**Predictive Modeling: An Overview and Options for Exploration at Cotiviti**

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            Artificial Intelligence (AI) has seen a rapid rise in its capabilities in recent years. With different subfields, AI’s capabilities now include the ability to automate processes, analyze large amounts of data, and generate original content. Machine Learning (ML), a key subfield of AI, has aided this advancement by considering how computers “think” and how they process data “intelligently” (Black et al., 2023, para. 2). Used in predictive analytics, ML plays a critical role in using statistical methods to forecast future outcomes based on historical and current data via predictive modeling, which either classifies data or predicts a numeric value based on ML algorithms coti(Wakefield, n.d.).

            Predictive analytics are rooted in the use of linear regression models and time series analyses, the foundation for newer techniques (Panda & Agrawal, 2024). Today, ML allows for the real-time analysis and forecasting thanks to the connectivity of the Internet of Things (IoT). Regarding its use in healthcare, 66% of healthcare leaders in the United States report implementing predictive analytics into their practices for uses such as personalized treatment plans, streamlining managerial practices, and anticipating outbreaks (Ahramovich, 2024; Panda & Agrawal, 2024).

            The implementation of these practices allows healthcare providers to make data-driven decisions for their patients and optimize resource allocation and usage. With ML’s ability to analyze large quantities of data, predictive models can uncover subtle trends that greatly impact public or personal health. By analyzing a vast amount of data, healthcare leaders can tailor their decisions to current and probable future trends. As more data is received, predictions often become more accurate (Ahramovich, 2024). However, with the benefits of predictive analytics and ML come some risks and challenges. One obstacle blocking accurate predictions is low-quality data. With healthcare data primarily coming from electronic health records, lab results, and patient surveys, data can often be inconsistent. Attempts to integrate and analyze this data may result in an incomplete picture and thus, poor modeling (Ahramovich, 2024; Soman, 2024).

            With its work in Risk Adjustment, Cotiviti already leverages ML to provide clients with a thorough understanding of their members’ missing or incomplete conditions. Cotiviti has already seen a reduction in the administrative time and resources required to manage and analyze clients’ data, and this benefit can be reaped in other areas of business as well (Cotiviti, n.d.-b). Cotiviti’s Zero Hour Alerts, actively demonstrate how predictive analytics can benefit retailers by potentially reducing over 30% of post-audit recoveries through prevention. While Zero Hour Alerts already introduced predictive analytics, another area for its implementation would be the Pillars of Payment Integrity, especially the Performance and Process Improvement pillars (Cotiviti, n.d.-a). By leveraging ML and predictive analytics, there exists a potential to improve the performance process by utilizing client data to predict overpayments by data classification or by identifying trends. Furthermore, Cotiviti already carefully collects industry and client data points to correct issues and mitigate risks, but with predictive modeling, Cotiviti could leverage ML to predict issues or risks and correct them via prevention.

            In conclusion, the implementation of predictive modeling has risen over the past few years, especially in healthcare. Despite risks and concerns surrounding privacy and poor data, predictive modeling shows no signs of slowing down. With benefits such as optimizing resource allocation reducing administrative time and tasks, combined with Cotiviti’s record of implementing it, predictive modeling continues to be a technological resource Cotiviti invests in.

**References**

Ahramovich, A. (2024). *Predictive analytics in healthcare: top use cases & adoption tips*. itransition. https://www.itransition.com/predictive-analytics/healthcare

Black, J. E., Kueper, J. K., & Williamson, T. S. (2023). An introduction to machine learning for classification and prediction. *Family Practice*, *40*(1), 200–204. https://doi.org/10.1093/fampra/cmac104

Cotiviti. (n.d.-a). *Forging the quickest path to profitability*. https://retail.cotiviti.com/

Cotiviti. (n.d.-b). *Suspect Analytics*. https://www.cotiviti.com/solutions/risk-adjustment/suspect-analytics

Panda, K., & Agrawal, S. (2024). Predictive Analytics: An Overview of Evolving Trends and Methodologies. *The Journal of Scientific and Engineering Research*, *8*(10), 175–180. https://www.researchgate.net/publication/380399051\_Predictive\_Analytics\_An\_Overview\_of\_Evolving\_Trends\_and\_Methodologies

Soman, N. (2024, June 25). *Future of Patient Care: Predictive Analytics in Healthcare*. Decent. https://www.decent.com/blog/future-of-patient-care-predictive-analytics-in-healthcare

Wakefield, K. (n.d.). *Predictive Modeling Analytics and Machine Learning*. SAS. https://www.sas.com/en\_gb/insights/articles/analytics/a-guide-to-predictive-analytics-and-machine-learning.html