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Pharma Analytics

A Dynamic Approach to Segmentation & Targeting

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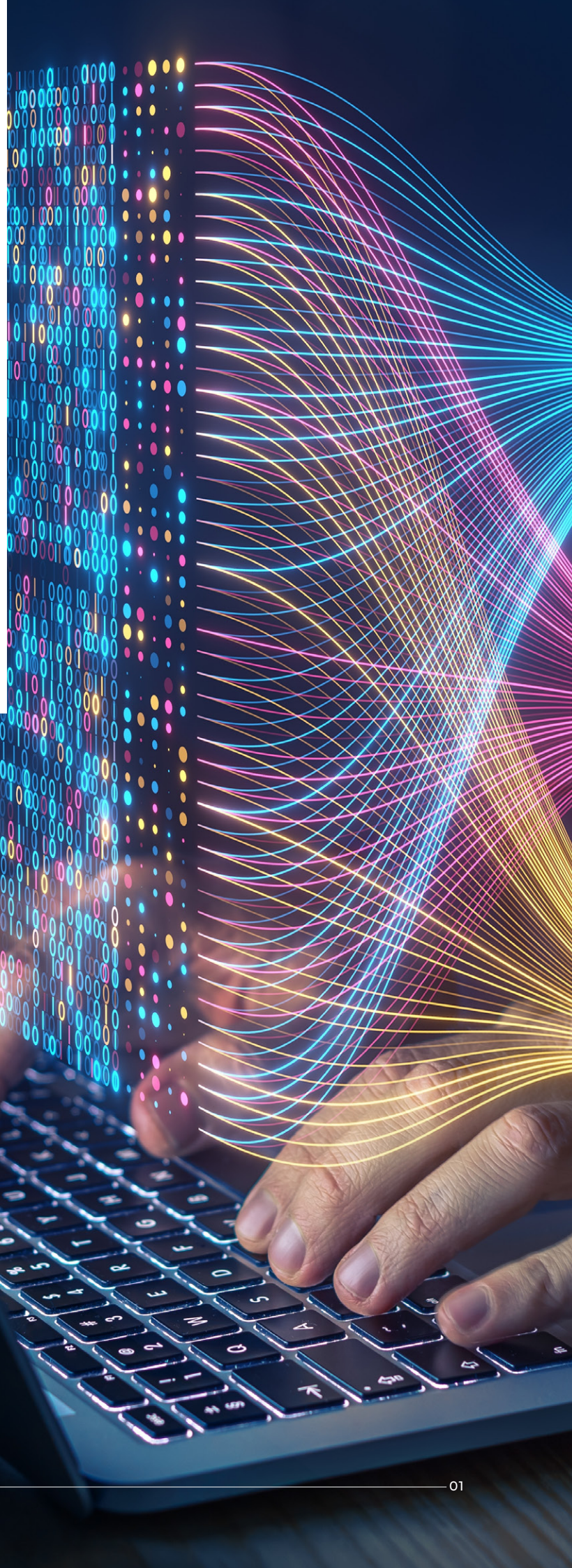
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Introduction

The [pharma industry](#) faces unprecedented challenges in a complex economic landscape, compelling enterprise leaders to balance business growth and cost optimization. In this endeavor, the role of [advanced analytical techniques](#) has become indispensable.

[Segmentation and Targeting](#) (S&T) analysis is vital in leveraging available data and advanced classification techniques to discern future prescription behavior. Yet, the conventional S&T approach, heavily reliant on historical prescription data, lacks the dynamism and adaptability needed in today's rapidly changing marketplace and intensified global competition. To address these limitations and usher in a new era of innovation, we propose a more dynamic approach to S&T analysis that accounts for the challenges faced in the conventional static method.



Current Targeting and Segmentation Process

The targeting and segmentation process currently involves creating multiple scores based solely on historical claims and demand data. This generates an initial list of Healthcare Providers (HCP), followed by combining these scores into a single valuation / potential score for each HCP. The current process encompasses the following steps:

1. Target List Processing

The Target List is processed using claims and demand data, supplemented by pharmacy and Key Opinion Leader (KOL) data.

- Identify the initial list of HCPs based on the period of interest
- Calculate various metrics for each HCP, such as **Dx Count** (diagnoses), **Tx Count** (Px procedures and Rx prescriptions), **Demand TRx** and **Competitor Products TRx**
- Compute **'Total Patient Equivalents (PE)'** and **'PE per HCP'**
- Assign weights to each metric to calculate the **Opportunity Score** for decile
- Assign deciles to HCPs based on the opportunity score, which is further aggregated at the accounts and regional levels
- Include supplemental data, such as KOLs, and filter HCPs based on business rules (specialty, suppression flags, etc.)

2. Segmentation Process

The segmentation process is carried out based on various parameters and may have distinct rules for each product indication, considering the product's life cycle stage and market landscape.

Product Indication	HCP Segmentation Criteria	HCP Segments
Product 1	Based on Launch Decile	High: Deciles 7-10 Medium: Deciles 3-6 Low: Deciles 1-2 Non-Segment: All other HCPs
Product 2	Based on CoE Affiliation, HCP Decile and HCP Patient Count	Segment 1: Includes HCPs affiliated to a Center of Excellence (CoE) or co-managing patients with an HCP from a CoE or HCPs with high deciles for diagnosis and treatment Segment 2: Includes HCPs with at least one patient equivalent in either diagnosis or treatment Non-Segment: All other HCPs
Product 3	Based on Multiple Therapies	Segment 1: HCPs with relatively high levels of patients treated with Therapy-A and Therapy-B Segment 2: HCPs with relatively high levels of patients treated with Therapy-A and Therapy-C (but not Therapy-B) Segment 3: Low volume of patients on Therapy-A and Therapy-B Non-Segment: All other HCPs
Product 4	Based on 12 Completed Months Patient Decile	High: Deciles 7-10 Medium: Deciles 3-6 Low: Deciles 1-2 Others: Decile = 0 or Null Non-Segment: All other HCPs

Figure 1: HCP Segmentation

The Road Ahead: Addressing Market Dynamism

The conventional approach to S&T relies primarily on historical prescription data (from HCPs) to determine segments based on past prescription behavior. Although this method remains valid and widely used, it lacks certain key elements:

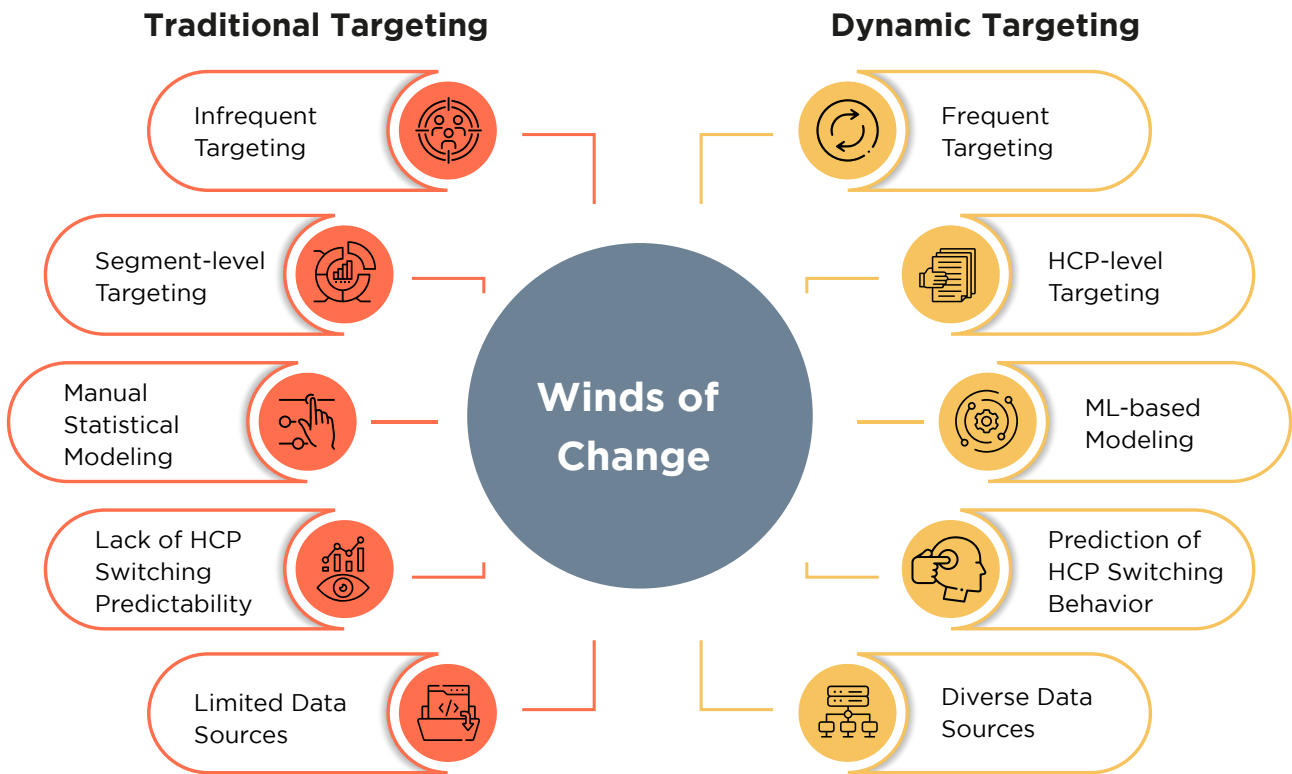


Figure 2: Traditional Targeting vs. Dynamic Targeting

The pharma industry stands at a pivotal juncture, contemplating how to approach targeting and segmentation, given the vast volume and velocity of data available today compared to a decade ago. In addition to standard prescription and claims data, we now have access to engagement data, such as personal (call activity) and Non-personal Promotions (NPP) data. This data enables us to analyze an HCP's likelihood to prescribe a drug or consider a recently launched medication.

The speed at which we receive data has significantly increased, shifting from monthly to weekly or even daily customer interactions through NPP channels. Consequently, the conventional S&T approach, driven by a manual statistical modeling approach, is inadequate to capture and utilize this data from various sources – making the static segments less precise and dynamic to respond to the ever-changing behavior of HCPs.

In the conventional S&T methodology, target lists are typically generated biannually to quarterly, relying on optimized segment-level response curves rather than considering individual prescriber particulars. The S&T process commences two to three months before the implementation of call plans, leading to a situation where it becomes obsolete even before the representatives can utilize it. Furthermore, customer interactions are exclusively planned for the representative channel, resulting in isolated efforts detached from other communication channels. As a result, there is a lack of capability to leverage the full potential of data obtained from NPP channels, effectively diluting the impact of such valuable insights. The traditional approach also fails to incorporate the influence of external events, such as the COVID-19 pandemic, which compelled representatives to shift their focus from face-to-face interactions to digital channels.

The Need for Dynamic Segmentation

Advancements in data volume and processing capabilities, along with the advent of technology, have transformed the landscape of [pharma analytics](#). Storing and processing gigabytes of data within minutes and seconds have laid the foundation for running complex algorithms that identify the best promotional journeys or sequences for specific HCPs and understand their channel preferences for content engagement. This transformation calls for S&T capabilities to be more agile and customer-centric.

Enter Dynamic S&T – a paradigm shift automated through Artificial Intelligence (AI) and utilizing all available datasets, including patient data, call activity data, NPP data, switch behavior, speaker programs, payer data and demographic data. This approach allows for weekly or daily analysis, enabling a more precise and customized targeting strategy for each HCP.

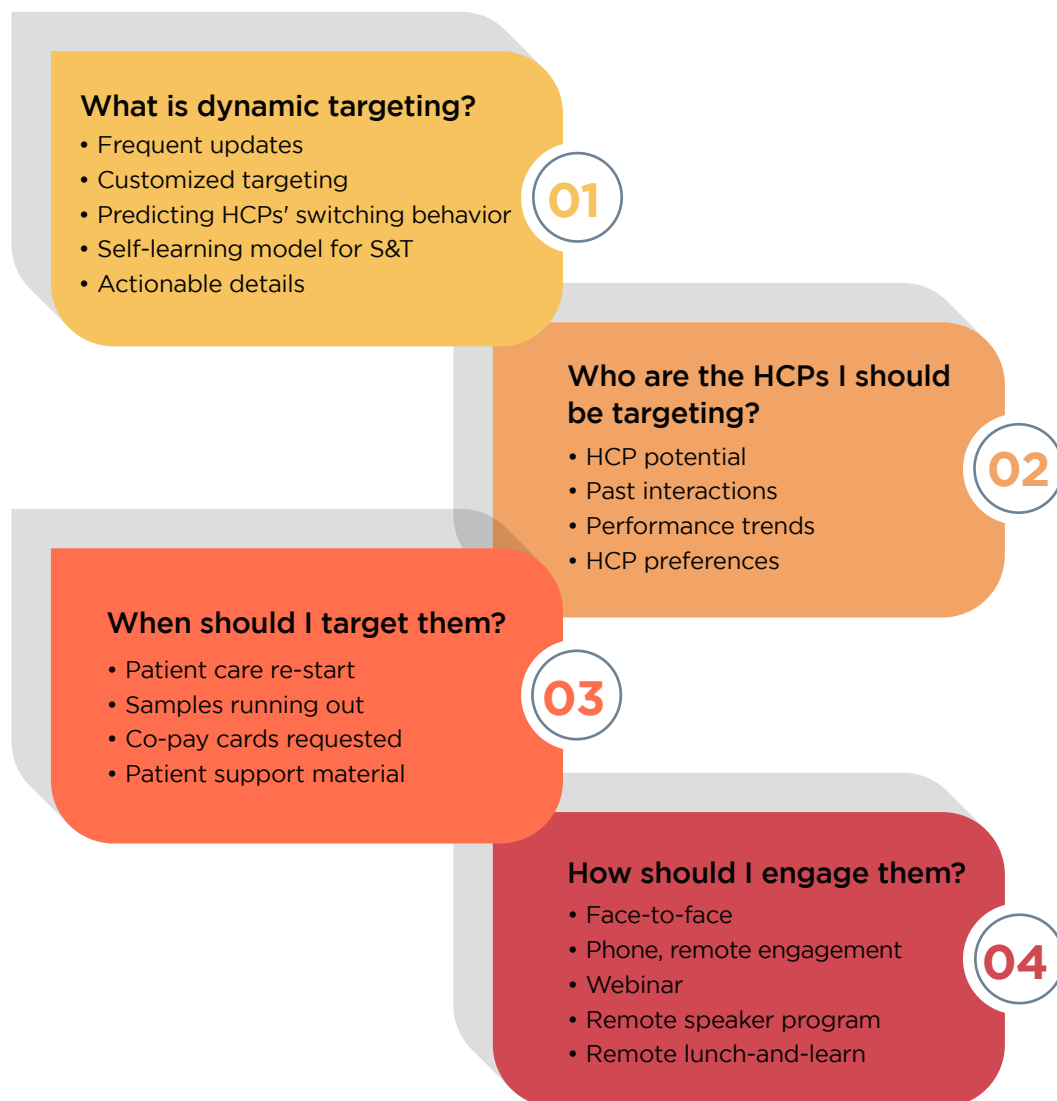


Figure 3: Dynamic Segmentation and Targeting

In dynamic targeting, a significant aspect of a representative's role is optimizing their time in the field each week. This entails engaging with the right customers at opportune moments and effectively conveying tailored messages rather than adhering to a rigid, pre-determined quarterly target list. Dynamic targeting empowers representatives to harness cutting-edge data science, thus elevating their customer engagement to unprecedented levels, ultimately culminating in an enriched patient experience.

The Recommended Approach to Dynamic Segmentation

To achieve the missing elements in the conventional S&T process, we propose an AI / Machine Learning (ML)-driven solution that enhances the framework to accommodate market dynamism. Our approach comprises the following stages:

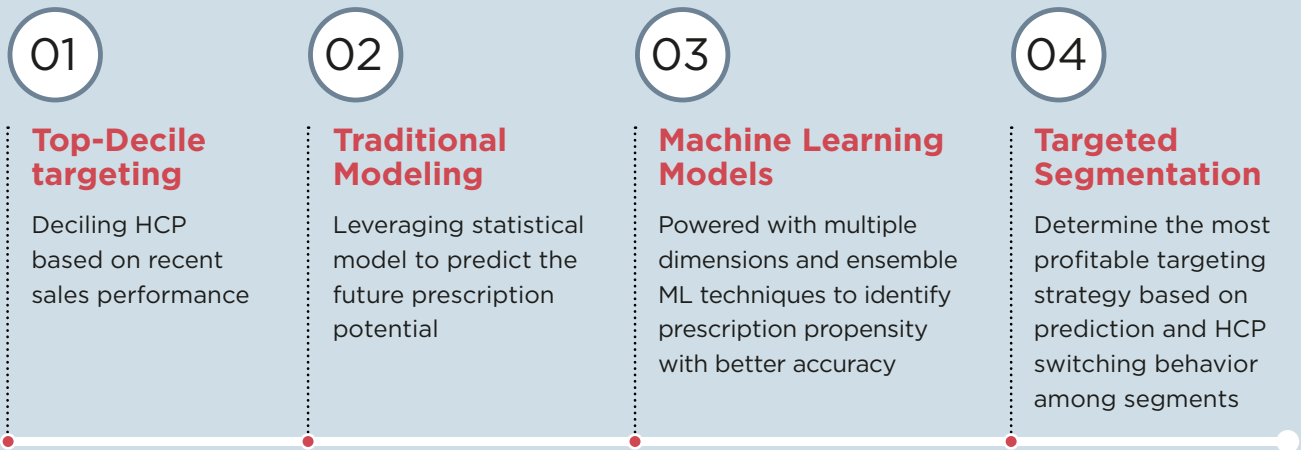


Figure 4: Approach to Dynamic Segmentation

1. Dynamic Attributes for Model Development

Incorporate dynamic variables into the system to enhance process robustness and provide real-time actionable insights for the field force. This enables a more customized targeting approach for each HCP.

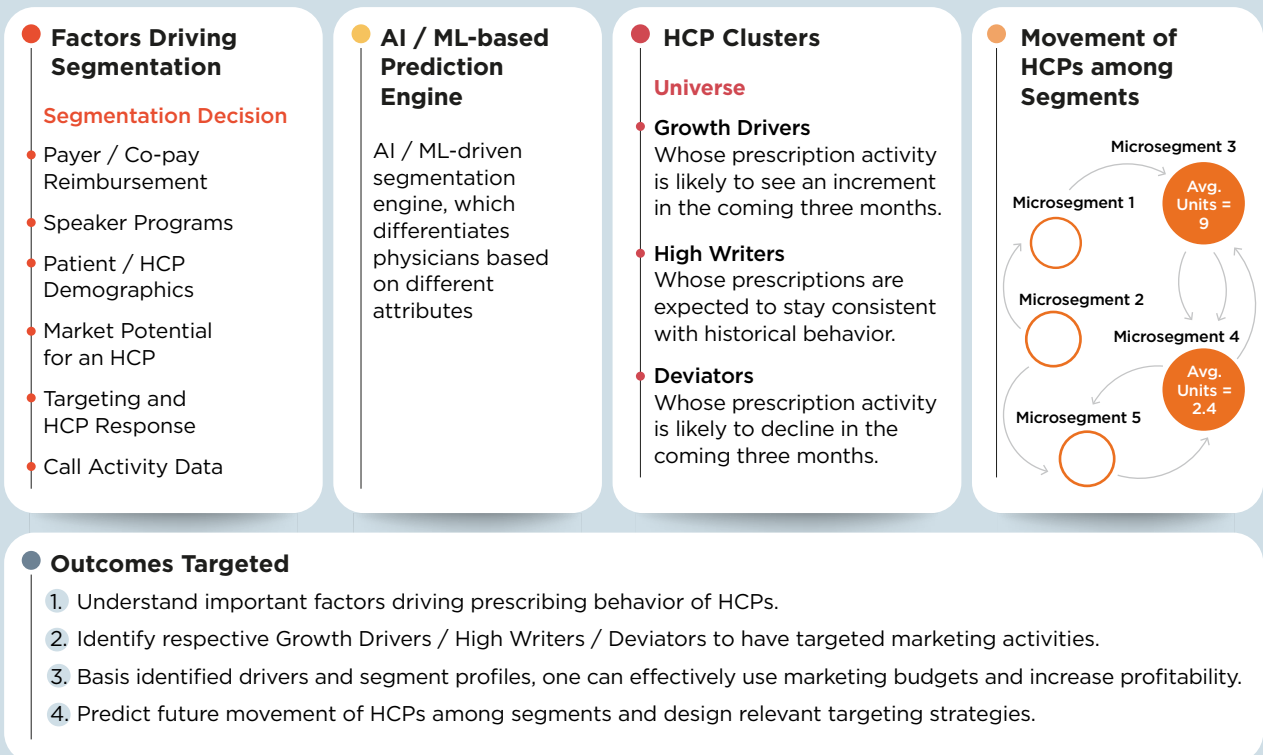


Figure 5: Attributes for Model Development

2. AI / ML-based Approach for HCP Segmentation Using Dynamic Attributes

Departing from the historical approach of creating multiple scores based on past data, our enhanced approach incorporates predicted future potential. By leveraging dynamic attributes (as depicted below) in our modeling process, we broaden the horizon and introduce agility.

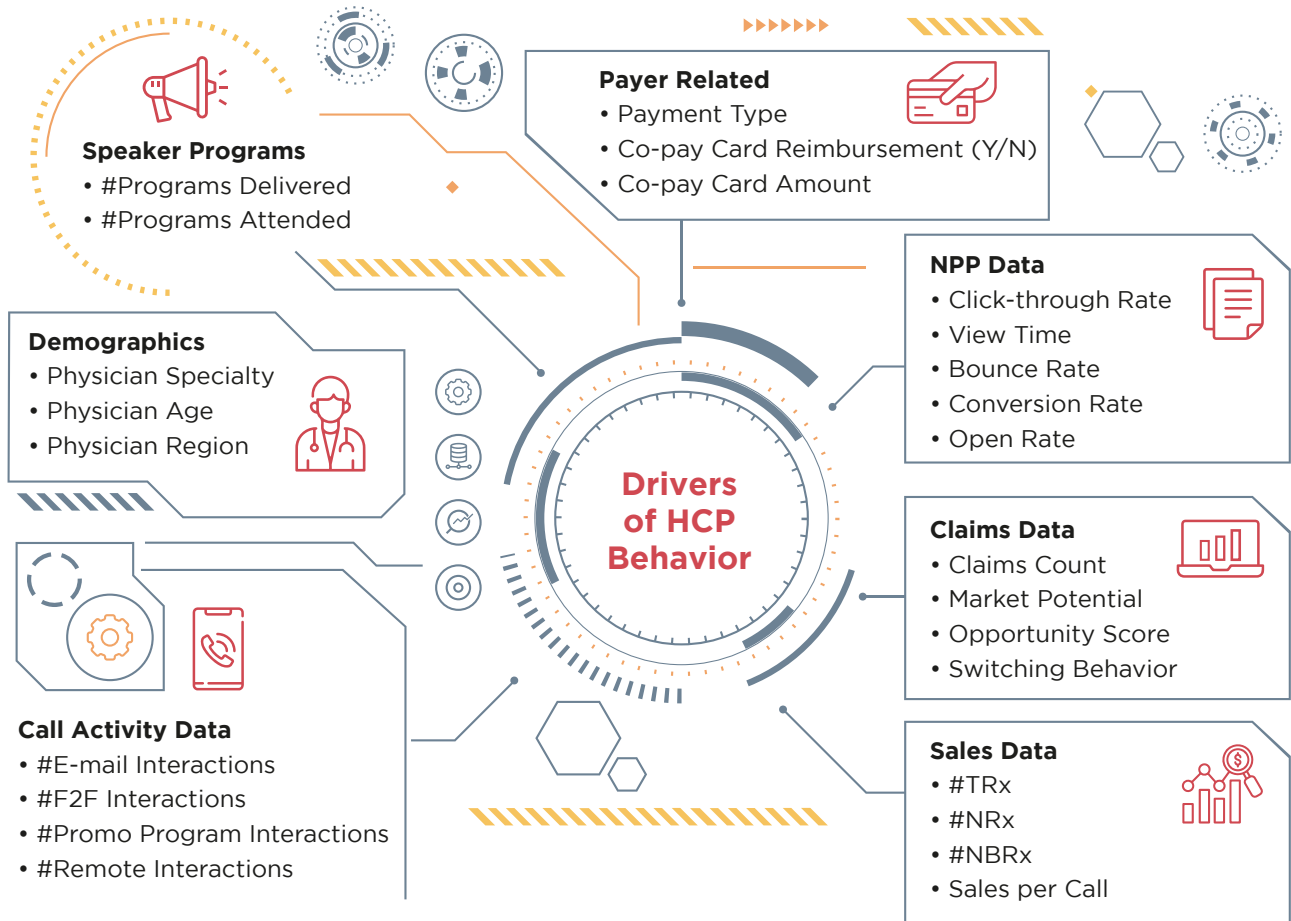


Figure 6: Dynamic Attributes Influencing HCP Behavior

After meticulously selecting the dynamic attributes for segmentation, we embark on an unsupervised learning-based clustering process to ascertain the ultimate dependent variable, primed for modeling purposes. Within this iterative procedure, we shall harness the prowess of state-of-the-art clustering algorithms tailored to suit the unique shape of our data. Leveraging the full breadth of dynamic attributes at our disposal, we shall seamlessly construct the requisite number of clusters, each crafted to distill meaningful patterns from the data.

Algorithm	Average Predictive Accuracy	Training Speed	Speed of Calculation	Can Work on Small Samples	Result Interpretability
Hierarchical Clustering	Low	Slow	No	High	Hierarchical Clustering
Affinity Propagation	Low	Fast	Yes	Good	Affinity Propagation
BIRCH Clustering	Good	Slow	No	Moderate	BIRCH Clustering
DBSCAN	High	Slow	No	Good	DBSCAN
K-Means	High	Fast	No	Moderate	K-Means

Figure 7: Unsupervised Clustering Techniques

Once the clusters have been deftly formed, it becomes imperative to endow them with practical business significance. To this end, we rigorously profile every cluster group, seeking to unravel and discern the distinctive traits that define each. By assigning descriptive business names to these clusters – such as "High Writers," "Growth Drivers," and "Deviators" – rather than relegating them to mere numerical designations, we elevate comprehension for stakeholders.

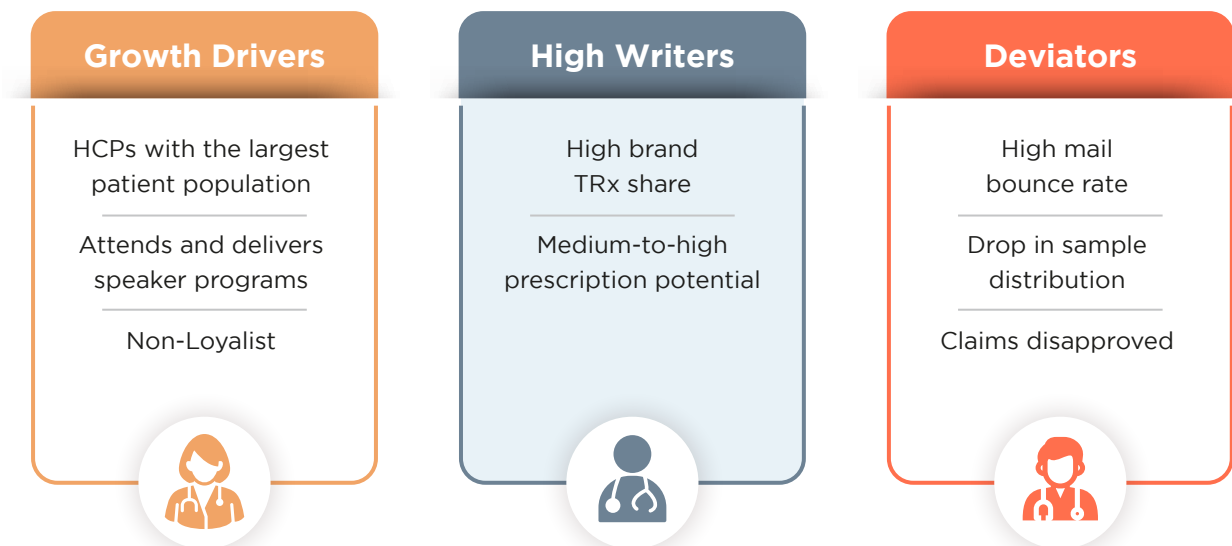


Figure 8: Assigning Profiles to the Clusters



3. Supervised Learning-based Approach to Predict Cluster Behavior with Changing Attributes

Employing the dataset with HCPs, dynamic attributes and their assigned clusters, we build a multi-class classification ML model. This model uses HCPs' dynamic attributes as independent variables and predicts their segments based on real-time changes in HCP behavior, such as switching to a new medication. Multiple state-of-the-art multi-class classification algorithms are compared for predictive accuracy, training, prediction speed and result interpretability.

The following are insightful comparisons among some of these ML algorithms, all uniquely equipped with the capability of handling multi-class classification tasks:

Algorithm	Average Predictive Accuracy	Training Speed	Prediction Speed	Can Work on Small Samples	Result Interpretability
Logistic Regression	Low	Slow	Slow	No	High
Decision Tress	Low	Fast	Fast	Yes	Good
Random Forests	Good	Slow	Slow	No	Moderate
SVM	High	Slow	Slow	No	Good
Deep Learning (H2O)	High	Fast	Fast	No	Moderate

Figure 9: Supervised Classification Techniques

4. Predict HCPs' Switching Behavior across Clusters

Statistical techniques like Markov Models are leveraged to manage frequently changing HCP behaviors that challenge the sales team's target decision-making. These sequence evolution models analyze and predict HCP switching behavior by describing transition probabilities between segments, allowing us to anticipate HCPs' likelihood of moving to another segment.

AI / ML-powered Approach for Dynamic Targeting

Upon successfully identifying clusters and segments of HCPs, the preparation of a target list ensues. Pharma companies now comprehend that tailoring the targeting methodology to each HCP is imperative. What may prove to be the ideal communication channel for one HCP might not hold true for another. Thus, the challenge faced by pharma companies is to discern the right channel, optimal timing and appropriate message to deliver to individual HCPs.

To address this complexity, a dynamic targeting platform can be constructed, leveraging the prowess of a Next-best Action (NBA)-based recommendation engine. It aids sales representatives in determining the most effective channel to target an HCP and the optimal timing for such interactions, all based on quantifiable improvements in market share. Calculating the market share lift entails analyzing past interaction data following touchpoints with HCPs. The period considered for measuring the lift is meticulously selected, encompassing the most significant impact on variables. Initially, the preferred channel for targeting an HCP is deduced based on the lift. Subsequently, the recommendation engine examines the best timing to approach the HCP, factoring in their availability.

This approach centers on prioritizing the HCP's perspective, considering various channels for targeting an HCP and ultimately determining the most effective means of communication for each HCP. Moreover, the NBA model can be bolstered through a self-learning framework built on Reinforcement Learning principles, enabling real-time decision-making and optimizing the likelihood of increasing market share. This intelligent recommendation engine continuously engages in incremental learning, assimilating the output from previous actions as input for subsequent decisions. The backbone of this Reinforcement Learning-based recommendation engine consists of powerful algorithms such as Deep Neural Network - Q learning, Deep Deterministic Policy Gradients and Monte Carlo methods.

Below, we illustrate how the recommendation engine operates, providing well-informed suggestions regarding the best communication channel and timing for targeting a specific HCP.

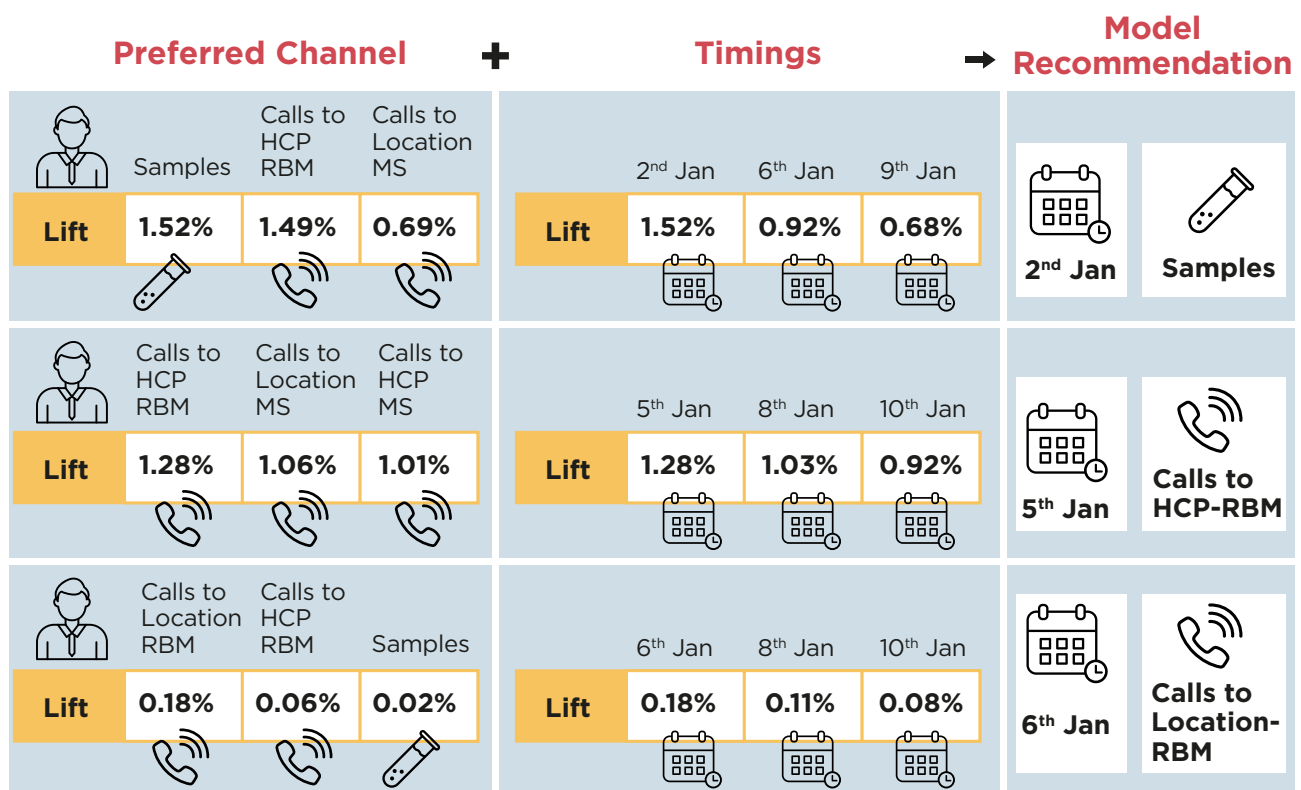


Figure 10: Recommendation Engine

Conclusion

The successful implementation of this dynamic segmentation approach necessitates training the internal brand and sales team on its key features. Additionally, assessing the performance of the new approach through initial tests and control studies is recommended. A significant benefit of this approach is its ability to align segmentation schema for both sales and marketing teams, bridging a common gap present in many organizations.

To learn how WNS is helping a top **10 US-based pharma company** leverage the dynamic segmentation approach to power growth while optimizing costs, visit [WNS Triange | AI, Analytics, Data & Research](#)



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About WNS Triange

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Driving a futuristic edge are WNS Triange's modular cloud-based platforms and solutions leveraging advanced AI and ML to provide end-to-end integration and processing of data to actionable insights. WNS Triange leverages the combined strength of WNS' domain expertise, co-creation labs, strategic partnerships and outcome-based engagement models.

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