USING MACHINE LEARNING TO ESTIMATE PERCEPTIONS AND FUTURE PRESCRIBING INTENTIONS OF HEALTH CARE PROVIDERS: A NOVEL APPLICATION FOR INTEGRATED PRIMARY AND SECONDARY DATA IN UNDERSTANDING HCP DECISION-MAKING

Amod Athavale[1], Brittany Smith[1], Jonathan Jenkins[1]
1. Trinity Life Sciences, Waltham, MA, USA

MSR70
ISPOR Annual 2025

SUMMARY

- Combining perceptual and attitudinal metrics with administrative claims data provides a holistic view of patient and provider experiences, aiding in understanding behaviors and improving healthcare outcomes
- This study used machine learning models to estimate healthcare provider perceptions from survey data, linked with administrative claims and CMS Open Payments data
- Machine learning models predicted survey data metrics, with robust precision and recall rates
- This approach has the potential to help understand and improve guideline adherence, inform policy changes, track long-term trends in HCP attitudes and behaviors, and enhance patient outcomes through targeted interventions
- Integrating HCP attitudes with administrative claims data can enrich public health research, enhance predictive analytics, and drive cost-effective, patient-centered care

INTRODUCTION & OBJECTIVES

- Administrative claims data provide essential behavioral and clinical metrics regarding healthcare providers (HCPs) and patients. However, these data sets often lack perceptual and attitudinal metrics, which are crucial for comprehending the underlying rationale behind observed behaviors. Understanding these metrics is vital for developing actionable strategies to influence these behaviors effectively. By integrating perceptual and attitudinal data, healthcare organizations can gain a more holistic view of patient and provider experiences. This comprehensive approach enables the identification of key drivers of behavior, facilitating targeted interventions that can improve healthcare outcomes and patient satisfaction.
- This study aimed to illustrate a novel application of machine learning techniques to estimate HCP perceptions derived from survey data, based on statistical associations with behaviors observed in administrative claims data.

METHODS

- A representative sample of neurologists from a US administrative claims database was administered a survey to capture their perceptions around treatment preferences, intended prescribing behaviors towards therapies in clinical development within a specific therapeutic area, and impact of their practice setting on prescribing decisions. Survey responses were linked to the administrative claims dataset used for recruitment, and publicly available CMS Open Payments data, using National Provider Identifier (NPIs).
- Machine learning (ML) models, including Random Forest, AdaBoost, GBM, XGBoost, LightGBM, and CatBoost were trained on the subset of NPIs surveyed. These models aimed to classify HCPs based on the associations between their survey responses and the secondary datasets. The models facilitated the estimation of key survey data metrics using the secondary datasets.
- Model performance was assessed using a hold-out test set, evaluating accuracy, precision, recall, and F1-score. As it was assumed that the administrative claims data used to recruit is representative of the universe of HCPs under consideration, ML models with the highest predictive metrics were selected as final. These final models for each key survey metric estimated were applied to the entire US administrative claims database used for recruitment to predict perceptions and intentions for non-surveyed HCPs.

Figure 1 | Secondary Data with Appended Predicted Primary Data Snapshot

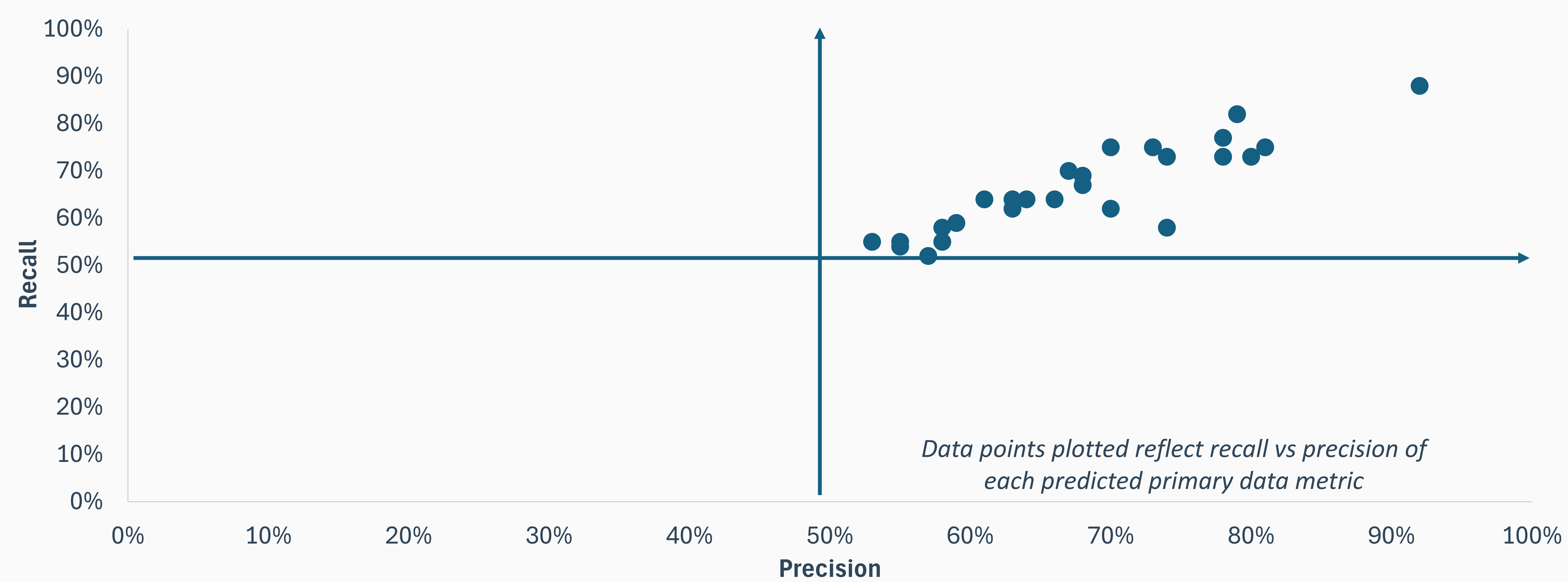
Secondary Data Metrics						Primary Data Metrics Captured in Survey for Respondents				
HCP	Total NBRX Product Y	Total NBRX Product X	Total TRX Product Y	Total TRX Product X	Total Payments to HCP (CMS data)	Favorable perception of Product Y	Favorable perception of Product X	Strongly influenced by insurance	Strong belief in early high efficacy treatment use	Strongly influenced by practice logistics
1	0	2.883654457	34.69086409	0	0	0	0	1	0	0
2	1.390787423	0	0	9	0	*Did not participate in primary research survey*				
3	8.862420365	33.91969565	914.7611516	293.3936058	0	*Did not participate in primary research survey*				
4	5.033961542	10.98542592	109.2890225	90.67780602	13.68	1	1	1	0	1
5	0	0	0	0	0	*Did not participate in primary research survey*				

Using secondary data, primary data metrics were predicted for every HCP in the broader universe that did not participate in primary research

Secondary Data Metrics						Primary Data Metrics with Predicted Values				
HCP	Total NBRX Product Y	Total NBRX Product X	Total TRX Product Y	Total TRX Product X	Total Payments to HCP (CMS data)	Favorable perception of Product Y	Favorable perception of Product X	Strongly influenced by insurance	Strong belief in early high efficacy treatment use	Strongly influenced by practice logistics
1	0	2.883654457	34.69086409	0	0	0	0	1	0	0
2	1.390787423	0	0	9	0	**0**	**1**	**1**	**0**	**1**
3	8.862420365	33.91969565	914.7611516	293.3936058	0	**1**	**1**	**0**	**1**	**0**
4	5.033961542	10.98542592	109.2890225	90.67780602	13.68	1	1	1	0	1
5	0	0	0	0	0	0	0	1	0	1

- Machine learning models generated secondary data-based (administrative claims and payments data) algorithms to estimate survey data
- These algorithms were applied to predict survey data metrics for the broader HCP universe, creating a dataset with both secondary metrics and predicted primary metrics for every HCP in the broader HCP universe, with predicted primary data metrics including (not exhaustive) …
  - Preference for high efficacy treatments
  - Belief that benefits of high efficacy treatments
  - Perceived product performance for 2 competitors
  - Influence of insurance status on prescribing
  - Influence of practice logistics on prescribing
  - Influence of perceived adherence on prescribing
  - Importance of patience preference
  - Perceived unmet need in specific therapeutic area
  - Likelihood to be an early adopter
  - Distrust in information from pharmaceutical companies
  - Practice setting
  - Preference for particular route of administration
  - Use of conferences for information

Figure 2 | Test Dataset Predicted Model Precision and Recall



- The models were able to predict positive metrics in the training data 62% to 98% of the time and correctly identify positive metrics 54% to 98% of the time
- The models demonstrated the ability to accurately predict positive metrics in the test data, with precision rates ranging from 53% for early adopters of novel treatments to 92% for HCP practice setting.
- The models demonstrated the ability to correctly identify positive metrics in the test data, with recall rates ranging from 52% for impact of manufacturer patient support programs to 82% for belief benefits outweigh risks of high efficacy treatments.

POTENTIAL APPLICATIONS

Better understand underlying causes of medical unmet need

- Aid in identifying attitudinal and behavioral factors to understand medical unmet needs, including adherence to guidelines and long-term trends. For example, if claims show low statin use despite guidelines, and attitudes reveal concerns about side effects, interventions can be developed to address misconceptions with real world safety data. Additionally, this integration enables tracking of how HCP attitudes and behaviors evolve over time, identifying patterns that indicate emerging issues or opportunities for improvement. For instance, exploring HCP behavior regarding biologics can reveal patterns such as high prescribing rates linked with efficacy-seeking attitudes, or low prescribing rates linked with concerns about capital investments or safety. Identifying these barriers can provide insights that help develop strategies to improve access and usage.

Design and orchestrate more effective medical education

- Understanding HCP concerns and attitudes can aid developing educational programs that are culturally and contextually appropriate, engaging stakeholders to ensure relevance and effectiveness. Using evidence-based strategies to promote behavior change and improve health outcomes is crucial. Furthermore, implementing educational initiatives that support the development of adaptive expertise among HCPs ensures that learning is enduring and applicable in real-world settings.

Policy

- Help identify drivers of behavior change, such as financial incentives, regulatory requirements, or educational initiatives, and inform future policy development ensuring that patients receive the most effective therapies available.

Outcomes

- If HCP attitudes towards shared decision-making affect patient compliance, combining that with claims data on follow-up visits or medication refills could show associations which can help in designing training programs for HCPs to improve outcomes. This can empower proactive monitoring versus reactive approaches.

CONCLUSIONS

Integrating HCP attitudes and perceptions with administrative claims data has the potential to enrich public health, health policy, and health outcomes research by bridging the "Why" and "What" of provider behavior. This synergy can enhance predictive analytics, policy design, and intervention efficacy, ultimately driving cost-effective, patient-centered care.

REFERENCES

1. Patey, A. M., Fontaine, G., Francis, J. J., McCleary, N., Presseau, J., & Grimshaw, J. M. (2023). Healthcare professional behavior: health impact, prevalence of evidence-based behaviors, correlates and interventions. *Psychology & health*, *38*(6), 766-794.
2. Powell, B. J., Waltz, T. J., Chinman, M. J., Damschroder, L. J., Smith, J. L., Matthieu, M. M., … & Kirchner, J. E. (2015). A refined compilation of implementation strategies: results from the Expert Recommendations for Implementing Change (ERIC) project. *Implementation science*, *10*, 1-14.

ABBREVIATIONS

HTA: Health Technology Assessment | **HEOR:** Health Economics and Outcomes Research | **HCP:** Healthcare Providers | **NPI:** National Provider Identifier | **EHR:** Electronic Health Record | **EMR:** Electronic Medical Record | **CMS:** Centers for Medicare & Medicaid Services | **ML:** Machine Learning

Ask A Question: bsmith@trinitylifesciences.com
Connect With Us: TrinityLifeSciences.com linkedin.com/company/trinitylifesciences