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Research Note

Using Individual Decision, Economic, and Health Status Data to Predict Health Checkup Behavior

Neetu Singh
University of Illinois at Springfield, nsing2@uis.edu

Apoorva Kanthwal
SEI Investments, akanthwal@seic.com

Prashant Bidhuri
Enterprise Cloud Solutions, prashant.bidhuri@eclouds.co

Anusha Vijaykumar Munnolli
Davita Inc., anusha.vijaykumarmunnolli@davita.com

Abstract

Annually, the Behavioral Risk Factor Surveillance System (BRFSS) survey is administered by the Centers for Disease Control and Prevention (CDC). This article uses 2016 SMART BRFSS data to predict the likelihood a person will get a health checkup and it identifies which factor(s) influence the decision to obtain a checkup. Patterns of individual decision making were analyzed using various supervised data mining techniques. The best predictive model, with a predictive accuracy of 80%, can improve future BRFSS surveys by better understanding the responses and provide insight into the factors affecting decisions. The model was scored on new data to verify its accuracy. These findings supplement ongoing research to identify how behavior leads to better decision making related to medical checkups. The model can help identify poor decision-makers in high-risk groups. This research can also be used by healthcare professionals to improve clinical prevention services. Potentially, the research can be extended by combining the BRFSS data with ICD-10 and CPT codes. Better knowledge of diagnosis (ICD-10) and the cost associated with diagnosis (CPT) will help to understand a person's health behavior. In the United States, expenditures on healthcare are rising significantly every year. Health decisions of individuals determine the overall health of a nation. Therefore, the U.S. Government should initiate health programs that encourage individuals to make better health decisions.

Keywords: Health behavior, high-risk behavior, decision making, public health, data mining

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1. Introduction

Expenditures on healthcare in the United States are rising every year. For example, U.S. health care spending grew 4.6 percent in 2018, reaching $3.6 trillion or $11,172 per person, cf., https://www.cms.gov/. It is important to understand the drivers of the cost of healthcare and how advanced technologies can be used to help people make better healthcare decisions. A study using Behavioral Risk Factor Surveillance System (BRFSS) data suggests that morbidity and mortality from chronic disease and injury are related to high-risk behaviors (e.g., physical inactivity, cigarette smoking, and drinking and driving) and lack of preventive health care, e.g., health plans (Holtzman et al., 2000).

Organizations try to influence positive health behavior among their employees through wellness programs. However, these efforts may be in vain because it is often observed that the healthier and less stressed employees have higher attendance while the more stressed and less healthy employees show less participation. Behavioral risk factors contribute to a high percentage of diseases in most of the developed countries (WHO, 2002). The health condition of individuals is primarily a direct consequence of behavior (Schwarzer, 2008). Critical factors such as morbidity and mortality rates are directly affected by the decisions that people make about their health (Sheeran et al., 2017). People recognize their health needs, are aware of them, but fail to act upon those needs (Rothman et al., 2015). Fear of terminal illnesses has often proven to lead to poor health behaviors (McErlean & Fekete, 2017). Prior research raises the question of what is the right approach to influence people's attitudes towards positive health behavior? Prior studies of health behavior have lacked predictive models based on data that is available.

The Centers for Disease Control and Prevention (CDC) administers a Behavioral Risk Factor Surveillance System (BRFSS) survey annually intending to gauge people's health behaviors in the United States. The BRFSS survey is used for the Selected Metropolitan/Micropolitan Area Risk Trends (SMART) to "provide prevalence rates for selected conditions and behaviors" (*SMART*, 2017). Surveys such as BRFSS offer a new direction for research on health behavior and the decisions impacting a person's health. Data-driven decisions have become more sophisticated with advances in technology (Power, 2008). This study aims to predict the likelihood of obtaining a checkup based upon behavioral factors, especially decision, economic, and health status data, and identify which factor(s) affect the decision to obtain a checkup. More specifically, the research objective of this study is to explore and identify the factors that influence the decision making of individuals to go for a routine medical checkup. The research question addressed in this study is: What factors predict an individual's decision to go for a medical checkup? To answer this research question, we developed a predictive model using a data mining approach using the 2016 SMART BRFSS survey data.

This article is organized as follows. In the next section, we examine existing studies in the field of health behavior, obtaining a medical checkup, and decision making. The literature review is followed by an explanation of the data mining approach used to develop our predictive model. Next, we discuss the results of our analysis including the scoring of the model using new data. We conclude the article by discussing the contributions, limitations and future research needs.

2. Literature Review

Decisions individuals make about health issues plays a vital role in determining their health outcomes. Health awareness in patients and the steps taken by them to take better care of their health is also one of the main factors that affect their decision making (Coulter et al., 2008). Individuals who are aware of their health condition, actively take part in making informed decisions about their health (Levinson et al., 2005). Existing studies have suggested that behavioral intervention should be used as it can not only prevent disease but can also help improve disease management. Also, the link between behavior and health is very high (Fisher et al., 2011).

Kasl and Cobb (1966), define health behavior as "any activity undertaken by a person who believes himself to be healthy for preventing disease or detecting disease in an asymptomatic stage". Gochman (2013) defined health behavior as patterns or actions taken by people that may have a good or bad effect on maintenance or health improvement. Often, individuals make decisions based on some risk assessment. A cognitive psychology study explains that informing individuals about long-term consequences would compel them to consider reflective information processing rather than making impulsive decisions (Mueller et al., 2017). Mueller et. al (2017) describes this as a feedback processing to enable better decision making in individuals. One of these decisions is to go for a routine medical checkup.

Several research studies have used the BRFSS data to identify the patterns of use of clinical prevention services. Also, routine medical checkups had been the outcome variable in several studies (Culica, Rohrer, Ward, Hilsenrath, and Pomrehn, 2002). In addition, Culica et al. (2002) noted that several studies have identified the association of health insurance coverage and health risk factors such as smoking, physical inactivity, drinking, and the presence of chronic disease with access to medical checkups. However, Culica et al. (2002) and some of the existing literature emphasize a moderating impact of a specific geographic location. So, the focus of this research is to determine the most important health behavior factors that help in predicting the likelihood of obtaining a medical checkup in the United States.

According to the 2010 Annual Status Report of the National Prevention, Health Promotion, and Public Health Council, the underlying risk factors that lead to poor health and death were physical inactivity, poor nutrition, tobacco use, and excessive alcohol use (Fisher et al., 2011). Education is considered as an important factor that determines an individual's behavior (Nordahl et al., 2014). It has been found that adults with higher education tend to make better choices concerning their health (Skalamera & Hummer, 2016). Higher education experiences seem to lead to more informed and intelligent decisions about improving one's health (Cutler & Lleras-Muney, 2006).

Better health literacy results in greater awareness and it improves an individual's health conscious. This awareness has led to numerous people making use of the dozens of smart devices and accessing their health information in real-time using health apps and mobile health devices (Bhavnani et al., 2016). Fitness trackers, wearables equipped with full-fledged electrocardiogram (ECG) capabilities are enabling individuals to make better decisions regarding their health (Manganello et al., 2017). With the advent of the Internet, there has been a tremendous growth of information sharing over social media and health applications, regarding health-related issues, by individuals anonymous or identified.

While concepts of health have often been related to the study of illness and its management and care aspects (Millstein & Irwin, 1987), few studies have focused on the decision making of individuals about their health conditions. Most health-related problems seem to arise from poor behavior such as indulging in bad drinking habits, smoking, physical inactivity, and substance use (Jensen et al., 2011; Kahn et al., 2002; Prochaska & Velicer, 1997; Schwarzer, 2008).

The growing effect of social media activities such as Facebook likes has been studied using SMART BRFSS data to predict county wise mortality, diseases, or lifestyle habits in the United States (Gittelman et al., 2015). This data has also been used to study whether variation in local health led to health disparities depending on demographics or ethnicity (Shah et al., 2006). Several similar studies have established a cause-effect relation between health conditions and health behavior (Chunara et al., 2013; McGuire et al., 2007; Pucher et al., 2010).

The BRFSS survey data has been used in prior literature to study health behaviors (Aaron et al., 2001; Denny et al., 2003; Leslie et al., 2012; Meyer et al., 2017; Nandi et al., 2013; Wang et al., 2018). The BRFSS survey data has also been checked for its reliability and validity (Pierannunzi et al., 2013). As per the statistics from 1984 to 2012 about 1,387 articles have used the BRFSS survey data for research. Out of these, 84.2% of the articles were published during 2002-2012 (Khalil & Gotway Crawford, 2015). Further, several behavioral studies have been conducted using BRFSS data (Khalil & Gotway Crawford, 2015). However, most of the models that have been developed have only considered a single condition or a category of responses (Dwyer-Lindgren et al., 2015; Frazier et al., 2011; Michimi & Wimberly, 2015).

3. Methodology

The Centers for Disease Control and Prevention (CDC) sponsor BRFSS phone survey to better understand current health conditions and general habits of the population. The goal is to guide a specific health programs to deliver better care. The BRFSS has over 250 variables, some are primary variables including the response of the individuals being surveyed and others are derived variables. In our study, we consider variables that are representative of high-risk behaviors while also providing considerable support for understanding human decision making when aware of current medical health conditions (Fisher et al., 2011). In past research done using BRFSS data, the key behavioral factors used were health status, tobacco use, physical activity, and alcohol use (Fisher et al., 2011; Meyer et al., 2017). The questionnaire in CDC's survey has been framed in terms of frequency of these factors and subsequent studies have then examined their influence on health.

We developed several predictive models to understand the implications of decision making in predicting health behavior using the SMART BRFSS survey dataset for the year 2016 (*SMART*, 2017). We sought to understand an individual's decision making by determining the most important factors influencing their decision to obtain a routine medical checkup. Data mining was performed using the SEMMA (Sample, Explore, Modify, Model, Assess) approach of SAS® Enterprise Miner (Shmueli et al., 2017). Multiple supervised learning techniques such as Logistic Regression, Decision Tree, and Neural Network were used to develop the best predictive model with the highest accuracy to identify whether a patient went for medical checkup in prior year. The data set was coded using conditional functions referring to the codebook of BRFSS data (*LLCP 2016 Codebook Report*, 2017) to create subsets and transform important information for analysis.

We explored the various factors influencing an individual's decision making towards their health, including tobacco use, alcohol consumption, cigarette smoking, physical inactivity, and income (Aaron et al., 2001; Liu et al., 2018; Nandi et al., 2013; Pate et al., 2019). In our research, poor health, mental health, and physical health are part of healthy days/health-related quality of life. Additionally, the research considers variables such as asthma and smoking habits of the general population to capture event variables for events such as a person being aware of a medical condition and his/her subsequent decision of controlling high-risk behaviors. One event variable could be a person having a medical condition such as asthma and while its associated decision-making event variable could be his/her smoking habit.

A study on asthma assessment suggests that asthma severity was highly prevalent among adults who were current smokers (Zahran et al., 2014). The first step in treating such asthma severity patients would be to change the course of habits worsening the medical condition. The routine medical checkup variable CHECKUP2, also considered as the dependent variable in the analysis, has been considered as a reliable source that an individual with some medical condition and health insurance is able to seek authorized medical advice (Culica et al., 2002; Oboler et al., 2002). Good health insurance makes it easier to afford a routine medical checkup which increases the propensity of an individual obtaining a medical checkup (Culica et al., 2002; Oboler et al., 2002; Pate et al., 2019). Our research assumes the event of going for a medical checkup is a high priority decision making point for individuals with a medical condition.

Our research adopts a feature engineering technique that focuses on responsive variables (determined by feature importance analysis, discussed below) such as physical health of an individual, general health, conditions determining mental health, poor health, medical cost for checkups, education level of individual, income, asthma, whether an individual exercise or not, health plan, smoking habits, dependency on e-cigarette, and alcohol days. All the predictor variables used in the study are described in Table 1.

Predictor Variables	Description
ALCDAY5	Alcohol consumption in last 30 days. (1=Yes, 2=No)
ASTHNOW	Asthma during past 12 month. 1=Yes, 2=No
ECIGARET	Ever used E-Cigarette. 1=Yes, 2=No
EXERANY2	Physical activity in last 30 days. 1=Yes, 2=No
HLTHPLN1	Healthcare coverage for individual between age 18-64. 1=Yes, 2=No
MEDCOST	Could not see doctor because of cost. 1=Yes, 2=No
POOR14D	Not poor health (Healthy person). 1= For Zero days, 2=1-13 days, 3=14+ days
EDUCAG	Education completed. 1=Not Graduated High School, 2=Graduated High School, 3=Attended College or Technical School, 4=Graduated from College or Technical School
INCOMG	Income categories. 1= Less than $15,000, 2= $15,000 to less than $25,000, 3= $25,000 to less than $35,000, 4= $35,000 to less than $50,000, 5= $50,000 or more, 9= Don't know/Not sure
MENT14D	Not good mental health. 1= For Zero days, 2=1-13 days, 3=14+ days
PHYS14D	Not good physical health. 1= For Zero days, 2=1-13 days, 3=14+ days
RFHLTH	Adults with good or bad health. 1=Good, 2=Bad
RFSMOK3	Current smoker. 1=Yes, 2=No

Table 1. Predictor Variables and Description

The target variable medical checkup (CHECKUP2) has two categories (1, 2) where "1" represents whether an individual had a medical checkup within the past year and "2" represents no medical checkup in the past year. The model comparison including the evaluation criteria of misclassification rate, Average Squared Error, ROC Index, and Gini Index is shown in Table 2. There was no overfitting of data as represented by the cumulative lift chart in Figure 1. QuickProp (QProp) Neural Network (Swastika, 2017; Xie et al., 2018) with three hidden units was chosen by SAS® Enterprise Miner as the best overall model with misclassification rate 18.80% and an accuracy of 81.20% (Table 2).

Selected Model	Model Node	Model Description	Train: Misclassification Rate	Average Squared Error	Train: ROC Index	Train: Gini Coefficient
Y	Neural7	QuickProp Neural Net with 3 Hidden Units	0.18801	0.14358	0.695	0.390
	Tree	Decision Tree (B2D6)	0.18989	0.14839	0.603	0.205
	Reg5	Interaction Logistic Regression	0.18998	0.14433	0.691	0.383

Table 2. Model Comparison

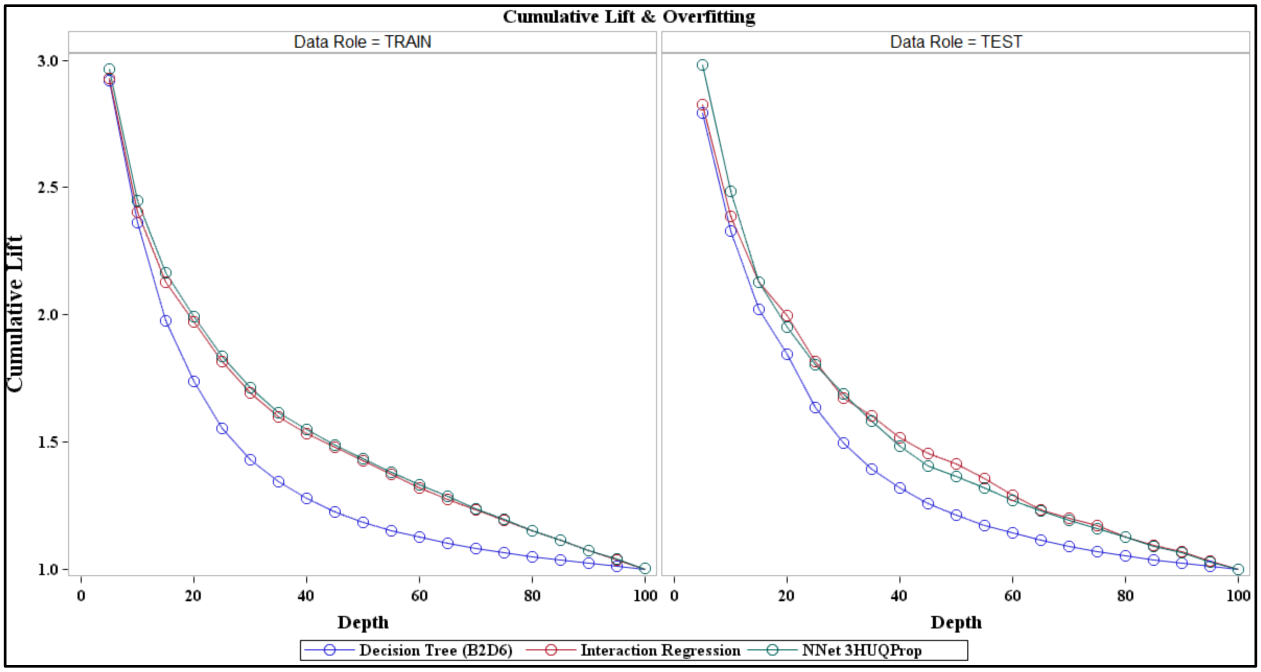

Figure 1. Cumulative Lift for Best Model

To identify the best model and evaluate model performance for a classification predictive model, the receiver operating characteristic (ROC) curve, and confusion matrix were used (Shmueli et al., 2017). The ROC curve shown in Figure 2 represents a Neural Net with three hidden units and using the QProp algorithm has the highest sensitivity both for training and test data. The confusion matrix was also analyzed for a detailed analysis of classifications by the best model (Table 3). Model performance was also analyzed by comparing the misclassification rate (18.80%) of the best model (QProp Neural Net) with a baseline misclassification rate (19.77%). To ensure that there is no overfitting misclassification rate was checked for training and test data. The same was also checked by analyzing the cumulative lift for training and test data for each model as shown above in Figure 1. The model was further scored to ensure the accuracy of the model on score data. The scoring of the developed model on new data is discussed later in this section.

False Negative	True Negative	False Positive	True Positive
1865	8426	143	246

Table 3. Confusion Matrix for Best Model (QProp Neural Net)

The analysis of results helps us to identify that the Neural Network model has an accuracy of 80% to identify if an individual had a medical checkup in the past year. The Neural Network is one of the supervised data mining techniques which provides the highest predictive accuracy (Shmueli et al., 2017). In this study, we used the multi-layer perceptron (MLP) architecture of the Neural Network. Several types of MLPs were used to identify the most accurate Neural Network where a perceptron is used as a classifier to map a predictor variable to the target variable as a function of predictors. Neural Networks do not have a specific model or equation to represent the outcome of the model.

In addition, the model is not summarized in a specific model as in the case of regression or decision trees (Cerrito, 2009). The accuracy of the Neural Networks model is examined the same way as other predictive models using ROC curves (Area under the curve), including the misclassification rate, the AIC (Akaike's Information Criterion), and the average error. The accuracy of the developed models was visualized using ROC which plots the sensitivity of the predictive model versus 1- specificity (Figure 2). The curve for a Neural Network with 3 hidden units is the highest, making it the most accurate model to predict the target variable medical checkup (CHECKUP2). After examining the overfitting of the models, we have observed that the Neural Network has the minimum overfitting with the highest accuracy. The appropriate method to identify the best model should be the one that can equally distinguish all classes (Cerrito, 2009).

The best model identified was a Neural Network with 3 hidden units. It had the highest overall accuracy. The result of scoring the best Neural Network model on the score data resulted in an accuracy of 80%. This means the Neural Network model accurately classifies 80% of the patients for whether they have regular health visits to the doctor. (Shmueli et al., 2017).

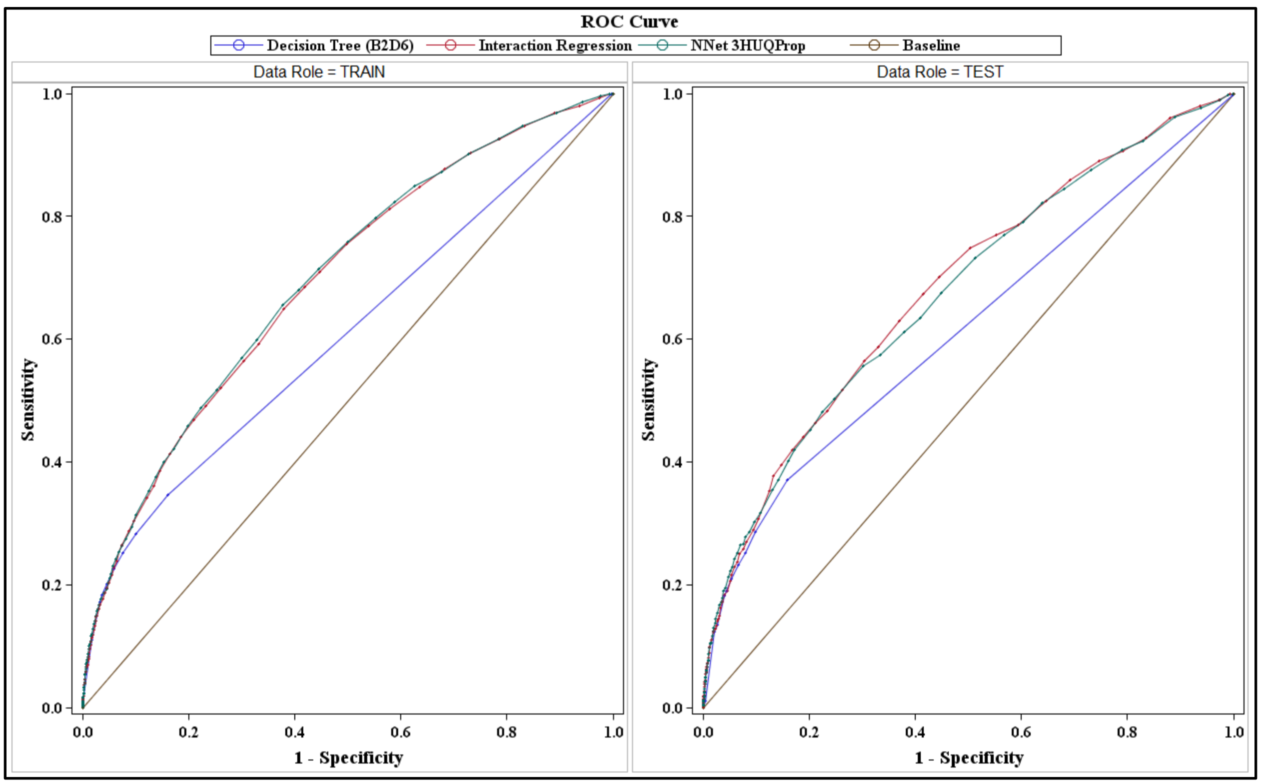

Figure 2. Receiver Operating Characteristic (ROC) Curve

We acknowledge the limitation that the Neural Network is a black box that does not help us to identify the factors which help the individual to make the decisions for a regular health checkup. So, after further detailed analysis of the developed models, we identified a Decision Tree that is the second-best model with a misclassification rate of 18.989%. This misclassification rate for the Decision Tree is slightly higher than Neural Net model but less than the misclassification rate of Interactive Logistic Regression (Table 2). Also, the cumulative lift chart of Figure 2 ensures there is minimum overfitting. In addition, it was observed that the input variables asthma, health plan, external (leisure) exercise, medical cost, poor health, physical health, and smoking (e-cigarette) habits were significant as shown in Figure 3.

As shown in Figure 3, if an adult has health coverage and there is no medical cost associated with a medical checkup, there is an 83% chance that an individual will have a medical checkup (Figure 3, Node Id 7). On the other hand, if an individual does not have healthcare coverage, but there is no cost associated with doctor visit, and individual didn't have an asthma episode in past 12 months, and did not have good health for approximately 10-12 days; then there was a 79% chance the individual did not go for a medical checkup (Figure 3, Node Id 16). However, if an individual has health coverage and there is no medical cost associated with doctor's visit, then there is a 95% chance that individual will go for a medical checkup even if he/she is a healthy person, does not have asthma episode in last 12 months, and did not even have any physical activity in last 30 days (Figure 3, Node Id 36).

The key observation is that individuals with health coverage have a greater likelihood of regular medical checkups. However, due to high healthcare costs associated with any diagnosis individuals prefer not to go for a medical checkup even when they are not healthy (Figure 3, Node Id 16).

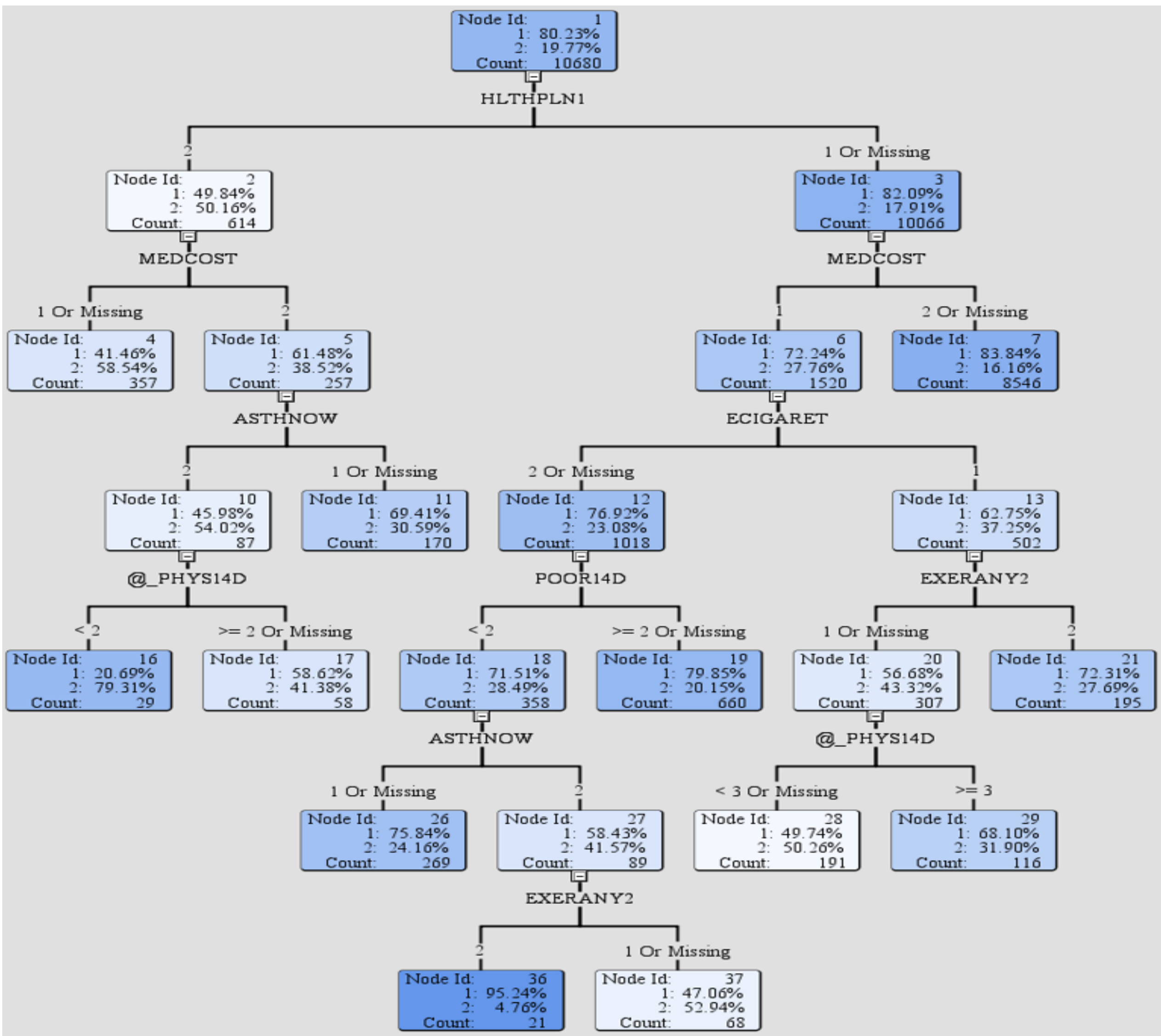

Figure 3: Factors Influencing Medical Checkup

4. Discussion and Conclusion

Primary prevention programs such as an annual medical checkup when focused on healthy behaviors can improve the quality of life and may increase the life expectancy (Brown et al., 2003; Fisher et al., 2011). We found that asthma, health plan, external (leisure) exercise, medical cost, poor health, physical health, and smoking (e-cigarette) habits are the important factors that influence the health decision of the individuals to go for a medical checkup or not. We observed that an unhealthy person who does not have healthcare coverage is less likely to go for a medical checkup even if there is no medical cost associated with it. However, a healthy person obtained a medical checkup in the prior year if he/she has health coverage and if there is no medical cost associated with the checkup.

We believe healthcare and behavioral education about preventive health interventions is needed to promote a healthy life. This research can also be used by healthcare professionals to develop a profile at the national level of persons who may not have a checkup so that prevention services could be targeted.

We used data from the BRFSS survey and performed predictive modeling in the study. Various factors related to physical, and mental health; medical cost for checkups, education level of an individual, income, asthma status, physical exercise, health plan, smoking habits, dependency on e-cigarette, and alcohol habits were analyzed using several supervised learning techniques. The results of scoring showed that 73% of people in the sample had asthma and 13% of them did not have a routine medical checkup. Furthermore, it was found that 11% of people suffering from asthma and who had health plans, did not have a routine medical checkup. Additionally, we observed 15.6% of individuals with smoking habits did not go for a health checkup and 3.6% expressed medical costs as a factor.

The analysis also suggested bad decision making for 14% of the people with poor physical health. This means even if people had poor health, they did not have a medical checkup. Based on our analysis it is evident that there is a need for encouraging better health decision making by individuals. This involves creating better health awareness programs and developing decision aids that enhance decision making. The results of this study provide a better understanding of the factors affecting health decisions.

The existing literature and the feature engineering technique helped us to identify the primary high-risk behavioral factors that can influence the decision to obtain a medical checkup, but there are other secondary variables that have not been used in this study. These secondary variables can be used to replicate and extend the research. Another key indicator is when a person responds “Don’t know” for critical health questions in health surveys (Orom et al., 2018). The SMART BRFSS data used in this study does not include such responses. “Don’t know” responses of individuals were eliminated before creation of the predictive model. Perhaps “Don’t know” responders should be provided with relevant health information.

Finally, the BRFSS data can be combined with ICD-10 (International Classification of Diseases) codes and Current Procedural Terminology (CPT) codes to better understand the diagnosis which will further lead to better healthcare decisions by the individuals (Medicare, 2018; Writers, 2018).

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Authors Biographies

Dr. Neetu Singh is an Assistant Professor of Management Information Systems at University of Illinois Springfield. She has received her Ph.D. in CIS from Georgia State University in 2016. Her research interests are in health information technology, healthcare analytics, big data/advanced analytics adoption, and actionable intelligence. More specifically, she has worked in the areas of medication adherence, interventions, healthcare analytics, data mining, and decision making. She has published several top-tiered refereed journal papers in information systems and medical informatics areas including European Journal of Information Systems (EJIS) and International Journal of Medical Informatics (IJMI). She has presented papers in national and international conferences including DESRIST, MWAIS, AMCIS, HCI International, International CIS (ICIS), ICHITA, and CHITA. She has received the third best paper award for her research on "Role of Decision Making in Predicting Health Behavior" in the MWAIS 2018 conference. She has also received the best paper award for her research titled "IT-based Patient Interventions for Opioid Abuse: Evaluation using Analytical Model" in ICHITA 2019 conference.

Apoorva Kanthwal is a Business Analyst at SEI Investments, Pennsylvania. She earned her MS in Management Information Systems from University of Illinois Springfield. Her research interests mainly include healthcare and financial analytics. She has presented her research in MWAIS 2018 conference and have received the third best paper award for the paper "Role of Decision Making in Predicting Health Behavior". She represented UIS in 2018 Society for Advancement of Management and their team received the first place at the Thomas Greensmith Open Division Collegiate Management Case Competition.

Prashant Bidhuri is the Senior Project Manager and a Salesforce Consultant at Enterprise Cloud Solutions. He got his MS in Management Information Systems at the University of Illinois at Springfield. His research interests are in healthcare information technology and business process mining. He has presented his research in MWAIS 2018 conference and has received the third best paper award for the paper "Role of Decision Making in Predicting Health Behavior". He represented UIS in the 2018 Society for Advancement of Management and their team received first place at the Thomas Greensmith Open Division Collegiate Management Case Competition.

Anusha Vijaykumar Munnolli, MIS Graduate from University of Illinois Springfield, is currently working as an Analyst at DaVita Inc. She is passionate about enabling data driven decision making as she continues to research new approaches to crunch data. She has presented her research in MWAIS 2018 conference and have received the third best paper award for the paper "Role of Decision Making in Predicting Health Behavior".

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