PATIENT SWITCHING BEHAVIORS IMPACT ON ADHERENCE AND ENGAGEMENT:

# A Predictive Analytics and Machine Learning Approach to Improving Hub Performance and Patient Outcomes

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## Introduction

Today we have access to more data, from more sources than we could ever dream possible. Living in a digital world, we increasingly need the ability to efficiently and effectively process this data for insights and actions in order to be competitive. The life sciences industry can leverage this data using analytic tools and machine learning to rapidly identify patient behaviors and patterns – allowing us to predict "next best actions" in our quest to improve patient outcomes.

The key for pharma brands who increasingly play a role in supporting patients through their care journey is to think about how to implement predictions in the apparatus of patient and hub services. A prediction alone is not interesting. A prediction that enables an action and learns from the outcome of that action is what creates a high performance operation.

## Problem Statement

Patient and hub services represent a significant and often ineffective spend surrounding overall patient support. How can we use data and analytics to build better patient services programs that predict next best actions and achieve improved patient engagement and outcomes across the treatment journey? As the industry continues its shift to value-based care, this challenge has never been timelier.

Company A was experiencing a universal brand challenge – lack of insight into and proof of what was working from both their product and operational sides of the business. Patients were either discontinuing use of their brand or switching to a competitor's brand after a single script. A true "One-and-Done" phenomenon had emerged. They believed that their brand challenges could be solved by investing in more Hub program services, but they couldn't tell which tactics were effective, and which were not.

We began our study by defining the challenges we wanted to solve: identifying the key drivers of a patient's switch to a competitor's brand or discontinuation of use of Company A's brand; and providing clarity on how hub efforts were affecting results. Using predictive analysis and machine learning, we would develop a model to inform personas of patients who discontinued and switched, provide data-driven predictions for patients to inform hub action, and then track how hub performance improved and the impact on hub resource utilization.

> "By showcasing how the actions at each step in **ACT**ICS BY EVERSANA™ added value to the model, we demonstrated a successful process for improving patient adherence by >50%."

To train our model we selected a list of features to assess during our analysis. These features represent both clinical attributes of the patient and socioeconomic factors such as financial status, insurance coverage, and interface with the healthcare system:

- Patient Demographics: age, gender, geographic location, medical measurements (BMI, weight, etc.)
- Medical/Clinical Characteristics: comorbidities and preexisting diseases, side effects (of therapy)
- Treatment-Related Metrics: duration and number of refills when on therapy, prior drug usage, compliance

- Physician Characteristics: therapy loyalty, HCP change (during switch), physician specialty
- Insurance Characteristics: Level of copay (high, medium, low), type of insurance/payment, prior authorizations (PA), step therapy (ST)

Leveraging our secure and compliant technology platform, **ACT**ICS BY EVERSANA™, we ingested claims, hub, formulary, social determinants of health, and clinical data. We trained multiple model types (SVM, LSTM, CNN, XGBoost, Regression, and others), optimized feature selection and weighting, applied techniques such as bootstrapping and ensemble analysis, and selected the most optimized model based on train/test techniques, data splitting, and a variety of statistical measures on model performance. Details on the study's methodology will be available July 24 on eversana.com/insights under the title: *Methodology for Predicting Switching Behaviors in Patients.*

## Terminology

Before we jump into the focus of this white paper let's level set on the terminology I'll be using throughout this piece. Take a look at the chart for key definitions.

| | |
|---|---|
| **Accuracy** | Proportion of true results predicted, either True Positive or True Negative, by a model |
| **Precision** | Proportion of predicted positives (desired); how many are True Positives |
| **Recall (Sensitivity)** | Proportion of actual positives, how many are accurately predicted (True Positives) |
| **F-1 Score** | Measure of model's true accuracy. How well balanced the model is between precision and recall (mathematically), is a harmonic mean of the two |
| **R-Square Value** | Statistical measure that represents the proportion of the variance for a dependent variable that's explained by independent variables in a regression equation |

## Approach and Importance of Data Integration

In my last paper, I discussed the importance of knowing your data integration and analytics platform strategy and how data is used. The solutions we build must establish metric-based patient segments along with data-driven approaches to patient profiles. This is important to understand because we know that patients have different adherence issues, communication preferences, and triggers that influence their behavior. The ability to track messages and segment performance, and be supported by a learning system that optimizes engagement is key to improving health outcomes. So, in building a model to capture the valuable insights that will help us improve patient outcomes, every aspect of the patient journey must be included.

## Clinical and Market Findings/Insights

The data we collected and analyzed on Company A's clinical challenge around brand switch showed us that:

- Patients with prior disease state experiences are likely to continue on therapy; however, that probability is influenced by comorbidity, side effects, insurance status and social determinants of health
- Patients with no prior disease state experiences may need more education and assistance (medical and financial) during initial days of therapy when compared with those having prior drug experiences
- Among patients who switched therapy, 16% switched back
- Higher out-of-pocket costs increases the probability of switching and discontinuing
- Patients initiated on commercial insurance or assistance programs demonstrated higher probability of discontinuation and switching
- Majority of patients who pay in cash discontinue from therapy
- 53% of patients who initiated on assistance programs (~11K), eventually switched or discontinued

Predictive analytics and machine learning have the potential to transform healthcare by driving performance optimization for patient services, field solutions, clinical trial recruitment, and supply chain distribution.

This insight provided the foundation from which we would build our model. Knowing that all of these factors impact patient behavior and action, we could then identify and create the personas that would provide a more accurate understanding of how patients are likely to engage with patient services providers and hub programs. In designing solutions, we needed to understand the environment in which our patients behave, as well as understand their coverage and affordability challenges. This insight helps us better predict next best actions and leads patient services providers to focus on customizing several different technology and engagement solutions.

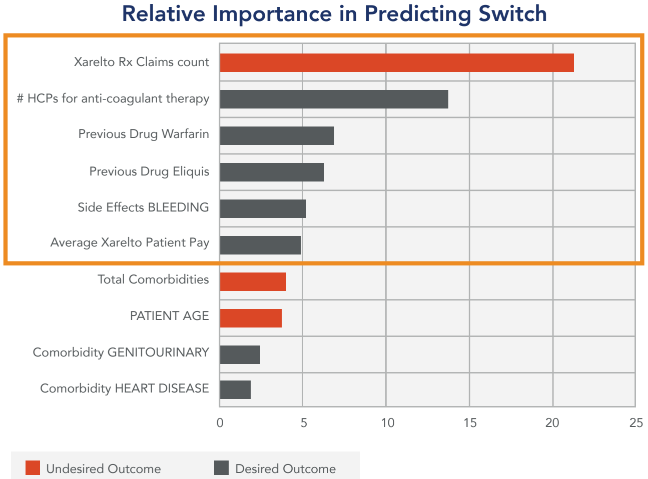
## Description of Model Findings

Patients fundamentally have different adherence issues – a one-adherence-solution for all patients ignores patient segments. We know that each path a patient takes during the treatment journey gives us the opportunity to build a patient persona and predict optimal adherence solutions. We segmented and described the unique persona patterns of patients who responded to existing hub services, and identified several patient persona paths including comorbidity, history of depression, no inpatient treatment, low cost of care, age, digitally engaged, and lower educational background.

**FIGURE 1** showcases the results of our switching model, validating the accuracy of our AI platform. In addition to being accurate, the model had a high Negative predictive value (NPV). In simple terms the model is particularly good at predicting correctly that a patient would continue therapy. From a hub utilization standpoint this means that we could accurately determine which patients didn't need additional hub support. This translates directly to resource savings, perhaps allowing us to offer more resources to patients that we did not predict would continue therapy.

**Figure 1**

**Relative Importance in Predicting Switch**




**Key Notes**

- Statistically, model contains significant predictive capacity
- More HCP switches indicate a likelihood of patient switch
- Previous anticoagulant therapy indicates likelihood of patient switch, provided there is other concerning situation (such as side effect, etc.)
- Side effects, especially bleeding, indicates likelihood of patient switch
- Higher average OOP costs indicate likelihood of patient switch

| Evaluator | Value |
|---|---|
| Accuracy | 93% |
| Precision | 87% |
| Recall (Sensitivity) | 74% |
| F1-Score | 80% |
| R-Square value | 60% |

| Actual/Predicted | Negative *(Patient Continues)* | Positive *(Patient Discontinues)* |
|---|---|---|
| Negative *(Patient Continues)* | 42,912 | 1,184 |
| Positive *(Patient Discontinues)* | 2,859 | 8,210 |

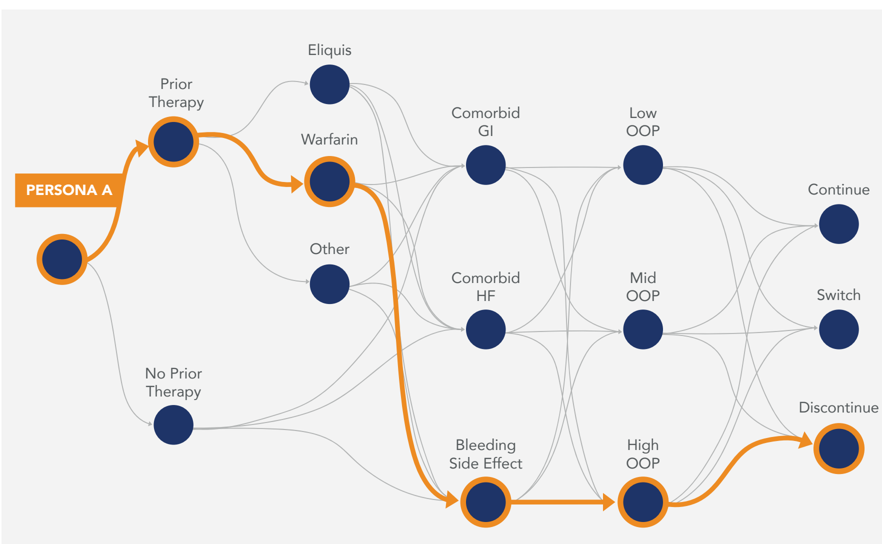
At hub intake, we have the capability to capture the following information to appropriately route each persona: comorbidity, inpatient vs. outpatient, medication expense, age, and location. We then identified that the optimal patient solutions support included app- and text-based communication and recommended physician engagement.

## Taking Action From Prediction That Has Measurable Impact

There are many circumstances that compound the probability of medical adherence. We needed to accurately predict patient personas who are likely to switch, abandon, nonadhere or require financial support. By identifying the path a patient is on we can predict probability of nonadherence and measure the size of the potential impact across the product lifecycle. Data points from all aspects of the patient's health journey were gathered, analyzed and incorporated to create an authentic persona. Once the persona was created, patients were matched to similar patients that shared that persona and contrasted based on their actions and engagement to predict the path that the patient is likely to take.

Every step of the patient journey generates actionable data that enables our ability to engage patients with personalized content. We know that by finding patients early in their treatment journey and by helping them engage with treating HCPs and Hub personnel, we can have a positive impact on their journey.

**Figure 2**




| Variable | Description | Variable Predictive Value | |
|---|---|---|---|
| Discontinue Timing | <30 days | | |
| Initial Fill (days) | Below 14 days | High | |
| Initiating HCP | Therapy Loyalist (50%+ scripts are Therapy) | Mid | |
| Co-morbidity | Musculoskeletal Disorders<br>High Blood Pressure<br>High Cholesterol<br>Non-Diabetic | | Overall Model Accuracy F-1= 0.89-0.98 |
| Payer Mix | Medicare, Assistance Programs, Commercial, Cash | 1% | |

- There are ~600 (0.7%) patients similar as Persona A
- The average initial Therapy fill for this cohort is 10 days
- The model can make up to 98% accurate predictions for this cohort
- This cohort is extracted from statistically significant classification exercise

Prediction enables actions to be taken and existing resources to be better utilized. In **FIGURE 2**, we trace the path of one of the personas we created, Persona A, who originally discontinued Company A's therapy. We developed a unified data set – consisting of demographics, income data, total Rx costs per year, estimated out-of-pockets, and total cost of care – to help train our model. Patients were identified from the database at the time of hub enrollment that matched Persona A and deployed/enrolled into the hub process. The results of our modeling showed a 98% accuracy rate in our ability to describe the type of patients, or personas, across the model.

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## Process and Resource Utilization Findings for HUB Performance

Data analysis on Company A's hub programs provided this insight:

- Current hub efforts included insurance/benefit verification, financial assistance, adherence programs, patient and physician education, and nursing support
- One and Done: Despite all programs less than 50% of patients stayed on therapy through second refill
- Targeted messages to patients with prior experiences were sent, yet pull-through was unclear, and the One and Done rate remained similar
- Increased adherence program outreach and copay coupon buy-up occurred simultaneously and the One and Done improved by 4%, but attribution was impossible and costs increased 30%

## Implementing Predictions in HUB, and Predicting Communication Response

Single communication types ignore a variety of patient engagement behaviors. We found that by altering content and communication mediums, and by delivering a copay card via an app, we maximized Persona A's ability to refill his script two days ahead of scheduled refill.

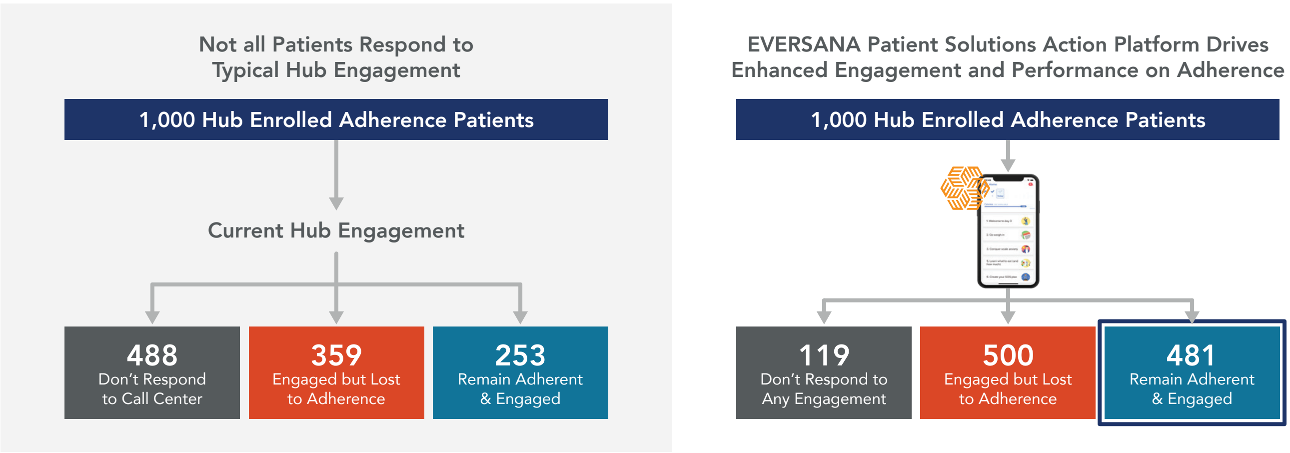
The system "learned" how well Persona A did with that action and improved its ability to predict – allowing us to successfully predict the next best action. Each persona would have a different predicted route to an optimal patient solution.

We recognize that not all patients respond to typical hub engagement, so we compared Company A's hub performance on 1000 patients against patients put through **ACT**ICS BY EVERSANA™ – a platform designed to focus on enhancing patient engagement and driving improved adherence performance. In **FIGURE 3**, you will see that EVERSANA's Platform led to a >50% patient adherence increase in just a 3-month period. Predictions on patient personas were used to drive utilization of hub resources. We took into consideration Company A's current hub activity with 253 adherent patients and we began to add:

- The adherence risk profile model increased adherence from 253 to 301
- Tailoring communications preferences predictions brought the number of adherent patients in the hub to 377
- Alternative messaging increased from 377 to 420 adherent patients
- Optimal financial support gave us a total of 481 adherent patients

**Figure 3**

*In side-by-side comparison of 1000 hub patients we compared the effect of the EVERSANA Platform.*



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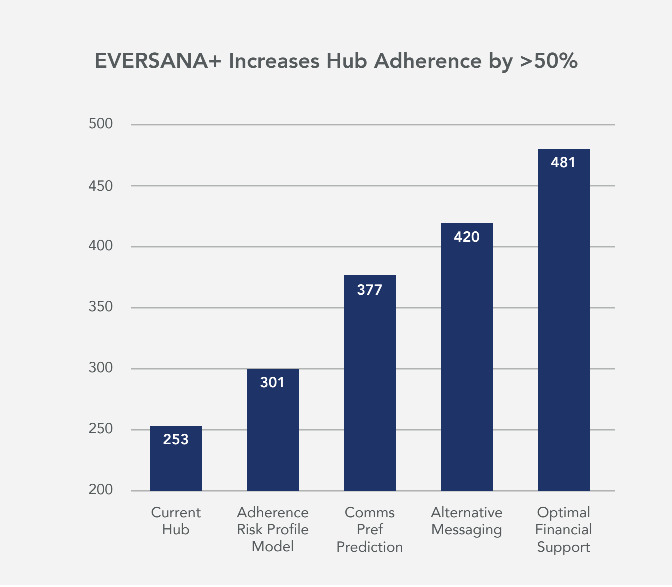
> EVERSANA's end-to-end analytics platform drives incremental value and actions across the product lifecycle and can help clients proactively improve patient identification, acquisition, conversion, and retention.

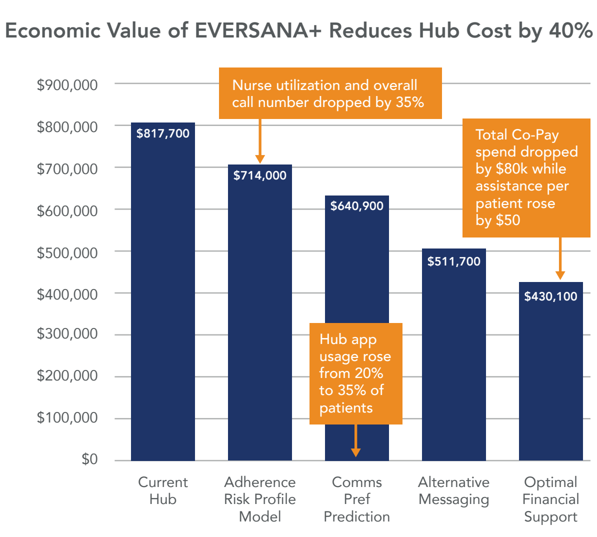
By showcasing how the actions at each step in the patient analytics platform process added value to the model, we demonstrated a successful process for improving patient adherence by >50%. **FIGURE 4** demonstrates the economic impact of **ACT**ICS BY EVERSANA™ vs. Company A's:

- Hub costs were reduced by 40%
- Nurse utilization and overall call numbers dropped by 35%
- Hub app usage rose from 20% to 35% of patients
- Total copay spend decreased by $80K while assistance per patient rose by $50

**Figure 4**

*Improvement in adherence plus cost savings for 1000 patients*



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## Conclusion

### What we demonstrated

The goal of this study was to demonstrate how the power of technology can drive the success of patient services hub programs operations, and showcase the value of predicting the next best action in increasing the effectiveness of keeping patients on therapy. Through predictive modeling, we showcased new ways to improve and manage patient outcomes and treatment pathways, increased the value of hub performance, and demonstrated measurable economic value.

### Why it is valuable

Through the accuracy of predictive analytics tools and machine learning we can identify and engage with patients across each stage of their treatment plans. These tools allow us to predict the probability of nonadherence, develop patient personas, recommend hub tactics actions, and measure the size of the potential impact. **ACT**ICS BY EVERSANA™ is designed to enable data integration and predictive actions. It drives incremental value and actions across the product lifecycle and can help clients proactively improve patient identification, acquisition, conversion, and retention.

### How we enhance both insight, problem identification, process and spend

We built a predictive model to give us insight into patient switch behaviors and actions in therapy in order to improve hub utilization. We created patient personas profiles and employed **ACT**ICS BY EVERSANA™ to showcase enhanced patient engagement and improved adherence performance by routing patients to optimal solutions. Our experience has proven that the best results are achieved by understanding and optimizing each step of the process.

### Ultimate brand goal

Predictive analytics and machine learning have the potential to transform healthcare by helping us identify diseases faster, decrease costs through precision therapies, improve clinical trial enrollment, and increase operational effectiveness. As demonstrated in this paper, the technology drives performance optimization, and can do the same for many services including field solutions, clinical trial recruitment, and supply chain distribution, just to name a few. We can expect the next generation of patient services will significantly improve health outcomes through high-touch patient engagement and, technology and data analytics will play a key role.