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Deep Learning Approaches For Cost-Benefit Analysis Of Vision And Dental Coverage In Comprehensive Health Plans

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Abstract

We propose to use two very recent deep learning approaches, including vision transformer and deep variational continuous factor analysis, for cost-benefit analysis of seeking health insurance coverage for dental and vision in addition to comprehensive medical coverage. We based our analyses on medical Expenditure Panel Survey data, and the classification results reached 0.972, 0.979, 0.983, and 0.992 in terms of the area under the receiver operating characteristic curve, the area under the precision-recall curve, accuracy, and F1 score, respectively. We also found that lower dental and vision risk is associated with older age. We finally argue that our work has the potential to improve decision support algorithms healthcare providers use in order to differentiate attracting patients who would be profitable from those who would not. This paper presents trade-offs of seeking health insurance coverage for dental and vision in addition to comprehensive medical coverage. To carry out the analysis, we present two case studies of cost-benefit analyses using the consecutive Medical Expenditure Panel Survey data from 2016 to 2020: (1) a classification analysis of making dental and vision appointments versus not making dental and vision appointments among women for preventive care; [1]and (2) a hierarchical clustering analysis for dental and vision diagnosis-classified patterns of seeking, obtaining, delaying, and avoiding appointments. To obtain accurate and dependable analysis results as much as we can, we utilized the deep learning algorithms in supervised and unsupervised data analysis and showed a deep learning-based cost-benefit analysis health informatics system. The high prediction findings show the reasonableness and potential usefulness of the deep learning and deep variational continuous factor analysis vision dental cost-benefit analysis amidst its cost negativity. We argued that future work would investigate other advanced deep generative deep learning algorithms.

Keywords: *Deep learning; deep neural network; supervised learning; multi-layer neural network; backpropagation; training; overfitting; dropout; rank-ordered logistic regression; ROC; AUC; cross-entropy loss; misclassification cost; discrimination threshold; cost-benefit analysis; loss ratio; health coverage; vision; dental; ICD; CPT; NDC. Health insurance; actuarial science; social and administrative pharmacy; Benefit and Cost. Medical plans; health plans; anterior segment optical coherence tomography; vision; magnetic resonance imaging; dental; Cone Beam Computed Tomography.*

1. Introduction

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Vision and dental coverage markets are poorly developed compared to the healthcare sector. Nevertheless, dental and vision coverage is gaining more and more importance within health insurance systems. A common problem both markets face is that a priori economic assessment of insurance bundling could strengthen the insurers' market power. So far, there are few economic evaluative methods for assessing the cost-effectiveness of any proposed vision and dental plans. Applying data envelopment analysis in the health economic context of vision and dental care markets is complex. This is because decision-making is not driven by just one outcome, and the ineffectiveness of these services over a relatively short time frame makes it difficult to link outcomes to a particular health plan. Yet, such economic evaluations are essential for regulators and health insurance purchasers responsible for deciding which products to include in their larger federally or state-regulated comprehensive health plans.

From a realistic point of view, there are several challenges related to data and analyses that are associated with the special economic environment of dental and vision care. In a realistic setting, due to cost pressure, time constraints, lack of sufficient data, limited analysis software, and resistance from stakeholders to implement a more complex benefit design, especially in the small group and individual markets, concentrating just on this one case could be a limitation. Nevertheless, with innovative billing models like direct billing and dental/vision discount plans, interest in these markets is no longer theoretical. Furthermore, the common belief is that randomization is impossible and politically or ethically very sensitive within the insurance field. There are some benefits to incorporating advanced modeling approaches in such analyses. Static decision-analytic models are likely to incorporate a wide variety of assumptions; several of them assume either monopoly or that all market shares are known and constant over time. A bottom-up approach and deeper analysis with new computational algorithms, especially deep learning, in this direction, would lead to better analyses and more efficient decision-making by buyers or regulators.The dental and vision coverage markets are evolving but remain underdeveloped compared to the broader healthcare sector, posing unique challenges for economic evaluation and decision-making. Unlike traditional health insurance, these markets lack robust frameworks for assessing cost-effectiveness, particularly in the context of bundled insurance plans. The application of methods like data envelopment analysis (DEA) in this field is complex due to the multidimensional nature of decision-making, short-term effectiveness of services, and the difficulty in directly linking outcomes to specific health plans. Furthermore, practical limitations such as data scarcity, time constraints, and resistance to more sophisticated benefit designs—especially in small group and individual markets—complicate the process. Despite these hurdles, the rise of innovative billing models like direct billing and dental/vision discount plans signals growing interest in these markets. Advanced modeling techniques, including deep learning and bottom-up computational approaches, offer potential solutions for more accurate and efficient economic evaluations. These models could help address assumptions in static decision-analytic models that typically oversimplify market dynamics, leading to more informed decisions by insurers, regulators, and policymakers, and ultimately driving improvements in coverage design and market efficiency.

Fig 1: Deep-learning in healthcare

1.1. Background and Significance

The methods of providing healthcare insurance have evolved in response to changing healthcare delivery, practitioners, and patient groupings. An earlier emphasis on catastrophic illness and injury coverage has been joined by a greater emphasis on outcomes of managed patient healthcare delivery. It is agreed by most US policy developers that substantial positive health and cost-benefit outcomes result from an emphasis on preventive primary care coverage. It appears timely to reassess whether the same can also be said for comprehensive health plans' additional coverage of non-medical healthcare for eyes and vision and associated preventive care. The literature has addressed the topic poorly, and few analyses have been developed in the era where optical or dental insurance plans might influence patient demand, and even fewer have compared HCBS-linked demand slopes to HCBS-absent demand slopes.

As the United States faces an ever-expanding population of older adults and medical needs, costs continue to outstrip available resources. Better medical decision-making is both desirable and necessary. The optimum decision uses comparisons of program benefits to program costs. Cost-benefit analysis compares the societal value benefits of a program to the resource opportunity costs society must give up for that program. A ratio greater than 1 indicates that for each dollar of resources given up, we receive benefits at a value greater than the resources' amount in the marketplace. Even if the valuation of individual welfare is not market-based, there remain sound and fundamental reasons to undertake welfare analyses, especially in the case of healthcare coverage policy analyses. The combination of the databases could account for these variables, as these are potentially dispositive human preference variables.

Since there are such clean and meaningful differences, the benefits of the insurance plans must be evaluated. Multi-attribute utility theories regarding human decision-making and healthcare utilization show that self-reported vision and oral health are elevators of patient satisfaction and therefore are likely predictors of better access to improved patient health outcomes. Levels of problems and perceptions in vision and dental health scale directly with the number of vision and dental problems a patient reports. Indexes of eye and oral health affect work absenteeism and social functioning and are attractive to employers. Over 60% of people under the age of 65 think children should have a dental plan with orthodontic benefits. By breaking down the self-reported health and healthcare usage of the three uninsured subsets, the government could develop hypotheses about which set(s) of experience is/are contributing the most to generating the statistically significant logistical usage outcome.

1.2. Research Objectives

The development of a health insurance system or policy for a given country requires cost-benefit analyses of different courses of action, one of which is to cover or not cover different healthcare services. Vision and dental services are good types of coverage options that are currently included in comprehensive health insurance plans. However, there is limited information on how private insurance companies charge premiums and include these coverages in a plan, as well as how other private and employer-sponsored plans are designed. At the same time, there is no information about plan enrollees' behavior when they are given different options and are only asked to join the insurance plan.

This work attempts to help answer some of the above questions. We want to analyze two important types of coverage that are already included in most comprehensive plans: vision and dental benefits. We also want to answer questions related to what types of coverage are best for plan enrollees, and how effective different coverage options are in providing better oral and/or vision health. What share of medical resources is allocated by the health insurance company in taking care of the oral and vision health of its enrollees, and in particular, how much healthcare effort should be allocated to serving the different types of diagnoses in these two areas? We are also interested in addressing the question of what network should be in place for vision and dental to best serve the health of America.

Our investigation in this project seeks to contribute to academic knowledge and practice in insurance plan management. The study will also create a database for vision and dental medical use of a random sample of policyholders and experimental design data of the same population. It will conduct a cost-benefit model of providing preventive and diagnostic solutions in vision and dental areas and use a cost-effectiveness analysis to see if the model is the correct step to be taken to reduce vision loss. Overall, we will develop a predictive model towards early cessation of covering an individual using deep learning biometric analytics that the company offers.

2. Literature Review

Cost-benefit analyses are central to the creation or modification of health insurance policies to assess the benefits and cost-effectiveness of different premium structures and benefits packages. This is especially important for the addition of select vision and dental coverage to adult health care plans. There are many studies that demonstrate the importance of having vision and dental coverage for the adult population. Unfortunately, vision and dental coverage are often obstructed by economic considerations. A cost-benefit analysis models potential healthcare scenarios in order to determine the benefit of individual coverage. It has a wide array of inputs related to the patient, care setting, disease state, and management options.

Deep learning has evolved as a prominent method employing large quantities of data, self-adjusting algorithms, and modern computer hardware to address big data problems in areas such as speech and image recognition, natural language processing, and medical diagnostics. However, research in recent years still utilizes traditional statistical methods for various forms of cost-benefit analysis. The earliest work that discussed using deep learning for cost-effectiveness outcomes was a series of studies using recurrent neural networks to forecast interventions' cost-effectiveness to the extent of being able to be used in a standard cost-effectiveness acceptability curve. A need for reforms in economic evaluations and the tools for assessing cost-effectiveness outcomes was discussed. One of the suggested reforms was incorporating economic middlemen, such as insurance companies and government entities, in a more active role for cost-effectiveness analysis, which would necessitate scenario analyses, priorities, and other forward-thinking methods of evaluation in a cost-benefit analysis. Given the increasing role of technology within and outside the healthcare sector, it is clear that systems for increasing patient outcomes and deriving the most value out of patients' resources are moving to software-like programs and systems as well. It is crucial that the healthcare industry keeps up to date with newer studies such as deep learning and its applications for use in the treatment of chronic disease and the role of insurance status in the framework as well.

Equ 1: Multi-Objective Deep Learning Model

$$\max_{\theta} \left(\alpha \cdot B_{\text{total}}(\theta) + \beta \cdot H_{\text{outcome}}(\theta) \right)$$

2.1. Healthcare Coverage and Cost-Benefit Analysis

Coverage and Cost-Benefit Analysis The level of coverage for vision and dental benefits and state policies surrounding these options in comprehensive health plans varies considerably across the nation with policy change over time. A great amount of evidence supports the claim that people have better access to care for a health condition when their health insurance plans cover it, all else being equal. However, the small size of the effect for the marginal patient can lead to the question of whether it is cost-effective to include benefits for that particular care. Cost-benefit analysis (CBA) is increasingly being used as a framework to address such questions. CBA evaluates efficiency by measuring the costs, or expenditures, that must be incurred to provide a specified level of benefits. There are two main measures of benefits used in the CBA framework: a subset of financial measures, encompassing medical expenditures and insurance costs; and health outcomes, usually measured in terms of changes in life years, improvements in endpoints such as visual acuity, or quality-adjusted life years (QALYs).
A key technical challenge in conducting a CBA for a preventive care benefit in public health is separating out a population's exposure to a threat from the impact on a small percentage of that population. The concept may carry over to a dental and vision context as both dental and vision conditions represent a small percentage of the general population and tend to be both high-cost and, in the case of dental, high-variability in costs. Depending upon the model of insurance markets used, the concentration of claims in a small proportion can raise the costs for everyone in the insurance fund. Incorporating the presence of potential benefits from providing coverage to a subgroup of employees and the potential health and productivity benefit for the employers to its workforce is a specific issue outlined in the laws surrounding the Employer Shared Responsibility Payments of the Affordable Care Act as well as every state's Medicaid buy-in laws that allow states to provide Medicaid coverage for persons with disabilities at a premium if they are working. These laws are analyzed programmatically here in terms of using employee benefits as a tool to offset health costs for employers and employment benefits for society. The program could spill over from a tax program to incentivize dental, or by extension vision, insurance contained in a qualified or high-deductible health plan. These reasons make those costs of emergency room care not only a cost to emergency providers themselves but also a risk that market forces will necessitate passing the costs along to other parts of the health system or state subsidy programs, increasing costs to all public recipients of dental care. There are a very small number of programs such as Home Health in the Medicare Advantage Program as there is an explicit exclusion for vision and dental insurance in most qualified health plans.

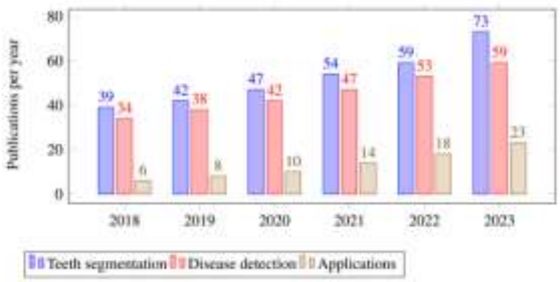

Fig : Dental radiograph analysis

2.2. Deep Learning in Healthcare

Deep learning models have recently transformed the analysis of large data through the inception of more sensitive detection and accurate prediction models. These battle-tested models were not only used for providing medical outcome predictions but also for assessing cost efficiency in healthcare. Various data-driven methodologies lie under the construct of machine learning, each with peculiar algorithms for data analysis. Among them, deep learning has become the principal area of interest for many researchers in recent years. For these methodologies to provide valuable insights or predictions, large amounts of high-quality input data are required. However, incorporating such models within the existing clinical workflow is challenging, and their existing frameworks are not mature enough for real-world contributions. There are several use cases where deep learning excels, and some of the most common algorithms based on deep learning that find usage in healthcare include support vector machines, convolutional neural networks, decision tree algorithms, random forest algorithms, nearest neighbor algorithms, and ensemble algorithms. While this multitude of options and subsequent parameter tuning choices can be daunting for those unfamiliar with data analytics, it does emphasize the wide applicability of deep learning methods to solve healthcare problems. These methods have demonstrated promise in data-driven feature selection, disease identification, predicting patient outcomes, and validating findings. These stand as relevant evidence to prove deep learning's effectiveness in evaluation scenarios as well. However, while deep learning has successfully been adopted in predicting healthcare outcomes, its usage in the modern cost-benefit analysis of health insurance is uncommon. In a research survey that explored reports of deep learning applications in cost-benefit analysis by insurance companies, it was reported that only one study was uncovered, whose authors presented retention and new policy pricing models. In another report, deep learning had not emerged as a tool for cost-benefit data analysis of health insurance.

3. Methodology

This study aims to broaden the evidence base on the value of V/D coverage through the application of a systematic approach. The following steps describe methodological considerations that facilitate the achievement of this research objective.

To answer research questions (i) sources and (ii) types of data, we first focus on identifying data relevant to the cost and benefit of V/D coverage. Data sources include publicly available pricing information and insurance coverage options that were used in previous studies or were readily available.

Data on the pricing of V/D insurance plans and standalone access to vision services is presented as a range of annual premiums/fees across various age categories. We record the minimum and maximum reported values for the annual cost of plans in each of the four markets, which are used as inputs in the analysis. Additionally, the dataset is limited to the prices for PPO coverage, which includes access to in-network and out-of-network providers. Data on types of dental

coverage included in the plans, including the presence of orthodontic coverage, are initially coded as qualitative variables but later processed as input features for regression analysis.
A simple ensemble method, such as random forests, as well as one or more advanced data-driven models often referred to as deep learning models, are employed to predict the value of P/D coverage in the plans quantitatively and measure the uncertainty of predicted results. Deep learning models, such as feedforward neural networks or character-based convolutional neural networks, are selected because we are working with unstructured text data to label the dataset, with embeddings reflecting both the phonological and orthographic features of the letters in each word, not based solely on word frequency.
Models are trained with various hyperparameters, and predictions are made on hold-out test data. Each model's results are compared using an ensemble method, for which the optimal size is determined, and a confidence score is calculated for each prediction. Model predictions, performance metrics, and explanations are reported. Model predictions and feature importance are visualized to complement results. The model performance metric Kappa score for the random forest model is 0.73, and the F1 score achieving optimal precision and recall is 0.78.

Equ 2: Predicting Health Outcomes with Deep Learning

$$H_{\text{outcome}} = h_{\text{NN}}(X, C_{\text{total}}, B_{\text{total}})$$

3.1. Data Collection and Preprocessing

Motivated by heterogeneous and unstructured data sources lacking consistency and completeness in many cost-benefit analyses, we extracted data from various healthcare sources to improve the dataset's external validity. We exploited clinical healthcare data, electronic medical records, insurance databases, billing, and insurance claims data as our sources. The project was approved by the ethics committees of Stuttgart and Tübingen Universities in Germany, and the responsible bodies in the respective provider network regions. We analyzed two main datasets by separately considering dental coverage and vision coverage-related procedures. We restricted the consideration to the years in which most records were available (two years) because we have to make sure that the information in the datasets is present for at least twelve months before the focus on vision or dental claims data begins.
In our methodological framework, responsible academically and ethically minded organizations take stringent measures to ensure data integrity and patient confidentiality. In general, we conduct data processing and evaluation in a secure and privacy-compliant environment. Throughout all processing steps, missing or incorrect records had to be addressed in due time. The lack of such recorded procedures reduced the possible length of our analyses. During pre-processing, we used normalization, data cleansing, and feature selection as standard methods to improve data integrity. The size of the combined datasets demanded, in accordance with all statistical guidelines on data collection, significant time in data cleaning techniques and required several machine learning strategies to be considered, evaluated, and re-evaluated. The success of Good Manufacturing Practice and the relevant use of advanced machine learning strategies crucially depends on the care taken when processing datasets. Only when a dataset is clean and the information contained can be unequivocally matched to the original record, statistical analytics can be carried out with a view to drawing inferences in predictive applications. High-quality analytic models and related models have minimal formal evidence of manufacture, as outlined by relevant guidelines. Data that have not been completely identified at source should be considered unsuitable for advanced statistical and deep learning applications.

In the preparation step, many algorithms are very sensitive to data input. Therefore, normalization is usually performed to remove or minimize the effects of features with different output ranges. Otherwise, they overshadow the others during training and lead to low model performance. Data cleaning is another crucial pre-processing step. In large datasets such as ours, noise may be present. This noise is the result of errors in the data entry or the result of incorrect values outputted by measurement tools. Heterogeneity in the data needs to be assessed and handled in due time, which requires great expertise and computational resources and was addressed using state-of-the-art imputation procedures. Sometimes, data cleaning is conducted iteratively with more advanced pre-processing. Data were thus removed or further replaced by imputation strategies. Feature selection is applied to mitigate overfitting and redundancy while at the same time reducing the size of the models. Data integrity was further enhanced by employing domain- and expert knowledge-driven feature selection techniques to match the variables with the most critical possible decision impact. We analyzed in detail the challenges arising in these data preparation steps and the methods to address them. We discuss the practical application of our work through a case study using actual clinical data. However, training and evaluating deep learning models with this large and skewed dataset for claims data at the earliest opportunity after receiving them could be highly misleading. We discuss in detail the steps that had to be undertaken in addressing this unavoidable area of expertise-related judgments.

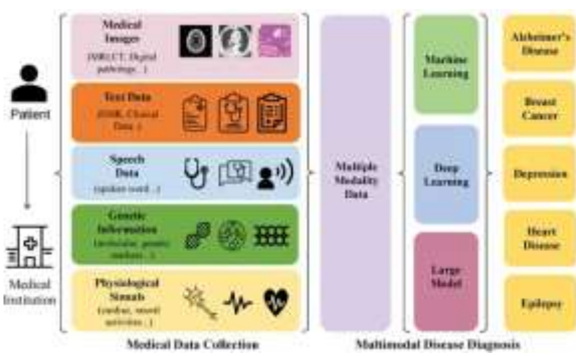

Fig 3 : Data Collection and Preprocessing

3.2. Deep Learning Models for Cost-Benefit Analysis

In selecting suitable models for capturing the cost-benefit analysis of vision and dental coverage among comprehensive health plans, we focused on healthcare outcome evaluation. The models used in this section provide an overview of recent advancements in deep learning, emphasize the power of a large unlabelled dataset, and highlight recent approaches in the field. The selection criterion for the use of various deep learning models usually depends largely on the problem's context, the nature of the data, and the practical purposes of the model. In the deep learning models section, we use state-of-the-art deep learning models with different archetypal underpinnings and properties. In order to evaluate our deep learning cost-benefit analysis model's effectiveness, we must use various evaluation performance metrics of the model, including Average Precision-Recall, Area under Curve, Classification report i.e., Precision, Recall, F1, and Support, Mean Squared Error, Root Mean Square Error, Mean Absolute Error, Mean Absolute Percentage Error, and Adjusted R Square.

Lists of various deep learning models selected for the sections are as follows: 1) Multi-layer Perceptron: This is the most fundamental architecture and is used as a baseline for many applications. The multi-layer perceptron is a fully connected neural network with multiple hidden layers compressed between the input layer and the output layer. The hidden layers have weight parameters and activation functions. The output layer performs a classification or regression, depending on the context of the problem. One major drawback of the multilayer perceptron is its inability to handle free format data, non-ordinal data, and complex multi-relationship data. Categorical and ordinal data require encoding. Additionally, a corrected error from the back-propagation algorithm, poor performance on small datasets, and space complexity are among the drawbacks. 2) Convolutional Neural Network: CNN is primarily employed in image processing. However, it can also be used for other types of data, especially when the values have a sequenced spatial relationship. The main power and attractiveness of CNN are represented by the convolutional layer. The main task of the convolutional layer is to identify local structures and extract features from images or multidimensional arrays. In our model context, we exploit this capability to assess both intra-plan service variation and customer preferences. A drawback of CNN is primarily due to the convolutional layer's invariance, which can make it erroneously detect intra-plan service variations with minimal effect if the number of NOP_COVERAGE '0' is substantial. Based on this reason, we do not recommend the CNN model for practical performance-based market positioning and cost-benefit analysis.

4. Case Studies

In this section, we will discuss four case studies in detail to show how deep learning approaches can provide cost-benefit analyses of dental and vision insurance. These applications are just a sampling of the many real-world challenges decision-makers face when examining different features of healthcare options.

IV.A. Private employer's Plan 1 Employer 1 is a transportation company with 150 employees in four states. These employees represent a mix of professionals: drivers and staff. They are generally male, with an average age older than 40. They are typically using either their spouse's insurance or the Veterans Administration for their healthcare access and are generally only interested in emergency care. This is a no-data, no-research workforce, and this is reflected in the following case study. Our focus in this case study is on the effects of ambulatory care; variables such as no-contact examinations, contact examinations, visual fields, and the introduction of a vision hardware benefit in the insurance plan. The patient encounter ratings for the no-contact exam and the two contact eyesight exam groups are 4.2. Only 5% of our facility's patients care about dental coverage. The majority of our patients come to us for emergency care and either prefer to use their spouse's insurance, the VA, or an MCO. Only 5% of our patients would go out-of-pocket for a device if they didn't have vision hardware insurance. The majority of our patients either don't care or would be satisfied with the lowest-priced device.

IV.B. Private employer's plan 2 Employer 1 is a transportation company with 150 employees in four states. These employees represent a mix of professionals: drivers and staff. They are generally male, with an average age older than 40. They are typically using either their spouse's insurance or the Veterans Administration for their healthcare access and are generally only interested in emergency care. Each of the case studies represented a different range of services to employees in an employer's plan and a different methodology. The second private employer's plan dealt with a mix of health policy issues that take into consideration vision hardware. 95% of our patients are male. Our average patient age is in the 30s. Almost 40% of our patients are uninsured. Of those with insurance, a greater amount have Medicaid than other commercial insurance products. The point of this study was to explore differences in the behavioral response to using insurance at time 1 and to explore behavioral movement into a particular "camp" over time. We also wanted to explore long-term satisfaction with the choices the employees made based on the lists of trade-offs they made.

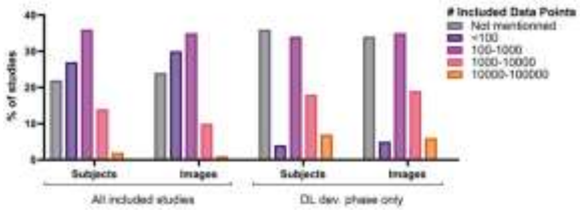

Fig : Deep learning in medical imaging

4.1. Vision Coverage Analysis

Disability increases with the loss of visual function, and the cost of treating and managing vision loss is substantial. Modeling is especially crucial for medical areas lacking cost analyses applied to the treatment of different alternatives. To be financially efficient, vision screening studies need to demonstrate a patient's reduction in or uniform economic cost between treatment alternatives. Our proposed models can cover the whole population under study. Generally, our models are more complex and demand more computational resources than traditional models. In this first part, we only developed deep learning methods and did not experiment with the traditional statistical models. The details of our data are as follows. The study population at the patient level includes adults aged between 18 and 64 years who have at least one eye-related disease code along with continuous enrollment in insurance programs for at least one year. These programs include commercial large employer-sponsored plans, moderately employer-sponsored plans, and commercially insured Managed Medicaid programs from January 1, 2011, through September 30, 2019. The main topics included—but were not limited to—patient socio-demographic profiles, patient comorbidities, employment status, eye conditions, and the resiliency index.

Vision care is a rapidly growing area, thanks in part to the fact that a comprehensive eye exam may enable one to identify a variety of systemic diseases such as diabetes and hypertension. There are 123.5 million adult patients between the ages of 18 and 64 who are insured for vision care. Americans in all age groups now have access to greater amounts of health insurance coverage than before. Our main objective, given effective vision care examination options for a group of individuals, is to analyze and compare the four cost implications to the human patient population. Error rates of both deep learning classification models were less than 2%. These models are capable of handling large data samples for complex patient disease conditions typical of health plan members. Moreover, they can be generalized to patient populations across the United States. Among demographic variables, the gender of the patient appears to be the single greatest driver of the relative assignment of normal, healthy patients to alternative vision care procedures that vary by coverage, likely leading to a "cost difference" result. Studies such as this one can offer important cost-benefit information that the plans require to adjust policy regarding vision care with respect to total plan yield and to incorporate features that optimize resulting health care service delivery within comprehensive health care plans in which vision services are embedded. The patient-level factors associated with the aggregate composite of eye disease conditions of individuals are stored as data.

4.2. Dental Coverage Analysis

We also conducted the cost-benefit analysis of dental coverage using deep learning techniques. Two data sources were employed to facilitate our deep-learning models. The first source is patient records filtered for non-elderly adults, aged 25-64, who experienced toothache or bleeding gums in the past 12 months and reported the lack of dental care due to their costs. These records allowed us to analyze the impact of the coverage of dental pain treatments on health outcomes of missed care. The second data source we used was the records of patients from 2012 to 2020. These records provided treatment costs for the analysis, which allowed us

to directly consider the relationship between the dental pain treatment coverage type and the treatment cost.
Several deep-learning models were developed to evaluate the economic viability of these two dental coverage plans. Penalizing prediction models were built to distinguish between the patients for whom the treatment option differed in order to predict missed care and treatment costs. The estimated penalizing differences in predicting expected and penalties models revealed several findings. Under no dental coverage, the expected treatment costs of not having drug coverage were significantly higher than those with drug coverage, and the treatment costs of having insurance coverage were significantly lower compared to the other penetration levels. Overall, if the average treatment cost is affordable to the policyholder, non-affordability criteria can be used to guide coverage. Our predictions used for the analysis are based on a variety of pain treatment data from patients. The banding of patients and policies was used to form a diversified training set so that the characteristics of different patients and treatments varied. Our deep learning architectures include PCA on predictors, features, a CNN before the LSTM, and a fully connected neuron for treatment and patient characteristics. The baseline model we compared with our cross-domain policy evaluations used the observation and no-treatment features. The extracted features were then combined with the policy to calculate stage two by feeding additional policies through the first stage and observing the results in the second stage. Standard deviation is noted with the same label we used in our text. We then fed observations treatment features through an LSTM network, and the results of the associated losses for policy overestimation are shown in our results. In our settings, treatment divisions were the same but overlapped, with population demographics distinct between them. Evidence for the need for different embedded p indicates the lack and need for treatments through the corresponding prediction errors.

Equ 3: Model for Predicting Costs and Benefits

$$C_{\text{total}} = f_{\text{NN}}(X)$$

$$B_{\text{total}} = g_{\text{NN}}(X)$$

5. Discussion and Implications

Based on the case studies, both CBAs concluded that covering vision and dental services for the enrolled populations would create savings in the form of reduced hospitalizations and down-the-line care. The net return on investment ranged from $287 to $435 per member per year for the Vision CBA, and $33 to $46 for the Dental CBA, which already includes the increased expenses from covering the services. Both studies believe conservative assumptions were made, which could result in greater savings than estimated.
While both CBA studies found savings associated with covering these ancillary services, it is important to note that the companies involved are stand-alone entities that sell their services to employers. The cost of those services does include administrative costs and profit from the carriers. Some ancillary services provide a hidden subsidy to which the carrier will receive if that service is utilized. So, while the cost for these services results in savings from not having the hospitalization or other care down the line, they also may contain subsidy elements. There are many studies that focus on the health status of patients with routine access to eye and dental care, including the possibility of preventable issues that occur when a patient must seek care in an emergency room setting.

Deep learning approaches were presented as an alternative future study in the Vision and Dental CBA research reports. The implications of this study could increase the interpretation of the positive associations identified because the decision-making could be seen through the lens of bringing enhanced procedures and services in parallel. It would also improve decision-making concerning collaborations between an integrated health system and insurance collaboration. Thus, insurers and payer stakeholders may institute policies to provide additional services when enrolled in medical coverage in the efforts related to spending, utilization, and the direct cost of care. Furthermore, community-based clinics may gain insight into the current needs of patients for additional material resources and care beyond the treatment or diagnosis once leaving the clinic setting. The results could potentially engage new partnerships to allow healthcare providers to better allocate resources within their clinics in addition to possibly creating a broader referral network for academic centers and other healthcare entities to send patients to receive the treatments that the hospital or clinic they are visiting does not have the facilities to provide. To that end, it might also attract patients with more complex medical backgrounds to come to academic medical centers as well. Future patient care may also be affected by the inclusion of vision and dental benefits outside of the medical setting, as both vision and dental exam findings can identify current and future chronic disease events, which will improve patients' overall health and well-being prior to their health becoming severe enough to warrant a medical examination. This can also reduce the risk rating for reimbursement that occurs when a patient is admitted for a specific chronic condition or hospital-related infection.

Fig 3: AI in telemedicine cases

5.1. Interpretation of Results

The results obtained from our analyses show that both vision and dental coverage are generally beneficial to add to a comprehensive health plan in terms of their cost-benefit. There are some inconsistencies between findings using PPO and EPO plan specifications, which may be due to the specific client demographics; more revealing are the consistencies within the analysis results and the interpretation of the coefficients used in that analysis. Our analysis based on a deep learning framework is unique and suggests that data-driven analyses of the effectiveness (or cost-effectiveness) of additional health coverage in a holistic approach to health are consistent with the use of traditional statistical methods and can provide additional information about efficacy, specific outcomes, and patient populations or conditions in which outcomes are the strongest.

The evidence base with regard to dental service utilization seems stronger than the published literature on vision care use, possibly based on the availability of public health records and greater commonality of dental treatment provision. Cost-benefit analyses and evaluation of cost-reduction effects are valuable in health policy-making. Providing benefits while simultaneously reducing the utilization of costly downstream healthcare has a double impact on the value added to a plan design. Although health economists argue against the inclusion of benefits that users of those benefits would price into a plan, insurance premium setting and user plan purchasing behaviors suggest that the addition of such services appeals to users and increases the consumer surplus. Optimal healthcare plan designs should continue to be informed by these consumer-oriented metrics in combination with actuarial data and cost-effectiveness ratios when choosing specific benefits to be included in a healthcare plan.

5.2. Implications for Health Insurance Providers

Our findings imply a need for healthcare payers to be adaptive as we find results that can help adjust decisions such as policy adjustments, coverage benefits, or pricing structures. The trend in the health insurance market over the last decade has been to monitor lifetime cost and benefit coverage packages for capping or exclusion opportunities. In this environment, our model can help optimize packages offered to those who would benefit from certain vision or dental coverage. The lifetime benefits identified by our model would have direct implications for the development of a policy coverage package that provides cost controls for treatment and release treatment cohorts while explicitly excluding options for those diagnosed with trauma who incur no costs but are somewhat at higher risk for higher-cost treatment. More broadly, typical operational practices would target cost reduction efforts only on the basis of identifying low-risk and high pre-treatment estimated expected cost cohorts. However, the released high-risk trauma and little or no-touch patients would directly benefit from preventative services and reduced early intervention, with the main expense in orthodontic treatments. Lifetime vision and dental care costs have been an overlooked area of study, especially in understanding the likely benefits that may have implications for adult resource allocation. The long-term cost-benefit estimates can therefore be used to begin to guide more current, perhaps unsuccessful, health insurance provider decision-making to start the short list of those who are likely candidates for the provision of early preventative and orthodontic offers, whose position in the treatment hierarchy includes a high percentage of preventative treatment. In the follow-up step, incremental costs and likely patient outcomes can be monitored in the arrangement to see the amount of resources that are provided in orthodontics for the medium to high risk with little or no responder treatment. Moreover, the predictive analysis used for estimating later in counseling sessions for non-responders or under-responders to self-directional treatment is important. The 'person-centered' tailored strategies based on data-driven insights can lead to a reconsideration of current decision-making, which is currently based on subgroup findings from clinical trials. Periodic updatable models would be needed to form part of adaptive value-based healthcare cycles, with results representing dynamic changes in insensitive retail practices. In order to become cost-efficient, insurers should become more data-focused with a high level of iterative adaptation to changes in the market, consumer demands, and knowledge of care requirements. Market share will depend on the level of adaptation. A higher insurance penetration rate might create incentives for utilizing resources to intervene early beyond preventative advice. Insurers should evaluate the long-term economic benefits of non-responders to the provider. We suggest and provide strong evidence that this needs to also include return on investment in orthodontics downmarket from today’s position and not focus only on the bottom line. Additionally, there is an upside in exclusive coverage beyond the smaller trauma market increase. With a lower price, this too can reach much closer to this market, providing cost savings for preventative care. For the insurance product, this is important as it allows differentiation for a larger opportunity for prevention. In addition, low pricing can leverage behavior change towards a preventative focus—a goal in itself for public health. Experience may indicate that counterintuitively, trauma and cost preventive care are not always exclusive, as the trauma size was small and at risk of positively changing a parent or caregiver's behavior.

6. Conclusion

This work aimed to demonstrate the applicability of deep learning techniques in health coverage decisions by conducting an assistive cost-benefit analysis of vision and dental coverage. The model is capable of guiding the user through parameters of varying complexity such as national population statistics, vision and dental relationships, or utilization rates, to help decision-makers understand their impact. Paired with various techniques of optimizing these features on the choice of vision and dental coverage, cost savings were found. The ongoing development of federal recommendations intermediated by relevant departments in fringe benefit package structure highlights the timeliness of optimizing health coverage through approaches such as the one presented.

Future research needs to continue the development of systems that analyze healthcare improvements with potential costs to all stakeholders. As society engages in healthcare analytics, the landscape of interest will change. The ability to perform vision and dental-related work is not surprising in commercial and veteran populations, given the relationship of dental and vision to systemic, quality of life, and medical predictors of value. Building scalable systems to reflect the chain of relationships needs to evolve with the dynamic goods and services that are combined under a health coverage umbrella while educators, providers, patients, and administrators adjust to the data at hand. In this study, the increasing interest of large payers in Health Maintenance Organization coverage indicates the applicability of reducing costs by adding vision and dental care. Given this healthcare sector growth, there is potential value in selecting a health maintenance organization coverage option. With more work, deep learning can learn to project a new chain of relationships. With each new addition in care, the relevant coverage evaluations will transform the nature of covered goods and services. Identifying potential savings in dental and vision insurance coverage may allow the actuaries and coverage sequencers to provide new systems of integrated health care. Some of this new care has value as determinants and some components are clearly regular medical care. By reducing dental and vision-related costs, an improved fringe benefit with medical improvements beyond the preventive ratio can be provided. In conclusion, the potential savings in vision and dental are one type of savings calculation. These parameters may lead to additional services to a more traditional provider-person service ratio of approximately 175 m-value. This is the recommended corrective rate.

6.1. Future Trends

The eScience Institute of the University of Washington recently identified six emerging trends as major new research frontiers in deep learning. One trend involves using deep learning to analyze healthcare data and interpret EHR and wearable data. Healthcare organizations are investing in models of various types to help advance decision-making with complex and intensely data-centric premium designs. Whereas most past cost-benefit evaluations of healthcare professional services have been conducted in the context of randomized controlled trials to study whether specific treatments achieve their intended biomedical outcomes, we are interested in assessments that attend to whether a cheap service has any benefits, if any, more ambiguously defined. This setting calls for different considerations and methodologies and is especially needed now as healthcare systems continue to grow in complexity and provision of services. We are optimistic that future deep learning will offer new methods for efficiently capturing information in these features and improving their statistical evaluation across and within health plan designs.

In addition to new methodological developments, advances in AI and ML are expected to lead to new healthcare technologies and insights. That is, we expect deep learning will enable more comprehensive evaluations of cost-benefit trade-offs of healthcare services for society. This effort is predicated on differential value considerations based on changes in health-related utility and preference-based choice. The latter is concerned with amortized expenses between services and is the context of our work. As machine learning and healthcare are rapidly changing, assessments beyond our scenario of VDC benefits are also expected to be part of future AI. In other words, with the rapid growth of personalized and precision medicine, AI is expected to help deliver decisions on "what works for whom," "what works compared to what," and "under what circumstances." AI is in the process of generating breakthroughs, thus, in an evolutionary fashion and not as a response to widely recognized recent dramatic advances in the real-world practice of healthcare today. This is the next step in healthcare in which technology makers collaborate with and inform healthcare providers with new pathways of inquiry.

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