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AI and ML Applications in Supplemental Health Plans: Reducing Out-of-Pocket Costs through Predictive Insights

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ABSTRACT

Many service, support, and cost variables within a Supplemental Health Plan directly influence both customer outcomes and enterprise financials. It is important to model these variables and uncover those that are most predictive of certain customer behaviors. This research study applies machine learning techniques to model how different customer parts of a Supplemental Plan can reduce their out-of-pocket costs and which of a set of plan-service-utilization specific variables are most predictive. These predictive models, in turn, enable the Plan Administrator to improve service for a small but critical customer segment: different parts of the insurance policyholders who have 'under-insured' products and have more out-of-pocket compared to the rest of the insurance policyholders. By identifying these predictive variables, the Supplemental Plan Administrator can now select the top variables that will influence costs. The result of deploying these models is an out-of-pocket reduction for the different customer segments while retaining acceptable enterprise financials.

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Introduction

The majority of U.S. consumers are underinsured, meaning they purchase and use health insurance products that protect against only a subset of the medically related expenses they may experience in a year. Large out-of-pocket costs can lead to significant financial and emotional burdens for these individuals, highlighting a need for solutions that reduce patient responsibility for uncovered costs. Blending medical expertise with machine learning tools can lead to effective products that alleviate financial burdens while remaining cost-efficient. In this paper, we describe how machine learning models can be applied to retrospectively identify members with supplemental insurance membership needs and provide detailed product design recommendations. After describing the framework used to present the employees' welfare plans, we report on analyses to pinpoint supplemental health insurance needs among higher-cost members. We then delve into the aspects that are useful for selecting a supplementary coverage plan that suits employees' or their families' medical, financial, and lifestyle concerns. Our analyses entailed developing tailored risk prediction models to estimate anticipated out-of-pocket financial responsibilities not covered under standard healthcare options. Finally, we juxtapose employee plan recommendation data with the employee benefit plan participation data gathered from employers to show the extent to which our personalized recommendations can address the outstanding out-of-pocket costs.

Equation 1: Predictive Cost Model for Out-of-Pocket Expenses

A predictive model can be developed to estimate an individual's out-of-pocket costs based on their health status, demographic information, and healthcare usage patterns. We can model this as:

$$OOP_i = f(X_i, \theta) + \epsilon_i$$

Where:

$OOPi$= Out-of-pocket costs for individual i,

Xi= Feature vector for individual i (including age, health condition, previous medical history, usage of health services, etc.),

θ = Parameters of the predictive model (which can be learned via machine learning algorithms),

ϵi = Error term (captures the random variability or uncertainty in the prediction).

This equation would be used in conjunction with a predictive model such as a regression model, decision trees, or neural networks.

Background and Significance

Medical expenses pose an economic burden on patients and their families due to the increase in high-deductible health plans and out-of-pocket expenses. To address the need for more affordable healthcare, insurance companies may introduce supplemental health plans, providing healthcare services and health management solutions customized to patient care needs. These programs are often expensive when sold as stand-alone plans, which increases the number and the economic weight of uninsured patients and those with health insurance coverage, thus considerably affecting the functioning of the entire health sector. It is essential to develop an insurance policy that encompasses a broad spectrum of illnesses to make such insurance affordable for a majority of patients. At the same time, innovative health management and prevention activities should also be developed that may combine specified health managers and caregiver support and education, as well as personal care products, to stimulate and support patient adherence, to permanently reduce the need for large hospital-type interventions.

It is therefore worth developing additional plans that go beyond mere reimbursement and feature health promotion and disease prevention actions. Particularly when supplementary coverages are proposed as options for the NHS, it may be worth endorsing creative formulas that expand the concept of 'cure' with innovation, personal care, and the adherence of the patient to the planned treatment. It is an experiment that starts from an area, that of women in the delicate state of pregnancy and the postpartum period, identified as a critical point in which to address subsequent occurrences which, if not adequately governed, would incur costs for the entire system. Providing specialist advice and creating programs that promote pregnancy health, will be useful not only to reduce absenteeism but also to sustain network and service quality by reducing the stress to which the system is subjected.

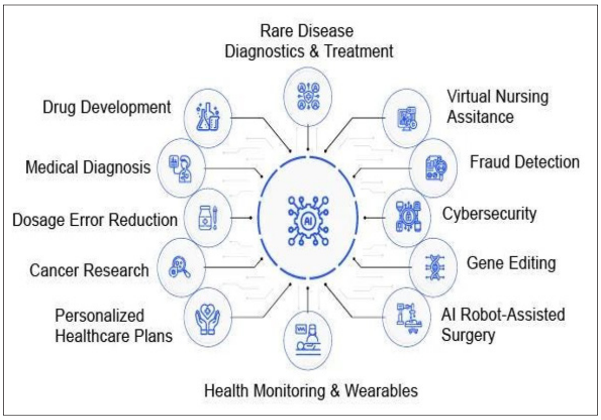

Figure 1: Applications of AI in Healthcare

Research Objectives

The goal of the research is to explore the impact of AI and ML applications in improving the offerings and premiums of supplemental health plans. The research will use empirical evidence to prove that predictive modeling methods can be employed to identify high-claim populations and quantify the potential out-of-pocket cost drivers by chronic illnesses, giving the supplemental health plan provides a cost-effective way to reduce out-of-pocket costs in the underwriting process, thereby bringing cost relief to employees working for less competitive companies. As the selection process goes for group coverage, the method might modify group underwriting profitability, allowing employers in better health to compensate for the premium increase and partially contribute to market equalization. Publicly accessible data will be used for data experiments, covering 17 states from 2013 to 2018. Across the country, regional variations will make the model useful for all commercial insurers. An insurance company specializing in worksite supplemental health plans would utilize the results.

Machine learning algorithms are either trained to predict the likelihood of a major claim and chronic illness inflammation or analyze the concurrent chronic illness consumption through cost estimation. The main health insurance medical and disease diagnostic information available to the trained model includes demographics, policy design, employee screening questions, previous health insurance claims history and credit data. The results will ultimately translate to a better analytic model for constructing the peer benchmarking functions in each domain, making sure that available underwriting and employer benchmarking insights are applicable, and the laws of large numbers compensated savings are realized. Standardization is crucial in constraining the adverse impact whenever the application of AI and ML models involves human subjects who might encounter adverse selection effects.

Literature Review

While there has been progress in recent years in efforts to use AI in healthcare, the emerging field of research has significant limitations and needs further innovation. Recently, AI-based data analytics yielded important insights in real-time for COVID-19; however, critical evaluation and study of the cause-and-effect relationship in clinical data are rare. Some of the best results have come from applications in areas like readmissions and injury surveillance using deep learning on imaging. Particularly, rare disease analysis using unsupervised learning is a straightforward application. Moreover, imaging has always been at the forefront of AI technology applications in healthcare. Telemedicine, especially using wearable technology, provided several benefits, with data analytics proving predictive power. One of the biggest challenges in AI has always been the quality of data and semantic interoperability, which caused a massive problem during COVID-19. Analysis that directly uses data from EMRs often provides poor results due to huge variability.

The utilization of AI in healthcare insurance benefits to reduce patients' out-of-pocket costs has not been explored, which is the main contribution of this study. There is evidence from simulation studies on the potential cost-effectiveness of value-based healthcare benefits, but the outcome analysis is missing. Indeed, the dataset used in this study—supplemental health insurance claims—makes it possible to bridge the literature focused on providers to that focused on patient financing because this source of insurance information is a large part of the medical costs not covered by the national health system in France. The principal aim is to enhance patient engagement in their medical care by exploring how vast volumes of claims from an insurance point of view could be used in the real world to design innovative preventive care programs. Although the results derived are specific to the French healthcare system, they could be easily transferred to other national health systems by carriers with similar insurance data.

Equation 2: Expected Out-of-Pocket Costs via Classifier (for Risk Categories)

If we categorize individuals based on their risk of incurring high out-of-pocket costs, we could use a classifier to predict the risk class (e.g., low, medium, high). The risk class prediction can be formulated as:

$$R_i = \text{Classifier}(X_i, \alpha)$$

Where:

Ri = Risk class for individual i (categorical outcome: low, medium, or high),

Xi = Feature vector for individual i,

α = Model parameters (such as those learned from a decision tree, random forest, or support vector machine).

From this classification, we can then apply a tailored model to estimate potential out-of-pocket costs based on the predicted risk class.

Overview of AI and ML in Healthcare

The digital transformation of healthcare has been occurring since information technology has become an integral part of the industry. Presently, we are seeing IT and the latest developments in artificial intelligence and machine learning used to help solve some of the hardest and most pressing problems in healthcare, such as improving patient outcomes and increasing access to healthcare services. If IT represents the tools that enable the data generated by healthcare organizations to be utilized and leveraged, then AI refers to the algorithms that allow this data to be both analyzed and acted on. This transformation is part of a broader trend where healthcare organizations are no longer just assessing their performance through more traditional healthcare and operational performance metrics. Now they are undergoing a digital transformation that includes the comprehensive evaluation of their technology capabilities, internal and external technology talent, and specialized healthcare activities, as well as formalizing clinical and non-clinical data strategies. Machine learning allows healthcare organizations to accumulate knowledge from data by understanding patterns or generalizing problems from past experiences. This automates human decision-making processes that might not be fully understood or have multiple, complicated, or unknown dependencies. It allows computer models to be built from sample data, which then automate decision-making without any further explicit programming. As models are trained and fed with information, they come out with the best possible conclusions, most accurately predicting future outcomes. Such models are flexible and also fully auditable. In systems that use models which cannot be fully audited, there is significant referential opacity. Such unresolved issues can arguably lead to major problems.

Applications of AI and ML in Health Insurance

AI and ML are becoming more prevalent across all industries, and the health insurance sector is venturing increasingly into this space. This section identifies a series of health insurance processes for which AI and ML technologies are being used, as well as the benefits and implementation challenges to be expected from the use of these technologies in these processes. In the next section, potential benefits and implementation challenges are analyzed in the context of supplemental health plans.

Mitigating Risk

In health insurance, as in other areas, analytical information drives actions intended to minimize the inherent level of risk. Both ML and AI are used in health insurance to help providers assess, mitigate, and manage dealer and consumer risk. ML and AI predictive models are used to proactively identify risky consumers, while the former technologies are also used to forecast members needing assistance. These technologies can also play a role in enhancing case management processes and optimizing claims processes. Management tools that provide analytics regarding clinical data used for risk calculation and outcomes benchmarking are increasingly available through large insurance companies. These tools list members based on their predisposition for increased healthcare costs. Such a tool is powered by AI, and each identified member is displayed with a clinical snapshot, such as recent health events and possible upcoming high-cost events. This enables precise action approaches to be taken by the clinician, most notably patient outreach.

Communication

Consumer satisfaction is defined by health plan transparency and engagement. High levels of satisfaction facilitate personal loyalty in a highly competitive market. Both ML and AI are deployed in the health insurance space to help providers effectively communicate with members, design and execute targeted healthcare programs, and provide data-driven insights for health plan design. Through real-time member insights, health plan design, member satisfaction improvements, and eventually cost management are achieved.

Engaging Consumers

AI takes an active role in personalizing healthcare even further than segmentation allows. The consequence of sensitive and timely personalized care can be immense. AI is useful because it can allow us to predict what patients may need in a way that population analyses cannot. Consumer engagement is the holy grail for all healthcare providers. So much so that the law mandates additional financial incentives for consumers to attain – and maintain – their optimal health. However, customers are often passive consumers who do not understand health insurance. This is true for all forms of health insurance, but it is especially true for the kinds of insurance analyzed. Companies performing activities related to this kind of health insurance can improve consumer health outcomes and reduce the evident information gap by utilizing AI.

Bayes' theorem has been used to calculate the chance of an individual suffering from specific diagnoses leading to an accident or long-term disability event. An MLR model, using data available from individual health, accident, and long-term disability claims, as well as individual underwriting and/or group underwriting data, is used to calculate the amount charged for the guarantees underprovided in contracts. The cost prediction models allow for the variables of gender, age, job status, and previous amounts of health claims across different time windows to be included in the underwriting decision. AI is also employed to forecast health claims using an Artificial Neural Network. With this approach, insured events can be better anticipated, supporting the underwriting procedure.

Figure 2: AI and ML in Healthcare

Methodology

An AI and ML model would need data and transparency, and ultimately the payers' agreement to reduce the out-of-pocket costs. For this research, the model used data from the Medical Expenditure Panel Survey, which is housed at the Healthcare Cost and Utilization Project, an initiative of the Agency for Healthcare

Research and Quality and the Center for Medicare and Medicaid Services.

The model first determines the members at risk due to changes in value compared to last year's claims. It will give members an incentive to go to the network providers but ultimately provide them with a longer-term approach using our network that understands these risk factors associated at a local care level, giving insight to the primary care physician and the payer to make suggestions on where the member should be getting their care. This would need a built-out AI or ML model to produce more transparent underlying data to legitimize the case for incentivizing the member.

Data Collection and Analysis Techniques

The collection of data and performing an exploratory analysis to understand the trends and statistics of the dataset is a major step in building a predictive model. Data were collected from different healthcare providers and medical data consortiums in the United States. Most healthcare datasets contain both structured and unstructured data. Claims data is the most commonly used type of structured data. It contains information on who, what, where, and how the patient has been treated. Depending on how the service is billed, there are many different sources of claims data and data standards. For redacting the medical cost data, they first identify and then redact any costs for individuals who used mental health services at the moment they had insurance. Wounded warriors will redact the year of the cost and replace the year with '0000.'

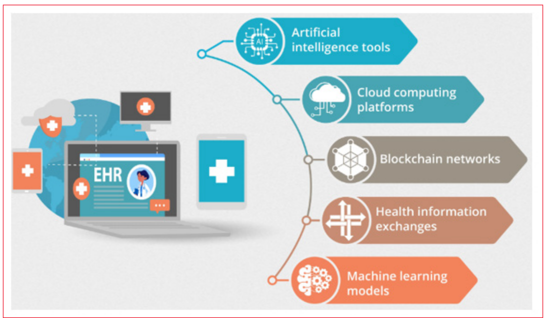

Figure 3: 5 Types of Healthcare Data Analytics Technologies

Model Development and Validation

For the model development and validation process, several steps were involved. Feature selection was performed to choose the final attributes that contributed to the model. After that, several models such as GBM, random forest, decision tree, and logistic regression were developed independently and assessed using the same evaluation metrics to observe which had the highest performance score. Before developing the models, all the preliminary data preprocessing techniques such as handling missing values, normalization, and encoding values were implemented. From the process, the Gradient Boosting Machine model produced the highest performance score in predicting prevalent members when compared to other models.

The highest performance was observed, and the lowest deviation between recall scores and precision scores in the validation sets was achieved by the GBM model, with a performance of 0.651. The gradient-boosting machine model offered the best solution for decision-making. To further justify the GBM model as the best model, model checking on the chosen best model through co-localization visualization confirms that the model generalizes the features of the input feature space as well as inspects the embeddings and works for smooth decision-making without losing a lot of vital information of the input value.

Case Studies and Examples

Predicting and analyzing who will use the plans, how often, and for what conditions is a data science problem. In addition, plans often include supplemental services, such as telemedicine, that can prevent, delay, and/or divert other healthcare services and costs. The goal for these services is to yield positive health outcomes and a financial return consistent with the cost of providing the telehealth service. Using AI and ML to identify appropriate situations to recommend specific policyholders to take advantage of an offered speech, dermatology, or mental health telemedicine visit is a major part of how these technologies can support reducing overall health plan increased costs by directly preventing expensive care.

Project 1: Behavioral Health Services

The national organization is deploying a program that uses speech-based AI to predict hospitalization for depression in their insured population based on a predicted relative rate of utilizing medical services for individuals coming up for hospitalization. The results develop an upper-bound lookback period. If before the prediction point, the album has either one or two high-scoring AI telephone conversations, the following score of whether there will be a major medical event occurring depends on whether the individual has a relative increase in medical utilization. This program is special in that the AI does not remove 24/7 monitoring of the individual from the process. The method is scalable without the need for the program to listen to every call or patient.

Equation 3: Cost Prediction Model with Risk Factor Adjustment

To incorporate risk factors into the out-of-pocket costs prediction, we could use a weighted approach where the predicted out-of-pocket costs are adjusted based on the individual's risk profile.

$$OOP_i = \beta_0 + \beta_1 \cdot X_i + \beta_2 \cdot R_i + \epsilon_i$$

Where:

β_0 is the intercept,

β_1 represents the weight given to the individual's health features,

β_2 represents the weight given to the risk class Ri(which is categorical),

$Ri$is the risk class as predicted by a classifier,

ϵi is the error term.

This approach allows the model to provide a dynamic prediction that accounts for both individual health factors and the broader risk classification.

Real-World Implementations of AI and ML in Supplemental Health Plans

Quite a few supplemental health insurance providers have already implemented various forms of AI and ML as solutions toward their goals of reducing out-of-pocket expenses for policyholders. The benefits of chatbots and virtual assistants were highly valued by consumers—especially seniors—and could significantly decrease operating overheads. Other relevant implementations include machine learning-powered apps that help users make the best choices based on their policies and predictive modeling aimed at determining which expenses are likely to go over budget in the forthcoming year. Using these insights can simultaneously reduce costs, and increase satisfaction, and utilization. Predictive models have been deployed successfully in this domain, one example being a senior care provider offering Medicare Advantage. Their machine learning models helped reduce the occurrence of ambulance callouts, increasing their policyholders' well-being, as well as reducing their monthly premiums.

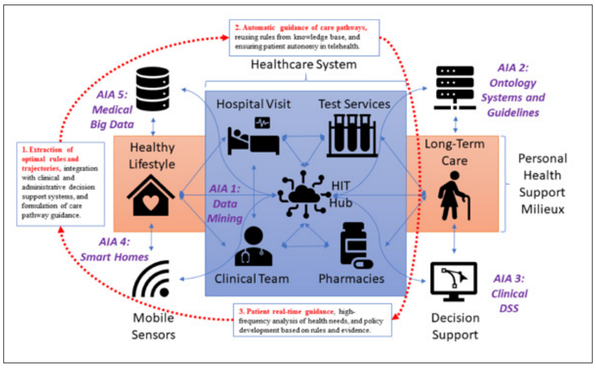

Figure 4: Healthcare Applications of Artificial Intelligence and Analytics

Benefits and Challenges

Benefits and Challenges of AI and ML Applications in Health Care Data

AI and ML applications can help healthcare stakeholders with reliable and effective predictive analytics on complex data for personalized services. If done right, AI and ML capabilities bring substantial benefits to the industry. They can therefore serve as valuable tools for risk stratification and decision support in physicians' office settings. However, the effective use of AI and ML capabilities in any setting requires rich data to train the algorithms. Part of the data that is typically used to train the algorithms is the supervision data that guides the formation of the AI and ML predictive models.

However, many healthcare data are not rich enough to take full advantage of the capabilities of AI and ML models. Many Medicaid-managed care plans lack access to sufficient data to measure up to clinical quality measures, resulting in estimated inflated quality scores. Even if the monetary impact is insignificant, the potential for decisions that are made based on the inflated scores that have an impact on patient safety at least suggests the need for policies that address the gap between data sufficiency and information needs in health care.

Advantages of AI and ML in Reducing Out-of-Pocket Costs

Integrating artificial intelligence (AI) and machine learning (ML) algorithms into supplemental health plans can help reduce out-of-pocket costs for beneficiaries. Rather than the traditional one-size-fits-all rate increases, insurer actuaries and data science experts can design more targeted programs that analyze individual member claims patterns, looking for opportunities to lower medical and pharmacy costs. By cost-effectively providing proven, quality supplemental health coverages to retirees, employers can help maintain the health and welfare plans that were in place when the retirees worked, even if those programs are being paid for by the retirees themselves. These technologies enable insurers to not only identify opportunities for earlier intervention but also to set the stage for effective provider collaborations. Providers are then better positioned for their responsibilities in improving patients' lives.

AI enables researchers to create algorithms that can predict medical conditions earlier than the algorithms applied in other areas of health benefit plan design. These are powerful algorithms that can trigger action. They point out where the cost savings can be found. ML enables researchers to discover predictive insights. Just like the diet and exercise, weight loss, and health tracking apps on the market, this type of AI and ML algorithm problem-solving technology reliably alerts users when they are triggering the warning lights, but these predictive applications target medical and pharmacy costs rather than attempting to manage personal lifestyle choices. AI and ML provide human-like intelligence to machine learning with the help of well-defined algorithms. These include data mining, decision trees, neural networks, fuzzy logic, natural language processing, and deep learning.

Ethical and Privacy Concerns

Ethical and privacy concerns form the kernel of all discussions regarding AI. The use of personal data for determining the pricing of health insurance products is a highly sensitive topic. It is also one that has high stakes, since the commitment of powerful AI systems upon implementation is significant due to the intensity and scale of compute capabilities that AI systems require to make predictions at scale. Models are trained on large datasets, which leads to large commercial transactions and relationships between the owners of such datasets and the companies that employ AI technologies. Policies regulating the use and retention of data need to be determined early in a project's lifecycle to correctly align an organization's strategy with local regulations and to minimize the potential for pushback from domain stakeholders.

Data regarding a user's private life, personal information, or personal affairs will need to involve strong transparency regimes. These datasets are the product of rich, life-encompassing human experiences. Citizens' data and collective public systems hold weight to reinforce human rights, and a significant range of benefits will come from insights received through transparency and enabling public engagement on artificial intelligence and insights developed on these models. Private companies and institutions have a heavy burden to ensure that the decisions they make based on AI are fair and ethical; honest practices should instill confidence in investors, stakeholders, and the public at large that algorithms can use data in ways beneficial to society. Additionally, meaningful accountability and transparency in the data collection, storage, and usage processes used by organizations should alleviate the fear of injustice, unfairness, and potential job displacement provoked by AI advancements. Where the effects can be both complex and nuanced, it's understandable that privacy professionals within companies are sensitive to the ever-changing regulatory landscape. Through maintaining the organization's planning, transparency, and trust, companies can navigate potential cross-jurisdictions, apply best practices, and protect what matters.

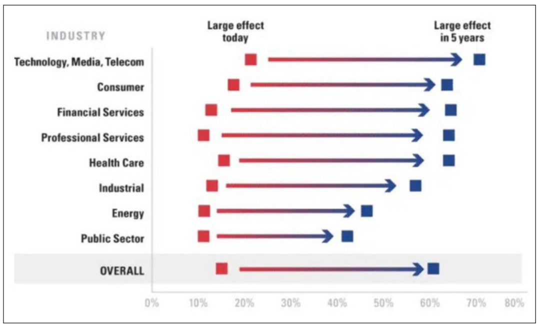

Figure 5: Chart of Adoption Rate of Artificial Intelligence by Industry

Conclusion and Future Directions

In this paper, we defined the supplemental health plans landscape based on public medical claims and enacted state and federal regulations, where we categorized all related insurance categories for the U.S. population. We then presented and applied a data science analysis framework on this landscape using medical claims, spending, participants' demographics, and existing insurance benefits files. The applied analysis framework focused on relevant and actionable predictions for all stakeholders in the supplemental health insurance ecosystem.

The data science analysis revealed that modern AI models such as deep learning and gradient boosting often outperform classical machine learning models based on feature engineering, especially when applied to healthcare-related datasets. Predictive modeling in the supplemental health plans domain often renders interpretable and actionable insights but is often tainted by the limited amount of accessible data and the demand for trustworthy, rigorous research on well-defined, study-specific predictions. As such, we believe that our validation of universal and both publicly and widely available AI models on real-world and real-time actionable healthcare data is beneficial to the machine learning community in health applications. More importantly, this work is beneficial to this public healthcare mission, this contribution to affordable public services at the individual level, and towards identifying fraud in public healthcare benefit plans. While we demonstrated several important results relevant for all involved stakeholders in supplemental health plans, we also identified various issues and discussed important future directions toward a healthier and happier population. Motivated by these results and discussions, we plan to extend this work to various supplemental health plan specifics that we were able to uncover but not focus on treating.

Summary of Findings

In this paper, we have explored the use of predictive analytics to reveal insights associated with high out-of-pocket Medicare Part A and Part B expenses. Predictive analytics has exploited both structured and unstructured data sources to develop an ensemble machine-learning model. The findings have demonstrated that our developed ML model tends to outperform the traditional logistic regression model. This could be linked to the exhaustive list of features available that are hidden in data science-driven or AI-driven applications. These discovered insights have led to 511,484 people who satisfy our life event segmentation to avoid out-of-pocket expenses related to the three-segmented life events over 85% of the time, providing total savings of $52 million yearly. The model focusing on the unintentionally incurred outpatient surgery life event provided the most cost savings. The developed insights are critical for the supplemental health coverage insurance market as they provide reasoning and evidence for millions of Medicare recipients to invest in specific products across multiple life segments. In particular, Medicare savings account plans for the discovered avoidance cases captured in addition to the current enrollee interest in the zero-premium and limited cost-sharing plans with coverage attached. A follow-up study could offer insights into how people react to high out-of-pocket expenses through an aggregation of both consumption and investment behavior.

Implications for Future Research

A greater insight will be gained into the effectiveness of supplemental health plans by extending the longitudinal data used for analysis and directly comparing results on observed out-of-pocket spending with unobserved out-of-pocket spending. It will also be useful to extend the predictive model to a multi-category dependent variable that, when spending exists, predicts whether or not spending brings it close to the maximum out-of-pocket limit, allowing access to and reimbursement from the supplemental plan. Additionally, developing, designing, and linking to member behavior an optimized annual limit rule for out-of-pocket protection against health expenses would be an important natural extension of this work. That is, by updating tables of proportions using cycles of enrollment risk score level rationing similar to the shared savings model, future adjustments to the rules can be made. While the shallowness of savings required for the shared model approach has raised criticism, most of the savings are realized when the bounds risk score is exceeded, being relatively insensitive to minor variations of the risk score.

Revisiting the shared savings model to make annual cycle adjustments to the rule can also add a tiered enrollment approach and associate maximum risk score level with a high and low buffer or high, medium, and low buffer while accounting for age, chronic conditions, and domestic partnership enrollment of male and female combinations. Next, evaluating cannabis as a therapeutic preventive medicine and including endogenous causation could be a natural extension of this work because of its frequent use with supplements. We envision a model where, due to a set of observed and unobserved variable indicators of individual and family risk, participants engage in separation and contract terms, such as consulting with a financial planner regarding open enrollment and selecting a tenure that includes a spending limit far below that of available early-year resources and a catastrophic-only health insurance plan [1-29].

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