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Leveraging AI and Machine Learning for Enhanced Preventive Care and Chronic Disease Management in Health Insurance Plans

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Abstract
COVID-19 has thrown a spotlight on the importance of improving prevention and long-term disease management. Despite substantial effort, preventive healthcare compliance remains suboptimal for a variety of reasons: financial, geographical, situational, awareness, or due to primary care physician access constraints. Health insurance companies can play a leading role in enhancing preventive healthcare by incentivizing members and shifting focus towards value-based care. By leveraging modern AI and machine learning, insurance companies can harness the vast amounts of digital health information that flows into their ecosystems to better understand the evolving health risk profile of their members. The resulting insights enable the companies to properly identify and engage such members promptly, with a focus on improving overall health outcomes and thereby reducing long-term cost burdens. To enhance risk prediction and patient outcomes further, companies can increasingly tap into digital mechanisms to deliver a variety of existing and innovative interventions. The outcomes achieved from the interventions can then be looped back into the health risk prediction models to enhance and refine the risk prediction capabilities continually. Finally, due care should be exercised at all times to sensitively and responsibly manage the digital health information generated at such a scale. As digital health information volumes scale up exponentially, both in breadth and depth of member-relevant health data, AI and machine learning can be deployed in concert with various modalities of health intervention for preventive care and long-term health management. With the right kind of oversight and responsible stewardship of patient data, these new insights can be acted upon effectively to improve overall health outcomes while creating a health environment that members are more than willing to engage with. With advances in both predictive modeling and intervention therapy arms, AI and machine learning have the potential to deliver significant improvements in health outcomes and decrease cost burdens associated with chronic health conditions, especially within the health insurance domain.

Keywords: COVID-19, Preventive healthcare, Healthcare compliance, Health insurance companies, Value-based care, AI in healthcare, Machine learning in healthcare, Digital health information, Health risk profile, Health outcomes, Long-term disease management, Financial barriers to healthcare, Primary care access, Predictive modeling, Risk prediction, Health interventions, Patient engagement, Chronic health conditions, Health data privacy, Health information stewardship.

1. Introduction

The use of AI and ML in healthcare services has become increasingly commonplace over recent years, used not only to improve and develop treatments but also to provide better population management. ML can be used to

identify at-risk individuals or cohorts within a population, supporting payers, providers, or the members directly in activities related to prevention and individualized health improvement, driving better long-term healthcare outcomes and lowering the overall cost of care. This paper will showcase examples related to preventive care, chronic disease management, and digital behavioral health, providing a perspective from the standpoint of a health insurance organization.

Health insurance organizations exist to maintain or improve the health of their members, preventing, addressing, managing, or repairing health-related issues. As such, they assume the risk for the future health of individuals rather than the risk related to what has already transpired. Individuals have incentives to maintain and improve their health – both life and how we live are valuable. However, there can be financial implications to maintaining or improving our health, including investments in active or preventive checks by providers and participation in various programs to address known or emerging health issues that could result in financial consequences if not addressed. Challenging questions from a health insurance organization perspective include segmenting the population to identify who would benefit the most from these activities and quickly identifying health-related issues as they arise, coordinating and providing individuals with access to timely care.

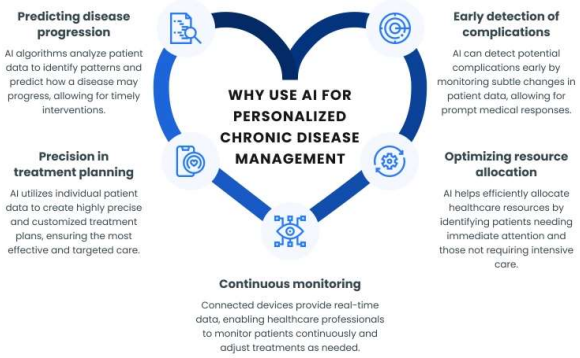

Fig 1 : AI in Chronic Disease Management

1.1. Background and Rationale

There is growing recognition that to achieve improved population health outcomes, we must shift our focus from treating diseases and illnesses to preserving health and preventing illness. Much of one's health is determined by a combination of individual behaviors, social and economic factors, physical environment, and healthcare services. Social determinants significantly influence health outcomes and account for almost 60% of healthcare spending. There is a need to address these social determinants affecting health outcomes through better preventive care management interventions with measurable benefits. It is widely recognized that the best way to manage and optimize the risk of any condition is through prevention and early detection.

Non-communicable and chronic diseases claim a large share of healthcare spending. Congestive heart failure, chronic obstructive pulmonary disease, coronary artery disease, chronic kidney disease, and type 2 diabetes are to name a few. If not prevented or diagnosed early, and optimally treated, these diseases can often lead to catastrophic and costly results. Advanced healthcare technology and services, specifically AI, machine learning, and big data, are beginning to offer several preventive care management strategic opportunities for identifying and mitigating these catastrophic and costly chronic and non-chronic risks. This study is to assess the prevalent practice of applying these technologies. Specifically, what types of healthcare organizations and businesses are currently applying AI and big data technologies to prevent the onset and early detection and ideally, prevention, of chronic respiratory disease conditions?

Equation 1 : Risk Prediction Model for Chronic Diseases

AI and ML can be used to predict the likelihood of a member developing chronic diseases (e.g., diabetes, heart disease) based on historical health data, demographics, lifestyle factors, and other variables.

Equation for Risk Prediction:

$$P(\text{Disease}) = f(\mathbf{X}, \theta)$$

Where:

P (Disease) = Probability of a member developing a chronic disease.

X = Input features (e.g., age, gender, medical history, lifestyle factors, genetic data, etc.).

θ = Parameters (weights) learned from historical data using machine learning algorithms.

$f(\cdot)$ = Machine learning model (e.g., Logistic Regression, Random Forest, Neural Network).

Example:

For predicting the likelihood of diabetes, the model might take into account factors such as BMI, age, family history, and blood glucose levels.

1.2. Research Aim and Objectives

The primary aim of this research study is to explore and assess the capabilities of AI in preventive care and chronic disease management within health insurance plans or systems. The ultimate objective is to establish if and how health insurers can leverage these technologies to prevent or delay the onset of chronic disease, in addition to effectively managing chronic disease and improving care coordination for the insured individual. Consequently, the research study seeks to obtain an in-depth analysis of how a health insurer can derive superior business outcomes while conducting a multi-faceted approach to leverage AI in enhancing the health of its insured population. The research study is underpinned by the following objectives: Long-term claims cost containment: Explore and specify how AI can be utilized for improving the prevention of chronic disease through personalized preventive care, health, and wellness promotion, supporting better adherence to recommended treatments, and subsequently improving long-term outcomes. Leveraging technology for improved outcomes: Understand how AI can assist in improved clinical decision support for physicians, enhance chronic disease management, promote personalized treatment path choice, and the effective analysis and identification of effective treatments and interventions for different demographic and sociological groups within the insured population.

2. AI and Machine Learning in Healthcare

AI and machine learning can provide a deeper understanding of the unique healthcare needs of patient populations within health plans by studying historical claims data, repeatedly observing the healthcare scenarios these patients endure, and building robust models that learn from patterns and construct contextual insights. These insights can then be systematically used in multiple diverse approaches for effectively communicating, managing, and improving the healthcare quality and overall health of patients. AI and machine learning can provide recommendations to health plans and care delivery organizations, empowering them to optimize their operational strategies to create a win-win situation for health plans, their members, and the care delivery organizations providing healthcare treatment services. The above-mentioned definition presumes that readers are conversant with concepts related to healthcare informatics, basic health plan operational strategies, and data science techniques such as machine learning and data mining. The quick and vast advancements in high-performance, distributed, and effective computing technologies, contemporary software frameworks, and more affordable, flexible, lower-energy, and faster-growing data storage and retrieval options are driving a rapid

transformation in capabilities related to artificial intelligence and machine learning.

2.1. Overview of AI and Machine Learning Technologies

Artificial intelligence has revolutionized several domains and subdomains within healthcare. AI applications leverage machine learning on data to make predictions or generate recommendations. AI and machine learning technologies can play an important role in enhancing the process and outcomes of preventive healthcare and personalizing the management of chronic diseases. In this part, almost all possible applications and relevance of these technologies in preventive and continuing care for health insurance plan members are discussed with real-world examples, challenges, and proposed strategies.

AI can perform in the areas of detection or diagnosis, personalized risk prediction and prevention, patient management, disease management, health system management, and data processing and analysis for decision support and provision of valuable insights.

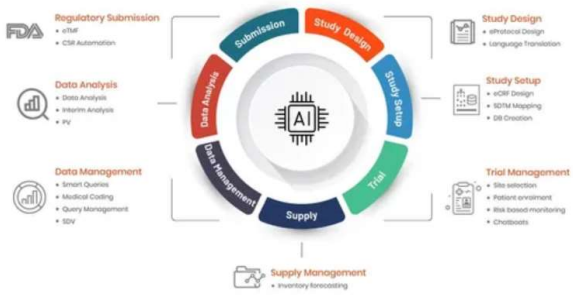

Fig 2 : AI and Machine Learning in Clinical Trials

2.2. Applications in Healthcare

In modern healthcare, AI and machine learning technologies are not only transforming the research and development of pharmaceutical products and new treatments but also have enormous potential to optimize patient care pathways. This could involve streamlining processes, improving diagnostics, better treatment protocols, and clinical decision-making. The AI systems used in healthcare that are currently the most explored are trained to perform specific tasks or predictive models. They can be trained on large amounts of data and can be used to make predictions or classifications about patient states. Their attractive feature is that they often do not require a knowledge base in the conventional sense. For use in clinical trials or as part of care pathways, it is critical that how these technologies are used is well understood and generally accepted, and that the underlying algorithmic decision-making is transparent and explainable.

Overall, there is a growing number of applications for AI and machine learning in the healthcare setting, and these are starting to emerge in various areas, including cancer diagnostics and wearable sensors that can detect diseases. These are focused on predictive analytics. Furthermore, the realization is dawning that individuals are different, and perhaps healthcare should be customized more towards what works best for each type of patient. This has also led to an exploration of personalized medicine, which is essentially an exploration of the interaction space for predictive analytics, usually between patient phenotype and drug properties, against a background of individual genetic diversity. A developing area is combining data from patients and clinical trial data to explore how a new drug or technology performs in a real-world setting. Such insights can support informed clinical decision-making and ethical decisions around access to the new drug or device. It also finds that although there are many exciting potential areas of application for AI and machine learning technologies, many of these are up-and-coming.

3. Preventive Care in Health Insurance Plans

In the US, health insurance regulations usually include a comprehensive list of wellness and preventive care

services that insurance plans are required to cover without cost sharing. Even though the services are covered, the gaps in the U.S. healthcare system result in health disparities due to various costs and cultural and financial barriers. Insurance companies should be proactive in encouraging insured beneficiaries to get the needed services; for members who are enrolled in their plans, insurance companies have demographic and medical data that can be used to predict health conditions at the individual level. Although these predictions cannot be used to perfectly prioritize interventions, they have the potential to increase the effectiveness of preventive programs. Using the member data that they already have, health insurance companies can identify members who are under-immunized and could benefit from immunizations. Each member can be assigned a risk score that identifies those who have an increased risk of having their flu infections escalate to pneumonia. For members who correspond to the highest risk scores, policy changes would encourage these high-risk members to be vaccinated for pneumonia. While the companies might not be aware of cultural, financial, and other barriers to these vaccinations, their actions might change their members' viewpoints as a result of the high value that the insurance company associates with this vaccination misinformation.

3.1. Importance of Preventive Care

Preventive care services save lives, improve quality of life, and reduce the financial burden of illness in the long run. They also help reduce the effects of widespread conditions such as heart disease, diabetes, and stroke, which can be difficult to manage and expensive to treat. The benefits of early detection of chronic diseases through preventive care, however, extend beyond cost savings. It is much easier for healthcare providers to manage chronic diseases diagnosed at an early stage, thus eliminating the need for costly procedures, increased hospitalizations, and reduced severe complications. Evidence also suggests that preventive care services are often underutilized.

As a result, payers, patient advocacy groups, and healthcare providers should strongly encourage the use of preventive care services. Health insurance providers can use machine learning to proactively reach out to patients who are eligible for preventive services but have not utilized them for a customizable period to better manage chronic diseases associated with risk. More than 70% of Medicare's current healthcare expenditure was attributed to people with more than one chronic illness and reduced quality of life. The financial burden associated with this cost can be reduced through preventive care and management of these chronic diseases.

3.2. Current Challenges in Implementing Preventive Care

Current challenges in implementing preventive care were summarized. In keeping with age-old wisdom, it is far easier to get the prevention and care a patient wants and thinks they need than it is to provide the prevention and care a patient needs and does not want. Unfortunately, we have a healthcare system that is well-designed to encourage demand for care and fund the treatment of specific conditions but does not fully capitalize on the broad array of prevention and care it should offer. The reasons for this paradox are many.

Healthcare is big business, and there is a lot of money to be made on overeating, under-exercising, smoking, and not watching enough TV. Health improvement that helps individuals spend less money on healthcare, have healthier children or employees, and live longer and happier lives are not so much a part of the business plan. Nor is the constant attention to day-to-day self-management of medical conditions. The economics and the ease of treatment overshadow cost-effective prevention, early detection, and care management, especially when the investment comes due in the future to an entity different from the one that makes the investments.

4. Chronic Disease Management in Health Insurance Plans

Chronic illness overwhelms health plans, and chronic disease management is becoming expensive. Unmanaged chronic illness is a significant burden on individuals, and with an increasing focus on chronic disease, health

plans need to take more ownership and responsibility for the health of their members. Healthcare technology is advancing rapidly, and health plans should utilize improvements in technology to combat the rise of chronic illness. There have been rapid advancements in the application of artificial intelligence in the healthcare sector, with machine learning technology being used to identify and analyze health risk indicators that were not previously possible, which can now help identify health risks earlier in a person's life, making prevention and earlier intervention more feasible. This presents a unique opportunity to reduce health costs and increase the physical and mental well-being of members, a dramatic improvement over the current healthcare model, which is based on treating the sick.

Numerous well-documented studies have concluded the benefits of early intervention and proactive management of chronic illness. It is no longer justifiable to avoid investing in breakthroughs that improve people's lives. Health insurance plans should give members continuously updated guidance and mechanisms to encourage them to achieve health and wellness aims. Plans benefit both financially and by increasing the mental and physical health of their members by investing in AI machine learning-driven breakthroughs in preventive care and chronic illness management. Plans that focus on these successful health measures will have a distinct competitive advantage in today's evolving products. The concept of patient-centered care must be redefined by insurers; only by focusing on improved healthcare quality, affordability, and patient engagement can plan sponsors provide sustainable value to their members.

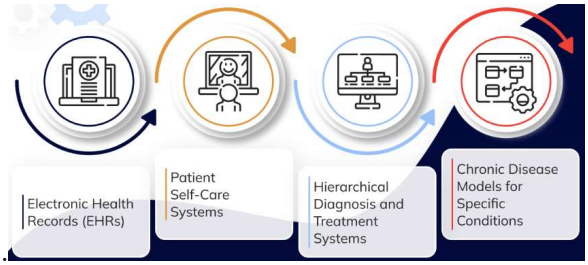

Fig 3 : Types of Chronic Disease Management

4.1. Significance of Chronic Disease Management

The effective management of chronic diseases, such as cardiovascular disease, diabetes, and chronic respiratory diseases, requires recognition of the central role of preventive care and an evolving business model that recognizes health factors, provides coverage for a broad range of clinical services, and addresses personal influences on health by focusing on integrating quality medical care with health behavior change. Research also shows that providers who actively manage patients, motivate patients, and drive them to set and achieve measurable health goals will be in a strong position to earn revenue sharing from insurance products.

Primarily, chronic care management and preventive care personnel use disease-specific high-touch interventions and focused educational programmatic content to address management gaps associated with catastrophic medical treatment episodes. However, the long-term goal of incrementally guiding members to wellness through informed, intuitive health and lifestyle decision-making, and favorable biometric outcomes is more important than making it to a doctor’s appointment for a specific known condition across often non-specific symptomatology associated with primary care or existing comorbidities. The healthcare model is practitioner-led rather than patient-led; we trust that the aggressive deployment of related technologies in health insurance can effectively address disparate comorbidities associated with psychometric discrepancies.

Equation 2 : Adherence Prediction for Chronic Disease Management

Predicting whether a patient will adhere to their prescribed treatment or lifestyle plan is critical for managing

chronic diseases.

Equation for Adherence Prediction:

$$A_i = h(\mathbf{C}_i, \mathbf{T}_i, \mathbf{D}_i)$$

Where:

Ai = Probability of adherence to the treatment plan for individual i.

Ci = Clinical history of the patient (e.g., previous diagnoses, treatment success).

Ti = Treatment plan and medication prescribed for individual i.

Di = Demographic and social factors (e.g., socioeconomic status, access to care, support systems).

$h(\cdot)$ = Machine learning model (e.g., Decision Tree, Support Vector Machine, Neural Network).

4.2. Barriers to Effective Chronic Disease Management

One of the biggest challenges to the adoption of AI in chronic disease management is the issue of risk selection versus risk management. Currently, health plans discriminate between risks to manage their finances, basically choosing to sell health insurance to people who are less likely to get sick. It's not a great value perspective to be driven by, and as a result, over the last decade or so, healthcare policies have gotten much stricter around not letting health insurance be a selling good. The consequence of that shift in payment and design is that no insurer, no matter how strong and smart, wants to sell formulas to the competitor, the other plans, with variable costs that are likely to persist in stacking up for the plan. Variable cost is likely to become a predictable annual cost of medical care for patients who have sought, were found to have, and have chronic diseases, and successfully received treatments.

Currently, hospitals may have some estimate of how variable costs may change under different scenarios of patient treatment, but these plans are frequently terrible. Continued care with a trusted individual at a clinical medical office—where office visits are suddenly not free for the patient but are variable in cost to the patient, or to that balance of care between health professional, patient, and cost—is more engaging and controllable. So we reach a clear impasse when the encouraged line of action is senior. At the business level, some asset will deliver a return on that capital, be it an incentive point forward to care for the healthiest workers, or a clear return via focused care delivery and management that is recognized and tried to be realized promptly, and whose predictability can also be relied upon to deliver financial returns. It is difficult to measure payment.

By analytic context or executives, some health providers incorporate these assets into their risk selection plans by dynamically trimming the identified risk through individualized patient care, and that is typically a good thing. Our current payment system, however, focuses on promoting reduced missed financial costs by minimizing administrative spending: risky, probably chronic, and potentially avoidable patients represent a 10 percent increase in a provider's annual medical care budget if such prospectively graded patient participation would be effectively detected and suppressed through an annual medical management action and could operate simultaneously through various patients as individual personalized care playbooks. Financial pressures to use an advanced administrative agency for producing annual forecasts for chronic diseases rendering carve-out and timing is approximately equal to $500,000 per million members, with average population training group rates.

5. Integration of AI and Machine Learning in Health Insurance Plans

Integration of Artificial Intelligence and Machine Learning in Health Insurance Plans Integration of AI and ML-based healthcare platforms into payors' systems can go a long way in remodeling the insurance industry. Insurers have access to large volumes of data that can be put to the best use if assessed for their analysis for planning preventive healthcare through insights drawn from historical claims and PHI available. In contrast, to lag indicators like historic high claims or doctors' visits, successful plans devised for enrollees for early prevention of diseases, health problems, or health changes can be empowered. By integrating comprehensive PHI and algorithms through AI and ML-enabled platforms, health insurance plan providers can use PHI for early and precise identification of health issues and diseases that their members might be experiencing. Additionally, AI and ML-based applications can support payers for go-to-market plans and pricing, actuarial analysis, and reporting effectively, underpinning loss ratio, fraud detection, and streamlining the enrollment and claim settlement processes.

5.1. Benefits and Opportunities

The role health insurance companies play in the wellness journey of their members is profound, and technology must be leveraged to enable better care for health insurance participants. Members look to their plan for guidance to take charge of their healthcare and are searching for clarity when making decisions. Proactive intervention in care ensures that minor problems do not balloon into major issues. AI and data offer powerful tools to innovate within established processes. Inundated with health data from various sources, employing AI to learn from the data and guide intelligent health decisions is without a doubt the future to leverage their utility to the fullest. They can improve their risk pooling, rating, pricing, medical underwriting, claims monitoring, recoveries, fraud, waste, and abuse management functions with AI and predictive analytics. These tools can assist in policy adjustments, wellness tracking, and trend analysis.

For a health insurance company, it can provide effort-free population health management, better claims risk management, more accurate and advanced underwriting, and prediction of risk factors in developing policies for small and micro-segments like selective corporate groups and credit entities. Today, with the help of technology, they can assist health insurance participants to better manage and monitor their health. Wearable devices help collect much more health data to leverage. Through analyzing and predicting the effectiveness of specific health plans, health insurance companies can help their patients find appropriate care, as well as manage costs. Finally, health insurance companies can reach out to members and encourage involvement when personalized and timely feedback is provided for healthier habits. High satisfaction rates and persistent stages occur whenever the system caters to individual needs.

Fig 4 : Distribution of published papers for diseases diagnosis using artificial intelligence techniques

5.2. Ethical and Privacy Considerations

Advancements in AI and machine learning have the potential to deliver improved patient health outcomes and

enhance preventive and chronic disease management in health insurance plans globally. Such advances offer the ability for AI and machine learning to analyze comprehensive longitudinal health and claim data, allow payers to expand coverage where such services are currently unavailable, and improve cost-management success benchmarks. Despite their promise, AI and machine learning come with challenges related to ethics, privacy, and compliance with global regulatory guidance requirements. Confidence and trust in these new technologies will also need to be established to encourage universal acceptance and approval by treating healthcare professionals and beneficiaries.

The privacy of patient data is a critical barrier to the application of data analytics in the healthcare setting. Machine learning heavily relies on the quality of the data set and the availability of data in a suitable format. Poor-quality and unreliable data sets will generate poor results, and poor compliance with data privacy requirements could have negative impacts on the detected models. The lack of clear guiding principles on the way patient data is used is a barrier to the use of emerging technologies in healthcare. These ethical and data use considerations must be taken into account in the deployment of AI technologies. The substantial subset of AI/ML models constitutes mostly black-box models that do not allow decomposition into interpretable segments – crucial information for physicians, regulators, or other stakeholders. Concerns about accountability for critical treatment and administrative decisions made by AI/ML models are valid. In certain models, it is impossible to control for historical bias in data, which exacerbates the ethical concerns. In essence, it is difficult to make sure that recent outcomes are not solely dependent or biased on prior decisions.

6. Case Studies and Examples

Case 1 - Getting Personalized for Improved Health: One success story is that of a health plan that uses machine learning to provide more personalized opportunities for people to improve their health and is experiencing great success. Started as a pilot in 2019 and brought to scale in 2020, the program is now being experienced by hundreds of thousands, and the results are clear. Ninety-day measurement shows that people who interacted with both solutions improved their Predicted Risk Score by -66.7%, had better medication fill adherence at +9.7%, and saw more reduction in healthcare financial burden at -4.7% compared to people who interacted with neither.

Case 2 - Targeted Health Recommendations for Healthier Living: The health of a population is determined by more than just the number of times an individual receives healthcare. Around 80% of a person's health status is determined by factors such as lifestyle, genetics, nutrition, environment, and social and economic needs. While mutual health coaching is a proven technique that results in improved health outcomes, we are now leveraging data and AI techniques in a privacy-preserving way, leveraging data science and machine learning to identify and recommend personalized, actionable insights that will resonate with each individual. The most important challenge is to identify the right recommendation that fits into the context of a person's life or situation.

6.1. Successful Implementations in the Industry

Certainly, given that the use of AI and machine learning solutions in health insurance is still currently in its early stages, projects in the industry are limited. Given this, a search was carried out among different business intelligence, machine learning, and artificial intelligence repositories to identify real problems in this line of business and their respective conclusions. In total, five different problems were identified that could be approached and resolved both from a theoretical perspective as well as through their practical implementation. These problems and business solutions will now be presented. It is worth noting that for a problem to be presented, comments on its approach and usefulness, the used data, as well as the conclusions of the business case, it is sufficient to refer to the recent article or repository link presented at the end of the chapter. Where

such a problem is of interest, the reader can find useful help to elaborate models of the same scope.

6.1.1. Understanding demographic information from potential customers A health insurance company is seeking a way to analyze the data of its potential customers to make the best decisions and strategies for the future of the company. With the customers' demographic data, the company can infer preferences, identify the most common age groups, and determine if women are more concerned about health, etc. The problem should be solved with exploratory data analysis. There are charts with insights that can help managers from the health insurance company.

6.2. Lessons Learned and Best Practices

Since many organizations in healthcare are novices at creating and managing "unconstrained" machine learning projects, this section describes best practices exemplified by the projects in this chapter. Here are a few detailed explanations. The data extraction and arrangement of the data flow are best done along with business objectives and are an iterative process with project scoping. Scoping and collection of data is a spiral and iterative process with data management experts and business experts that align business and objectives. This is not meant as a denial of the need for a data scientist representing the machine learning perspective, but the business perspective should be present throughout, and therefore a business expert should also be present. For many projects, the system designer should also be part of the team. Projects should deliver demonstrable ROI and operational ease from the outset. Do not start with "grab 12 TB of data and hire very senior people." While performance with data scientists and very good IT and health experts is often necessary to fine-tune and scale the required massive precision, we have discovered – to our pleasant surprise – the power of small teams. Most of the deliverable value is produced by a small segment of the project, and high performance in terms of the KPIs is frequently reached rapidly. For a substantial project with squeezed timelines, we had three people. Two of them, who delivered the main results, were students with moderate knowledge, including ETL, the basics of machine learning in the chosen domain, and significant coding experience. High performance from people with moderate skills was only possible in a small team, given that the coders were also business-oriented. And this happened at an unprecedentedly low cost and with good ROI. The third person was an expert enough to keep challenging the two results.

7. Future Directions and Recommendations

This paper provides recommendations for life and health insurers, policymakers, standards development organizations, health information exchange networks, clinical informatics professionals, and payers to effectively develop and deploy AI- and ML-based risk predictions targeting multiple composite chronic conditions risk estimates so they may take action to diagnose or prevent these conditions early in life or before conditions take hold. This offers the potential to slow the growth trajectory currently forecasted in chronic disease incidence, morbidity, and mortality, thus enabling individuals to live longer, healthier, and more financially secure lives. While commercially available and widely used in the provider and payer sectors of health, disease-specific risk scores are not currently offered by life and health insurers other than on a trial basis. General chronic disease prediction models exhibit relatively poor performance and are used infrequently. Multimorbidity models, also called composite chronic condition models, can be used to predict the risk of a patient having two or more conditions on onset. However, the few such models that have been developed do not perform particularly well, and those models are not designed to sort members by risk. Achieving the high prediction accuracy needed to make healthcare utilization cost savings and quality performance improvement possible will require careful cohort creation for model training, utilization of widely available data sources, steps to minimize data challenges, choosing the right AI- and ML-based subfield, and including additional non-

medical input features to achieve the needed performance targets that will enable deployment, measurement, and renewal of incentives aimed at achieving meaningful spikes in disease prevention and early diagnosis.

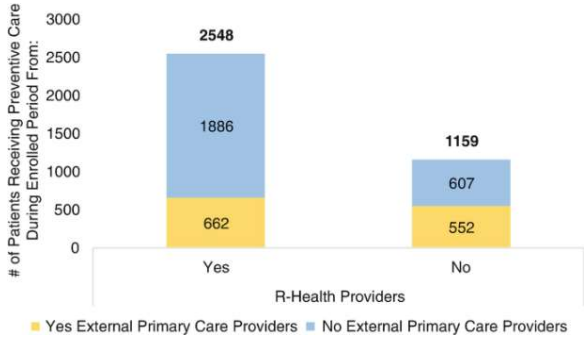

Fig 5 : Predicting Preventive Care Service Usage in a Direct Primary Care Setting Using Machine Learning

7.1. Potential Innovations and Technologies

At the most fundamental level, health insurance will ultimately benefit from seeking to maximize population health through the application of AI and machine learning to facilitate clinical care in the preventive and chronic disease areas. Drawing on data of all kinds, ranging from population-level data to the individual physician-patient relationship, and wide-ranging data sources from the economy, social platforms, and genetics to behavior and consumer sentiment to literature in complementary fields, new methodologies can be developed to benefit health insurance plan participants. These data sources can empower clinical progress through a robust and broadened continuum of health information exchange, individualization of care, and delivering the right data and algorithms to the right place at the right time.

Innovators can capitalize on data sources rarely accessed for clinical care decision-making today. For example, novel economic measures proven to be significant determinants of health, such as future earnings growth exposed for the fetus during war, inflationary effects of surviving a heart attack, and the higher costs of health insurance due to zip codes in areas with lower physical health, can be quickly and effectively linked to health care decision-making if the data are combined with wearable technologies and longitudinal data. In parallel with the rollout of the hospital charge data that powered diagnosis-specific quality measures, followed by the expansion of publicly reported quality measures, we can create cost-effective algorithms from the new tax-exempt settlement, procedural, incidence, and rehospitalization data, developed through a competitive incentive for the creation of useful decision support tools. With applications from easy and low-cost life insurance offers, we can provide a consumer perspective on the costs associated with each disease state.

Equation 3 : Fraud Detection in Claims for Preventive and Chronic Care

Machine learning can also be used to detect potential fraud in claims, ensuring that interventions and treatments are necessary and cost-effective.

Equation for Fraud Detection:

$$F_i = \eta(\text{Claims}_i, \mathbf{D}_i, \mathbf{P}_i)$$

Where:

Fi = Fraud score for the claim of individual i.
Claims$i$ = Submitted claims for individual i.
Di = Patient demographics and clinical history.

Pi = Pattern recognition from previous claims (e.g., sudden changes in care patterns).
$\eta(\cdot)$ = Fraud detection algorithm (e.g., anomaly detection, supervised learning).

7.2. Policy Implications and Regulatory Frameworks

Policymakers need to institute suitable regulations that ensure the protection of privacy and ethical AI while fostering the development and deployment of applications across the healthcare continuum through better collaboration between the public and private sectors with open data systems. The healthcare system needs to be reoriented to a preventative, patient-focused systems approach through deep structural reforms, enabling AI to optimize and personalize individualized care. Several AI technologies have been in the marketplace experimenting with these principles, and the questions are increasingly moving from to what extent and how these technologies will transform the national healthcare system effectively, and if it will be inclusive for all.

We argue that AI has the potential for data to be harnessed to deliver a very valuable goal to a defined need, such as increasing transparency in delivering AI value through assessments of the present functioning and planning of future use of AI, supporting shared learning between AI adopters and investors, and delivering equitable health systems. In particular, by enabling multidimensional profiles of patient populations, AI has the potential to deliver for the health insurance sector as both the payer of medical bills and as the parent of individual and public health decision-making. Through the acceleration of AI algorithms to improve and drive health data integration, economic evaluations by incorporating healthcare beliefs and priorities of human individuals and communities align with the data anomaly model and broader theories of human, economic, and society.

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