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AI and Deep Learning Techniques for Health Plan Satisfaction Analysis and Utilization Patterns in Group Policies

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ABSTRACT
Health insurance aims to protect and safeguard against incurring unexpected heavy healthcare bills. There are three main types of health insurance, namely indemnity, proprietary administration, and prepaid arrangement. Depending on the structure and type of benefits, policies are classified into individual, family, and group policies. The main concentration in the health insurance domain is on personal (individual or family) health policy, but in this work, group policy is emphasized where a large number of people are involved. Commitments that improve satisfaction with the health insurance-related functionalities for the consumer corporation can result in long-term advantages, such as transparency and business opportunities. Utilization patterns of the current insurance responsiveness are unknown and can lead to guidelines and approaches for profitable policy development and enhancement. The deep learning model has the inherent capacity to understand and represent an experienced person's problems very effectively, as well as their outlook on a particular product or system. In recent days, as a new potential dimension, several data-driven artificial intelligence methods and theoretical learning models have been used in healthcare-related satisfaction or mental illness predictive analysis, but the application of these techniques on the stochastic utilization statistics of health strategies is untold. Also, probabilistic data-driven AI technical learning methods will be used for further enhancement of these results, which will be computationally expensive but also a potential measure of surveillance use, in terms of performance and the development of policy forecasting groups. The organizations then use this data to prepare improved or more attractive plans for the upcoming operations on evaluating purposeful consumption organizations. This specific module's extent will be dealt with in a forthcoming paper. In this work, we recognize the use of AI methods to analyze the diagnostic instructions and operating information of these types of health strategies of organizations. We are designed to break the distinct outcomes into authentic utilization-styled prognoses of the available groups of these strategies. After defining these modules and debates in relevant environments, we then generalize the unknown effects that demonstrate outcomes of the above human-made game. Health plan satisfaction analysis is of considerable significance in health insurance contexts. Traditional methods validated through patient surveys can be subjective, time-consuming, and expensive. Advanced technologies have opportunities to understand the relative preferences and dislikes of the patients regarding these group policies optimized by the health plan companies. The policies are important and have considerable implications for the healthcare sector to optimize their priorities. To enhance these issues, in this module, we focus on audited stochastic utilization statistics of services in group policies during the last two years. Herein, it is important to formulate group policies, in detail, health strategies of the cellular and personal group, with their operating rates, as well as an appropriate attendance to utilization environment hazardous extremes: one which falls in the 'Safe Environment' and the second entitled 'Niched Friendly-Fire Environment.' Analyzing utilization statistics is one of the major branches of big data emerging visualization, and accessible assistance policies are expected to grow more prominently within the vicinity.

Keywords: AI-driven Health Plan Analysis, Deep Learning for Health Policy Utilization, Predictive Modeling in Health Plans, Customer Satisfaction in Healthcare, Healthcare Utilization Patterns, Group Insurance Claims Analysis, AI for Healthcare Decision Support, Healthcare Consumer Behavior Modeling, Natural Language Processing in Healthcare, Personalized Health Plan Recommendations.

1. INTRODUCTION

The growing relevance of patient satisfaction with their health plan/work is being increasingly recognized in the outcome-oriented healthcare and health insurance industry. Several studies have acknowledged or renewed interest in the 'intermediate outcomes' including perceived quality, patient satisfaction, etc., that are important in their role as probable antecedents or outcomes affecting the clinical status or functioning of patients, the direct costs of the care provided, and indirect costs, all of which are relevant for obtaining the desirable patient-centered outcomes. It is this interaction of patient care, outcome, and satisfaction that forms the groundwork for using AI and deep learning applied to health outcomes.

While several studies have attempted to understand the determinants of health plan satisfaction, very little is understood with respect to the behavior of patients in the backdrop of group medicine policies. In this paper, we have attempted to derive a rich and intuitive set of factors on drivers of patient health plan satisfaction while working with group medicine policies. Patients in recent years have been heavily using their data to generate insights into their health, and their behavior and interactions with health delivery need to be understood well. For this, the research community has been establishing analytical processes to enable health institutions to develop informed services that are required for the well-being of patients. It is very important to stay vigilant about the actual health of the patient, based on historical data and collaborative health tools available in the form of mobile-based applications. These tools provide real-time health data, based on mobile inputs and apps, and the intelligence community can leverage these to perform advanced health policy research effectively.

Given that diseases could have incidents based on geographic factors and also the lifestyle decisions of patients, early detection of high-incidence diseases could help provide early treatments. To be able to do this, the approach encouraged in this paper is to utilize the historical burden of disease and apply deep learning for patients and insurance companies to know the probability of certain high-incidence diseases that a population could be affected by down the line, and if required, take annual beneficial policy decisions, and early premium decreases/increases could be decided. This research, done from the patient's perspective on high-incidence diseases from the demographic perspective, will be beneficial for policymakers in health with respect to annual state-level investments, and insurance companies could build products with respect to the early detection of diseases and help in decision-making regarding premiums and other aspects.

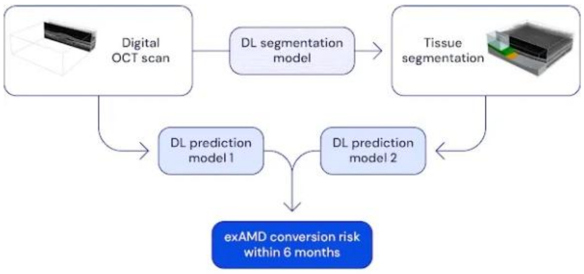

Fig 1: Deep Learning in Healthcare

1.1. Background and Significance

The healthcare environment is dynamic, and healthcare consumers are increasingly turning to the internet and visiting healthcare-based websites for access to information about healthcare providers or specialists to guide their care decisions. There is a widening movement in the healthcare sector towards a more patient-centered approach, which is assuming increasing importance in healthcare. Results are also used to award achievement incentives. Both healthcare providers and health plans are continually looking for ways to improve their patient care services. Clinical results are valuable for helping to measure health outcomes; however, it is also important to review the patient's own insight to understand the patient's point of view on care. It is indisputable that patient satisfaction can drive greater healthcare use, shorten hospital stays, and lead to more regular recommended treatment plans, resulting in improved health-related quality of life. It was previously mentioned that there are a number of organized and rigorous factors affecting patients' satisfaction with health plans. From the patient's perspective, a primary external promoter is the physician. Additionally, healthcare delivery is in collaboration with payers or health plans.

Unfortunately, earlier studies have documented many challenges in measuring individual lifetime care satisfaction in different groups of patients. While studies can evaluate short-term satisfaction with some elements of care, the common form of care is difficult to evaluate. A concern from the patient's perspective is that recent management problems with health policies in a group of employees may need to be reviewed and presented. The research aims to help patients and patient organizations plan health plans. This study makes use of a tech-based methodology, which is known to be innovative. Methods focus on assessing a large amount of data to identify patterns for potential predictions. To date, no study has analyzed group health enrollee satisfaction between different health plans or policies using this methodology. This is the directory in which this analysis spans. More importantly, it allows this discussion to be more empirically grounded. The long-term objective of the research is to conduct a similar study in different advanced medical settings. The primary finding will be whether any of the innovative methods make meaningful recommendations based on the satisfaction rankings recorded in the investigated group of enrollees or if further study is essential.

1.2. Research Objectives

The primary objective of this study is to unmask patterns of satisfaction with a health plan against the backdrop of one or several common attributes and their utilization in the context of group policies. In addition to the primary interest in the attributes, it would be opportune to identify important indicators of each group. For these purposes, one can both apply AI for the analysis of different data sources and assist the deep learning techniques directly with the respective attributes reported by the policyholder.

The study presented herein aims at bridging some unmet needs within the literature. It will explore the development of health plan satisfaction and state-of-the-art satisfaction studies on the subject. The main objective of this study is to unmask different patterns of satisfaction with a health plan in the context of group policies against the backdrop of one or several common attributes, as well as by their utilization. Further insights may be of interest about a specific group, such as a relevant auxiliary or main attribute. Disconfirming, the markups are a distraction towards attributes when purchasing them, as the new ones overestimate part of customer characteristics and voice-based characteristics.

Our principal objective is to generate a satisfaction style by AI deep learning, based on an unstructured or indirect relationship between attributes of the two constructs. Our ultimate goal is to unmask important attributes that shall assist in the policy analysis. That is, to examine unsackable attitudes that incite holders to use in areas like retention, pricing, and health plan design that can be directly influenced. It is also expected to contribute to establishing new themes that will not be approached theoretically or practiced by traditional groups. Our work is exploratory in nature, channeling results obtained both in the case of surveys of new business contracts and satisfaction with health plans.

2. LITERATURE REVIEW

Satisfaction is an important metric for understanding a person's experience with health policy services. Several studies have used technology integration to improve their investigation in the area of health plan analysis and patient satisfaction. Our approach analyzes claims from the health plan to explore health plan selection trends and satisfaction with the service. The utilization pattern of health services and the analysis of patient behavior in claims analysis is a relatively new field. The focus is mostly on the use of modern technologies like artificial intelligence and deep learning, especially to estimate the quality of health care delivery at an institution. While there is an increasing interest in the area of artificial intelligence and health insurance, there is very little growth in research that directly checks health plan satisfaction, and this study was conducted to address this gap.

The analysis of customer satisfaction does not use a wide range of health claims data, integrated with manual surveys. This approach in the industry may allow health care providers and individual health policies to know what methods are used in the claims to estimate the assessment of health care delivery at an institution. Technological improvements and advances in data mining and machine learning complement the idea of service analysis and the knowledge provided to patients. Healthcare organizations can significantly improve customer care by understanding their values and treatments. Analysis of the patient's domain can be used to develop the health sector by providing a better understanding of service delivery and patient satisfaction. In this study, we present a support system based on the analysis of health claim data for satisfaction in relation to policies and health plan services provided.This study addresses the gap in research regarding patient satisfaction with health plans by analyzing health claim data to explore trends in health plan selection and satisfaction with services. While much of the existing research focuses on artificial intelligence and deep learning to assess the quality of health care delivery, there is limited work directly examining health plan satisfaction. By integrating health claims data with manual surveys, this approach provides a more comprehensive understanding of patient behavior, service utilization, and overall satisfaction with health policies. Technological advancements in data mining, machine learning, and AI enhance the ability to assess and improve service quality in the healthcare sector. The findings from this analysis can offer valuable insights for healthcare providers, enabling them to better understand patient preferences, improve care delivery, and optimize health plan offerings to meet patient expectations.

Equ 1: Reinforcement Learning (RL) for Optimization of Utilization

$$V(s) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r_t \mid s_0 = s\right]$$

2.1. Overview of AI and Deep Learning in Healthcare

Global investment in AI was already robust and set to increase over the coming years. A majority of healthcare executives surveyed were already well acquainted with AI, and a promising percentage planned to invest over $186 million from 2018 to 2020. AI has myriad applications in healthcare. Uses for diagnostic and interpretation tools, selecting between treatment options, engaging with patients, and helping to develop new pharmaceuticals are notable. When combined, data science and AI can "bring people's intelligence, experience, and domain expertise into every decision," a particularly exciting transformation in an industry that values personalized care. Two recent case studies help to illustrate AI's profound impact on healthcare. In 2020, researchers at a prominent eye hospital trained a model to diagnose eye disease using more than 100,000 retinal scans. The trained system was 94% accurate in identifying disease after reviewing just a few dozen images, making it a tool that could identify patients needing urgent disease management. In another case, researchers created an AI capable of predicting readmission risk among heart patients with up to 90% accuracy. The center's lead researcher said the AI could dramatically help heart patients. "It's our hope that we can study those factors and maybe interact with patients in a different way to perhaps decrease their risk in the future," he said.

Although there is enthusiasm for healthcare's embrace of AI, other scholars point to its significant ethical and operational implications. Concerns exist about the potential for workplace preparation among coders, clinicians, and administrators, all of whom will need tools and information to operate or oversee an AI. The use of AI in scheduling, triage, and diagnosis decisions is further complicated by potential privacy issues and social and legal questions about fairness and accountability. As a result, there is a stress on the need for research that can direct AI design and use so that all individuals can receive the highest degree of personalized, patient-centered care. In light of this potential impact, a greater appreciation of AI's role in personalizing care could be a partial explanation for performance outcomes. Some suggest that the field hasn't yet realized the payoff of sophisticated AI investment but that further research, prioritizing neural network capabilities, textual summarization, fuzzy logic, deep learning, and NLP techniques can bring healthcare's use of AI to maturity.

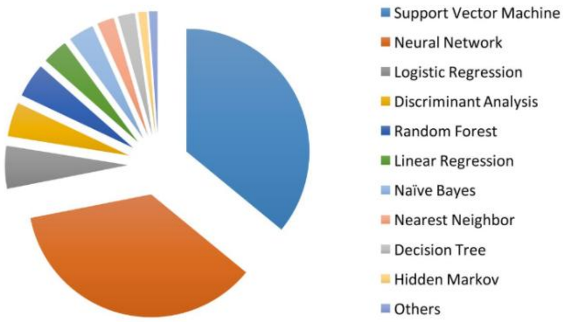

Fig 2: Top AI Algorithms in Healthcare

2.2. Health Plan Satisfaction Analysis

Health plan satisfaction analysis is conducted on the basis of patients' self-reports on their satisfaction with services. Researchers have studied patient satisfaction with particular aspects of health plan services such as access to care, quality of care, and customer service, to examine possible correlations between patient satisfaction ratings and actual quality of care, therapeutic outcomes, and health plan utilization. It is believed that when health plan clients receive adequate and comprehensive care, they will feel satisfied with the service they are receiving. Satisfied health plan clients will establish better relationships with their healthcare providers and will comply better with treatment regimens; a byproduct of satisfaction is an overall reduction in healthcare costs.

Since the early 1980s, several treatment protocols have been designed to improve patient satisfaction by focusing on the customer, that is, the patient. However, relying on patient satisfaction scores to assess the efficacy of these protocols is problematic due to the absence of a universally accepted definition of patient or customer satisfaction, its multi-dimensional variability, and the subjectivity of the measurement tools used to gauge it. Furthermore, patients come to health care with different perceptions of their personal health status, health care beliefs and expectations, preconceptions, and philosophies, which inform their health values and needs. Nevertheless, more papers on the subject have been published in recent years than at any other time, attesting to the importance of patient satisfaction scores in health care delivery. This paper adds original knowledge to the available pool of information. We have thus far found no other paper in the current literature that discusses health plan satisfaction analysis and satisfaction utilization patterns as we have done in this paper.

3. METHODOLOGY

According to the research questions and utility of this work, the appropriate research design is selected. The next step is to elaborate on the method used in analyzing the data, including the following three approaches: a) Individuals' assessment of health plan satisfaction or dissatisfaction. b) Description of utilization patterns of a health plan, including hospitalization, hospital length of stay, and fast provider and emergency department utilization for plan members. c) Descriptive statistics of the types of hospitals utilized by plan members. For each aspect above, we collected information that involved comprehensive sources. Contract plan provision documents were collected from the plan as the source of information. Data such as insurance premiums were extracted from annual surveys of the plan. Health plan satisfaction survey data, including interviews with insurance plan members, are another important data source.

All the data we use are observational data. Descriptive analysis is significant for our research because we have never analyzed this data before. After the application, we developed indicators for each aspect of health plan quality, such as health plan satisfaction, utilization of hospital/ER/home services, and health care plan quality. Utilization of health care is an important indicator for both assessing the efficiency of a health plan in delivering care and for profiling health plans and doctors. The patient survey of a healthcare organization must be reliable and valid enough to assess not just the experience of care but also the issues that may influence the perception of care. Data should be preprocessed to ensure reliable and valid attributes in the database that will be used to develop the PDN model. Finally, the care provider profile and hospital quality profile are developed by applying AI. The criteria for selecting AI and deep learning models are reliability, adaptability, and credit as an unsupervised feature extraction model that could be trained for both labeled and unlabeled data to help the PDN model build feature vectors that have good properties for discriminating the response variables. All of these characteristics in AI are different from the machine learning model and the traditional Cox hazard model that is commonly used for building care providers and hospital quality.

Equ 2: Neural Networks (for more complex relationships)

$$S = f\left(\sum_{i=1}^{n} w_i^{(1)} X_i + b^{(1)}\right)$$

3.1. Data Collection and Preprocessing

Data Collection and Preprocessing Primary data were obtained from the insurance organization's weekly surveys on participant satisfaction with the health plan. The insurance organization also provided all the policy utilization data that included personal information about individuals and the size of the groups that have acquired the benefit. Some demographic data were obtained from the medical records of volunteers, such as age, BMI, and hypertension, using a sphygmomanometer. Lastly, we obtained the claims index, whose score indicates whether the participant was responsible for medical costs below the average or above the average.

Centralized data stored in the extranet were captured using SQL and exported to statistical software for further analysis. Several individuals have terminated the use of the benefit within the time window. Thus, a variable with two categories, reducing the number of adults (yes vs. no), was created to explore if this group variable would affect consumer satisfaction and behavior. To analyze consumer satisfaction, each adult participant was asked to fill out the Consumer Satisfaction Assessment Tool, which provides an assessment of satisfaction and loyalty to the insurance organization. The questionnaire used in this survey had three satisfaction questions ranging from 1 (poor) to 5 (very good). The reliability index calculated to determine data quality was 0.79. In order to perform the analysis, the components of the loyalty construct were aggregated to create one variable using the variance components decomposition technique. Then, the variable was dichotomized to create another variable with the following intervals: “0 = satisfied” and “1 = dissatisfied.”

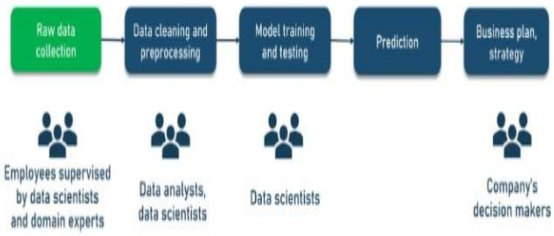

Fig 3: data collection in Deep Learning in Healthcare

3.2. AI and Deep Learning Models Selection

In this research, ten different AI and deep learning-based models have been evaluated based on their performances in similar contexts. Additionally, some criteria have been selected for choosing the appropriate model, such as the unique features of each model, the objective of the research, how well the model can operate with the provided data, and the interpretability of model behavior. K-means clustering, classical Naive Bayes, Random Forest, Extreme Gradient Boosting, Neural Network, Convolutional Neural Network, Recurrent Neural Network, Long Short-Term Memory, Inception Time, and Hybrid Savitzky–Golay filtering technique have been evaluated in this research. Model performances are compared in terms of accuracy and misclassification rate, as shown in the results section under all necessary details. Moreover, in such multi-class classification problems, model performance is also evaluated in terms of sensitivity and specificity for each class.

Loss and accuracy are used as performance metrics in all the models in this research for both training and validation. Additionally, sensitivity and precision are used as performance metrics in the test data. While the loss is aimed to be minimized, accuracy is aimed to be maximized during the model development section in the training and validation datasets. Furthermore, sensitivity and precision are aimed to be maximized during the test phase in terms of model evaluation. Based on these criteria, model performances are analyzed. It is crucial to train the model with different training and validation datasets and obtain the results in terms of different performance metrics. Then, the best-performing model is selected based on the statistical performance analysis conducted with all results.

4. RESULTS AND DISCUSSION

This study predicts satisfaction scores and identifies affiliation code datasheet leads for group plans. The numerical values of satisfaction scores are predicted through the application of AI and deep learning techniques on raw data available from various data sources. The satisfaction scores were further used to analyze whether there exists any correlation with utilization patterns of group policy by members. We found that the dissatisfaction scores were directly proportional to the average frequency of utilizing associated healthcare benefits. The reduction of satisfaction scores suppressed the inflation of healthcare utilization costs, making it more predictable. We also implemented a remedy system to eliminate the influence of dissatisfactory scores on healthcare utilization patterns to inform stakeholders or policymakers. The developed remedies prevent specific members from utilizing healthcare services if satisfaction scores are reduced significantly, thus making them less predictable. The developed satisfaction scoring remedy system may motivate providers to more satisfactorily deliver their promised healthcare services.

Our research tried to predict satisfaction scores for health plans having different sizes and different affiliations in groups. The proposed method successfully estimated overall and multiple parameters satisfaction scores for all group sizes, minimally using an affiliation code datasheet and a satisfaction scoring based on raw datasets. The overview of the structures and content of the provided dataset is discussed intensively. Besides, an affiliation code sheet was analyzed to explore the relationship between size category, main, and multiple affiliations. The primary research question and outlined healthcare utilization pattern analysis through predicted satisfaction scores at the group social level are also discussed. Lastly, we proposed several topics for future work. To ascertain the potential impacts on the performance of the developed predictive model of satisfaction scoring, the deep learning-based approach was applied to estimate raw satisfaction scores. It was verified by comparing the accuracy with other state-of-the-art techniques.

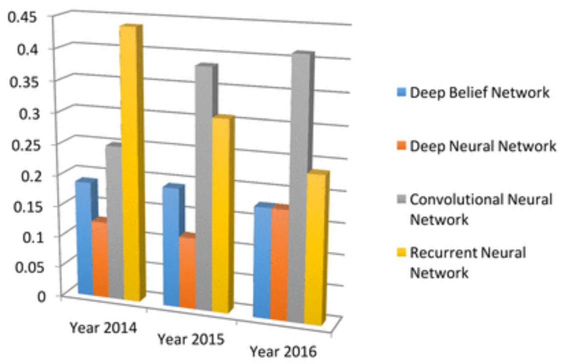

Fig 4: Artificial intelligence in healthcare

4.1. Health Plan Satisfaction Analysis Results

In this subsection, we present the results from our health plan satisfaction metrics collected during the twenty years investigated. The primary satisfaction metrics of our study derived from a single overall satisfaction question from health plan members, indicating satisfaction with the overall health plan, dissatisfied and satisfied recommendations of coworkers, prayers, and group members. This subsection of results will reveal trends identified as being of positive attributes and concurrently some of the most negative aspects of health plan delivery. Satisfaction with the health plan is compared across the groups of individuals: a) who were, and were not involved in a project with the health plan, and b) those who have been with us for 6 months to 3 or more years. Those study results clearly indicate that notice and interpretation of satisfaction outcomes need to consider the complexity of comparing across different and various adult men and women in the addressed populations of families in both urban and rural areas in multiple states using a fee-for-service type delivery system.

Routinely, satisfaction results are reviewed by senior staff, discussed generally and specifically with providers, and tracked for action. Staff are trained to respond to, and assist in responding to, any dissatisfaction reported by members. The use of results and discussion for action is an important part of the patient feedback loop to improve facility and system responses. Regular staff meetings are one forum for discussing satisfaction and working on improving processes. Further, top clinical pharmacy questions are included in meeting agendas. Systematic and comprehensive quality and satisfaction trend analysis can and should lead to facility, system, or state plan areas for improvement. Steps can then be taken to improve access, increase satisfaction, and retain family practitioner prescribers in the program. Satisfaction results, together with the frequency and content of formal complaints, inform senior policymakers and administrators where opportunities for process and practice innovations and enhanced recruitment and retention efforts exist. Routine review with discussion for action is an essential component of quality management and continuous quality improvement techniques.

4.2. Utilization Patterns Analysis Results

We study and analyze various trends and patterns that are associated with the utilization of services, including:

- Distribution of age, gender, and individual/group policy preferences among members. - Relationship among the frequency of use, individual/group coverage, and satisfaction. - Negative or positive correlation between the provision of each available service in particular states and satisfaction. - The trend and fluctuation of patient utilization corresponding to the types of services and patients' satisfaction levels in different states and locations.

The relationship between the level of satisfaction and the utilization patterns in terms of the frequency of services used is studied. It is revealed and confirmed in the study results that individuals who opt for the services more frequently, whether those services are included in the group policies or not, are expected to be less satisfied or unhappy. The core meaning of this trend highlights the acute utilization pattern of high-risk patients regarding the use of covered or non-covered services. Most dental and vision patients in certain states tend to have their gum treatment in year 1. Additionally, the fact that patients have constant and monotonous dental service usage could indicate a rejected care group in general.

There is also a marginal negative trend of decreasing frequency of service usage in dental and vision from S1 to S5, except for the eye exam procedure in S1, which shows less than 1% increase between S1 and S5. The observed frequency of using the services chosen by individuals can be exploited to inform the healthcare delivery sector and benefits management to allocate resources, such as planning the right types and frequency of services and managing the supply and demand chain. As such, the results of the correlation between patients' satisfaction and utilization patterns can be used in future healthcare planning. The results can help predict which group policies and health coverages are likely to be used more. Consequently, increasing the level of satisfaction can lead to the enrollment of more employees in group policies due to the cost and value of the services delivered for free or at low costs through health plans in the workplace.

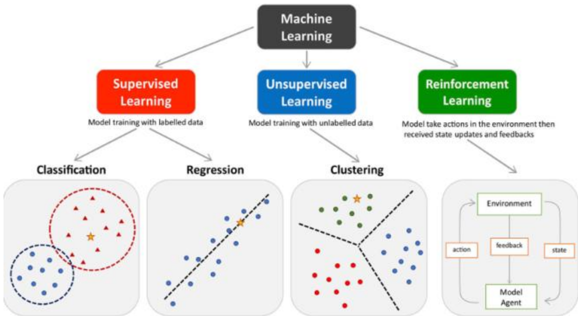

Fig 5: Utilization Patterns Analysis

5. CONCLUSION

The healthcare industry, especially health insurance, incurs a tremendous amount of expenditure for gaining satisfaction and patient acquisition. Health providers and policymakers need to know their patients, their preferences, utilization patterns, and satisfaction with plans for maintaining patient lifetime value, reducing the costs incurred for patient acquisition, retaining patients, and decreasing readmission rates. Our research proved the potential of using artificial intelligence and deep learning for services and policy improvement by revealing satisfaction and utilization patterns in mandated health plans. Based on continuous analysis by running the proposed model, players can enhance their services by learning, predicting, and deep-diving into satisfaction and dissatisfaction patterns in a group policy. As such, the answer to RQ1 is a resounding yes; AI, ML, and DL techniques can be used to understand satisfaction, and we can also identify the utilization and satisfaction associated with it.

In the future, we can have real-time predictive analysis of feedback data for continuous involvement in improving satisfaction. The rates of feedback or responses directly reflect the satisfaction or dissatisfaction of the consumers, and therefore, a study is ongoing to execute a 360-degree feedback loop from payment data, claims data, CRM, and IoT data for providers and payers while also monitoring the web reviews data for healthcare plans and providers. We could process more recent data, once available, due to a continually evolving healthcare plan and policy design change, which can help in producing a generalizable model. It is also imperative that providers, payers, and patients collaborate and propose vision-based satisfaction studies and personalized medicine studies for precision care and genotyping studies for more transparency on this subject.

Equ 3: Logistic Regression (for classification into satisfaction categories)

$$P(y=1|X) = \frac{1}{1+e^{-(w_0+w_1X_1+\cdots+w_nX_n)}}$$

5.1. Future Trends

Owing to the recent advancements in the field of AI and deep learning, we believe that there are new techniques available for the analysis of health plan satisfaction, and there will be changes to the way utilization patterns are analyzed in the future. As healthcare delivery evolves, AI and machine learning are anticipated to be helpful in predicting medical events while also boosting the delivery of preventative and diagnostic care. With improvements in the accuracy of satisfaction levels in group policies, personalized approaches may become a trend and are expected to raise patient satisfaction levels because one size does not fit all. This information will also be of interest to policy writers and others who are interested in marketing and conducting pedagogical studies in the insurance area since the satisfaction of policyholders in group plans is relevant to a company’s growth and healthcare compliance. Potential areas for future work include developing best practices for the use of patient data for deep learning as well as advanced machine learning. In particular, data privacy and ethical concerns direct the focus of this area. Navigating this transition could be difficult, but it is critical as perceptions and expectations of patients change—they want their physicians not only to take good care of them but to know them. The population may move from merely complying with physician instructions to engaging with personalized care, anticipating their care needs and treatments in advance. In this case, the market will change dramatically. For example, with this shift, it is possible that a few people will be less concerned about price shopping and be more interested in satisfaction with care level coordination. To summarize, this chapter offers several new concepts and opens future research avenues.

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