature is associated with a negative impact on the likelihood of therapy discontinuation. For those patients where medical claims exist and are not missing, there is an increased risk of discontinuing the therapy before 6 months.



The bar plot above indicates that all members who discontinued their therapy within 180 days had at least one medical claim. Therefore, the presence of a medical claim for a member could potentially signal that they may be experiencing adverse drug effects or require more personalized care and support. This observation can be utilized as an indicator for implementing targeted interventions.

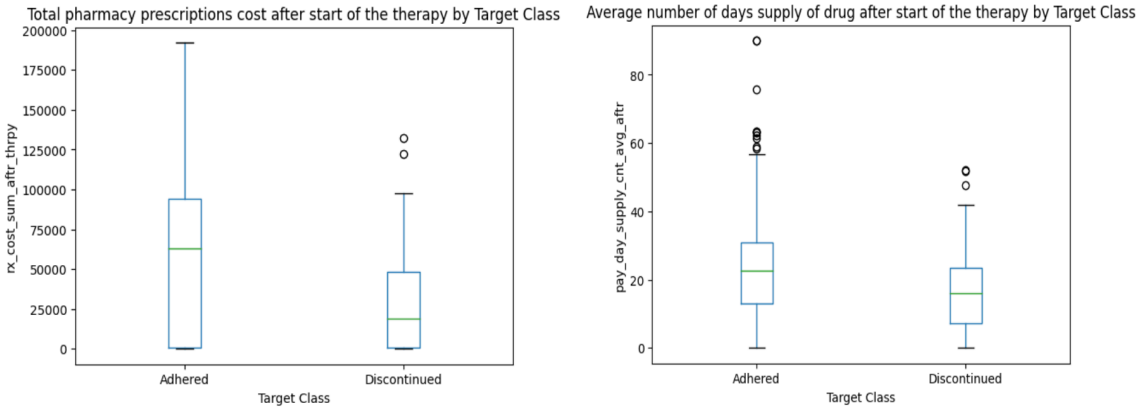
(ii) service_date_last_from_thrpy_strt: This feature represents the duration between the initiation of therapy and the patient's most recent visit to the pharmacy. Given that this feature has a negative impact, it suggests that patients who have been visiting the pharmacy for an extended period from the therapy start date are relatively less likely to discontinue therapy compared to those who haven't.

Interpreting the model coefficient: Our model assigned a coefficient of -0.659 to the feature service_date_last_from_thrpy_strt, which means that the

Feature name	Coefficient value	Odd ratio
service_date_last_from_thrpy_strt	-0.6599	0.51686

The odds ratio signifies how the odds of the outcome change for a one-unit change in the predictor variable, while holding all other variables constant. From the calculated odds ratio specific to this feature, we can infer that considering the start of the therapy as a reference date, for each day increase in pharmacy prescription fill, the odds of members discontinuing therapy decreases by 48.31% (100%-51.68%). As the odds decrease, the necessity to intervene and provide any adherence assistance to such members also decreases.

(iii) rx_cost_sum_aftr_thrpy: This represents the total cost of all pharmacy prescriptions after the initiation of therapy. A higher cost in this context suggests that the patient frequently visits the pharmacy and is more likely to pick up their prescribed medications on time. This behavior indicates that they are adhering to their treatment plan as prescribed by their healthcare provider.



The box plot on the left displays the distribution of values for total pharmacy prescription costs considered after therapy started, comparing members who discontinued therapy with those who exhibited adherence. Notably, for members who adhered to the treatment, the median value of pharmacy prescription costs (indicated by the line at the middle of the box) is significantly higher than for members who discontinued. This discrepancy arises because members who demonstrated adherence consistently followed their medication plan. The box plot on the right further supports this observation by showing that the median value of the average payday supply count of drugs is higher for members who adhered to the treatment compared to those who discontinued therapy.

(iv) rx_claims_Missing: This missing indicator variable takes a value of 1 if pharmacy claims are missing for a patient and 0 when they are present. Notably, this feature positively impacts the probability of discontinuing therapy, implying that patients who visited a pharmacy at least once have lower chances of discontinuing therapy compared to those who never did.

(v) visit_date_lst_from_thrpy_strt: This feature represents the duration between the initiation of therapy and the most recent medical visit. Given that this feature has a positive impact, it suggests that members who have been visiting the doctor for an extended period from the therapy start date are more likely to discontinue their therapy.

Category 2: Features representing impact of side effects and adverse drug events

(i) anticoag_prop_aftr_thrpy_strt: This feature calculates the ratio of anticoagulant drugs taken from the pharmacy after the start of therapy to the total number of anticoagulants taken within a total time span of 9 months. A higher proportion is associated with an increased likelihood of patients discontinuing therapy.

(ii) ade_diagnosis_prop_aftr_thrpy_strt: This is equal to the proportion of number of times medical claims report an adverse drug event after the start of the therapy to the total number of times ADE is reported in the medical claims. This variable positively impacts the likelihood of discontinuing therapy which means higher number of adverse drug event reports after the therapy start is associated with higher chances of members discontinuing the therapy.

(iii) fatigue_diagnosis_prop_aftr_thrpy_strt: This feature calculates the ratio of fatigue diagnosis reported medical claims after the start of therapy to the total number of fatigue diagnosis codes in all the medical claims. A higher proportion is associated with an increased likelihood of patients discontinuing therapy.

(iv) constipation_diagnosis_prop_aftr_thrpy_strt: This feature calculates the ratio of constipation diagnosis reported in medical claims after the start of therapy to the total number of constipation diagnosis codes in all the medical claims. A higher proportion is associated with an increased likelihood of patients discontinuing therapy.

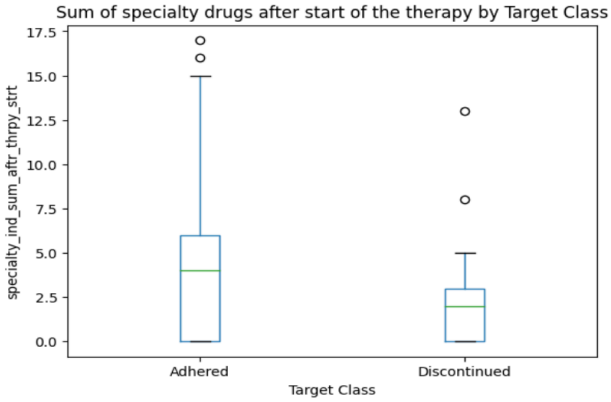
(v) nausea_prop_aftr_thrpy_strt: This feature calculates the ratio of nausea treatment drugs taken from the pharmacy after the start of therapy to the total number of nausea treatment drugs taken to date. A higher proportion is associated with an increased likelihood of patients discontinuing therapy.

Insights: All the above features indicate that occurrence of side effects and adverse drug events after the start of the therapy are related to increased likelihood of members discontinuing their therapy.

Category 3: Features representing variations in drug consumption

(i) generic_ind_sum_bfr_thrpy_strt: This feature represents the count of generic drugs consumed prior to the initiation of therapy. Our model suggests that if a member has a history of consuming a substantial number of generic drugs before starting therapy, they are more likely to discontinue the treatment. Possible reasons for this behavior could include a stronger belief in the effectiveness of generic drugs over branded ones or a lack of immediate perceived benefits, which might lead them to opt for therapy discontinuation. For these members, it's important to educate them regarding the effectiveness of prescribed therapy emphasizing its advantage over generic drugs.

(ii) specialty_ind_sum_aftr_thrpy_strt: This variable calculates the number of specialty drug prescription fills after the initiation of therapy. This variable has a negative impact on the likelihood of discontinuation. This may be attributed to the fact that specialty drugs, frequently employed in the treatment of complex, chronic, or rare medical conditions, can be associated with a range of potential side effects that may contribute to increased severity and intolerance.



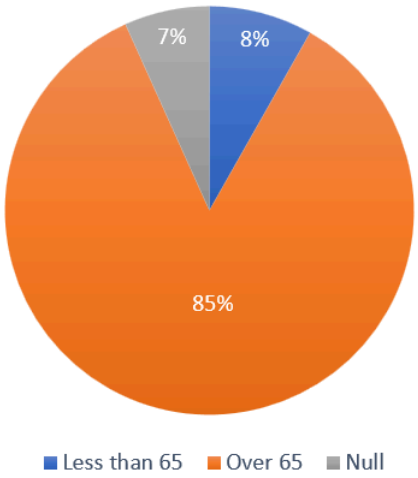
The box plot above suggests that discontinued individuals are likely to have consumed lesser specialty kinds of drugs after the initiation of therapy when compared to members who adhered to their treatment plan. The decision to discontinue therapy might have also resulted from shared decision-making between the patient and their healthcare provider.

6. Business Implications

Observations

In the Humana dataset, approximately 85% of the patients are aged 65 or older. The company provides substantial financial support, particularly for specialty drugs, through Medicare Advantage (MA) and Medicare Part D. Humana is actively implementing a range of senior-focused services, including drug mail delivery, home health care, senior primary care, and community centers, among others, to cater to the specific needs of its senior customers.[1]

[1] Humana Impact Report 2022



According to its value-based care report, Humana has been implementing healthcare practices that have embraced various strategies to enhance patient care and accessibility including the ongoing use of telehealth for virtual visits, expanded transportation services provided by healthcare providers to assist patients in attending medical appointments, the deployment of mobile clinics to bring care directly to patients, and intensified patient outreach and follow-up efforts through integrated care teams. These initiatives aimed to better understand and address the obstacles to patient well-being, ensuring more comprehensive and accessible healthcare services.[2]

Our analysis suggests that the cost of medication is not the primary driver of cancer treatment discontinuation. In fact, patients who continued their treatment for at least six months tended to submit more pharmaceutical claims and spend more on medications compared to those who discontinued their treatment. However, it's important to note that our model indicates that patients, especially older individuals, display a heightened sensitivity to adverse drug effects (ADEs), which emerged as a significant contributing factor to treatment discontinuation. This observation aligns with existing research that highlights the increased vulnerability of older patients to drug toxicity and associated side effects,[3] [4] emphasizing the need for tailored approaches in cancer treatment for this demographic.

Therefore, addressing this issue is crucial to encourage elderly patients, who make up the majority of the target group undergoing cancer treatment, by developing a new approach and reevaluating the current program.

[2] Humana value-based care Report 2022
[3] Paula A Rochon (2023), “Drug prescribing for older adults”
[4] K E Cherry (1989), “Drug sensitivity in older adults: the role of physiologic and pharmacokinetic factors”

6.1 Caregiver Reward Program

Optimizing Medication Adherence Through Risk Stratification

Our predictive model offers a valuable strategy to enhance medication adherence by stratifying patients based on their risk of discontinuing therapy due to adverse drug events. This approach enables tailored interventions for patients to support and motivate them in adhering to their prescribed medication plans.Our model's predictions enable the following strategies:

Risk Stratification	The model categorizes patients into different risk groups, distinguishing high-risk individuals prone to discontinuation due to adverse drug events and moderate-risk patients.
Tailored Interventions	High-risk patients benefit from early interventions, including personalized counseling, education on potential side effects, and strategies to mitigate adverse drug events, aiming to encourage them to adhere to their medication regimen.
Monitoring for Moderate Risk	Moderate-risk patients receive regular monitoring to detect any emerging adverse drug events. Consistent follow-ups and open communication help address issues promptly, reducing the likelihood of discontinuation.

High-Risk Patients' Experience on Osimertinib Treatment

The high-risk group consists of patients who are more likely to encounter severe side effects, demonstrate non-adherence to their treatment regimen, or exhibit signs of wanting to discontinue therapy. To further understand their experience, a study of qualitative interviews were conducted during the clinical trial of osimertinib. The first interview took place around 4-6 weeks after treatment initiation, a period when patients typically undergo a peak in Adverse Drug Events (ADEs). The second interview occurred approximately 4 months into treatment, by which time ADEs were expected to have stabilized, and patients should have started benefiting from the treatment.

Interestingly, the research findings revealed a significant shift in patient perspectives between the two interviews. Side effects that were initially rated as bothersome and severe received lower-to-moderate scores in the second interview. This suggests that individuals in the high-risk category, especially within the first 4-6 weeks of their treatment, might find ADEs to be particularly bothersome.[5] This understanding can inform targeted interventions and support mechanisms for this specific group of patients to enhance their adherence to the treatment plan and alleviate their concerns regarding side effects.

[5] Rydén, A.(2017). “Patient Experience of Symptoms and Side Effects when Treated with Osimertinib for Advanced Non-Small-Cell Lung Cancer: A Qualitative Interview Substudy.”

The Caregiver Rewards Program

In line with our understanding of high-risk patients' experiences, we recommend the implementation of the "Caregiver Rewards Program." Humana can assign identified high-risk individuals to trained caregivers, ensuring compatibility and specialized expertise in handling their unique challenges. Caregivers can organize sessions where they provide nutritional education and dietary modifications to help mitigate side effects and enhance overall health. Moreover, they can conduct mental counseling sessions to motivate these individuals to adhere to their medication regimen.

To ensure the well-being of high-risk patients, caregivers should closely monitor their health status through frequent follow-ups. These individualized caregiving sessions can be offered until the first four months of treatment initiation, as side effects tend to stabilize later on. Additionally, the caregiver groups can be utilized to provide assistance to new groups of individuals identified at that point in time.

As a key motivational component of this program, Humana can incentivize caregivers with rewards based on their success in enhancing their assigned patients' treatment compliance and medication adherence. While Humana has already implemented the go365 wellness and rewards program, tailored incentives for caregivers can provide essential emotional and physical support to patients during their challenging journey. This approach can lead to improved patient outcomes, enhanced medication adherence, and a stronger support system for patients navigating the complexities of their treatment.

6.2 Adaptation of Comprehensive Geriatric Assessment (CGA) for Senior Lung Cancer Patients

Underreported toxicity

In the context of cancer treatment decisions, there are often trade-offs, such as accepting the adverse effects of chemotherapy to extend life. While many studies in oncology primarily focus on what physicians consider important, such as recurrence, and survival, research indicates that functional and cognitive outcomes, including the ability to live independently, may be more significant for older patients. Interestingly, when patients are asked about their top priorities for cancer research, they prioritize the impact of cancer on their quality of life, specifically the psychological consequences and functioning. This reveals a disconnect between physicians' and patients' perceptions. Moreover, physicians tend to underreport patient-reported toxicities, even when collected in randomized trials, highlighting the importance of considering the patient's perspective in the assessment of treatment outcomes.[6]

[6] Marije E. Hamaker (2017), “Time to Stop Saying Geriatric Assessment Is Too Time Consuming”

What is Geriatric Assessment (GA)

The geriatric assessment is a comprehensive evaluation aimed at assessing the functional, physical, cognitive, and mental health aspects of elderly individuals, along with considering their socio-environmental factors, medication usage, and immunization status. This assessment serves several purposes, including aiding in diagnosing medical conditions, formulating treatment and follow-up plans, coordinating care management, and determining long-term care needs and optimal placement.[7] In the context of cancer care, geriatric assessments are particularly valuable in predicting chemotherapy-related complications and outcomes, providing more reliable insights than clinical judgment alone.[8]

Components of a Geriatric Assessment	
Domain	Example
Physical performance	Assess balance, gait speed, and strength
Functional status	Assess difficulty with activities such as bathing, dressing, and eating
Comorbidities	Assess the presence of other illnesses, as well as hearing and visual impairments
Cognition	Assess orientation, memory, and concentration
Nutrition	Assess weight and change in weight over 6 months
Social Support	Assess the presence of social support in activities of daily living when needed
Polypharmacy	Assess the number of regularly scheduled medications and high-risk medications
Psychological status	Assess depression and anxiety

Table: Components of a Geriatric Assessment (Source: National Cancer Institute)

What is its value?

The studies have shown that incorporating the CGA in the management of older patients with cancer (i) improves clinical outcomes by helping select the most appropriate therapy, (ii) promotes the inclusion of patient preferences in the decision-making process, (iii) improves communication between oncologists and patients, (iv) reduces the risk of over- and

[7] BASSEM ELSAWY, MD (2011), “The Geriatric Assessment”
[8] Cheryl Platzman Weinstock (2019). “A Cancer Care Approach Tailored To The Elderly May Have Better Results”, NPR news

undertreatment, (v) enhances treatment tolerance and completion and (vi) predicts the frequency of hospitalization and long-term care for older cancer survivors.[9]

With over 60% of U.S. cancers occurring in individuals aged 65 and older and an anticipated 67% increase in cancer rates among the elderly between 2010 and 2030, there is a pressing need for improved cancer care for seniors. Recent evidence suggests that Geriatric Assessments can enhance cancer care for older adults. revealing that recommendations for 27% of 197 cancer patients aged 70 and above changed after a geriatric assessment, often leading to less intensive treatment or palliative care options.[10]

In the other study, it was found that implementing various adjustments, such as prescribing single chemotherapy drugs instead of combinations to reduce side effects and starting with lower-than-normal doses, can improve the tolerability of cancer treatment. According to this study, only 50% of patients in the intervention group experienced these side effects, compared to 70% in the usual care group. Additionally, the intervention group received more comprehensive care, including referrals to social workers and nutritionists, as well as medication adjustments to mitigate side effects. The study also addressed polypharmacy, or the concurrent use of multiple medications, to reduce the risk of falls and complications. Consequently, the intervention group experienced a lower rate of falls (12%) compared to the usual care group (21%) over the 3-month study period.[11]

How Humana can utilize this for early stage lung cancer patients

Humana can synergize the integration of mandatory Comprehensive Geriatric Assessments (CGAs) into the treatment plan for elderly early-stage lung cancer patients with the broader context of its value-based care oncology program initiated in 2019. This comprehensive program, born from a collaboration with physician groups nationwide, is dedicated to offering more cohesive and integrated cancer care services to Humana's Medicare Advantage and commercial members.[12]

To further bolster the success of this program, Humana can proactively introduce specialized training programs tailored for oncologists. These programs would focus on illuminating the vital role of Geriatric Assessment (GA) in the realm of geriatric oncology. One of the persistent challenges has been that many oncologists are hesitant to integrate GA tools into their practice due to perceived difficulties in implementation and skepticism about their overall value.[13]

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[9] Sara Zuccarino (2022), “Exploring Cost-Effectiveness of the Comprehensive Geriatric Assessment in Geriatric Oncology: A Narrative Review”

[10] Suzanne Festen (2019), “How to incorporate geriatric assessment in clinical decision-making for older patients with cancer. An implementation study”

[11] Sharon Reynolds (2021), “For Older Adults, Geriatric Assessment Reduces Cancer Treatment Side Effects”

[12] Humana (2019) “Humana Launches Oncology Model of Care Program to Improve the Patient Experience and Health Outcomes in Cancer Care”

[13] Ajeet Gajra (2022), “The Use and Knowledge of Validated Geriatric Assessment Instruments Among US Community Oncologists”

By actively engaging oncologists and offering education on the numerous benefits associated with GA-directed therapy, Humana can play a pivotal role in increasing the utilization of GA tools within the community oncology setting. This educational effort serves a dual purpose – it not only empowers oncologists with valuable insights to enhance patient care but also aids in bridging the understanding gap between physicians and patients.

Ultimately, the widespread adoption of Geriatric Assessment within the oncology community can significantly improve the accuracy of treatment assessments, making patient outcomes more reliable and tailored to individual needs. This, in turn, contributes to the overarching mission of Humana's value-based care oncology program: providing comprehensive, integrated, and patient-centered cancer care services.

Success Criteria

The suggested evaluation criteria for measuring the success of the integration of CGAs are as follows:

Patient Satisfaction	Gather feedback from patients regarding their satisfaction with the care received, including their experience with the CGAs and the personalized treatment plans.
Treatment Tolerance and Completion	Monitor the rates of treatment tolerance and completion among patients who undergo CGAs compared to those who do not, to determine the impact on treatment adherence.
Reduction in Adverse Events	Evaluate the frequency and severity of adverse drug effects (ADEs) and side effects among patients who have undergone CGAs, with a focus on the reduction of ADEs.
Reduction in Polypharmacy	Examine the impact of CGAs on reducing polypharmacy by addressing the concurrent use of multiple medications.
Hospitalization Rates	Analyze the frequency of hospitalizations and long-term care requirements for elderly cancer survivors after integrating CGAs.
Personalized Treatment Plans	Measure the extent to which treatments are personalized based on CGA findings and patient characteristics
Cost-Effectiveness	Evaluate the cost-effectiveness of CGA integration by comparing the cost savings associated with improved patient outcomes.

Cost-Benefit Analysis

Incorporating Comprehensive Geriatric Assessment (CGA) into geriatric oncology may initially entail certain costs. However, comprehensive cancer treatment is frequently more cost-effective than addressing advanced-stage cancers or complications stemming from discontinued treatment. Preventing the necessity for supplementary surgeries, emergency room visits, or hospitalizations can lead to significant cost savings. The potential for long-term financial benefits and enhanced patient outcomes renders this approach not only cost-effective but also a valuable investment for Humana and the well-being of elderly patients.
According to a study conducted in nineteen primary care practices in Sweden, which aimed to assess the cost-effectiveness of implementing comprehensive geriatric assessment in primary care compared to usual care, the analysis revealed a notable difference in total cost (incremental cost) between the intervention and control groups, amounting to USD -11,275 (95% CI -407 to -22,142). While the incremental effect on quality-adjusted life years showed a modest decrease of -0.05 (95% CI -0.17 to 0.08), the findings indicate that the primary care comprehensive geriatric assessment intervention is cost-effective when applied to older adults at high risk of hospitalization, particularly evident during the follow-up period of 24 months.[14]

Under the given conditions, which include (1) a cost-benefit per capita of USD 11,275, (2) cost-effectiveness over a 24-month follow-up period, and considering (3) a current U.S. interest rate of 5.5%, the adjusted cost-benefit per capita (Present Value) is USD 9,602.

It's important to note that the cost of conducting a Comprehensive Geriatric Assessment (CGA) can vary widely based on factors like the healthcare provider, location, specific assessments performed, and the patient's medical condition. Generally, a CGA can range from several hundred to a few thousand dollars.

In this case, focusing on early-stage lung cancer patients, we estimate the maximum cost to be less than USD 1,000. Therefore, the final cost-benefit per patient is calculated as USD 9,602 - 1,000 = USD 8,602.

6.3 Motivational Management

Research shows that patients with lung cancer often experience multiple side effects associated with both the disease itself and the treatment. Some of the most common side effects are listed below.

[14] Magnus Nord (2022), "Cost-Effectiveness of Comprehensive Geriatric Assessment Adapted to Primary Care"

Surgery	Chemotherapy
● Pain ● Cough ● Difficult breathing ● Bronchopleural fistula - an abnormal opening between the pleural space and an airway tube of the lung ● Collapsed lung ● Heart problems ● Fatigue ● Blood clots	● Fatigue/constant tiredness ● Ongoing infections ● Hair loss ● Infections ● Anemia ● Bruising and bleeding ● Sore mouth ● Loss of appetite ● Decreased white blood cell count, called neutropenia ● Numbness/tingling/pain/weakness in hands and feet ● Changes in liver function tests
Targeted Therapy	Immunotherapy
● Skin problems and changes (dry skin) ● High blood pressure ● Bleeding or clotting issues ● Slow wound healing ● Heart damage ● Autoimmune reactions ● Swelling	● Diarrhea ● Fatigue ● Cough ● Nausea ● Skin rash ● Poor appetite ● Constipation ● Muscle and joint pain

Table: Possible side effect by treatment type (Source: Lung Cancer Resource Foundation)

The disease and therapy-related adverse effects may lead to poor quality of life (QoL) and increased psychological distress.[15] These impairments are reported in the emotional, physical, social, and cognitive domains, as well as the activities of cancer patients in their daily living.[16] For example, findings showed that fatigue negatively affected QoL with a pooled prevalence of 49%.[17] Another effect is depression which plays an important role in a patient diagnosed with lung cancer as the symptoms will make it harder for the people to do normal activities. The depression group showed an 18% increase in risk for a cancer diagnosis overall, with largest increased risk in lung cancer.[18] Additionally, an observation states that caregivers have their psychological distress surpasses the challenges faced by cancer patients. This underscores the significance of assessing the psychological well-being of caregivers for individuals with cancer.

[15] Prapa P, Papathanasiou IV, (202). "*Quality of Life and Psychological Distress of Lung Cancer Patients Undergoing Chemotherapy*."
[16] Schad F, Steinmann D,(2023). "Evaluation of quality of life in lung cancer patients receiving radiation and Viscum album L.: a real-world data study"
[17] Muthanna FMS,(2023). "Prevalence and Impact of Fatigue on Quality of Life (QOL) of Cancer Patients Undergoing Chemotherapy: A Systematic Review and Meta-Analysis.".
[18] Mössinger H. (2023) "Depression Is Associated with an Increased Risk of Subsequent Cancer Diagnosis: A Retrospective Cohort Study with 235,404 Patients."

[19] So, motivation plays a pivotal role and can be effectively imparted to individuals by discussing the perceived health benefits and the support offered by social groups.

What can Humana do?

Humana has the capability to establish strategic partnerships with non-governmental organizations, such as GO2, which is dedicated to addressing lung cancer comprehensively, with a focus on improving survival rates for individuals at risk, diagnosed patients, and those living with cancer. This would be a similar collaboration like the one existing with Interwell health which has helped to increase the Quality of life exclusive for kidney care. This agreement is key to helping even more patients with kidney disease live their best lives.[20] Furthermore, Humana can integrate the benefits of the "Humana Cancer Program" in collaboration with GO2 by incorporating exclusive programs tailored for lung cancer patients, including:

PhoneBuddy Program: Humana can use the PhoneBuddy initiative by GO2, connecting patients with lung cancer survivors. This program allows patients to engage in meaningful conversations with survivors who can provide insights into the perceived health benefits and improved quality of life after their treatment. Such interactions will address patients' concerns regarding the effectiveness of their treatment, offering reassurance and valuable support.

Lung Cancer Living Room: Another opportunity is the Lung Cancer Living Room program, consisting of in-person and virtual monthly meetings. These gatherings unite patients, survivors, and caregivers to create a supportive community. In these meetings, participants can engage in discussions covering a wide range of topics related to lung cancer, including education and various support services. The total number of views for this platform for the year 2022 is nearly 42,000.[21] This initiative fosters a sense of community, provides educational resources, and enhances the overall well-being of individuals affected by lung cancer.

By collaborating with GO2 and utilizing these initiatives, Humana can significantly contribute to improving the care and support available to those impacted by lung cancer. These programs offer valuable resources, emotional support, and educational opportunities for patients and their caregivers, ultimately promoting a more comprehensive and holistic approach to lung cancer care.

Supporting Evidence for GO2

Greatnonprofits.org, a website that features feedback from individuals about non-profit organizations, provides compelling data:

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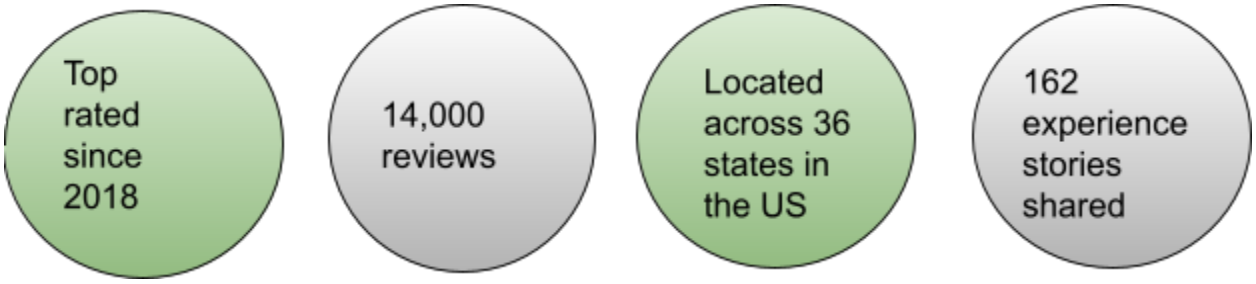
[19] Bellomo Cheryl. (2019) “Physical, Psychological, Social, and Spiritual Well-being of Patients and Caregivers Following Lung Cancer Diagnosis: A Scoping Review”
[20] Humana (2023).“Humana Announces New Agreement with Interwell Health That Expands Comprehensive Care for Members Living with Chronic Kidney Disease”
[21] GO2.(2022) *Impact Report*

- In 2018, GO2 was rated as a top organization, signifying its excellence and effectiveness.
- The organization's web page garnered nearly 14,000 views, indicating significant interest and visibility.- Furthermore, there were approximately 162 stories shared by volunteers, donors, and supporters, showcasing strong endorsements for GO2's collaboration.



This data strongly suggests that partnering with GO2 would greatly benefit Humana. It not only aligns with achieving patient's motivation management goals but also enhances access to extensive lung cancer research data and facilitates connections with doctors throughout the United States, thereby facilitating the achievement of Humana's objectives.

Cost Effectiveness Analysis

Through a partnership with GO2 and a generous contribution of $75,000, as indicated by their maximum donation amount on their website,[22] Humana can establish a cost-effective solution to address the substantial noncoverage insurance expenses linked to mental counseling for lung cancer patients. As of 2022, the average cost of a counseling session is $100.[23] To provide a comparison of these costs, please refer to the table below:

Organization	**Counseling per session**
Average counseling session in US	$100
Counseling by collaboration with GO2	$20

This strategic partnership has the potential to offer nearly 3000 counseling sessions, assuming that $60,000 of the donation is used to sponsor the Peer buddy program to Humana insurance beneficiaries. Breaking this down further, assuming each patient undergoes a course of 12 sessions over a six-month period starting from the therapy_start_date, we can anticipate assisting approximately 250 individuals.During this time, Humana can witness the comprehensive use of GO2's resources by patients, ensuring maximum impact. Beyond the direct cost savings, this approach provides Humana patients with an exclusive and more

[22] GO2. *Your Support makes an impact*
[23] Chai Carmen.(2022) "How much does therapy cost? Plus 7 tips for finding affordable options"

affordable option for mental counseling, specifically tailored to those dealing with lung cancer. This, in turn, can reduce patient attrition due to a diminished quality of life, enhancing overall patient satisfaction. Furthermore, it will boost awareness of Humana insurance among a broader audience, leveraging the extensive network of GO2 connections.

Counseling Type	Cost per session	Number of patients	Total cost
Non- collaboration counseling	$100	250	$300,000
Counseling by collaboration with GO2	$20	250	$60,000
Dollars saved			**$240,000**

Expected Outcomes

Through this collaboration, Humana can achieve the following key outcomes:

1. **Broad Reach:** Humana will have the capacity to reach a substantial number of individuals in the United States seeking patient caring healthcare programs, positioning itself as a leading provider in this critical healthcare area.

2. **Affordable Counseling:** By offering mental counseling sessions at a significantly reduced rate, Humana can effectively motivate and support lung cancer patients through their challenging journey to recovery.

3. **Expanded Educational Resources:** This collaboration grants Humana access to an impressive repository of 82,000 additional educational materials, complementing their existing resources. This wealth of educational content can be used to increase awareness and knowledge about lung cancer thereby benefiting patients and the broader community. As Humana already encourages by providing educational materials to learn about the disease, treatment regimens and possible side effects by "Humana Cancer Program", gaining additional access to the materials is extremely beneficial thereby benefiting patients and the broader community including the doctors and the caretakers. Humana can reward the patients who covered the majority of people.

6.4 Overall Cost-Benefit Analysis

According to Sheila R. Reddy (2022), total cancer-related healthcare costs of lung cancer by stage at diagnosis, time period, and cost quintile is as below[24]:

	Stage I		Stage II		Stage III		Stage IV	
	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	(SD)
Year 1	54,606	116,903	85,118	125,923	110,815	144,585	148,426	162,632
Year 2	19,759	60,444	33,188	71,159	53,520	93,565	81,584	112,886
Year 3	16,039	50,659	28,785	74,887	41,553	104,707	68,446	104,565
Year 4	14,120	53,306	21,241	55,876	34,052	68,844	57,445	103,267
Year 5	12,027	43,897	20,497	61,217	27,585	79,764	46,219	83,845
Total	116,551		188,829		267,525		402,120	(USD)

When comparing the total 5-year costs for Stage 1 and Stage 4 lung cancer patients, the difference amounts to approximately USD 285,000. This represents the maximum potential benefit for Humana if they can encourage patients to remain on their current treatment plan, preventing the progression of symptoms. On the other hand, the minimum potential benefit for Humana is USD 30,512 if they successfully prevent a Stage 1 patient from progressing to Stage 2.

The table below represents "Cost-Benefit Analysis per capita (USD)." Considering all the costs associated with our three business recommendations: Caregiver Reward Program, CGA Adaptation, and Collaboration with GO2, which provide high-quality counseling services, we assume that the total cost required for one customer is USD 2,700.

- Caregiver Reward Program: This involves providing a USD 100 reward to caregiver for each patient who continues their treatment as part of the program.
- CGA Adaptation: The cost of implementing the Comprehensive Geriatric Assessment (CGA) does not exceed USD 1,000.
- Collaboration with GO2: A total of 12 counseling sessions will be offered to each patient over 6 months, with a yearly cost of USD 240 per person.

	Caregiver Reward Program	CGA Adaptation	Collaboration with GO2	Total Cost	Total Saving	Profit	PV
Year 1	100	1,000	240	1,340	30,512	29,172	27,651
Year 2	100	-	240	340	13,429	13,089	11,760
Year 3	100	-	240	340	12,746	12,406	10,565
Year 4	100	-	240	340	7,121	6,781	5,474
Year 5	100	-	240	340	8,470	8,130	6,221
	500	1,000	1,200	2,700	72,278	69,578	61,670

*Total saving: cost difference between stage 1 and 2 cancer patients by year
**Profit: Total saving - Total cost
***PV(Present value) = Profit/(1+Interest rate)^year)

[24] Sheila R. Reddy (2022) "Cost of cancer management by stage at diagnosis among Medicare beneficiaries"

For early-stage lung cancer patients, the first-year cost is highest at USD 1,340. However, the total savings exceed approximately USD 29,000 compared to the cost, ultimately resulting in a benefit of *USD 27,651* for Humana when considering the present value. If this trend continues over 5 years, the total net benefit for Humana will be *USD 61,670* per person.

7. Conclusion

In summary, adverse drug effects pose a substantial challenge for individuals dealing with lung cancer, offering Humana an opportunity to provide solutions and awareness to those discontinuing their treatment. We recommend the implementation of a Logistic Regression model with lasso regularization to uncover the reasons behind treatment discontinuation, with our final model achieving remarkable performance, showcasing an AUC of 0.937 on the validation set and 0.869 on the official leaderboard. Once deployed, we propose three targeted recommendations: a Caregiver Incentive program to enhance caregiver involvement, a Comprehensive Geriatric Assessment for senior patients, and motivational management strategies to improve the patient's Quality of Life, all aimed at addressing adverse effects. While these initiatives may entail operational costs, further research is needed to assess these expenses. Nevertheless, we estimate potential cost savings of USD 27,651 per capita for the first year and USD 61,670 for five years, making proactive adverse effect mitigation a financially sensible approach while improving patient care.

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