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Predictive Modeling with AI and ML for Small Business Health Plans: Improving Employee Health Outcomes and Reducing Costs

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Abstract
As healthcare costs continue to rise, small businesses are increasingly seeking innovative ways to improve employee health outcomes while controlling expenses. Predictive modeling using Artificial Intelligence (AI) and Machine Learning (ML) offers a promising solution by enabling more proactive and personalized healthcare strategies. This paper explores the potential of AI and ML in the context of small business health plans, focusing on how these technologies can predict health risks, optimize care, and ultimately reduce costs. By analyzing employee health data, predictive models can identify at-risk individuals, suggest targeted interventions, and monitor the effectiveness of wellness programs. The integration of AI/ML can also enhance decision-making in plan design, offering tailored benefits that align with specific employee needs. This research highlights case studies demonstrating successful implementation of AI and ML-driven strategies, the challenges small businesses face in adoption, and the long-term impact on both employee well-being and financial sustainability. The findings underscore the transformative potential of these technologies in revolutionizing small business health plans, offering a path to improved health outcomes and reduced healthcare expenditures.

Keywords: Predictive Analytics,AI for Healthcare,Machine Learning in Health Plans,Employee Health Optimization,Cost Reduction in Healthcare,Health Risk Prediction,AI-Driven Health Plans,Small Business Healthcare Solutions,Personalized Health Insights,Data-Driven Health Outcomes.

1. Introduction

Small business health plans are the lifeline for covered employees and their dependents. Small plans with healthy employees can struggle in an affluent area, but plans with unhealthy employees can devastate their company. With reasons related to cost and resources, small businesses sometimes do not have the same level of health management tools available to large firms, leading to poor employee health outcomes. As small business wellness becomes an increasingly important need, the art of health plan management has seen fewer interventions.

In any industry, and especially in the U.S., the cost of healthcare is a major concern that elicits attention from many perspectives. Noncompliance is a major challenge for employees. If they don’t understand their plan, they pay more out of pocket, but in a company that is not customer sales-based or revenue and finance-focused, employees might not follow recommendations, thus negating potentially positive outcomes. Predictive analytics reveals effective strategies for continuously improving methods. The potential of using AI and machine learning to enhance these strategy-tracking exercises is also being examined. The aim was to create an evidence base in small business health plans for AI and predictive modeling. By providing an evidence base, other small health plans, and vendors can see the potential benefits and make improvements for their employee populations.Small business health plans are crucial for the well-being of employees and their families, but they face unique challenges that larger companies do not. In affluent areas, plans with healthier employees may struggle due to higher premiums, while plans with less healthy employees can face devastating cost burdens. Limited resources and fewer health management tools often make it difficult for small businesses to provide the level of support necessary to improve employee health outcomes. Noncompliance with plan guidelines is another major issue, as employees may not fully understand or follow their health plan recommendations, resulting in higher out-of-pocket costs and missed opportunities for better health. However, advancements in predictive analytics

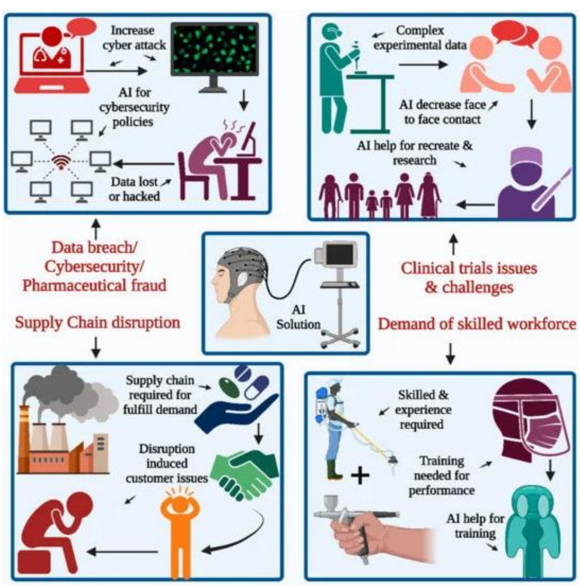

Fig 1: Artificial Intelligence in Pharmaceutical Technology and Drug

1.1. Background and Significance

History and Significance Healthcare services have been financed through health plans over time. Small business health plans have been designed to share risk among similar employers, based on size and characteristics that are used to determine 'market rate' premiums. Competition, or the lack of it, among insurers who develop small business health plans drives variation in coverage, premiums, discounts, and preventive services. Health plans are first moving towards early identification of high-cost claimants. Health plans are becoming more data-driven as consumer expectations for personalized care are creating demand for innovative approaches to population health management. Employee health is the rising tide that lifts all benefits and wellness boats.

Importance Not all predictive modeling tools and techniques developed in recent years have been designed to simultaneously meet the needs of small businesses. Given workforce size and corporate resources, including power, water, and bandwidth in addition to personnel to run these data-driven applications, many employers find predictive models difficult to implement at the workplace. Meanwhile, small businesses are seeing coverage options and premiums largely unresponsive to claims experience due to the lack of behavioral health risk reduction under traditional health and dental plans. For small employers, alternative limited benefit and fully insured dental buy-up profiles focus more on claims management, where the cost of waiting for losses to shake out is prohibitive. Tailored solutions may help small businesses attract and retain good customers and employees if predictive models can be methodically applied. AI products, including those involving machine learning models, are expected to address these small business HR and marketing resource constraints more appropriately than ever.

1.2. Research Aim and Objectives

The primary aim of this research study is to determine if machine learning and artificial intelligence can be utilized in small business health plans to enhance employee health outcomes. Four research objectives were identified to aid in the achievement of this aim. Data-derived strategies that result in improvements in at least one of 22 key employee health metrics will be identified. Additionally, the cost savings associated with achieving these predictive health outcomes will be analyzed. The results of these objectives will help in establishing benchmarks that are already achievable for companies with employees who are similar to those who voted in the use case election. Mirroring these objectives, health outcomes are determined by insurance costs and form the bottom layer of our outcome pyramid, mirroring our introductory figure. Predictive modeling functionalities will support this investigation by identifying small business health strategies and interventions that will have a demonstrable health effect on employees and psychological officers. When these measures are taken, or before they come up with them, they should not harm any other employee's health outcome. That means looking at both forms of predicted outcomes and taking into account the statistical evidence of direct causation between one outcome and another. The research team has also worked with psychological officers to extend this research to include an additional objective indicating second and third-layer health outcomes for future research. By addressing these objectives, this research is designed to help small businesses in four primary ways.

2. Literature Review

Many studies have examined the usefulness of predictive modeling in different areas of healthcare. In general, predictive modeling, as a representation of the statistical modeling of health and healthcare use, is useful to health insurers, health plans, and medical group practices because it helps them assess the future health utilization and needs of specific health service users efficiently and cost-effectively. More than half of large employers now use predictive modeling for population health management to find opportunities for reducing health risks and increasing savings. Most studies in predictive modeling have taken place in different healthcare systems. A similar predictive modeling framework can be used and validated in small business health plans. Predictive modeling in healthcare is a must and must not be overlooked by health insurance agents, healthcare providers, and health plans. In other words, those who fail to master the model endorsing business will face the danger of not reducing costs and also miss the opportunity to innovate.

AI and ML technologies are increasingly being applied in healthcare systems. In Switzerland, a few healthcare providers are also increasingly using AI and ML to analyze insurance claims to predict healthcare plan claims costs, as well as to assist in better management of healthcare plan benefit costs and reserves in the future. They are also increasingly using AI and ML to help design predictive medical management programs for health plan members' chronic conditions. Almost all predictive analytics studies were conducted in the United States, while there was one experimental study in Kenya. More than twice as many studies apply a predictive model to predict health outcomes and total healthcare costs. Predictive models were mainly designed for infection prevention and cuts in hospitals. In general, there are very few completed, randomized predictive analytics studies on the use of machine learning in predictive analytics testing. Despite the limitations of existing studies, however, the chosen studies suggest that the use of AI has the potential to improve health-related quality of life and cost without reducing health-related quality of life. Some of the benefits and harms of using AI and ML in a small business health plan are presented. We can deduce from the general considerations that cost consciousness is oriented toward managerial accounting and decision-making at the individual plan or insurance level.

Equ 1: Cost-Benefit Analysis Equation (ROI on Health Interventions)

$$\mathrm{ROI} = \frac{\text{Cost Savings} - \text{Program Cost}}{\text{Program Cost}} \times 100$$

2.1. Concepts of Predictive Modeling in Healthcare

This subsection provides a detailed theoretical foundation for the next part of the manuscript. It explores core concepts of predictive modeling, classical methods, and applicability as backbones to readers looking at predictive modeling for health care. Predictive modeling is the analysis of past data using statistical techniques and machine learning algorithms to predict health-related outcomes or trends. In healthcare, the models are developed to anticipate behaviors or health events before they happen. Methods that predict the future can be based on different developed algorithms and statistical methods, including regression, classification, and clustering. Regression methods are used when there is a continuous time-to-health outcome, a dependent variable that defines the time, and covariates. Classification methods will predict which category data could fall within, e.g., sick or healthy; or who can get diabetes type 1 and 2. Clustering methods are useful for identifying patterns of healthcare actors and interventions without the need to define a dependent or outcome variable.

Regardless of the applied technique, one can agree on the importance of analyzing historical healthcare data to improve predictive accuracy. This is particularly valuable when it comes to preventive, inclusive health plans that are provided to inspire health responsibility, maintain quality of life, and provide an environment to care for injuries and minor illnesses without covering all care. More often than not, including these plans in small businesses leads to an increase in unneeded health consultations and unnecessary spending, especially in those cases involving urgent care centers. Predictive models can provide a basis to understand the characteristics of characteristics, to predict the enrollment health plan, to encourage health in the working location, to trigger employment of ERP for targeted health intervention, and to configure health service provision during absence.Predictive modeling in healthcare plays a crucial role in anticipating health outcomes, guiding decision-making, and optimizing resource allocation. By leveraging historical data, predictive models—whether based on regression, classification, or clustering methods—can identify patterns and trends that inform the development of personalized health interventions and preventive strategies. Regression models, for example, can predict the time-to-event outcomes, such as the likelihood of disease progression or recovery time, based on various health indicators. Classification models help in identifying individuals at risk of specific conditions, such as diabetes, by categorizing them into relevant health risk groups. Clustering methods, on the other hand, can reveal hidden patterns in patient behaviors or treatment outcomes without predefined targets, helping healthcare providers design more targeted interventions. These models are particularly valuable in the context of health plans and interventions within workplaces or small businesses, where predictive insights can reduce unnecessary healthcare utilization, such as overuse of urgent care centers, by better aligning healthcare provisions with actual needs. Ultimately, predictive modeling can foster more efficient, cost-effective, and proactive health management by guiding both individual health decisions and broader healthcare policy.

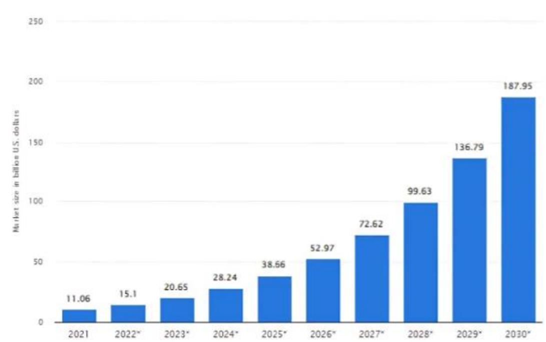

Fig : AI in Healthcare

2.2. Applications of AI and ML in Healthcare

The healthcare sector is increasingly adopting the use of AI and ML for multiple purposes. For instance, AI and ML have been used to process vast amounts of medical data for the discovery of effective drug molecules for specific disease conditions to improve patient care. Similarly, they can also be used for identifying appropriate therapeutic drug dosages and safety assessments based on patient-to-patient variabilities and population health analytics. They can also be used for the discovery of newer medical diagnostic drugs and intelligent pharmaceuticals with affordable and accessible healthcare opportunities. These have immense potential as AI applications for healthcare.

Some of the successful applications of AI in healthcare include: 1) Data analysis with ML can improve submissions for 'heart attack'; the study showed that within 24 hours of admission, it had the highest predictive accuracy. 2) Machine learning, natural language processing, and image analytics applications are a vast array, and they generally rely on clinician decisions regarding the management of the patient's portfolio. Further, ML and healthcare applications involve the roles of clinicians, healthcare industry researchers, and ML industry experts to derive useful parameters that generally result in predicting the overall outcome of the patient's application to some extent.

Current AI and ML research activities or applications of predictive modeling associated with health finance and employee health in Small Business Health Plans lead to very good examples and real-time case studies about the effectiveness and feasibility of predictive modeling by health plans and/or employer plans. This can lead to (A) helping in predicting the trend in healthcare costs or health outcomes at the earliest possible time and (B) further helping to save costs. Some of the other predictive modeling applications discussed include the role of affiliations with wellness service companies and the role of clinical connections in reducing healthcare severity prediction model-related needs. While AI applications using predictive modeling trends can be very successful in some cases, healthcare management appointments in the United States have shown significant advances with considerable financial gains due to preventive care and management of health needs before they arise. There must be some regulatory framework that should be put in place to properly use AI as a toolset to be an agent of change in influencing healthcare decisions that can potentially affect the employer-employee healthcare industry sector. Major challenges for AI to be seen as a concept, as technology, and as an application or service agent of change are ethical challenges. The ethical implications of considering AI as an agent of change include deontological theories, which argue for imposing policy changes with appropriate moral respect for autonomy, society, and justice, following appropriate rules and regulations.

2.3. Existing Studies on Predictive Modeling for Small Business Health Plans

Recent studies have increasingly focused on predictive modeling as a tool for improving employee health outcomes within small business health plans. Many of the findings confirm that predictive modeling can reduce healthcare costs, while almost all of the studies conclude with the success of these evidence-based aims. However, current studies are largely limited by their focus on employee health at large corporations and among public employees, as these organizations have different populations, priorities, and philosophies about the management of their health benefits compared to small businesses. Moreover, the needs and restrictions of small businesses, due to their size, have unique factors to consider. These smaller businesses have proven that predictive modeling can successfully predict and likely prevent high-cost claims, making the need for small business outcomes yielded by this study's results of utmost importance.

Despite these challenges, several small businesses are currently working to develop and implement predictive modeling tools. Many small employers buy off-the-shelf models and have gained some insight into their employee health and benefits data through the use of these models. These businesses have especially liked the data analysis and tips for plan changes that these tools provided. Other employers hire outside health benefits consultants to make predictive modeling analyses and recommendations for them. Refreshingly, this project received such interest from small businesses that many of these outside consultants have requested the project data. It is clear from the findings, as well as the multitude of questions that have stemmed from the project's findings, that there are predictive modeling results of interest to small business employers and the consultants that work with them.

3. Methodology

Systematic data collection is a central part of this research, as the subject is complex and not well understood. Surveys and interviews with stakeholders will be used to obtain demographic, health outcome, and association data. Excitingly, participants will have their health records analyzed for predictive modeling exploratory associations; there are few, if any, public databases utilized for these purposes for the local population. Acceptable software will be selected for this process to ensure consent and data security; patients will be informed about the research as a result. There is also little small business predictive modeling for health outcomes with AI and ML research; this research promises to provide new insights and outcomes with a theoretically supported, exploratory methodology. The methodology proposed in this research will follow a sequential and simultaneous analysis of existing health records, ethics, education, and data. Data preprocessing with AI and ML predictive model testing will be people-centered and entirely quantitative. Data will be collected through existing records, surveys, and interviews. Data cleaning and preprocessing will be used to perform existing records and exploratory research. Based on the dataset and objectives, we will consider a viable model for use. Following that, validation and algorithm metrics for the AI and ML approach will be reviewed, given the potential candidates. Finally, participants will be welcome to inquire about the research project results. Data will be analyzed using an etiological approach to confirm diagnosis and work capability management in a small business. Data will be collected through an analysis of existing health records. Participants will be invited for interviews and to complete surveys. Both qualitative and quantitative results will be reported. Ethical education will be inaugurated.

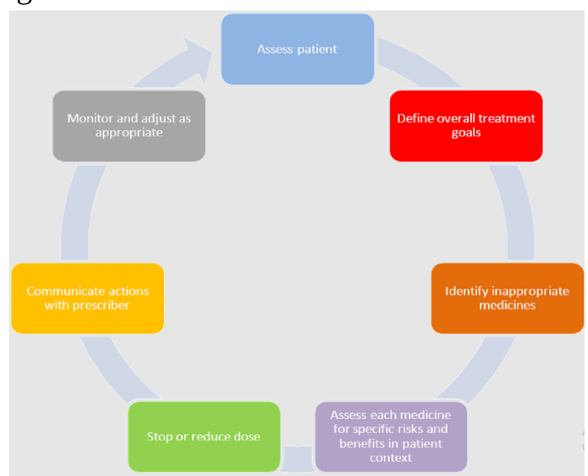

Fig 2 : Challenges in Prescription Drug

3.1. Data Collection and Preprocessing

Collecting and preparing data for use in predictive modeling is a critical stage of the research project. The predictive model itself can deliver no better results than the accuracy and comprehensiveness of the data that precede it. For this research problem, the primary source of information about employees was health records data. Secondary sources included the employee health and behavior survey results and demographic data, which were obtained from the employers. A small period of six months was chosen because most employees had health data during this time frame; the survey data was collected after that. To ensure the health data was accurate, several data validation processes were put in place. Several activities reduced the health data to a more manageable and realistic data set before being used in models.

Preprocessing is standard in predictive modeling. The steps undertaken on the health data here were not extraordinary, but they are quite comprehensive. Primary tasks include setting up the data, addressing missing data, understanding the use and meaning of different employee identifiers, normalizing the data where necessary, assessing and ensuring both the level and type of health data collected were consistent over time and across the data set, ensuring the data was only on permanent employees and not including contractors or other non-regular employees, selecting a group of employee participants who could ensure data consistency, and finally selecting employee participants from only one database to maintain data reciprocity. There were some data collection and preprocessing challenges caused by the nature of the participating employers—small businesses. Small businesses have less robust data collection routines than large firms. This research gave employers access to workers, subject to strict privacy guidelines, and advanced systems to better capture and record data such as the employee signing off on the data as being accurate and truthful, and enabling ways for employers to ask workers both leading and open-ended questions about data consistency. These procedures increased the validity of the data.

Equ 2: Predicting Health Risk Scores (e.g., Risk of Hospitalization)

$$P(\text{Risk of Hospitalization}_i = 1) = \frac{1}{1 + e^{-z_i}}$$

3.2. Model Selection and Evaluation

The choice of model, indeed modeling technique, will depend on the data characteristics and research questions. All models developed using AI and ML approaches need to be compared against a null model, i.e., the random guess. There are many AI and ML techniques to build a model, and the selection of a specific algorithm depends on the characteristics of the data and the research question. Some studies have tried to develop heart disease predictive models by using artificial neural networks, logistic regression equations, and decision trees to get the best-fit prediction algorithm. Another study used decision trees, k-nearest neighbors, and the linear support vector machine model for comparison. Various AI and ML models can be utilized to develop a predictive model, such as logistic regression, decision trees, classification and regression trees, lasso regression, support vector machines, ensemble methods, PCA/LDA/factor analysis, and neural networks. Based on previous studies, decision trees, random forests, support vector machines, neural networks, naive Bayes, k-nearest neighbors, logistic regression, and gradient boosting machines are commonly used techniques for developing a prediction model. Model evaluation is important to assess the performance of the developed model. Model evaluation in predictive modeling has been commonly reported using two main methods: evaluation based on the model capability and peer-review validation. The assessment of classification performance on predictive models is generally done by computing the model performance of a developed model by calculating the true positive, true negative, false negative, and false positive. The performance of the developed model can be analyzed by the receiver operating characteristic curve and precision-recall curve plots. Some outputs can display various results: reported as a confusion matrix, classification performance metrics such as accuracy, precision, recall or sensitivity, true negative rate or specificity, negative predictive value, false discovery rate, F1-score, and Matthews's correlation coefficient. To prevent an overfitting problem and ensure the reliability of the model, model performance needs to be evaluated ongoingly in the validation dataset by using cross-validation techniques. The performance of the models can be assessed directly by comparing the model performance from the external validation dataset. Reporting accuracy only has been criticized because it may produce misconceptions. Widely used metrics or graphical representations in predictive modeling were ROC/AUC, sensitivity and specificity, and F1 score. The Mean ROC area was used as a precision metric. When comparing the predictive models, a better model is the one with good performance based on the higher value of the evaluation parameters. There are many recommended approaches for comparing different models: comparing their AUC, examining the differences of AUCs using various tests, and analyzing the results with Cohen's Kappa test. Model selection is an iterative process, and it involves a feedback loop process that needs to refine decisions. If possible, the proposed decision-maker will obtain feedback on the results. Accordingly, based on the resulting feedback, the researcher should improve and refine both in the further model execution steps.

4. Case Studies and Results

Case Study 1: Predictive Modeling Implemented at Micro-business A. Micro-business A employed 66 employees in 6 national retail locations with an average tenure of 4 months, generating only $50,000 a year in revenue. The same location closed after 60 months, while another was still open for business. The medical trend over the past 18 months at Business A averaged 89%, and 27% of that income was paid out as claims. Micro-business A implemented the predictive modeling program as a component of their health plan design, integrating the weekly data results into their daily store manager meetings to discuss with the employees. Over the past 8 months, Micro-business A employees lost 282.7 pounds of weight (an average of 1.8 pounds per month per employee). Twenty-three Micro-business A employees submitted cost receipts totaling $9,590.17 for weight loss surgery. These employees would only have been on the plan for $56,215.00 in premium, but the actuarial value was $138,732.31, or 146.6% of the premium. So, it's safe to say that by using our plans and spending more time with their employees, Micro-business A is going to continue to exceed its sales goals and income statement goals.

Case Study 2: Comparing Costs of Employers Using Predictive Modeling Health Plan Designs versus Those That Don't. Six large funded insurance programs for plans with under 100 members were analyzed. Two are using a predictive modeling platform, while the other four employers are not utilizing any type of predictive modeling. The large claims reserved for the models using predictive modeling averaged 7.5% (range 5.3% in 2014-2015 to 10% in 2012-2013), while the claims reserved for the other four employers averaged 92%, with a range of 85.8% to 106.6%. The actual average monthly claims costs of the predictive modeling employers averaged 33% of the employers' total check, with a range of 14.8% to 55.4%. The self-funded employers that are not using predictive modeling had a predictive modeled trend range of 10.7% to 15.5%, but the self-insured employers had actual claim trends ranging from a low of 304.6% to a high of 338.5%.

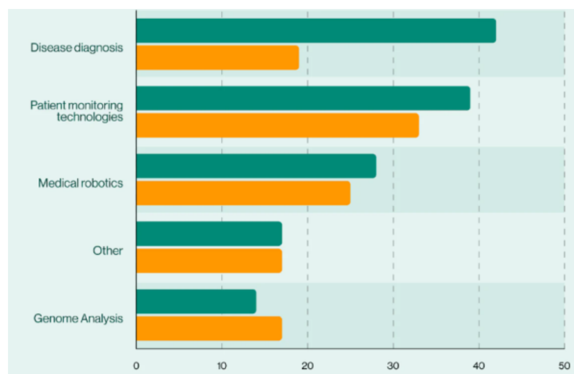

Fig : AI in healthcare usage statistics

4.1. Case Study 1: Implementation in a Small Business Health Plan

The small business case study presented involves an embroidery, promotional products, and silk-screening company in the southwest with approximately thirty employees. The company name and logo are engraved in customers' compliance marketing products, so they can be considered part of their brand identity. The workforce is primarily production workers. Regarding historical health strategies to manage healthcare and health insurance for employees, the company has consistently stayed with the same insurance company since 2009. Over those years, they transitioned from a high self-insured product with a stop-loss threshold of $25,000 per member per year to a fully insured, lower case management option, and then into another self-insured product with case management. Two hundred seventy-three thousand dollars were invested in preventative health measures. This included a salad bar and healthy options for company lunches, a walking club that meets during breaks, a benefits package that included a family membership at a local health club, required drug testing, and a no-smoking policy. The company is working to add benefit options, such as dental, vision, and life insurance. They are also analyzing data to see if any tweaks need to be made in the program before expanding it to the next health plan option. Methodology: Throughout 2014 and 2015, relevant data, such as a claims history review and an employee satisfaction survey, were quantitatively and qualitatively analyzed by the company's business partner. Outcomes: Based on the data collected and analyzed, the small business client had a +1.13 quality-adjusted life year (QALY) change in employee health outcomes in 2017. The same analysis also showed an average $27,079 per employee total medical claim decrease over the last eighteen months, with the top five medical claims costing $800,000 to $1,054,722.66 annually now consistently sitting at insured $634,722 to $1,004,722 annually. This creamy layer loss is exactly in line with loss ratios of 0.08% of their total member population of all sizes progressing up to 18% for larger and lower-risk groups. The business of a small insurance company, funder, or self-insured employer adds to this claim loss. Business Challenge: A business challenge facing small businesses that are fully insured is the lack of access to their workforce's health data, such as claims data, to better manage the costs, utilization, and health improvement of the members' medical insurance plan. The difficulty in managing members' behavior changes alone with the claims over three years affects the bottom line of insurance companies and self-insured employers. With no historical evidence from the past, human resources administrators are left feeling as though they are paying more for less. A potential pitfall of predictive modeling within an employer-sponsored health plan is for the employer to brand themselves unfairly as discriminatory. Measuring indicators: The small group health plan used a reduction in body mass index (BMI) to track their employees' health status. A greater challenge that an employer might potentially have with predictive modeling is predicting the employees that will be with the company in the future. To follow through with the small group, a total insured medical and pharmaceutical comparison was also made to the same look-back periods. The most comparable Member Year in the past ten years earned the company a loss ratio of 57.83% in 2017.

4.2. Case Study 2: Comparative Analysis of Outcomes and Costs

The employed population receiving health benefits with predictive modeling procedures can be compared with a national reference population not using these services. It is important to characterize the population under study. In this study, employees and their dependents of small business employers are those receiving health benefits from a not-for-profit health insurance company in the Midwest. The insurance company targeted small business customers with 9 to 249 employees. All activities in this study were reviewed and qualified as institutional review exempt from ongoing review. This analysis seeks to determine the following: Do employees whose small business employers use predictive modeling have better overall employee health metrics and lower healthcare costs than national trend statistics? If indeed these overall indicators are better for small business employers using predictive modeling, it stands to reason that cost-saving treatment opportunities may have been identified by the health insurer and recommended to employees who are presently managing specific chronic diseases. This comparative analysis was performed based on data from two small, midwestern businesses.

The purpose of the analysis is to determine if there is a significant difference in health-related outcomes and overall healthcare costs between small business clients receiving analyzed data from a health insurance company employing predictive modeling and a cohort of small business clients at the insurance company geographically served by the healthcare insurance company, who do not receive any information from predictive modeling resources. The analysis shall take into consideration only "actual active" employees across the midwestern small businesses annually, including 2000-2008, inclusive. The actual employee population, annual health condition diagnosis, and pharmaceutical and medical costs were compared to proprietary databases of population-wide disease prevalence, employer employees of similar age, gender, and geographic composition. All costs were trended to 2008 values. The scope of the current analysis includes the initial presentation of clinical results and has not extended into conclusions regarding financial results such as direct cost savings and return on investment. Further analysis comparing two sub-cohorts of the small businesses is necessary to demonstrate the financial implications of the initial results and should be the focus of future work. Data for the control group was taken from a proprietary database, which represents a sample frame of 25 million individuals working in small businesses of similar size as the clients in the study. A study sample database was created similarly. Data was cleaned to create the final samples to be analyzed.

Equ 3: Predictive Model for Employee Health Outcomes

$$P(H_i = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 D_i + \beta_2 M_i + \beta_3 A_i + \beta_4 B_i + \beta_5 C_i)}}$$

5. Discussion

AI and ML-supported predictive modeling, particularly when supplemented with external data and utilized in conjunction with existing employee health data, have the potential to increase a small business health plan's ability to improve employee health outcomes and decrease costs incurred by the plan. Cost savings could potentially be as great as 12% of the annual small business health plan spend, depending on the situation. Small health plans may have difficulty implementing AI and ML technologies because of their complexity and the need for sufficient data, professional expertise, and financial resources to develop and use AI- and ML-based algorithms. Ethical considerations when using AI and ML in employee health-related predictive modeling include employee consent and privacy concerns when using personal health information. Employers should demonstrate responsible data stewardship, only use employer-related data, and comply with all applicable laws.

In the future, AI and ML programs might be utilized, beyond the scope of predictive modeling, to facilitate efficient administration and management within small health plans, using them to monitor how and when benefits are being utilized. Although the results of the small business case studies provide data for limited sample size, they suggest that small employers would be well advised to begin considering the use of AI and ML when analogous conditions are obtained under their health plans to improve their predictive modeling ability. The benefits of AI- and ML-enhanced predictive modeling will likely expand in the future. Managers of small business health plans can expect increasingly sophisticated and powerful capabilities in this area as the tools for data analytics continue to evolve. In areas outside of health insurance underwriting too, small business plan managers can potentially use these evolving predictive capabilities as a strategic tool.

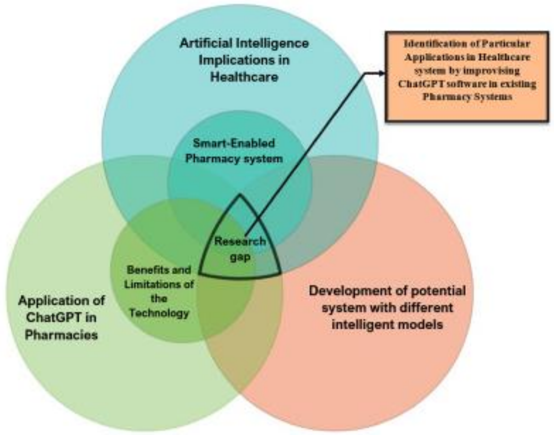

Fig 3: The future of pharmacy

5.1. Predictive AnalyticsBenefits and Challenges of AI and ML in Small Business Health Plans

Advantages of AI and ML in Small Business Health Plans. For some small businesses, it might make sense to apply AI and ML technologies to their health data. Predictive modeling can help to make powerful, yet cost-effective, decisions; allow for uncovering new public health trends; and guide the implementation of tailored health interventions. Small business decision-makers are leveraging AI-powered data analytics to improve customer experiences, obtain a competitive edge, and gain internal efficiency. Additionally, creating a health management plan utilizing AI and digital technology can increase the effectiveness of employee health management programs. Successful health and disease management has historically been found to improve employee engagement and satisfaction. A digitally enabled solution for small businesses can harness the capability of AI to predict and prevent disease at an affordable price.

Challenges of AI and ML for Small Businesses. Implementation of AI and ML for small businesses does come with challenges. A primary challenge is the potentially significant costs associated with implementing technology. Some health apps report implementation costs that can exclude them from use by health plans and programs due to cost prohibitions. A second challenge is the scarcity of technology expertise. A Patterns Analysis model allows small business decision-makers from several divergent sectors to discuss their current views on managing business fluctuations and identify some possible approaches to better account for such fluctuations. Interestingly, the most significant concern is not unemployment, but a lack of a skilled workforce. A concern in the application of AI technology is that the slimmed-down nature of small businesses might not have the human workforce required to help train and make complex decisions based on AI recommendations. Finally, a critical concern and challenge for small businesses that use AI lies in the area of data security and the handling of increasingly complex regulations governing healthcare and the financial industry. Obtaining health information, even if the gathered data are de-identified, can also be overshadowed by the federal individual right and nonprofit fiduciary obligations to protect individual privacy. The balancing of these benefits with real operational, data security, deep-and-wide technical expertise, and substantial financial risks offers an interesting study of implementation. Case studies are valuable for showcasing a series of overlapping implementation environments that provide a comprehensive examination of the key challenges and risks over time.

5.2. Ethical Considerations and Data Privacy

AI and ML can make full use of data to build predictive models, but special attention is needed to ensure their ethical use and respect for individual beliefs and privacy. In particular, techniques should be aimed at large, vulnerable, or marginalized groups and should be transparent and accountable in their actions. From the data and from how the employees use it, employers should treat it with confidentiality and make sure that people know enough to give informed consent. The close supervision of the multiple stages, algorithms, and outcomes will help both users and policymakers build confidence in the model and take positive action to address social inequalities.

There are three main sources of potential bias in mechanisms; in which preventive care resides in only one of the two categories. When introduced into a predictive model, it can lead to negative outcomes, suggesting low confidence and weaker performance in small groups, as well as indirectly promoting higher discrimination, increased stigma, and the social exclusion of small groups. As a higher proportion of the data includes variables that include positive bias or inadequate sample size, it may lead to biased predictions. Finally, any analysis of the resulting prediction model by software or contract analysts will help to ensure that it is transparent, explainable, and fair. The advantage of using big data AI and machine learning technologies is that predictions can cover individuals with known conditions that may be associated. Further, insight may be gained from knowing the predictive results for the data set as a whole or for specific conditions or ethnic groups, or by clearly defining the potential of the resulting model that needs to be validated by a leading agent.

When analyzing the data to minimize predictive precision, it is possible to make significant financial and operational differences when pursuing employer intent. People working for businesses are likely aware that if they are to be optimistic, their behavior will be significant in data and games, and hence they may have been included in the company data treasury. If under-representation of the minimally observant is added due to weight, physical, or bargaining pressures, the self-selection of a three-way IRT risk can lead to too pessimistic an outcome in real situations. It is also possible to take these metadata deceptions by the employee with very costly metaphysical and statistical data. Ethically, compliance with the law not only requires adherence to relevant medical and data privacy regulations but also the confidentiality and informed consent of each employee about the use of data provided, regardless of medical staff, third-party insurers, or other business parties. At a minimum, several important steps must be taken for an e-health-related program. To secure and protect health-related data, employers are obliged to comply with relevant regulations. Other rules may also apply. Ethical compliance also requires a comprehensive analysis, drawing on the fields touched upon in this research, e.g., labor law and especially workers' rights and confidentiality, informatics law and intellectual property rights, social-technical change and the impacts of transparency and possible litigation, and corporate behavior research. The process of preventing unethical algorithm design and usage is necessary and should be audited and verified regularly. An event where de-identification failed when the publisher invested in improved data security was an example of the failure in a small software firm. Detailed case studies show not all businesses invest in the necessary security.

6. Conclusion

Predictive modeling can provide small businesses that self-fund a health plan with the ability to develop strategies to improve employee health while reducing or controlling costs. AI and ML can refine these models and methodologies to increase the impact, sometimes exponentially. At present, measures that improve health are typically expected to be at least cost-neutral and, in the best situation, cost-effective. The capabilities to review the effect on claims costs allow plan sponsors to implement only those plan features that are most effective at improving health. Even with a small sample and a short period, the process of predictive modeling has value in striving to create a better health plan. Selecting five vendors allowed for a brief survey of the AI and predictive modeling landscape. Limitations of this study include a limited analysis in this turbulent field. The proposed methodologies of the vendor were too similar to allow for a broader exploration of potential improvements in health.

The ability to compare predictive analytics firms at a deeper level is of significant value. The next step in this analysis is to research additional methodologies and technologies. The important aspect of the specific predictive model is to leverage accurate predictions into actual outcomes of improved health. Future collaborations between small businesses and AI/ML model vendors are as clear as the recommendation to continuously evaluate, adapt, and refine strategies. Researchers keep abreast of tools and AI/ML technologies that are as imperfect and rapidly evolving as the participants in this field. This work might help small businesses to understand the power and potential of one specific application.

6.1. Future Trends

Healthcare and Advanced Technologies Currently, artificial intelligence (AI) and machine learning (ML) do not get as much attention as in the fields of technology and finance. However, is recognized as the year of exponential AI and ML technologies in healthcare. These two technologies (AI and ML) will be game changers across different healthcare-related domains, including predictive modeling. AI enhances the ability to perform tasks in healthcare that exist today but with a higher degree of accuracy. It will easily create a new era of health management, predictive treatment, health providers' behavior during treatment, and much more. With AI comes the big brother ML at an even deeper level. This technology enables tools to inspect healthcare data and behavior. AI and ML are expected to bring significant changes to the healthcare landscape in different areas. Predictive modeling tools based on AI/ML can improve the prediction of outcomes significantly. For example, the integration of wearable devices and predictive tools can improve the measurement of health outcomes for health providers and health insurance companies. AI and ML are expected to bring significant innovations in healthcare in the form of behavior analytics, personalized medicine, and digital capabilities. A combination of AI/ML, predictive tools, telehealth/telemedicine, and other systems can significantly improve the performance of small business health insurance. In addition, AI and ML integration with predictive tools are experts in health management. Tools can analyze results, make accurate predictions, and provide actionable insights to improve risks. They can quickly address the costs of chronic and problematic patients. Furthermore, advancements in telehealth will also help reduce chronic patient drug costs by providing a remote monitoring station. Diabetes and kidney disease patients can gain early attention through AI and ML communication analytics.

Predictive Analytics Helps to Smoothen Health Plans: The good news is that insurance carriers and self-insured employers can use these AI and ML models to understand and improve patient behavior management by enhancing small business health plans. Based on the positive output, an improvement in participation can help achieve the desire for a healthy future. Additionally, it can also improve health outcomes and manage the triggered health claim improvements. The next scenario dashboards are therefore expected to be available that include comparative health-based HR scorecards for all small business members. The dashboards can include a series of ML-based visits that are revised and personal recommendations. However, some challenges need to be addressed while achieving significant changes in the health insurance plans of small businesses. Some of them are the ethical use of AI and ML; and avoiding bias if AI and ML continually pull the same conclusions to regulate ethical data. The health insurance sector is going to witness significant innovations due to AI/ML technologies. Therefore, small business HR managers need to stay updated about these technologies to stay ahead of their competitors. They need to have a group of workers who can analyze sophisticated statistical ML models that can predict actual health/claim outcomes. The study of these leaders is particularly critical. Only those who maintain their positions informed will gain the expertise and, for that reason, also be effective collaborators. Because future insurance sector innovations are likely to revolve around AI and ML, enabling that sector of leaders is arguably the best approach for further enhancements to be made while also overseeing struggling industries such as Medicare and Medicaid.

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