Machine Learning Approach on Evaluating Predictive Factors of Fall-Related Injuries

McMaster University

MSc Thesis

Machine Learning Approach on Evaluating Predictive Factors of Fall-Related Injuries

Author:
Sameen Ateeq

Supervisor:
Dr. Reza Samavi

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in eHealth

in

eHealth

August- 2018

McMaster University, Master of Science eHealth (2018) Hamilton, Ontario

TITLE: Machine Learning Approach on Evaluating Predictive Factors of Fall-Related Injuries

AUTHOR: Sameen Ateeq

SUPERVISOR: Dr. Reza Samavi

NUMBER OF PAGES 142

Abstract

According to the Public Health Agency of Canada, falls account for 95% of all hip fractures in Canada; 20% of fall-related injury cases end in death. This thesis evaluates the predictive power of many variables to predict fall-related injuries. The dataset chosen was CCHS which is high dimensional and diverse. The use of Principal Component Analysis (PCA) and random forest was employed to determine the highest priority risk factors to include in the predictive model. The results show that it is possible to predict fall-related injuries with a sensitivity of 80% or higher using four predictors (frequency of consultations with medical doctor, food and vegetable consumption, height and monthly physical activity level of over 15 minutes). Alternatively, the same sensitivity can be reached using age, frequency of walking for exercise per 3 months, alcohol consumption and personal income. None of the predictive models reached an accuracy of 70% or higher.

Further work in studying nutritional diets that offer protection from incurring a fall related injury are also recommended. Since the predictors are behavioral determinants of health and have a high sensitivity but a low accuracy, population health interventions are recommended rather than individual-level interventions. Suggestions to improve accuracy of built models are also proposed.

Acknowledgments and Dedication

I would like to thank and acknowledge Dr. Reza Samavi for meeting with me individually and offering his expertise in supervising this thesis for 2 consecutive years. His efforts in reviewing my work have provided the constructive feedback to complete the thesis in a scientific manner. Dr. Cynthia Lokker and Dr. Maryam Ghasemaghaei are also acknowledged for their efforts in reviewing, providing feedback and evaluating my work.

I would further like to thank Jawad Ateeq and Omar Boursalie for providing moral support for the thesis. Ali Ariaeinejad provided instruction while presenting his thesis in the research group and I am grateful for his peer support. Iris Kehler has provided administrative support for the program requirements and I am grateful for her help. Lastly, Arjumand Ateeq has provided writing help, encouragement and moral support for completing the thesis and my graduate journey would be incomplete without her. I am, therefore, grateful for her continued support.

I would like to dedicate the work to victims of fatal injuries. While fall-related injuries remain the focus of work covered in this thesis, I acknowledge injuries due to violence are also a serious cause of mortality and morbidity.

Contents

List of Figures

List Of Acronyms

CCHS - Canadian Community Health Survey

CIHI - Canadian Institute of Health Information

DAD - Discharge Abstract Database

HMD - Hospital Morbidity Database

GLM - Generalized Linear Modeling

LR - Logistic Regression

SVM - Support Vector Machine

RF - Random Forest

MLA - Machine Learning Algorithm

INJGCAU - Cause of Injury

INJ_01 - Injured in past 12 months

INJ_10 - Most serious injury - result of a fall

PACDFM - Monthly frequency - physical activity > 15 minutes

DHHGAGE - Age

HUIDHSI - Health utilities index

PAC_2A - Number of times - walking for exercise

INCDRRS - Household income distribution - health region level

INCDRPR - Household income distribution - provincial level

PAC_2B - Number of times - gardening/yard work

INCDRCA - Household income distribution

ALC_2 - Frequency of drinking alcohol

INCGPER - Total personal income from all sources

ALC_3 - Frequency of drinking 4(female)/ 5(male)or more drinks

PAC_3A - Time spent - walking for exercise

INCG7 - Main source of personal income

PAC_3F - Time spent - home exercises

HUIDCOG - Cognition problems - function code

HHWTGWTK - Weight (kilograms)/selfreported

HWTGHTM - Height (metres) / selfreported

CHPGMDC - Number of consultations with medical doctor

LBSGHPW - Total usual hours worked current

CHPG04 - Number of consult. - family doctor

FVCDSAL - Daily consumption - green salad

FVCDJUI - Daily consumption - fruit juice

FVCDPOT - Daily consumption - potatoes

Chapter 1

Introduction

According to the Public Health Agency of Canada (PHAC), injuries are a leading cause of hospitalization in all age groups (PHAC, 2014). Unintentional injuries are the 5th leading cause of hospitalization[1] in Canada (Canada, 2016b). Vulnerable populations are children, youth, seniors and aboriginal populations (Parachute, 2015). Data from 2004 indicates that the economic burden of injuries is highest among seniors and approximately equal to $2 billion annually (PHAC, 2014).

Falls in pregnant women are common and are often traumatic (Dunning et al., 2003). About 27% of employed women surveyed in the study by Dunning et al. (2003) reported falling. While falls and injuries may be common in several age groups, the population over 65 years is at the greatest risk of dying due to an injury incurred from falling (Deandrea et al., 2010). Among all causes of hospitalized injuries, falls mean something different for seniors which hitherto refers to the age group over 65 years. Falls are an indicator of poor overall health and declining function in seniors (Fuller, 2000). Approximately 95% of all hip fractures occur from falls in seniors, and 20% of these cases end in death (WHO, 2015). One-third of community dwelling seniors and 60% of nursing residents fall each year (Fuller, 2000). Consequences of falls include life-long disability, mortality and

[1]data about complications in pregnancy was removed

Table 1.1: Clinical Burden of Injuries in Canada in the year 2004 (Parachute, 2015)

Cause of Injury	**Deaths**	**Hospitalizations**	**Emergency Room Visits**
Transport Incidents	2,620	28,350	290,782
Falls	4,071	128,389	1,036,079
Drowning	369	247	1,251
Fire/Burns	234	2,099	43,684
Unintentional Poisoning	1,568	7,893	54,245
Struck By/Against Sports Equipment	¿5	664	68,355
Other Unintentional Injuries	1,792	36,462	1,845,277
Suicide/Self-Harm	3,948	16,131	34,677
Violence	515	8,069	97,360
Undetermined Intent/Other	749	3,292	20,438

loss of autonomy in the senior population (Kamińska, Brodowski, & Karakiewicz, 2015).

There are many risk factors of falls such as age, gender and polypharmacy (Ambrose, Paul, & Hausdorff, 2013; Huang et al., 2012). The large number of risk variables uncovered through research makes the task of selecting a subset of risk factors for devising targeted interventions to prevent falls and related injuries difficult. The aim of this study is to find the most predictive factors of fall-related injuries and evaluate them. The research question posed in this thesis was: Can machine learning algorithms be used to predict fall-related injuries and concur with previous findings from the health literature?

Table 1.1 shows that fall-related injuries are the leading cause of death and hospitalization among all other causes of injuries. According to the statistics in the same table, falls are the second leading cause of injury-related emergency department visits. To study fall-related injuries, the Canadian Community Health Survey (CCHS) dataset was used. This survey is conducted by Statistics Canada annually and was chosen for this thesis because of its inclusion of a diverse set of variables about determinants of health and a variable about fall-related injuries. In answering the research question, a process for reducing the dimensionality of the CCHS dataset was established so that the predictors could be chosen objectively.

The most suitable variable in the CCHS dataset that evaluated fall-related injuries was the cause of injuries. Respondents were first asked if they incurred an injury in the past 12 months. Those who responded affirmatively were further asked about the cause of their injury. The sample size was 9,497 cases of reported injuries. The independent variables were first analyzed using chi-square tests to assess whether the cause of the injury was associated with any other variables. All statistically significant variables that were associated with the cause of injury were ranked by importance for predicting fall-related injuries. The variables that were most predictive of fall-related injuries, such as age and alcohol consumption, were used as independent variables. The predictive models were then evaluated using linear and non-linear classification approaches (generalized linear modeling, random forest and support vector machine).

This thesis focuses on processing a high-dimensional dataset to establish criteria for determining predictors and to evaluate the performance of the built predictive models. In this thesis, the work conducted expands the methodological approach used to analyze census data for a target outcome by using generalized linear modeling (GLM), support vector machine (SVM) and random forest (RF) mapping to train and predict injuries due to falls in the Canadian population.

1.1 Thesis Contributions and Structure

In this thesis, the following contributions were made:

1. A process is defined using a combination of prediction methods for selecting the most important predictors of fall-related injuries out of a wide variety of independent variables.

2. Social, economic and behavioral determinants of health are used as predictors, in addition to demographics.

3. New factors of fall-related injuries are discussed. Performance evaluation

of the predictive models built using the new factors suggests a sensitivity of 80% can be reached. These factors are: frequency of consultations with medical doctor, food and vegetable consumption, height and monthly physical activity level of over 15 minutes.

The rest of the thesis is organized as follows:

- Chapter 2: A discussion is presented about previous work in the field of fall-related injuries and fall prediction.
- Chapter 3: The dataset and the proposed model are discussed in depth.
- Chapter 4: The evaluation and discussion are described in this chapter. Additionally, sections about limitations of this thesis and the application of results in policy development are discussed.
- Chapter 5: Conclusion of the overall thesis and recommendations for future work are proposed in Chapter 5.
- Appendix A: A supplement to Chapter 3 is attached as the first appendix. This supplement lists the variables by importance in a random forest map. The relative importance of each variable was obtained by computing the mean decrease in node impurity at each split (denoted by mean decrease in Gini index).
- Appendix B: The table presented in Appendix B is a mapping of the variables. It also details the results of chi-squared tests conducted to test for statistical significance. It can be considered a supplement to Chapter 3 as well.
- Appendix C: Summary statistics of all variables grouped by cause of injury are included in Appendix C.

Chapter 2

Literature Review

Given the burden of fall-related injuries, much research has been conducted to study risk factors associated with falls and injuries. In this chapter, the literature has been studied from two perspectives. First, a discussion of some case-control studies is covered in section 2.1 which examines the association of risk factors with falling and incurring an injury. Machine learning experiments are also described in the same section which aimed to predict or detect falls. In section 2.2, the social determinants of health approach is described; in addition to determinants of health and their association with policy are also described. In section 2.3, machine learning algorithms used in the thesis are discussed.

2.1 Fall-related injuries

According to Masud and Morris, various definitions of falls have been used; one broad definition cited is the one developed by The Frailty and Injuries: Co-operative Studies of Intervention Techniques (FICSIT), which is "intentionally coming to rest on the ground, floor or other lower level" (Masud & Morris, 2001). Different methods of classifying falls also exist; a fall might be explained by an intrinsic factor such as syncope or an extrinsic factor, such as footwear, or it may be unexplained (Masud & Morris, 2001).

The rate of fall-related injuries increased by 54% from 2005 to 2013 in the population aged 65 and above (Do, Chang, Kuran, & Thompson, 2015). Within this group, women and younger age groups were more likely to incur a fall-related injury than males and those in older groups (Do et al., 2015). Thirty percent of adults aged above 65 years and living in their homes experience a fall-related injury; about 50% of these individuals do not report their fall to caregivers and medical professionals (Kamińska et al., 2015). Not every fall results in an injury and so individuals may not feel a need to report the fall to caregivers or take action. The increase in the rate of fall-related injuries may partially be attributed to a demographic shift which resulted in the baby boomer generation reaching the age above 65 years in 2011 (of Canada, 2014).

The Falls Risk Factor Model was developed by WHO to show that many risk factors can cause falls and the factors are interdependent (WHO, 2007). The risk factors are divided discretely into four categories: behavioral, biological, socioeconomic and environmental and are shown in Figure 2.1 (WHO, 2007). Behavioral risk factors include alcohol use and sedentary behavior or physical activity levels. Age and race are biological risk factors while education and income are socioeconomic factors. Environmental factors are extrinsic to the individual and include loosely fitted carpet and low lighting.

Systematic reviews have also studied risk factors of falls. History of falls, strength, gait and balance abnormalities are the strongest risk factors of falls (Ambrose et al., 2013). Female gender, age above 85 years, vestibular dysfunction, impaired depth perception in vision, cognitive impairment, cardiovascular disease, poly-pharmacy, and pharmacological interactions due to aging are all known risk factors of falls (Ambrose et al., 2013). Functional decline in normal aging (Ambrose et al., 2013) and specific medications (Huang et al., 2012) have also been associated with higher odds of falling. It is very hard to determine a few risk factors which can

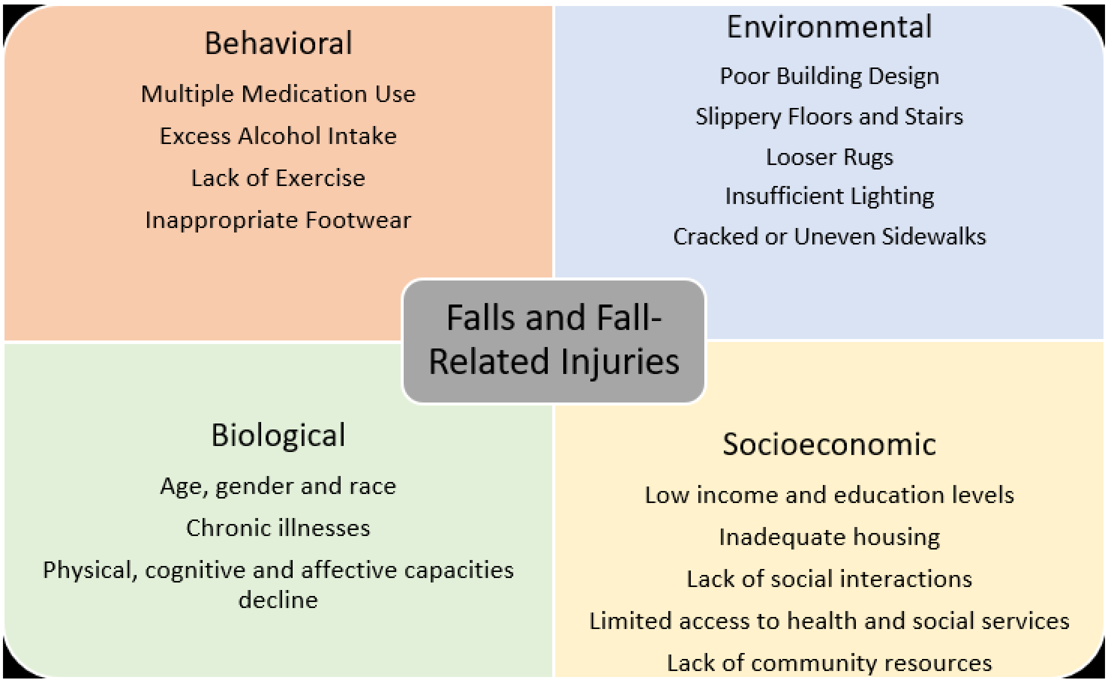

Figure 2.1: Risk Factors of falls and related injuries (based on WHO, 2007)

be used as universal predictors of falls so that all policy and clinical interventions can be directed in a focused manner.

Tong, Song, Ge and Liu (2013) built a fall detection system using acceleration time series data to model a fall and employed hidden Markov models. Their system predicted falls 200-400 ms before the actual fall (Tong, Song, Ge, & Liu, 2013). In their experiment, 8 student volunteers with a mean age of 25 years simulated falls. Motion patterns from 80 falls and 40 samples of other motion patterns, including sitting and standing were collected. Features were the motions captured directly before hitting the sponge mat which was the equivalent of a ground in the experiment. The falling process was described by state transitions of the human body over time intervals. Two probability levels were important in this study, P_1 and P_2. P_1 was the value which separated normal household activities from p values obtained in fallen states; This p value was used in fall prediction. P_2 was the p value of the body when it had lost balance and was used in fall detection. The authors proposed use of their predictive system in triggering an airbag upon detection of lost balance and thereby preventing injury upon hitting the ground (Tong et al., 2013). Fall detection devices can prevent injury from a fall by triggering quick actions such as airbag inflation or alert a caregiver for quick medical attention to prevent prolonged effects of lying on the ground without medical attention. Fall detection systems do not prevent the fall itself.

Lipsitz et al (2016) conducted a 6-month prospective study with 37 nursing home residents as subjects to test a fall detection device comprising of a triaxial accelerometer. The number of falls reported by healthcare professionals was compared with the number of falls detected by the triaxial system and the concordance rate was determined to be low; 19% of those who were reported to have fallen by staff were detected by the device (Lipsitz et al., 2016). Fall detection systems that perform well in laboratory settings do not perform as well in real-world settings. In another study, a similar accelerometry-based fall detection system was tested on 16 subjects with and without history of falls; only 6 subjects remained until end of the study. 12 out of 15 falls were detected reaching a sensitivity rate of 80% (Kangas, Korpelainen, Vikman, Nyberg, & Jämsä, 2015). An average of 10 false alarms per person were generated per day by the system during a field test (Kangas et al., 2015). Their study used 15,500 hours of real-life data, which equates to about 640 days or 21 months. (Kangas et al., 2015). Although this system was good at detecting falls and alerting caregivers, the false alarm rate was high and the authors recommended further work in improving accuracy.

Howcroft and colleagues reviewed use of inertial sensors for falls risk assessment (Howcroft, Kofman, & Lemaire, 2013). They found that accelerometers and gyrometers were the most common sensors used to measure inertia and the most common location of sensor placement on the body was the lower back (Howcroft et al., 2013). Models with the best accuracy, sensitivity and specificity were found to use neural networks, naive Bayesian classifier, Mahalanobis cluster analysis or a decision tree, while regression and support vector machines were associated with models that performed less well (Howcroft et al., 2013). It is worth noting that these studies used data collected from sensors to study movement patterns associated with falls. In contrast, Fernández-Delgado et al (2014) found random forest was the best classifier across 121 datasets that they compared accuracy for, followed by support vector machine (Fernández-Delgado, Cernadas, Barro, & Amorim, 2014). One observation is that machine learning experiments aim to predict falls a few minutes before falling when it is possible to predict falls several weeks before the fall using data about biological, behavioral and socio-demographic variables.

Population Health Intervention Research (PHIR) aims to assess evidence on what can improve the health of a population as a whole (Hawe, Di Ruggiero, & Cohen, 2012). PHIR aims to maintain good health among populations, rather than target sick populations; this approach is called primary prevention (Hawe et al., 2012). In the context of falls and related injuries, by identifying the conditions that are most predictive of fall-related injuries, policies and programs can be mobilized to prevent fall-related injuries by rectifying the risk variables at an early stage in future populations. Secondary prevention is also possible by enabling programs and policies to rectify the identified risk factors in the current population, such as those with a history of falls.

Castro and colleagues (2014) tested a predictive model for falls using multiple logistic regression on data from electronic medical records (EMRs). They studied clinical and sociodemographic features for predicting hospital or emergency department visit for a fall-related injury. The features were identified based on ICD-9 codes for fall-related injuries, such as fracture and dislocation. Old age, female sex, white or African-American race, public insurance, polypharmacy, burden of adverse effects score were independent predictors of fall-related injury (Odds Ratio(OR) ≥ 1) (Castro et al., 2014).

Rajkomar et al (2018) showed that data from health records can be used to build predictive models for predicting multiple medical events after it has been represented using the Fast Healthcare Interoperability Resources (FHIR) standard. They first organized events in temporal order then trained the model using deep learning and complete patient history (Rajkomar et al., 2018). Their dataset comprised of 46.8 billion data points from patient records from two hospitals. The area under the receiver operating characteristic curve (AUROC) for inpatient mortality at 24 hours after admission was above 90% in both hospitals. The AUROC for predicting length of stay and classification of all diagnosis codes was above 80% in both hospitals (Rajkomar et al., 2018). The model's accuracy is promising for demonstrating the use of machine learning in the field of healthcare; however, medical records are hard to link due to existing privacy laws, especially in Canada.

Vaughon et al (2018) analyzed the Canadian Community Health Survey on Healthy Aging (Public Use Microdata File 2008–2009) using Logistic Regression (Vaughon, Lee, Gallo, Kaufman, & Unuigbe, 2018). Their data set contained 2,934 participants who were involved in performing care-giving tasks for one year or more (Vaughon et al., 2018). The authors examined the association between frequency of performing care giving tasks and incidence of falls. Their logistic regression model detected significantly lower odds of falling associated with those who reported performing household activities ($p \leq 0.05$) (Vaughon et al., 2018). The ability to perform household activities indicates an individual's functional capacity. As formerly stated in Chapter 1, falls are an indicator of poor health. Those who are likely to fall are individuals who experience other health problems that are the likely cause of poor health. In studying falls, a more comprehensive set of variables than gait, posture and demographic characteristics is needed.

In the ambulatory care setting, simple fall prediction models utilizing self-reported data have been shown to optimize the AUROC in comparison to models using performance-based data for falls (Gadkaree, Sun, Huang, Varadhan, &

Agrawal, 2015). They found that prediction models based on self-reported data about demographic variables reached an AUROC of 0.57 and the predictive value increased as more predictors were added. Adding physical performance test results to the predictive model resulted in a slight improvement; the AUROC measure was 0.69. An AUROC measure of 0.71 was reached with addition of chronic disease characteristics, such as hypertension and osteoporosis (Gadkaree et al., 2015). The work by Gadkaree et al. shows that falls may be the result of a combination of demographic characteristics, gait and coordination issues and chronic illnesses experienced by an individual.

Machine learning experiments in the past have not studied fall-related injuries in relation to determinants of health. Current literature has examined falls based on the age group of above or below 65 years, institutional setting (i.e. community-dwelling versus patient setting), and frailty status. Two main interventions for fall prevention are clinical risk assessments for falls and motion sensing devices to alert a caregiver. Policy level decision support to understand which risk factors should be targeted for population-level interventions are not well established in the scientific literature. Health status of an individual can be determined by many non-biological factors, such as income and education status (M. Marmot & Allen, 2014).

2.2 Determinants of Health

Social determinants of health often precede biological mechanisms of illnesses (Braveman & Gottlieb, 2014) and contribute to disease progression. Determinants of health are a group of factors beyond genetics that influence health status (Canada, 2018). Social determinants of health are a combination of social and economic factors, such as education status, income, race and gender which affect health status (Canada, 2018). The mechanisms can be several; access to healthcare services and healthy environments is easier for those in the upper class. Clean air, water and safe neighborhoods are a few of the characteristics of healthy environments that can affect longevity.

According to the Economic and Social Research Council (ESRC), the Dahlgren-Whitehead rainbow model is one of the most prominent models used in public health policy and is shown in Fig.2.2 (Economic & Council, 2018). This figure conveys that biological factors, individual lifestyle choices, social and macro-level factors influence one's health. The Falls Risk Factor Model is consistent with this model of viewing the interconnections of various levels of determinants of health (Figure 2.1). Biological, social and behavioral determinants affect one's risk of an outcome. The level of change possible at an individual level is only one consideration. The social environment and supports available to an individual also shape the risk of an outcome. The Falls Risk Factor Model is consistent with the Dahlgren-Whitehead model shown in Fig. 2.2 and separates biological, behavioral, social and environmental factors into separate categories.

The Whitehall study is a landmark longitudinal study by (M. G. Marmot, Rose, Shipley, & Hamilton, 1978) designed to examine risk of coronary heart disease (CHD) by social class. British civil servants were followed for 7 and a half years and were stratified based on social class differences into 4 groups: Administrative, Professional/Executive, Clerical and Other. The group 'Other' comprised of messengers and unskilled workers which were implied to be of the lowest class grade. The Whitehall Study determined that workers in the lowest grade were 3.6 times more likely to die from CHD than administrative employees (M. G. Marmot et al., 1978). The results imply that socioeconomic status plays a significant role in determining risk of illnesses.

Determinants of health are studied to inform public policy and direct funding towards programs that are proven to improve outcomes in the predefined population (Solar & Irwin, 2010). In contrast to recommending individual level tasks,

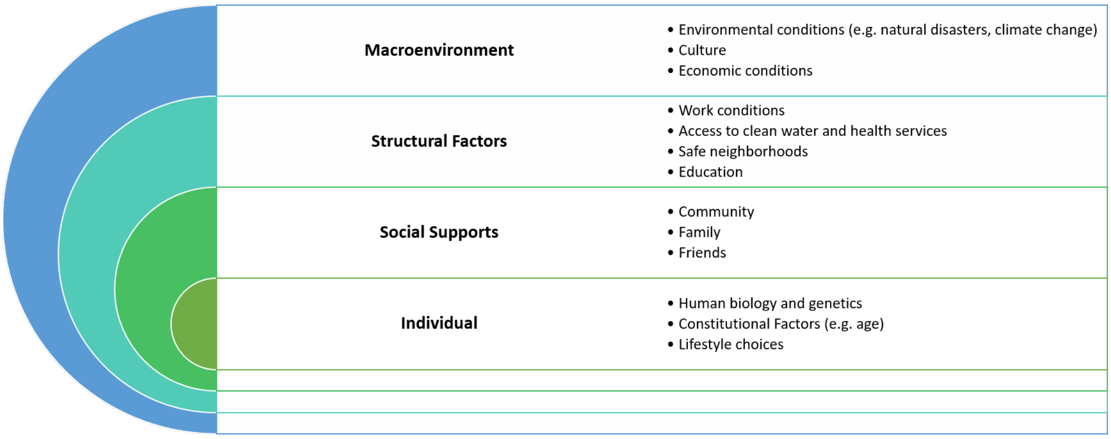

Figure 2.2: The Dahlgren-Whitehead Rainbow Model (based on (Economic & Council, 2018))

policy level changes offer social supports to increase access to needed resources to improve health outcomes. Initiatives for preventing falls related injuries include promotion of healthy aging (Canada, 2016a). The Go4Life campaign by the National Institutes of Health (NIH) in the United States was launched in 2011 and promoted physical activity for seniors (Herman, 2014). Canada's strategy focuses on the built environment and promotes 'age-friendly communities' which focus on well-lit streets, availability of community support services, well-designed housing to prevent falls and related injuries among other recommendations (Canada, 2016a). Other actionable priorities by the government include enabling financial benefits and guidelines to counteract social isolation among seniors (Canada, 2017).

The CCHS dataset comprises entirely of self-reported data and presents a different set of variables than used in other fall and injury prediction experiments. Traditionally, performance tests are used to collect data about predictors. Performance tests, such as the chair stands and 3-minute walks used in the study by Gadkaree et al., are performed under supervision and do not capture the impact of the social and behavioral determinants of health. By studying census data, it is possible to take the social determinants approach to elaborate on the association of risk factors that can go beyond biological risk factors to predict an outcome. As explained in section 3.1, the CCHS dataset is a census of the Canadian population and includes variables about various determinants of health.

2.3 Machine Learning

Machine learning is becoming an increasingly common technique for mining large datasets to uncover new insights. Training a machine requires a set of input variables which are processed by the computer to learn a pattern which can then be used to predict responses (Jain, Duin, & Mao, 2000). The statistical approach of machine learning involves a representation of input features in a d-dimensional space (Jain et al., 2000). In supervised classification, the representation is based on a pattern identified in relation to each class of the target variable and is determined by the algorithm employed (Jain et al., 2000). In unsupervised learning problems, the classes are not predefined (Jain et al., 2000).

In population health research, only parametric regression methods have been used to predict health outcomes (Rose, 2013). Machine learning algorithms, which are predominantly non-parametric, non-linear approaches of learning have also been used for fall prevention and detection. Such experiments use sensors to predict falls based on movement patterns (Narayanan et al., 2010) but these focus on predicting falls a few seconds before the individual hits the ground. In adopting machine learning algorithms for mining census data, three classifiers were used: Support Vector Machine (SVM) and Random Forest (RF) are non-parametric approaches that are referred to as supervised machine learning techniques while Generalized Linear Modeling (GLM) is a parametric regression approach and is also referred to as a supervised machine learning technique.

1. Generalized Linear Modeling (GLM): GLM is a form of parametric regression where data points constitute an input vector x. The goal of the GLM function is to classify the input vector x into a discrete class from all possible classes C_K (Bishop, 2006). GLM is based on linear modeling techniques, but

includes a non-linear activation function ($\int$) and so the modeling technique is not purely linear (Bishop, 2006).

Where the outcome is binomial, the classification is completed through logistic regression models which uses the 'logit' link function (Quick-R, 2017). Logistic regression calculates the logarithm of the odds ratio (Peng, Lee, & Ingersoll, 2002). The odds ratio is derived from 2 odds or probabilities: the probability of presence of the characteristic and the probability of absence of the characteristic (MedCalc, 2018). First an odds ratio is calculated using 2.1 and then a coefficient is produced by transforming the ratio using the logit function as per 2.2 (MedCalc, 2018).

$$odds = \frac{p}{1-p} = \frac{\text{probability of presence of characteristic}}{\text{probability of absence of characteristic}} \tag{2.1}$$

$$logit(p) = ln(\frac{p}{1-p}) \tag{2.2}$$

2. Support Vector Machine (SVM): SVM is a category of kernel methods. Kernels are similarity functions which map the input data points into a high dimensional feature space (Hofmann, Schölkopf, & Smola, 2008; Cortes & Vapnik, 1995). This mapping is created by dot-products of pairs of input vectors (Hofmann et al., 2008). The feature space mapping is denoted by ϕ(x)

   SVM finds an optimal hyperplane separating the points in the input variable space (Brownlee, 2016). The distance between the separating data points is maximized and is termed 'margin'; thus, the optimal hyperplane maximizes margin (Brownlee, 2016). Depending on the pattern of the input space, different SVM kernels are employed which can produce linear, polynomial or radial decision boundaries (Brownlee, 2016). Radial Basis functions determine the class of an input vector x by calculating the distance from a center μ_j (Bishop, 2006).

3. Random Forest (RF): The statistical approach of building classification trees is non-parametric in RF (Lemon, Roy, Clark, Friedmann, & Rakowski, 2003). Classification by RF involves drawing n_{tree} bootstrap samples from the data and using each sample to build a classification tree (Liaw, Wiener, et al., 2002). For each tree, the algorithm finds mutually exclusive subgroups within the population which are similar only in respect to the dependent variable of interest (Lemon et al., 2003). The classification trees are independent of each other and each tree casts one vote for the class of the input vector x (Breiman, 2001).

   The nodes are divided into 2 using a splitting criterion; these criteria look for impurity within the node (Lemon et al., 2003). The parameter, m_{try}, determines the number of predictors to be randomly sampled and used for splitting at each node of the classification tree (Liaw et al., 2002). The impurity is simply the variability in the dependent variable (Lemon et al., 2003). Three common splitting criteria are the Gini index, entropy and minimum error (Lemon et al., 2003). Further information is found in the work by (Lemon et al., 2003). The first level of the tree structure takes the whole sample population into account and is termed the parent node, while subsequent iterations of the process produce child nodes (Lemon et al., 2003).

   The predictions from the n_{tree} trees are then used to predict on new data through majority votes (Liaw et al., 2002). The data not in the n_{tree} is called out-of-bag (OOB) data; an OOB estimate of error is calculated by using the built classification trees to predict on the OOB data and aggregating the predictions (Liaw et al., 2002).

2.4 Conclusion

Based on the literature review, one observation is that determinants of health are rarely used alongside indicators of physical activity in predictive models. Other researchers (Tong et al.; Yacchirema, de Puga, Palau, and Esteve) aim to predict fall-related injuries a few seconds before an individual hits the ground. This thesis aims to predict fall-related injuries at a longer time span using behavioral and social determinants of health. These conditions may be chronic illnesses (e.g. heart disease) or a number of other risk factors most predictive of falling and incurring an injury.

Machine learning algorithms extend the methodological approach of looking for patterns of association between predictors and the target variable. The algorithms, RF and SVM, look for non-linear decision surfaces to separate training data and offer a different approach from GLM to finding an association between independent variables and the target outcome. In conclusion, social and behavioral determinants of health have not previously been used to predict risk of incurring fall-related injuries using non-linear, non-parametric machine learning algorithms.

Chapter 3

The Proposed Model

All variables in the CCHS dataset were considered for predicting fall-related injuries. With 1128 variables in the dataset, the initial task was to eliminate variables that were not associated with fall-related injuries. The variables that were most strongly associated with the incidence of a fall-related injury were chosen as the predictors. In the CCHS dataset, the *Cause of injury* (INJGCAU) was chosen as the target outcome because it included injuries that were incurred due to falling and other reasons. A number of steps were executed, such as statistical testing, to select the right variables as predictors from the dataset for predicting the outcome of interest. Fig.3.1 presents the overview of the proposed model for predicting fall-related injuries. The input dataset and target outcome are described in section 3.1. Section 3.2 describes the details of each step in Fig. 3.1. The results of the evaluation are presented in the next chapter.

3.1 Selection of the Data Set

There are various sources of data about health of Canadians. Statistics Canada (StatsCan) conducts national surveys to collect data about the Canadian population. Reports of the data are available from their website (S. Canada, 2018b).

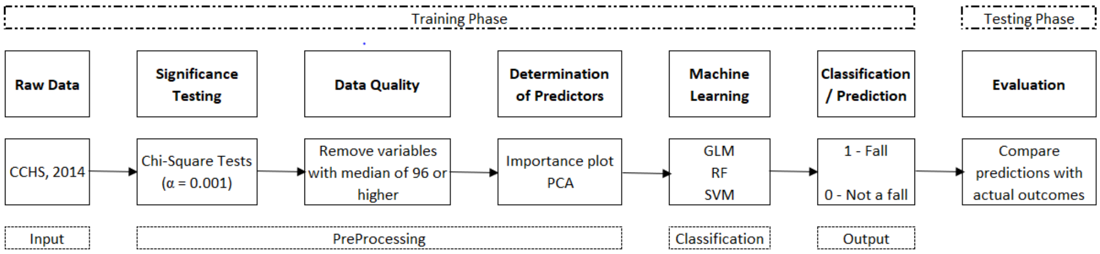

Figure 3.1: The proposed model for training and testing phases

Similarly, Canadian Institute for Health Information (CIHI) collects data from hospitals and prepares reports from that data (of Health Information, 2018). Three sources of candidate datasets to study injuries were: Discharge Abstract Database (DAD), Hospital Morbidity Database (HMD) and Canadian Community Health Survey (CCHS) (S. Canada, 2018a).

The Discharge Abstract Database (DAD) contains hospitalizations due to injury that resulted in death while the Hospital Morbidity Database (HMD) contains hospitalization data from non-fatal injuries (for Health Information, 2018). Both databases use the indicator 'Injury Hospitalization' to describe injury data. Hospitalization data was avoided in this thesis because few risk factors of injuries are captured in patient records. Since the survey is self-reported, it does not capture information about individuals who died due to an injury. This limitation was neglected because the aim of this study is to find the most predictive factors of fall-related injuries, not whether the injury was serious enough to result in death.

The CCHS was an appropriate choice of dataset because it included populations of varying demographics of age and geographic location within the Canadian population. The CCHS dataset is rich and diverse because it includes variables about social and behavioral determinants of health, such as sedentary behavior, alcohol use and diet. The data is openly accessible through the ODESI Scholars Portal due to the Data Liberation Initiative (DLI) (Statistics Canada). The CCHS (2014) data set contained 1128 variables, excluding the target variable. The survey accumulated data through computer assisted telephone interviews from 63,522

Canadians aged 12 years or above (S. Canada, 2017b). The study employed cross-sectional survey design and is a census of the Canadian population.

There were 1129 questions in the survey and each question was represented as one variable in the dataset. The sample was selected using three sampling frames – 40.5% of cases were selected based on geographic area frames, 58.5% were selected based on telephone list frames and the remainder of the cases were generated through random digit dialing. The CCHS collected data on various variables which were grouped by main subject areas and these subjects are referred as 'Groups' or 'Modules'. Several questions within each group are interdependent but the groups do not imply a statistical grouping. More information about the CCHS (2014) dataset can be found in the 'Canadian Community Health Survey, 2014: Annual Component: Study Documentation' (S. Canada, 2017b). Derived variables are described in the 'Canadian Community Health Survey, 2014: Derived Variable Specifications' (S. Canada, 2017a)

The data was collected and processed by Statistics Canada, and the responses in the dataset were assigned a numeric code. For most questions, the last four responses were coded with a number ending in 6, 7, 8 and 9 to indicate responses of Not Applicable, Don't Know, Refusal and Not Stated respectively. The dataset excluded certain populations: persons living on reserves and other Aboriginal settlements in the provinces; full-time members of the Canadian Forces; the institutionalized population and persons living in two health regions within Quebec - Région du Nunavik and Région des Terres-Cries-de-la-Baie-James.

3.1.1 Target Variable

The target variable studied is the *Cause of Injury* (INJGCAU). The target variable is also referred to as the dependent variable and the outcome variable in this thesis. Within the Module Injuries, respondents were asked: "In the past 12 months, that is, from this date one year ago to yesterday, were you injured?"; the responses were coded in variable INJ_01. Respondents who answered "Yes", "Don't Know" or "Refusal" to the question were prompted for a *Cause of the Injury* (INJGCAU).

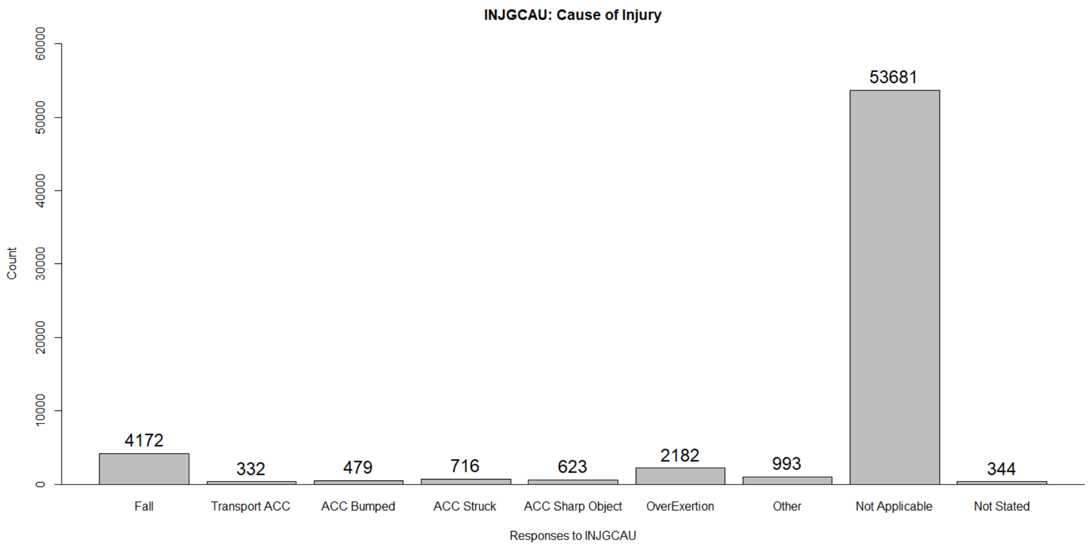

Figure 3.2: Bar Chart showing count of responses for INJGCAU

A bar chart illustrating the count of responses in each category of INJGCAU is shown in Fig. 3.2. Responses for INJGCAU were categorized as Falls, Transport Accident, Accident Bumped, Accident Struck, Accident Sharp Object, Overexertion, Other, Not Applicable and Not Stated. Cases that responded 'Not Applicable' or 'Not Stated' were removed, leaving a total of 9,497 cases. The injuries that were not due to a fall (Transport Accidents, Accident Bumped, Accident Struck, Accident Sharp Object, Overexertion, Other) were combined into one category, called 'Not a Fall'. Fig. 3.3 on page 22 includes a bar chart showing count of responses for *Cause of Injury* (INJGCAU) after all non-fall related injuries were combined in to one category. The figure highlights that the number of fall-related injuries in the sample was 4,172. As seen in the same figure, the number of non-fall related injuries was 5,325. Based on the literature review covered in Chapter 2, fall-related injuries are associated with some intrinsic factors such as age, gender and chronic illnesses. The category of responses encoded in Group 0 (non-fall related injuries) is assumed to compose of individuals who did not incur injury due to an intrinsic health issue and are healthy as far as falls are concerned.

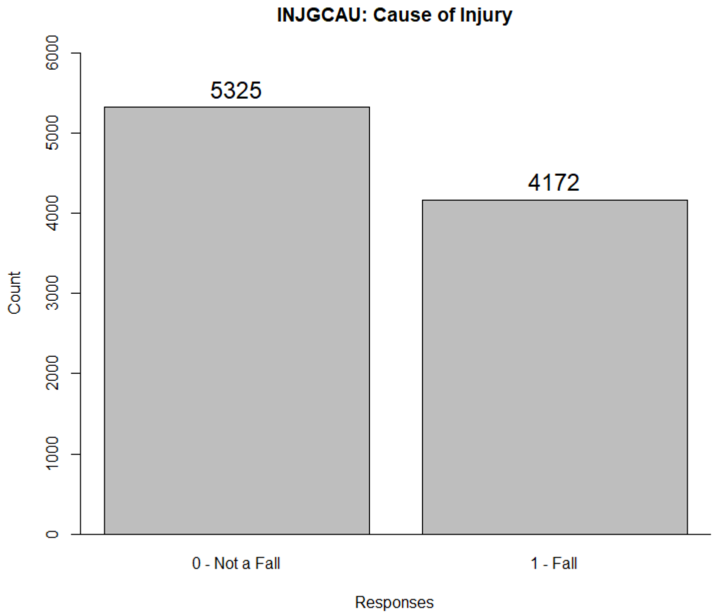

Figure 3.3: Bar chart showing count of responses for INJGCAU after modification of non-fall related injuries.

Although falls have predominantly been studied in relation to age, the dataset was not subset by age of 65 years and above. This is because age itself is a predictor of falls and related injuries. The number of data points within each category would also be reduced if the data was subset by any of the input variables. Hence, no modifications were made to the dataset other than combining non-fall related injuries into one category. Fig. 3.4 on page 23 shows that the median age in the group that incurred an injury due to falling is 50 to 54 years. The variation of age groups in those who were injured is high and ranges from age groups 4 to 13 (i.e. 20 to 69 years). There are no outliers in the data and all age groups reported incurring an injury due to falls. Similarly, non-fall related injuries were reported by all age groups. The median age of those who reported being injured for a reason other than falls is 7, i.e those between 35 to 39 years.

Within Group Injuries, another variable - *most serious injury – result of a fall* (INJ_10) - was not chosen as the target variable because the question only asked

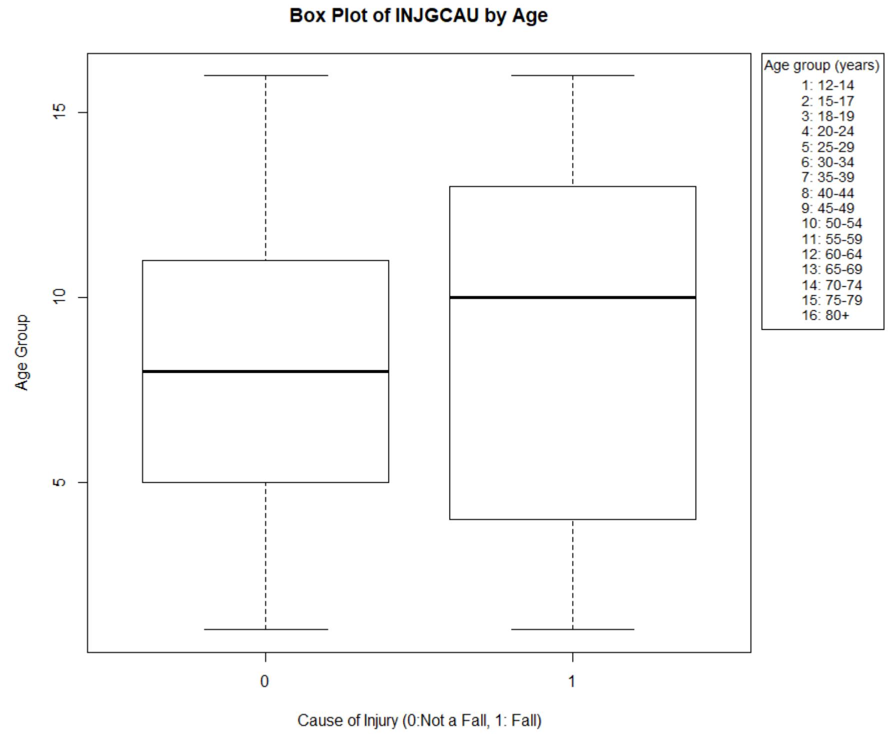

Figure 3.4: Box plot of cause of injury and age in the CCHS dataset

for the cause of the most serious injury. The responses omitted less serious injuries. In computing the total responses in each category, *Cause of Injury* (INJGCAU) and *most serious injury – result of a fall* (INJ_10) have the same number of falls reported (n_{falls} = 4,172). Fig. 3.5 shows responses in each category of *most serious injury – result of a fall* (INJ_10). As seen from this figure, the number of reported fall-related injuries is the same as *Cause of Injury*(INJGCAU) (n_{falls} = 4,172). According to this figure, the number of people who did not report incurring an injury at all was greater than 53,000.

Group Workplace Injuries included variables about occupational injuries. This group excluded falls occurring due to intrinsic factors and populations who are unemployed or retired. Previous research has already shown that many of the variables in the CCHS are associated with injuries due to intrinsic factors (Ambrose et al., 2013) and the economic impact and mortality rate is high for the injuries captured in the variable *Injury within past 12 months* (INJ_01). Hence, predictors

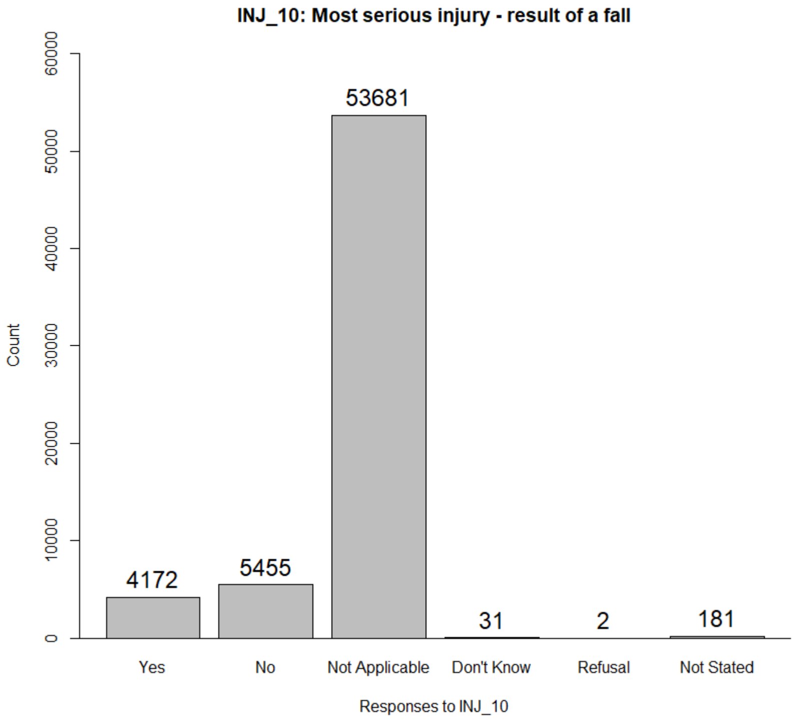

Figure 3.5: Bar Chart showing the count of responses for INJ_10

of workplace injuries were not the target of this thesis.

3.1.2 Independent Variables

The number of independent variables considered for prediction of fall-related injury is very high. A description of each variable in the dataset is found in Appendix B and a statistical summary of the independent variables is attached in Appendix C. Two different approaches were tested for measuring the association between independent and dependent variables. The first approach was to select variables manually based on whether the group was found in the Falls Risk Factor Model (see Figure 2.1 in Chapter 2). Another possibility for selecting independent variables was to statistically compute differences in the *cause of injury* (INJGCAU) with respect to the input variable. Both possibilities were examined separately by conducting two separate studies.

In Study 1, variable groups were manually based on whether the Falls Risk

Factor Model listed the variable group in it or not. In accordance with the Falls Risk Factor Model, the groups selected for inclusion were as follows: Alcohol Use, Physical Activities, Chronic Conditions, Health Utilities Index, Income, Education, Health Care Services, Unmet Health Care Needs, and Alcohol Use During Pregnancy. In addition, age and sex of the individual were also included as risk factors from the group 'Dwelling and Household Variables'. Furthermore, the CCHS 2014 data set did not contain variables in the Environmental factors category and so this category of risk factors was not included in the study. The total number of independent variables in Study 1 was equal to 207.

In Study 2, all variables except *Cause of injury* (INJGCAU) were included as independent variables (n=1,128). In a later stage, the variables within Group Injuries were manually removed as independent variables for Study 2 because the variables were too similar to the dependent variable, *Cause of Injury* (INJGCAU) [1].

3.2 Training Phase

The general overview of determining which variables from the data set were used as predictors is depicted in Fig. 3.6 and discussed in this section. In general, statistical testing was used to eliminate variables that were not significantly associated with fall-related injuries. The relative importance of each variable's association with fall-related injuries was ranked using the Gini coefficient used in random forest mapping. The 15 most important variables were selected for further consideration [2]. Among the 15 most important variables, co-linear variables were removed using a Principal Component Analysis map. The remaining variables were selected as

[1] The number of variables that were within Group Injuries and manually removed was equal to 15.

[2] The number 15 was arbitrarily chosen. The number can vary based upon how many different variables a population health team is willing to consider. The complexity of population health interventions might increase as the number of variables is increased.

predictors.

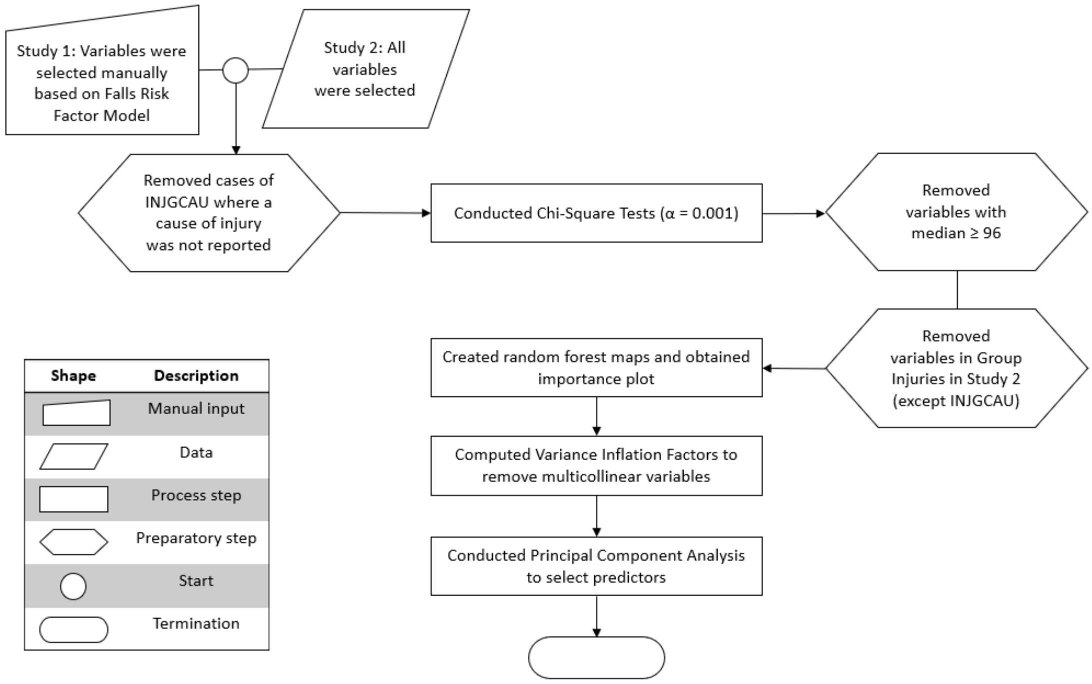

Figure 3.6: The process adopted for narrowing down the pool of 1128 variables to select predictors

3.2.1 Data Processing

Given two sets of input variables, further techniques were needed to reduce the variables down to only the most important predictors. As shown in Fig. 3.6, this was done by computing statistical significance, use of Gini index[3] to rank variables by importance and by removing multicollinearity in the data using the variance inflation factor and PCA.The process of selection was terminated after the PCA maps were obtained. Since variable in Group Injury might be co-linear and related to *Cause of Injury* (INJGCAU), they were manually removed. Data about injuries was not considered useful in predicting whether those individuals were more likely

[3]Genuer et al (2010) proposed use of random forests to reduce high dimensionality in their dataset; two uses of random forests proven in their study were to find important variables for interpretation and to develop a parsimonious prediction model (Genuer, Poggi, & Tuleau-Malot, 2010).

to incur a fall-related injury. The steps leading up to selection of predictors is described below.

1. Significance Testing: All input variables were tested against *Cause of Injury* (INJGCAU) using Pearson's chi-squared tests using the 'stats' package (R Core Team, 2017). The chi-squared test was used to determine whether a significant difference ($\alpha = 0.001$) between the expected and observed frequencies in either category of *Cause of Injury* (INJGCAU) could be attributed to input variables. The null hypothesis stated that the two variables are independent of each other ($\alpha = 0.001$). A probability (p) value was obtained for each input variable and *Cause of Injury* (INJGCAU). A p value of 0.001 or higher indicated that the null hypothesis was true and that the input variable and the cause of injury were independent of each other. If the cause of injury was independent of an input variable ($p \geq 0.001$), the variable was eliminated.

   (a) In Study 1, the null hypothesis was rejected for 129 variables ($p \geq 0.001$) using chi-squared tests.

   (b) In Study 2, the null hypothesis was rejected for 446 variables($p \geq 0.001$) using chi-squared tests.

   Additionally, difference between continuous[4] input variables and INJGCAU was checked using paired Wilcoxon's Signed Rank Test ($\alpha = 0.05$). The p value for all variables was below 0.05 and so no statistically significant differences were found between continuous input variables and INJGCAU using Wilcoxon's test.

2. Data Quality: The median of the statistically significant variables was computed and where the median was equal or greater than 96, the variable was

[4]These variables were marked continuous by the CCHS Annual Component, 2014. Continuous variables were additionally fed as factor variables for chi-squared tests.

removed. This is because the code '96' or higher indicated an irrelevant response for the study, such as 'Don't Know' or 'Not Applicable' (CCHS Annual Component, 2014).

(a) In Study 1, a total of 22 variables were eliminated due to a median of 96 or higher.

(b) In Study 2, a total of 34 variables were eliminated due to a median of 96 or higher.

3. Variable Importance Plots: The remaining variables were fed into the machine to train using a random forest classifier using the 'randomForest' package (Liaw et al., 2002). Variable importance measures were determined using the Gini index which computed the total decrease in node impurities resulting from splitting on the variable. An importance plot of variables arranged in decreasing order of importance was produced and the first 15 variables were selected for further analysis. In Study 2, the variables from the Group Injuries were manually removed. The importance plots are shown in Fig.A.1 and Fig.A.2.

4. Variance Inflation Factor (VIF) Scores: Variance inflation was calculated using the 'car' package (Fox & Weisberg, 2011) to assess co-linearity of the variables. Any variables that had a mean VIF of 10 or more were considered co-linear and only the more important variable from the importance plot was retained for further consideration.

(a) In Study 1, *Household income distribution- health region level* (INCDRPR) and *Household income distribution* (INCDRCA), and *Frequency of drinking alcohol* (ALC_2) and *Frequency of drinking 4(female)/ 5(male) or more drinks* (ALC_3) were co-linear (mean VIF $\geq$ 10). *Household income distribution* (INCDRCA) and *Frequency of* *drinking 4(female)/ 5(male)or more drinks* (ALC_3) were removed from the data set.

(b) In Study 2, *household income distribution- health region level* (INCDRPR) and *Household income distribution* (INCDRCA) were co-linear (mean VIF $\geq$ 10). INCDRCA was removed from the data set.

5. Principal Component Analysis (PCA): To avoid co-linearity and visualize the variance in the remaining data set, PCA was conducted using the 'FactoMineR' package (Lê, Josse, & Husson, 2008). In PCA, the set of variables that explain the most variance is clustered together into a principal component. The first principal component explains the most variance and the subsequent components decline in the amount of variation they explain. Using the variables factor map, component 1 was represented in the xaxis and component 2 was placed orthogonally in the y-axis to visualize the variables in each component. Variables that correlated the most with each component were selected as predictors provided other variables in the same group were not present.

6. Machine Learning: Eighty percent of the data set was used to train the model (n = 7,598), while the remaining 20% was held out as the test set (n=1,899). The training models were fitted using generalized linear modeling (Everitt & Howell, 2005), support vector machine (Cortes & Vapnik, 1995), and random forest (Liaw et al., 2002). The models were fitted on the training set using 10-fold cross validation to estimate mean accuracy. This trained model was then used to predict falls-related injuries on the held out testing data.

   Generalized Linear Modeling (GLM) has been previously used to analyze similar data (Zeger & Karim, 2012) and was used as a standard reference for support vector machine and random forest performance results. Previous literature has demonstrated use of applying support vector machines to survey data (Yu, Liu, Valdez, Gwinn, & Khoury, 2010).

3.2.2 Selection of Predictors

The variables factor map produced ranks of variable importance. Since a population health strategy cannot target several variables, the first 15 variables were chosen to assess for co-linearity. Additionally, variables in the same Group were considered to be indicators of the same problem and only one variable was selected from each group. The factor map produced from Study 1 is shown in Fig.3.7. In Study 1, the first and second components explain 18.11% and 14.64% of the total variation respectively. In total, the first two components explain 32.75% of the total variation in the training data set. The variables can be summarized as follows:

- In the top-right quadrant, *Total personal income from all sources* (INCGPER) and *Main source of personal income* (INCG7) are from Group Income and correlate with component 2 more closely than component 1. Since *Total personal income from all sources* (INCGPER) has the larger vector, it was selected as a predictor from the Group, in addition to *Frequency of drinking alcohol* (ALC_2) from Group Alcohol Use. *Number of times - gardening/yard work* (PAC_2B) and *Cognition problems - function code* (HUIDCOG) are almost perfectly co-linear and since *Number of times - walking for exercise* (PAC_2A) from Group Physical Activities appears longer than all other variables within Group Physical Activities, *Number of times - gardening/yard work* (PAC_2B) was dropped from being considered as a predictive factor. *Total personal income from all sources* (INCGPER) and *Frequency of drinking alcohol* (ALC_2) were used as predictors from the top-right quadrant.

- *Monthly frequency - physical activity ¿15 minutes* (PACDFM), *Health Utilities Index* (HUIDHSI), *Time spent - walking for exercise* (PAC_3A), *Number*

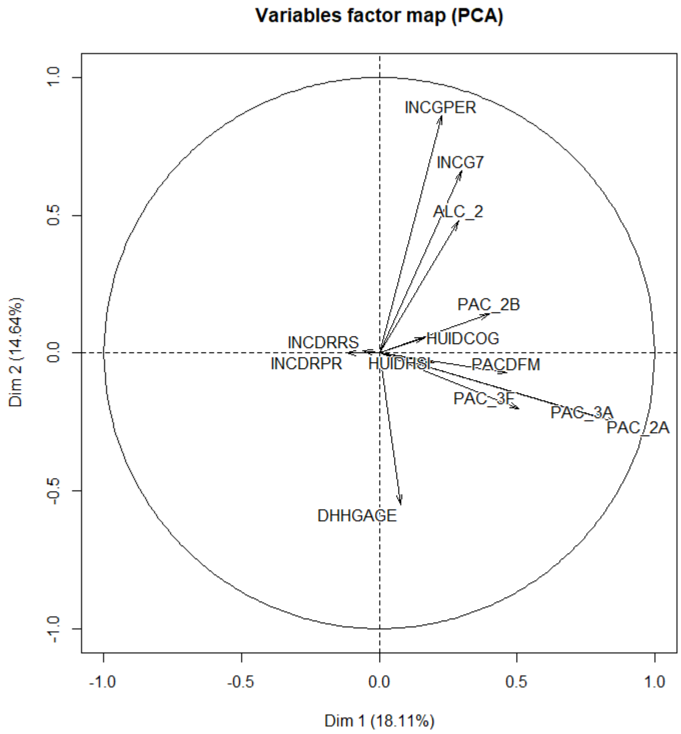

Figure 3.7: Variables Factor Map in Study 1. 'Dim' refers to dimension or component.

of times - walking for exercise (PAC_2A) and *Time spent - home exercises* (PAC_3F) are positively correlated and contribute to component 1 the most. *Health utilities index* (HUIDHSI) has a small vector and was thus ignored as a predictor. *Number of times - walking for exercise* (PAC_2A) has the largest vector among other Group Physical Activity variables in the same quadrant and was the only variable selected from the group. *Age* (DHHGAGE) represents the age of the individual and closely correlates with component 2. We, therefore, select *Number of times - walking for exercise* (PAC_2A) and *Age* (DHHGAGE) as the predictors from this quadrant.

- *Household income distribution- health region level* (INCDRRS) and *Household income distribution - provincial level* (INCDRPR) are closely correlated; however, they do not explain component 1 significantly and were therefore dropped from being considered as predictors.

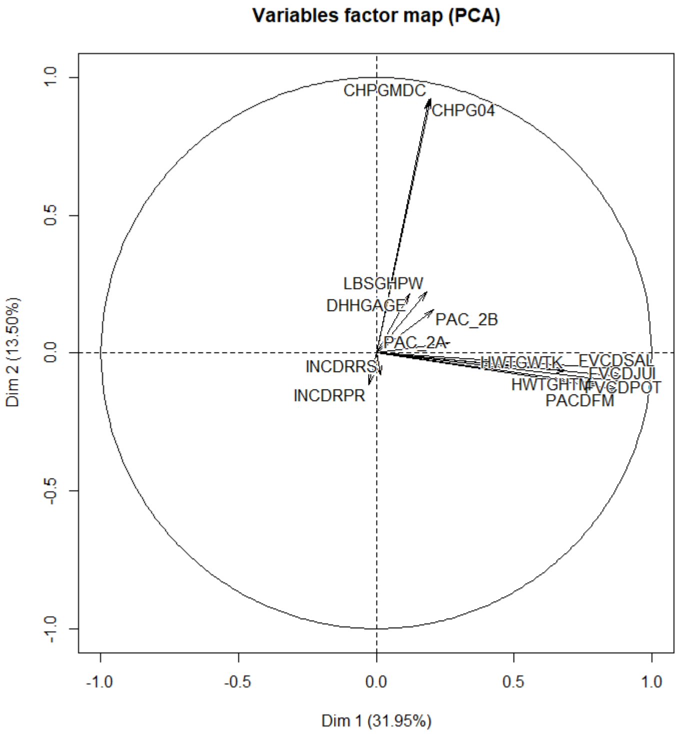

Figure 3.8: Variables Factor Map in Study 2. 'Dim' refers to dimension or component.

As seen in Fig. 3.8, Component 1 and Component 2 in Study 2 explain 31.95% and 13.50% of the total variation respectively in the training set. The total variation explained by the first 2 components is equal to 45.45%.

- As seen from the top-right quadrant of Fig. 3.8, *Number of consultations with medical doctor* (CHPGMDC) and *Number of consultations with family doctor* (CHPG04) are almost perfectly co-linear and correlate closely with Component 2; both variables belong to the Group Contacts with Health Professionals. *Number of consultations with family doctor* (CHPG04) was used as a predictor since it is slightly closer to Component 1 than *Number of consultations with medical doctor* (CHPGMDC). *Total usual hours worked* (LBSGHPW), *Age* (DHHGAGE), *Number of times participated in gardening or yard work* (PAC_2B) and *Number of times participating in walking for exercise* (PAC_2A) have small vectors and were therefore considered negligible in explaining variance in either component.

- *Daily consumption of green salad* (FVCDSAL), *Daily consumption of fruit juice* (FVCDJUI), *Daily consumption of potatoes* (FVCDPOT), *Weight* (HWTGWTK), *Height* (HWTGHTM) and *Monthly physical activity of 15 minutes or more* (PACDFM) are closely clustered together and correlate almost perfectly with component 1. *Daily consumption of green salad* (FVCDSAL), *Daily consumption of fruit juice* (FVCDJUI) and *Daily consumption of potatoes* (FVCDPOT) are variables within the Group Food and Vegetable Consumption, and since FVCDSAL correlates the most closely with component 1, it is the only variable from the group selected as a predictor. *Weight* (HWTGWTK) and *Height* (HWTGHTM) are from Group Height and Weight; since HWTGHTM has a larger vector, it was selected as a predictor while HWTGWTK was not. *Monthly physical activity of 15 minutes or more* (PACDFM) is also used in the prediction model built from Study 2 and belongs to the Group Physical Activities.

3.3 Conclusion

By following the rigorous statistical and co-linearity checks, four variables were selected as predictors in Study 1 and Study 2. In Study 1, the predictors selected were *age* (DHHGAGE), *number of times of walking in the past 3 months* (PAC_2A), *frequency of drinking alcohol in the past year* (ALC_2) and *total personal income* (INCGPER). In Study 2, training data was modeled using the following predictors: *number of consultations with family doctor* (CHPG04), *consumption of green salad* (FVCDSAL), *height* (HWTGHTM) and *monthly frequency of exercise lasting over 15 minutes* (PACDFM). The models were then evaluated by predicting on the test set and evaluated for performance.

Chapter 4

Evaluation and Discussion

This chapter discusses the results obtained from evaluating the predictive models in section 4.1. Furthermore, a few interpretations of the results are offered to outline how the results are useful and applicable in the real world setting in sections 4.2 and 4.3. The limitations of the dataset and data mining process are outlined in section 4.4.

4.1 Performance of Models

The accuracy, sensitivity and specificity achieved in Study 1 and 2 is reported in Table 4.1 and Table 4.2 respectively. The mean accuracy was not equal to 0.7 or more across all models; however, the sensitivity rate was consistently above 0.7 when GLM and SVM were employed. Thus, it is possible to predict fall-related injuries with a high sensitivity given the predictors used in Study 1 and Study 2 using GLM and SVMRadial. In both studies, the sensitivity reached using RF is below 0.80.

The mean accuracy in Study 1 is approximately 0.6, while the mean accuracy in Study 2 is around 0.56. An accuracy above 0.70 could not be achieved using any of the algorithms. The sensitivity of the models built using GLM and SVM is higher than 0.7; however, the specificity is very low (≤ 0.36). We conclude that random forests do not add value to building predictive models, while GLM and SVMRadial can help build predictive models that produce a good sensitivity. Having a low sensitivity has the implication that the chances of inducing false alarm is high, whereby patients are erroneously informed of a high risk of incurring a fall-related injury.

Table 4.1: Results from Study 1

	Study 1: DHHGAGE, PAC_2A, ALC_2 and INCGPER		
	LR	RF	SVMRadial
Mean Accuracy	0.60	0.58	0.61
(95% C.I.)	(0.58-0.62)	(0.55-0.60)	(0.59-0.63)
Sensitivity	0.84	0.66	0.77
Specificity	0.29	0.46	0.40

The results in Study 1 imply that age (DHHGAGE), number of times of walking in the past 3 months (PAC_2A), personal income (INCGPER) and frequency of alcohol consumption (ALC_2) can correctly identify fall-related injuries at a rate of 80% or higher, but the risk of missing true negatives is high due to the low specificity rate. Age is not a modifiable risk factor, while the effects of a low income among seniors can be offset by enabling social assistance programs. Physical activity and alcohol consumption are two individual-level modifiable behavioral risk factors that can be used for targeted prevention of fall-related injuries.

Table 4.2: Results from Study 2

	Study 2: CHPG04, FVCDSAL, HWTGHTM and PACDFM		
	LR	RF	SVMRadial
Mean Accuracy	0.57	0.55	0.58
(95% C.I.)	(0.55-0.59)	(0.53-0.57)	(0.55-0.60)
Sensitivity	0.98	0.65	0.84
Specificity	0.03	0.42	0.23

The results in Study 2 imply that the number of consultations with family doctor (CHPG04), frequency of daily consumption of green salad (FVCDSAL), height (HWTGHTM) and monthly physical activity of greater than 15 minutes (PACDFM) as a combination can also correctly identify fall-related injuries at a rate of 80% or higher; however, the risk of missing true negatives is still high because the specificity rate is less than or equal to 0.38. Group Physical Activity is the only group which was found to be a predictor in both studies.

4.2 Predictors of fall-related injuries

Behavioral risk factors are modifiable and within an individual's control, while socioeconomic risk factors can be targeted through policy changes, such as income supports. Biological risk factors, such as age and height, are not modifiable. Table 4.3 lists the groups associated with each predictor in Study 1 and Study 2. Group Physical Activity is common in both studies. In study 1, Alcohol Use, Income and Dwelling and Household Variables are other groups that predictors belong to. Physical activity and alcohol use are behavioral determinants of health which can be modified. It makes sense to recommend an individual to change their behaviors. In contrast, age is not modifiable and some changes occur in the body as a result of age. In study 2, other groups of predictors were Consultations with Health Professionals, Fruit and Vegetable Consumption and Height. Physical activity levels and consumption of fruits and vegetables are modifiable by individuals. The number of consultations with family doctor (CHPG04) is an indicator of health problems faced by the subject. On its own, the predictor is not informative of what the health problems were. Height is non-modifiable; taller height indicates a greater distance of falling than shorter height. The corresponding impact upon hitting the ground would be higher for taller individuals.

In Study 1, there was little justification required for the variables used as

Table 4.3: Groups of predictor variables in Study 1 and Study 2

Variable Code - Variable Description	CCHS Group	Risk Factor Model Group
Study 1		
INCGPER - Total Personal Income	Income	Socioeconomic
ALC_2 - Frequency of drinking alcohol	Alcohol Use	Behavioral
PAC_2A - Number of times walking for exercise	Physical Activities	Behavioral
DHHGAGE - Age	Dwelling and Household Variables	Biological
Study 2		
CHPG04 - Number of consultations - family doctor	Consultations with Health Professionals	Socioeconomic
FVCDSAL - Daily consumption - green salad	Fruit and Vegetable Consumption	Not found
PACDFM - Monthly frequency - physical activity $\geq$ 15 minutes	Physical Activities	Behavioral
HWTGHTM - Height	Height and Weight	Not found

predictors because prior research had already established the association of those variables with risk of incurring a fall-related injury. It is worth noting that Study 1 achieved a higher accuracy than Study 2 across all algorithms.

4.2.1 Predictors in Study 2

Daily consumption of green salad (FVCDSAL) is not an easily identifiable risk factor of falls and related injuries from existing literature. Based on Appendix C, the median frequency of daily salad consumption is 0.4 for both groups, those who were injured due to falling (Group 1) and those who were injured due to some other reason (Group 0). However, the skew measure is higher for Group 0 at 6.04, while the skew measure for Group 1 equals 4.18. Those who incurred non-fall related injuries consumed more green salad than those who incurred fall-related injuries.

Further research needs to be conducted to understand whether consumption of green salad is a significant risk factor on its own for predicting falls. Changes in gastrointestinal functions, such as perception of taste and smell may affect appetite while difficulty in chewing is believed to lead to an increased intake of soft, low-fiber diets (Amarya, Singh, & Sabharwal, 2015). Difficulty in chewing and palatability of green salad might contribute to its reduced intake in seniors and so the risk factor could be biological. Furthermore, dental problems might be a sign of frailty whereby individuals loose teeth and therefore the ability to chew high-fiber foods such as vegetables. Low consumption of green salad would then simply be an indicator of overall age-related frailty. However, no variable indicating dental visits were found to be important predictors according to the importance plot.

Consumption of green salad can also be understood as a behavioral risk factor, whereby individuals motivated to lead a healthy lifestyle consume vegetables and maintain physically active. As seen from the PCA map in Fig.3.8, *Daily consumption - green salad* (FVCDSAL) and *Monthly frequency - physical activity* (PACDFM) are closely co-linear. Vegetables are a source of micro-nutrients (Amarya et al., 2015) and comprise a high fiber food group. Fruit and vegetable consumption is linked to a reduced risk of hypertension, osteoporosis, adiposity, microvascular function, improved weight maintenance among other benefits (Appleton et al., 2016). These benefits were evaluated with fruits and vegetables considered as one food group rather than two separate groups (Appleton et al., 2016). In contrast to fruits, vegetables are often perceived as bitter tasting and contain protein and fiber (Appleton et al., 2016). While the results from this work suggest that vegetable consumption is a predictor of fall-related injury, it cannot be conclusively determined how vegetable consumption is related to risk of incurring a fall-related injury.

Height, on its own, was not found to be a predictor of falls or related injuries from the scientific literature. As seen from Fig.3.8, height and weight were very closely co-linear. Height and weight are often measured together and reported as Body Mass Index (BMI). Obesity, characterized by a BMI of 40 kg/m^2 or above, increases the risk of falling but is protective against sustaining an injury due to the fall (Himes & Reynolds, 2012). The soft tissue in obese individuals may counteract the impact of hitting the ground and offer protection from the injury (Himes & Reynolds, 2012). Aging brings changes in body composition, such as decrease in lean body mass and an increase in body fat (Amarya et al., 2015). The excessive weight may cause bowing of the bones (Amarya et al., 2015) which in turn affects gait and posture. This change may increase the odds of falling in obese individuals.

Remaining active is protective against incurring a fall and reduces the risk of incurring an injury if a fall occurs (Pereira, Baptista, & Infante, 2013). In contrast, vigorous physical activity can increase the risk of falling and incurring an injury (Pereira et al., 2013). Therefore, in designing targeted intervention programs, monthly physical activity of greater than 15 minutes (PACDFM) and number of times of walking (PAC_2A) should be heeded and warnings against vigorous activity could be included.

4.2.2 Interpretation of Results

Models in Study 1 and Study 2 predominantly yielded a high sensitivity rate. Therefore, we recommend that health promotion efforts focus on the predictive factors to reduce their rate of fall-related injuries in the Canadian population, particularly those from Study 2 because it was more comprehensive. For example, incentives such as tax subsidies for increasing physical activity and fruit and vegetable consumption in the population above 65 years can be considered. Population level advisories or educational campaigns to reduce alcohol use in the at-risk population can be mobilized. The need for financial incentives for fruit and vegetable consumption and physical activity is well established in the Canadian senior population (CARP, 2015) and the findings of Study 2 confirm that focusing on those factors is likely to prevent fall-related injuries.

Oscar, Sasaoka and Vaughn (2016) found that balance confidence was the best predictor of falling among candidate predictors such as gait balance confidence, history of falling, functional mobility, pathological conditions and performance on other physical tests, e.g. Timed Up and Go Test (Landers, Oscar, Sasaoka, & Vaughn, 2016). In the study done by Halvarsson, Franzén and Ståhle (2014), a physical activity training program to train on dual and multi-task balance improved fall-related self-efficacy, gait speed, balance performance, and physical function in seniors with osteoporosis (Halvarsson, Franzén, & Ståhle, 2015). Results of both studies indicate that physical activity should be encouraged in populations.

"The ability of a test to correctly classify an individual as disease-free is called the test's specificity" (Parikh, Mathai, Parikh, Sekhar, & Thomas, 2008). The low specificity of all models is harmful and increases likelihood of inducing the fear of falling. The 'fear of falling' is a state of fear which often inhibits seniors from participating in activities of daily living and reduces quality of life (Suzuki, Ohyama, Yamada, & Kanamori, 2002). It has been found that fear of falling can induce activity avoidance and adversely affect balance performance; thereby deteriorating the individual's mobility and quality of life (Denkinger, Lukas, Nikolaus, & Hauer, 2015). The low specificity of the prediction models indicates that the predictors will induce false alarm among individuals, especially seniors.

Age and income are socio-demographic determinants which were found to be highly important in determining risk of incurring a fall-related injury in Study 1. Physical activity and alcohol use are behavioral determinants. In study 2, food and vegetable consumption and physical activity were 2 behavioral determinants of health found to be important predictors of fall related injuries. Contacts with health professionals can be interpreted to be an indicator of health problems that required medical attention, but the variable has little information about what the health problems were. Height (HWTGHTM) is an individual level predictor of falls-related injuries which the falls risk factor model does not include.

In Study 1, the input variables were selected based on the Falls Risk Factor Model manually. The model does not include several variables such as polypharmacy and impaired vision. Study 1 also limited the scope for exploratory analysis by eliminating variables that were not presented in the Falls Risk Factor Model. However, the results were easier to justify and concur with previous research in this study. In contrast, Study 2 allowed for statistical evaluation and minimal bias in selection of features. Results from Study 2 are more believable than Study 1 because Study 2 was more comprehensive in considering possible risk factors. Age was found to be less important as a predictor in Study 2 when other variables were considered, such as height.

Variable selection in accordance with Study 2 is recommended because adhering to any one falls' risk assessment model would bias the study by excluding other variables. All variables should be included and assessed for statistical significance. Further techniques to reduce dimensionality can be applied before conducting the principal component analysis to visualize co-linearity. After the data set's dimensionality is successfully reduced, predictive modeling techniques can be applied.

4.3 Mining high-dimensional datasets for important predictors

This thesis was devised to apply machine learning algorithms to study fall-related injuries. It is possible to tune parameters to optimize the predictive models (Claesen & De Moor, 2015). The emphasis of this thesis was on reducing high dimensionality in a dataset and mining important variables for building prediction models. Parameter tuning and choice of algorithms are other important considerations for future work to improve performance of trained models. In the future, machine learning experts and population health experts should jointly aim to understand how census data can be used to model outcomes of interest using machine learning algorithms.

Post-hoc tests determine how response categories in the input variables are associated with the outcome variable. The approach undertaken in this thesis did not prove that an age of 65 or above is associated with an increased risk of incurring a fall-related injury; that was found from previous literature. However, the methodological approach of taking a set of 1128 variables and then processing through statistical testing and generating the importance plot is a method to reduce high-dimensionality in the dataset. Applying machine learning algorithms to a dataset does not uncover cause-effect relationships but mines the data and offers a method to eliminate less important variables associated with the target variable.

In conducting the literature review, very few sources were found that had analyzed census data using machine learning techniques beyond linear and logistic regression. Considering that the field of health information and analysis is new to machine learning, only classification algorithms were used. The structure of census data is simpler than data extracted from EMRs because medical records are subject to strict privacy laws and require conversion to a machine-readable format, such as FHIR codes for executing data analysis methods. Since self-reported data was used, injuries that resulted in mortality are not captured in the data and the actual rate of fall-related injuries is expected to be higher.

4.4 Limitations

The design of the CCHS questionnaire does not offer workplace hazard as a response within the variable, *cause of injury* (INJGCAU). To study injuries in all age-groups, injuries reported in Group Workplace Injuries and Group Injuries would need to be combined. The thesis did not adjust for workplace injuries. Falls among pregnant women are common (Dunning et al., 2003) and these falls may have been captured in the Group Workplace Injuries. Alternatively, the response 'Other' may have captured the causes of injury not provided as a multiple choice option.

Remembering events in the past year is subject to recall bias. Remaining alive to answer the question, i.e. survivor bias, is another source of bias in the survey due to which fatal fall-related injuries could not be captured through self-reported data. Desirability bias for several variables is possible where individuals may self-report values that they perceive more consistent with social norms, such as taller height.

Classification by RF involves calculation of information gain and according to (Liaw et al., 2002), information gain can be dramatically higher with a greater number of predictors. The approach used in this thesis involved narrowing down the pool of candidate predictors and feeding a minimal number of predictors to the algorithm. This approach was not appropriate for random forests. In this thesis, RF was used for the same predictors as the other algorithms to ensure a fair comparison of the prediction models. If the priority is to reach a high accuracy, it is advisable to use random forest on its own for the entire dataset or for a larger number of variables determined to be important by the importance plot.

Chapter 5

Conclusion and Further Work

Chapter 5 highlights the conclusions that can be drawn from the thesis in section 5.1 and recommends future work in the area of finding factors that are most predictive of fall-related injuries in section 5.2.

5.1 Summary of Findings

The high sensitivity rate in both studies across all models proves that the risk factors chosen as predictors are very good at truly predicting that a person with those risk factors will incur an injury. However, the sensitivity rate is very low in both studies regardless of the algorithms used. The models need to be optimized with respect to the parameters used to achieve better results in the future and a more diverse set of algorithms could be used to improve accuracy. Random forests were useful in creating importance plots, but the predictive power in the final models is lowest with random forest modeling.

Studying a population has value for generating new insights for the research community and can serve as a reality check for age-old health care problems. Conducting a literature search for falls and related injuries in the elderly population only highlights fall-related injuries as a significant problem for the population over

65 years, while learning about injuries in the population reveals that factors other than age should be studied and targeted for interventions. In public health spending and funding allocation decisions, the priority of variables can allow justification for selectively targeting some risk variables than others in the programs that are allocated public funds.

According to Amarya et al., Mediterranean and Okinawa diets are associated with longer life (Amarya et al., 2015). Mediterranean diets are high in a variety of foods, including dairy products and vegetables. Dairy products are a high source of calcium which can contribute to a reduced risk of osteoporosis. Okinawa diet uses sweet potato as a staple food and 30% vegetables (Amarya et al., 2015). Future work should compare individuals on different diets while controlling the effects of race and culture. In long term care homes, there is little choice about which food groups to choose since meal plans are shared. National guidelines for shared meal plans outlining specific food groups to involve in meal plans should be generated. Among community-dwelling seniors, income is a variable that needs to be considered alongside generating recommendations for which food groups to consume because community-dwelling seniors pay for their own meals.

5.2 Further Work

Further work in predicting from census data using machine learning algorithms is recommended; however, the methodological approach needs modifications to improve accuracy. A modified approach could be to use unsupervised machine learning algorithms based on the review by (Howcroft et al., 2013) which identified neural networks, naive Bayesian classier and Mahalanobis cluster analysis to perform better than SVM and GLM. To increase the amount of data points, it is possible to combine data from multiple years and then build predictive models. Manual tuning of parameters in training the model to achieve a higher accuracy is recommended. Comparative analysis of algorithms used to predict fall-related injuries should be executed based on the method of pattern recognition while keeping predictors the same.

One suggested change is to make the variable selection method and model-fitting procedures consistent. For using GLM, variables could be selected by calculating the strength of association between all variables and the target outcome variable. The first 15 variables with the strongest association could be used as predictors. For SVMRadial, all input variables could be analyzed using principal component analysis and only variables comprising component 1 could be used as predictors. For random forest, all 15 variables ranked as within the first 15 in the importance plot could be used as predictors. It would be interesting to see if the accuracy improves when such variable selection procedures are applied. Considering that previous researchers, such as (Tong et al., 2013; Yacchirema et al., 2018), found higher accuracy in their predictive models, it is useful to note that predictors such as gait and posture might be better predictors. Future work should aim to combine determinants of health with gait and posture to build predictive models.

This thesis divided the sample by those who incurred a fall-related injury and an injury due to some other reason. In hindsight, the population should be stratified by those who incurred a fall-related injury and those who did not incur any injury. The cases that did not incur an injury responded 'No' for INJ_01 (Injured in the past 12 months). There would be a class imbalance problem and so up-sampling or down-sampling techniques would need to be employed. Therefore, comparing fall-related injuries with those who were not injured at all could be work for future research. Those who reported incurring an injury due to any factor other than a fall was still considered acceptable for this thesis. This is because accidental bumps or trips did not indicate an intrinsic factor that was attributable to the individual's health condition. However, classification algorithms look for differences in the input vectors belonging to each class of the target variable. More drastic differences in input patterns would likely result in detection of more dissimilarity by the learning machine. Hence, in the future, it is advisable to compare fall-related injury cases with no injury cases.

In conducting this thesis, the overwhelming observation was that scientific literature from health sciences used different statistical methods than literature on machine learning experiments, even where the subject examined was falls. Data collection methods were also different; longitudinal studies use self-reported, clinician- or researcher-reported data on risk variables while machine learning experiments on fall prevention collect data about motion and acceleration through sensors to predict falls. The choice of algorithms is an important consideration that needs to be thoroughly decided; however, systematic reviews comparing parametric and non-parametric methods were not found.

Further work in providing a systematic literature review comparing the pattern recognition process based on the different algorithms used is recommended. In such a synthesis, it is integral to mention characteristics of data types, dimensionality of data sets and explain differences between the pattern of recognition. Advancement in health care and population health is hard to achieve without adequate patching of scientific knowledge from epidemiology and computational methods involved in machine learning. Furthermore, comparative analysis of why different algorithms yield different performance results given the same input are also needed.

References

Amarya, S., Singh, K., & Sabharwal, M. (2015, sep). Changes during aging and their association with malnutrition. *Journal of Clinical Gerontology and Geriatrics*, *6*(3), 78–84. doi: 10.1016/j.jcgg.2015.05.003

Ambrose, A. F., Paul, G., & Hausdorff, J. M. (2013). Risk factors for falls among older adults: a review of the literature. *Maturitas*, *75*(1), 51–61.

Appleton, K. M., Hemingway, A., Saulais, L., Dinnella, C., Monteleone, E., Depezay, L., ... Hartwell, H. (2016). Increasing vegetable intakes: rationale and systematic review of published interventions. *European Journal of Nutrition*, *55*(3), 869–896. doi: 10.1007/s00394-015-1130-8

Bishop, C. M. (2006). *Pattern recognition and machine learning.* Springer.

Braveman, P., & Gottlieb, L. (2014). The social determinants of health: it's time to consider the causes of the causes. *Public Health Reports*, *129*(1_suppl2), 19–31.

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32.

Brownlee, J. (2016). *Support vector machines for machine learning.* Retrieved from `https://machinelearningmastery.com/support-vector-machines-for-machine-learning/`

Canada. (2016a). *Age-friendly communities.* Retrieved from `https://www.canada.ca/en/employment-social-development/corporate/seniors/forum.html`

Canada. (2016b). *Leading causes of hospitalizations, canada, 2009/10,* *males and females combined, counts (age-specific hospitalization rate per 100,000).* Retrieved from `https://www.canada.ca/en/public-health/services/reports-publications/leading-causes-death-hospitalization-canada/2009-10-males-females-combined-counts-specific-hospitalization-rate.html`

Canada. (2017). *Federal/provincial/territorial ministers responsible for seniors forum.* Retrieved from `https://www.canada.ca/en/employment-social-development/corporate/seniors/forum.html`

Canada. (2018). *Social determinants of health and health inequalities.* Retrieved from `https://www.canada.ca/en/public-health/services/health-promotion/population-health/what-determines-health.html`

Canada, S. (2017a). *Canadian community health survey (cchs): Derived variable (dv) specifications.* Retrieved from `gsg.uottawa.ca/data/cchs/2014/CCHS_2013-2014_Derived_Variables.pdf`

Canada, S. (2017b). *Canadian community health survey dataset, 2014: Annual component [study documentation].*

Canada, S. (2018a). *Health status.* Retrieved from `https://www150.statcan.gc.ca/n1/pub/82-221-x/2017003/hs-es-eng.htm#hs2_17`

Canada, S. (2018b). *Results and documentation of surveys and statistical programs.* Retrieved from `https://www150.statcan.gc.ca/n1/en/type/surveys#topic_h`

CARP. (2015). *Carp and over 50 groups form seniors vote campaign to promote interests of older canadians ahead of upcoming federal election.* Retrieved from `http://www.carp.ca/2015/04/25/carp-and-over-50-groups-form-seniors-vote-campaign-to-promote-interests-of-older-canadians-ahead-of-upcoming-federal-election/`

Castro, V. M., McCoy, T. H., Cagan, A., Rosenfield, H. R., Murphy, S. N., Churchill, S. E., ... Perlis, R. H. (2014, oct). Stratification of risk for hospital admissions for injury related to fall: cohort study. *BMJ*, *347*(aug06 2), g5863–g5863. doi: 10.1136/bmj.g5863

Claesen, M., & De Moor, B. (2015). Hyperparameter search in machine learning. *arXiv preprint arXiv:1502.02127*.

Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, *20*(3), 273–297.

Deandrea, S., Lucenteforte, E., Bravi, F., Foschi, R., La Vecchia, C., & Negri, E. (2010).

Epidemiology, 658–668.

Denkinger, M. D., Lukas, A., Nikolaus, T., & Hauer, K. (2015). Factors associated with fear of falling and associated activity restriction in community-dwelling older adults: a systematic review. *The American Journal of Geriatric Psychiatry*, *23*(1), 72-86.

Do, M. T., Chang, V. C., Kuran, N., & Thompson, W. (2015, sep). Fall-related injuries among canadian seniors, 2005–2013: an analysis of the canadian community health survey. *Health Promotion and Chronic Disease Prevention in Canada*, *35*(7), 99–108. doi: 10.24095/hpcdp.35.7.01

Dunning, K., LeMasters, G., Levin, L., Bhattacharya, A., Alterman, T., & Lordo, K. (2003). Falls in workers during pregnancy: risk factors, job hazards, and high risk occupations. *American Journal of Industrial Medicine*, *44*(6), 664–672.

Economic, & Council, S. R. (2018). *The dahlgren-whitehead rainbow.* Retrieved from `https://esrc.ukri.org/about-us/50-years-of-esrc/50-achievements/the-dahlgren-whitehead-rainbow/`

Everitt, B. S., & Howell, D. (2005). *Generalized linear models (glm).* Wiley Online Library.

Fernández-Delgado, M., Cernadas, E., Barro, S., & Amorim, D. (2014). Do we need hundreds of classifiers to solve real world classification problems. *Journal of*

Machine Learning Research, *15*(1), 3133-3181.

for Health Information, C. I. (2018). *Injury hospitalization.* Retrieved from `http://indicatorlibrary.cihi.ca/pages/viewpage.action?pageId=5111839`

Fox, J., & Weisberg, S. (2011). *An r companion to applied regression.* Sage Publications.

Fuller, G. F. (2000). Falls in the elderly. *American Family Physician*, *61*(7), 2159–68.

Gadkaree, S. K., Sun, D. Q., Huang, J., Varadhan, R., & Agrawal, Y. (2015). Comparison of simple versus performance-based fall prediction models: data from the national health and aging trends study. *Gerontology and Geriatric Medicine*, *1*, 1–10.

Genuer, R., Poggi, J.-M., & Tuleau-Malot, C. (2010). Variable selection using random forests. *Pattern Recognition Letters*, *31*(14), 2225–2236.

Halvarsson, A., Franzén, E., & Ståhle, A. (2015). Balance training with multi-task exercises improves fall-related self-efficacy, gait, balance performance and physical function in older adults with osteoporosis: a randomized controlled trial. *Clinical Rehabilitation*, *29*(4), 365–375.

Hawe, P., Di Ruggiero, E., & Cohen, E. (2012). Frequently asked questions about population health intervention research. *Canadian Journal of Public Health*, *103*(6), e468–71.

Herman, S. W. (2014). Go4life:¡ http://go4life. nia. nih. gov¿. *Journal of Consumer Health On the Internet*, *18*(3), 271–278.

Himes, C. L., & Reynolds, S. L. (2012). Effect of obesity on falls, injury, and disability. *Journal of the American Geriatrics Society*, *60*(1), 124–129.

Hofmann, T., Schölkopf, B., & Smola, A. J. (2008, june). Kernel methods in machine learning. *The Annals of Statistics*, *36*(3), 1171–1220. doi: 10.1214/009053607000000677

Howcroft, J., Kofman, J., & Lemaire, E. D. (2013). Review of fall risk assessment in geriatric populations using inertial sensors. *Journal of Neuroengineering and Rehabilitation*, *10*(1), 91.

Huang, A. R., Mallet, L., Rochefort, C. M., Eguale, T., Buckeridge, D. L., & Tamblyn, R. (2012). Medication-related falls in the elderly. *Drugs & Aging*, *29*(5), 359–376.

Jain, A. K., Duin, R. P. W., & Mao, J. (2000). Statistical pattern recognition: A review. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *22*(1), 4–37.

Kamińska, M. S., Brodowski, J., & Karakiewicz, B. (2015). Fall risk factors in community-dwelling elderly depending on their physical function, cognitive status and symptoms of depression. *International Journal of Environmental Research and Public Health*, *12*(4), 3406–3416.

Kangas, M., Korpelainen, R., Vikman, I., Nyberg, L., & Jämsä, T. (2015). Sensitivity and false alarm rate of a fall sensor in long-term fall detection in the elderly. *Gerontology*, *61*(1), 61–68.

Landers, M. R., Oscar, S., Sasaoka, J., & Vaughn, K. (2016). Balance confidence and fear of falling avoidance behavior are most predictive of falling in older adults: prospective analysis. *Physical Therapy*, *96*(4), 433–442.

Lê, S., Josse, J., & Husson, F. (2008). FactoMineR: AnRPackage for multivariate analysis. *Journal of Statistical Software*, *25*(1). doi: 10.18637/jss.v025.i01

Lemon, S. C., Roy, J., Clark, M. A., Friedmann, P. D., & Rakowski, W. (2003). Classification and regression tree analysis in public health: methodological review and comparison with logistic regression. *Annals of Behavioral Medicine*, *26*(3), 172–181.

Liaw, A., Wiener, M., et al. (2002). Classification and regression by randomforest. *R News*, *2*(3), 18–22.

Lipsitz, L. A., Tchalla, A. E., Iloputaife, I., Gagnon, M., Dole, K., Su, Z. Z., &

Klickstein, L. (2016). Evaluation of an automated falls detection device in nursing home residents. *Journal of the American Geriatrics Society*, *64*(2), 365–368.

Marmot, M., & Allen, J. J. (2014). Social determinants of health equity. *American Journal of Public Health*, *104*(S4), S517-S519. (PMID: 25100411) doi: 10.2105/AJPH.2014.302200

Marmot, M. G., Rose, G., Shipley, M., & Hamilton, P. J. (1978). Employment grade and coronary heart disease in british civil servants. *Journal of Epidemiology & Community Health*, *32*(4), 244–249.

Masud, T., & Morris, R. O. (2001). Epidemiology of falls. *Age and Ageing*, *30*(suppl_4), 3–7.

MedCalc. (2018). *Logistic regression.* Retrieved from `https://www.medcalc.org/manual/logistic_regression.php`

Narayanan, M., Redmond, S., Scalzi, M., Lord, S., Celler, B., & Lovell, N. (2010, mar). Longitudinal falls-risk estimation using triaxial accelerometry. *IEEE Transactions on Biomedical Engineering*, *57*(3), 534–541. doi: 10.1109/tbme.2009.2033038

of Canada, P. H. A. (2014). *The chief public health officer's report on the state of public health in canada 2014 – changing demographics, aging and health.* Retrieved from `https://www.canada.ca/en/public-health/corporate/publications/chief-public-health-officer-reports-state-public-health-canada/chief-public-health-officer-report-on-state-public-health-canada-2014-public-health-future/changing-demographics.html`

of Health Information, C. I. (2018). *Access data and reports.* Retrieved from `https://www.cihi.ca/en/access-data-and-reports`

Parachute. (2015). *About injuries.* Retrieved from `http://www.parachutecanada.org/injury-topics`

Parikh, R., Mathai, A., Parikh, S., Sekhar, G. C., & Thomas, R. (2008). Understanding and using sensitivity, specificity and predictive values. *Indian Journal of Ophthalmology*, *56*(1), 45. doi: 10.4103/0301-4738.37595

Peng, C.-Y. J., Lee, K. L., & Ingersoll, G. M. (2002). An introduction to logistic regression analysis and reporting. *The Journal of Educational Research*, *96*(1), 3–14.

Pereira, C. L. N., Baptista, F., & Infante, P. (2013, apr). Role of physical activity in the occurrence of falls and fall-related injuries in community-dwelling adults over 50 years old. *Disability and Rehabilitation*, *36*(2), 117–124. doi: 10.3109/09638288.2013.782355

PHAC. (2014). *Seniors' falls in canada: Second report.* Retrieved from `https://www.canada.ca/en/public-health/services/health-promotion/aging-seniors/publications/publications-general-public/seniors-falls-canada-second-report.html`

Quick-R. (2017). *Generalized linear models.* Retrieved from `https://www.statmethods.net/advstats/glm.html`

R Core Team. (2017). R: A language and environment for statistical computing [Computer software manual]. Vienna, Austria. Retrieved from `https://www.R-project.org/`

Rajkomar, A., Oren, E., Chen, K., Dai, A. M., Hajaj, N., Hardt, M., ... others (2018). Scalable and accurate deep learning with electronic health records. *npj Digital Medicine*, *1*(1), 18.

Rose, S. (2013, jan). Mortality risk score prediction in an elderly population using machine learning. *American Journal of Epidemiology*, *177*(5), 443–452. doi: 10.1093/aje/kws241

Solar, O., & Irwin, O. (2010). *A conceptual framework for action on the social determinants of health.* Retrieved from `http://apps.who.int/iris/bitstream/handle/10665/44489/9789241500852_eng.pdf;jsessionid=`

EDE1B95005D8A32FE6C17E5D4B43B501?sequence=1

Suzuki, M., Ohyama, N., Yamada, K., & Kanamori, M. (2002, dec). The relationship between fear of falling, activities of daily living and quality of life among elderly individuals. *Nursing and Health Sciences*, *4*(4), 155–161. doi: 10.1046/j.1442-2018.2002.00123.x

Tong, L., Song, Q., Ge, Y., & Liu, M. (2013, may). HMM-based human fall detection and prediction method using tri-axial accelerometer. *IEEE Sensors Journal*, *13*(5), 1849–1856. doi: 10.1109/jsen.2013.2245231

Vaughon, W., Lee, Y., Gallo, W., Kaufman, J., & Unuigbe, A. (2018, jan). Association between falls and caregiving tasks among informal caregivers: Canadian community health survey data. *Canadian Journal on Aging / La Revue canadienne du vieillissemen*, *37*(01), 70-75. doi: 10.1017/s0714980817000496

WHO. (2007). *Who global report on falls prevention in older age.* Retrieved from http://www.who.int/ageing/publications/Falls_prevention7March.pdf

WHO. (2015). *World report on ageing and health.*

Yacchirema, D., de Puga, J. S., Palau, C., & Esteve, M. (2018). Fall detection system for elderly people using IoT and big data. *Procedia Computer Science*, *130*, 603–610. doi: 10.1016/j.procs.2018.04.110

Yu, W., Liu, T., Valdez, R., Gwinn, M., & Khoury, M. J. (2010, mar). Application of support vector machine modelling for prediction of common diseases: the case of diabetes and pre-diabetes. *BMC Medical Informatics and Decision Making*, *10*(1). doi: 10.1186/1472-6947-10-16

Zeger, S. L., & Karim, M. R. (2012, mar). Generalized linear models with random effects a gibbs sampling approach. *Journal of the American Statistical Association*, *86*(413), 79–86. doi: 10.1080/01621459.1991.10475006

Appendix A

Chapter 3 Supplement: Importance Plots for Variables Ranked by Importance

The importance plots in Fig.A.1 and Fig.A.2 depict the variables ranked by importance in Study 1 and Study 2. The use of RF with a seed set at 276 yielded both the importance plots.

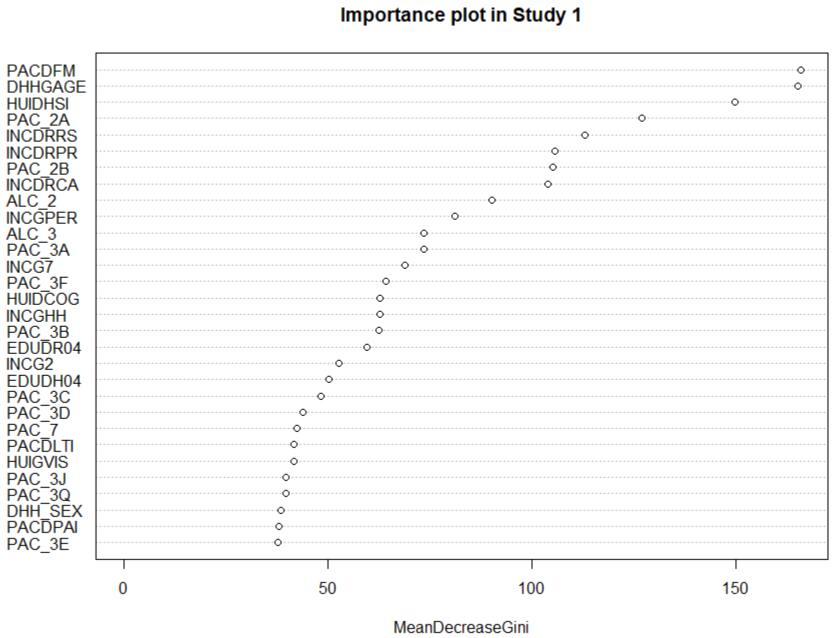

Figure A.1: The Importance Plot generated when Study 1 was executed. The first 15 variables were analyzed further using PCA.

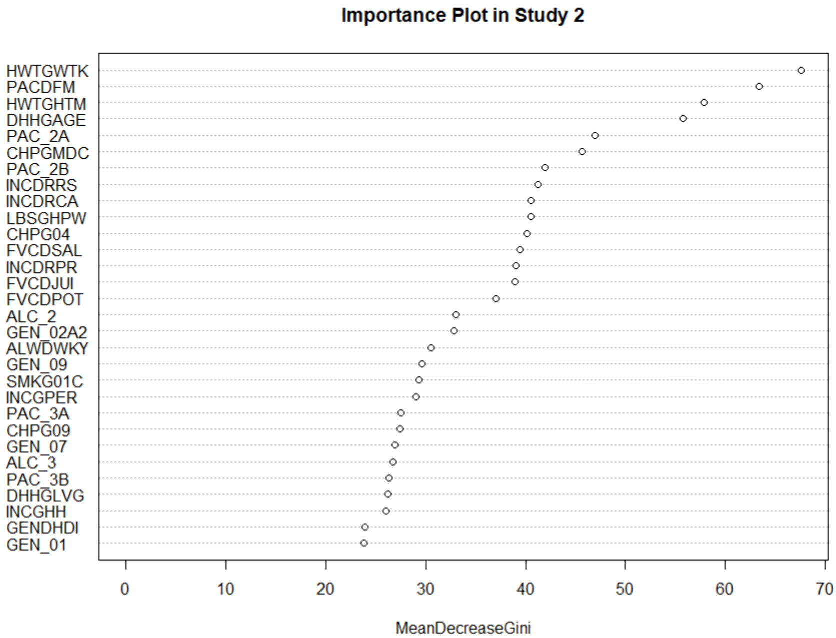

Figure A.2: The Importance Plot generated when Study 1 was executed. The first 15 variables were analyzed further using PCA.

Appendix B

Chapter 3 Supplement: Data Mapping

The table that follows on the next page provides details about all the variables in the CCHS dataset. The details include the Group name and variable code. Results obtained from statistical testing are also included in addition to Yes/No responses to whether the variable had a median above 96 and Variance Inflation Score above 10.

Appendix B Data Mapping

Variable Group Name	Variable Type	Variable Name	Variable Description
ACC : Access to health care services	Discrete	ACC_10	Required visit to medical specialist
ACC : Access to health care services	Discrete	ACC_11	Experienced difficulties getting specialist care
ACC : Access to health care services	Discrete	ACC_12A	Difficulty - getting a referral
ACC : Access to health care services	Discrete	ACC_12B	Difficulty - getting an appointment
ACC : Access to health care services	Discrete	ACC_12C	Difficulty - no specialists in area
ACC : Access to health care services	Discrete	ACC_12D	Difficulty - waited too long for an appointment
ACC : Access to health care services	Discrete	ACC_12E	Difficulty - waited too long to see doc.
ACC : Access to health care services	Discrete	ACC_12F	Difficulty - transportation
ACC : Access to health care services	Discrete	ACC_12J	Difficulty - general deterioration of health
ACC : Access to health care services	Discrete	ACC_12K	Difficulty - appointment cancelled/deferred
ACC : Access to health care services	Discrete	ACC_12L	Difficulty - still waiting for visit
ACC : Access to health care services	Discrete	ACC_20	Required non-emergency surgery
ACC : Access to health care services	Discrete	ACC_21	Experienced difficulties getting non-emerg. surgery
ACC : Access to health care services	Discrete	ACC_22E	Difficulty - waited too long for surgery
ACC : Access to health care services	Discrete	ACC_22H	Difficulty - language
ACC : Access to health care services	Discrete	ACC_22J	Difficulty - personal or family responsibilities
ACC : Access to health care services	Discrete	ACC_22L	Difficulty - appointment cancelled/deferred
ACC : Access to health care services	Discrete	ACC_22M	Difficulty - still waiting for surgery
ACC : Access to health care services	Discrete	ACC_30	Required MRI, CT Scan, angiography
ACC : Access to health care services	Discrete	ACC_31	Experienced difficulties getting test
ACC : Access to health care services	Discrete	ACC_32A	Difficulty - getting a referral
ACC : Access to health care services	Discrete	ACC_32B	Difficulty - getting an appointment
ACC : Access to health care services	Discrete	ACC_32C	Difficulty - waited too long to get an appointment
ACC : Access to health care services	Discrete	ACC_32D	Difficulty - waited too long to get test
ACC : Access to health care services	Discrete	ACC_32H	Difficulty - language
ACC : Access to health care services	Discrete	ACC_32J	Difficulty - general deterioration of health
ACC : Access to health care services	Discrete	ACC_32K	Difficulty - did not know where to go
ACC : Access to health care services	Discrete	ACC_32L	Difficulty - still waiting for test
ACC : Access to health care services	Discrete	ACC_32M	Difficulty - unable to leave house / health problem
ACC : Access to health care services	Discrete	ACC_40	Required health information for self or family member

ACC : Access to health care services	Discrete	ACC_40A	Contact for health information - doctor's office
ACC : Access to health care services	Discrete	ACC_40B	Contact for health information - community hlth ctr / CLSC
ACC : Access to health care services	Discrete	ACC_40C	Contact for health information - walk-in clinic
ACC : Access to health care services	Discrete	ACC_40D	Contact for health information - telephone health line
ACC : Access to health care services	Discrete	ACC_40E	Contact for health information - emergency room
ACC : Access to health care services	Discrete	ACC_40F	Contact for health information - other hospital service
ACC : Access to health care services	Discrete	ACC_40G	Contact for health information - other
ACC : Access to health care services	Discrete	ACC_41	Experienced diff. getting health information - self/family
ACC : Access to health care services	Discrete	ACC_42	Experienced difficulties during regular hours
ACC : Access to health care services	Discrete	ACC_43C	Difficulty - could not get through
ACC : Access to health care services	Discrete	ACC_43D	Difficulty - waited too long to speak to someone
ACC : Access to health care services	Discrete	ACC_43E	Difficulty - did not get adequate info or advice
ACC : Access to health care services	Discrete	ACC_43G	Difficulty - did not know where to go/call/uninformed
ACC : Access to health care services	Discrete	ACC_44	Experienced difficulties during evenings/weekends
ACC : Access to health care services	Discrete	ACC_45C	Difficulty - could not get through
ACC : Access to health care services	Discrete	ACC_45D	Difficulty - waited too long to speak to someone
ACC : Access to health care services	Discrete	ACC_45E	Difficulty - did not get adequate info or advice
ACC : Access to health care services	Discrete	ACC_46	Experienced difficulties during middle of night
ACC : Access to health care services	Discrete	ACC_47D	Difficulty - waited too long to speak to someone
ACC : Access to health care services	Discrete	ACC_47E	Difficulty - did not get adequate info or advice
ACC : Access to health care services	Discrete	ACC_47F	Difficulty - language
ACC : Access to health care services	Discrete	ACC_50	Required routine care for self/family
ACC : Access to health care services	Discrete	ACC_50A	Has a regular family doctor
ACC : Access to health care services	Discrete	ACC_51	Experienced diff. getting routine/on-going care - self/fam.
ACC : Access to health care services	Discrete	ACC_52	Experienced difficulties during regular hours
ACC : Access to health care services	Discrete	ACC_53A	Difficulty - contacting a physican
ACC : Access to health care services	Discrete	ACC_53B	Difficulty - getting an appointment
ACC : Access to health care services	Discrete	ACC_53D	Difficulty - waited too long to get an appointment
ACC : Access to health care services	Discrete	ACC_53E	Difficulty - waited too long to see doc.
ACC : Access to health care services	Discrete	ACC_53F	Difficulty - service not available at time required
ACC : Access to health care services	Discrete	ACC_54	Experienced difficulties during evenings/weekends
ACC : Access to health care services	Discrete	ACC_55A	Difficulty - contacting a physican
ACC : Access to health care services	Discrete	ACC_55B	Difficulty - getting an appointment
ACC : Access to health care services	Discrete	ACC_55D	Difficulty - waited too long to get an appointment

ACC : Access to health care services	Discrete	ACC_55E	Difficulty - waited too long to see doc.
ACC : Access to health care services	Discrete	ACC_55F	Difficulty - service not available at time required
ACC : Access to health care services	Discrete	ACC_55I	Difficulty - language
ACC : Access to health care services	Discrete	ACC_55L	Difficulty - unable to leave house / health problem
ACC : Access to health care services	Discrete	ACC_60	Required immediate care/minor health problem - self/family
ACC : Access to health care services	Discrete	ACC_61	Experienced difficulties getting immediate care - self/fam.
ACC : Access to health care services	Discrete	ACC_62	Experienced difficulties during regular hours
ACC : Access to health care services	Discrete	ACC_63A	Difficulty - contacting a physican
ACC : Access to health care services	Discrete	ACC_63B	Difficulty - getting an appointment
ACC : Access to health care services	Discrete	ACC_63D	Difficulty - waited too long to get an appointment
ACC : Access to health care services	Discrete	ACC_63E	Difficulty - waited too long to see doc.
ACC : Access to health care services	Discrete	ACC_63F	Difficulty - service not available at time required
ACC : Access to health care services	Discrete	ACC_64	Experienced difficulties during evenings/weekends
ACC : Access to health care services	Discrete	ACC_65A	Difficulty - contacting a physican
ACC : Access to health care services	Discrete	ACC_65B	Difficulty - getting an appointment
ACC : Access to health care services	Discrete	ACC_65D	Difficulty - waited too long to get an appointment
ACC : Access to health care services	Discrete	ACC_65E	Difficulty - waited too long to see doc.
ACC : Access to health care services	Discrete	ACC_65F	Difficulty - service not available at time required
ACC : Access to health care services	Discrete	ACC_66	Experienced difficulties during middle of night
ACC : Access to health care services	Discrete	ACC_67I	Difficulty - language
ACC : Access to health care services	Discrete	ACC_67J	Difficulty - cost
ACC : Access to health care services	Discrete	ACCG12N	Difficulties - specialist care - (G)
ACC : Access to health care services	Discrete	ACCG22B	Difficulties - surgery - (G)
ACC : Access to health care services	Discrete	ACCG22D	Difficulties - surgery - (G)
ACC : Access to health care services	Discrete	ACCG22O	Difficulties - surgery - (G)
ACC : Access to health care services	Discrete	ACCG32F	Difficulties - getting test - (G)
ACC : Access to health care services	Discrete	ACCG32N	Difficulties - getting test - (G)
ACC : Access to health care services	Discrete	ACCG43B	Difficulties during regular hours - (G)
ACC : Access to health care services	Discrete	ACCG43I	Difficulties during regular hours - (G)
ACC : Access to health care services	Discrete	ACCG45B	Difficulties during evenings/weekends - (G)
ACC : Access to health care services	Discrete	ACCG45I	Difficulties during evenings/weekends - (G)
ACC : Access to health care services	Discrete	ACCG47C	Difficulties during middle of night - (G)
ACC : Access to health care services	Discrete	ACCG47I	Difficulties during middle of night - (G)
ACC : Access to health care services	Discrete	ACCG53G	Difficulties during regular hours - (G)

ACC : Access to health care services	Discrete	ACCG53J	Difficulties during regular hours - (G)
ACC : Access to health care services	Discrete	ACCG53M	Difficulties during regular hours - (G)
ACC : Access to health care services	Discrete	ACCG55G	Difficulties during regular hours - (G)
ACC : Access to health care services	Discrete	ACCG55M	Difficulties during evenings/weekends - (G)
ACC : Access to health care services	Discrete	ACCG63G	Difficulties during regular hours - (G)
ACC : Access to health care services	Discrete	ACCG63L	Difficulties during regular hours - (G)
ACC : Access to health care services	Discrete	ACCG63M	Difficulties during regular hours - (G)
ACC : Access to health care services	Discrete	ACCG65G	Difficulties during evenings/weekends - (G)
ACC : Access to health care services	Discrete	ACCG65M	Difficulties during evenings/weekends - (G)
ACC : Access to health care services	Discrete	ACCG67E	Difficulties during middle of night - (G)
ACC : Access to health care services	Discrete	ACCG67M	Difficulties during middle of night - (G)
ADL : Activities of Daily Living	Discrete	ADL_01	Needs help - preparing meals
ADL : Activities of Daily Living	Discrete	ADL_02	Needs help - getting to appointments / running errands
ADL : Activities of Daily Living	Discrete	ADL_03	Needs help - doing housework
ADL : Activities of Daily Living	Discrete	ADL_04	Needs help - personal care
ADL : Activities of Daily Living	Discrete	ADL_05	Needs help - moving about inside the house
ADL : Activities of Daily Living	Discrete	ADL_06	Needs help - looking after personal finances
ADL : Activities of Daily Living	Discrete	ADLF6R	Help needed for tasks - (F)
ADM : Administration information	Discrete	ADM_N09	Interview by telephone or in person
ADM : Administration information	Discrete	ADM_N10	Respondent alone during interview
ADM : Administration information	Discrete	ADM_N11	Answers affected by presence of another person
ADM : Administration information	Discrete	ADM_PRX	Health Component completed by proxy
ADM : Administration information	Continuous	ADM_RNO	Sequential record number
ALC : Alcohol use	Discrete	ALC_1	Drank alcohol in past 12 months
ALC : Alcohol use	Discrete	ALC_2	Frequency of drinking alcohol
ALC : Alcohol use	Discrete	ALC_3	Frequency of drinking 4 (female)/ 5 (male) or more drinks
ALC : Alcohol use	Discrete	ALCDTTM	Type of drinker (12 months) - (D)
ALD : Alcohol use - Dependence	Continuous	ALDDINT	Alcohol interference - mean - 12 mo - (D)
ALD : Alcohol use - Dependence	Discrete	ALDDPP	Probability of caseness to respondents - (D)
ALD : Alcohol use - Dependence	Discrete	ALDFINT	Alcohol interference - 12 mo - (F)
ALD : Alcohol use - Dependence	Discrete	ALDGSF	Alcohol dependence scale - short form score - (G)
ALW : Alcohol use during the past week	Discrete	ALW_1	Drank alcohol in past week
ALW : Alcohol use during the past week	Continuous	ALW_2A1	Number of drinks - Day1
ALW : Alcohol use during the past week	Continuous	ALW_2A2	Number of drinks - Day 2

ALW : Alcohol use during the past week	Continuous	ALW_2A3	Number of drinks - Day 3
ALW : Alcohol use during the past week	Continuous	ALW_2A4	Number of drinks - Day 4
ALW : Alcohol use during the past week	Continuous	ALW_2A5	Number of drinks - Day 5
ALW : Alcohol use during the past week	Continuous	ALW_2A6	Number of drinks - Day 6
ALW : Alcohol use during the past week	Continuous	ALW_2A7	Number of drinks - Day 7
ALW : Alcohol use during the past week	Continuous	ALWDDLY	Average daily alcohol consumption - (D)
ALW : Alcohol use during the past week	Discrete	ALWDWKY	Weekly consumption - (D)
BPC : Blood pressure check	Discrete	BPC_010	Ever had blood pressure taken
BPC : Blood pressure check	Discrete	BPC_012	Last time blood pressure was taken
BPC : Blood pressure check	Discrete	BPC_013	Pregnant - blood pressure taken
BPC : Blood pressure check	Discrete	BPC_16A	Blood pressure not taken - have not gotten around to it
BPC : Blood pressure check	Discrete	BPC_16B	Blood pressure not taken - respondent didn't think necessary
BPC : Blood pressure check	Discrete	BPC_16C	Blood pressure not taken - doctor didn't think necessary
BPC : Blood pressure check	Discrete	BPC_16H	Blood pressure not taken - transportation problems
BPC : Blood pressure check	Discrete	BPC_16I	Blood pressure not taken - language problem
BPC : Blood pressure check	Discrete	BPC_16N	Blood pressure not taken - unable to leave house/health prob
BPC : Blood pressure check	Discrete	BPCG16M	Blood pressure not taken - (G) - other
CCC : Chronic conditions	Discrete	CCC_031	Has asthma
CCC : Chronic conditions	Discrete	CCC_035	Asthma - had symptoms or attacks
CCC : Chronic conditions	Discrete	CCC_036	Asthma - took medication
CCC : Chronic conditions	Discrete	CCC_041	Has fibromyalgia
CCC : Chronic conditions	Discrete	CCC_051	Has arthritis
CCC : Chronic conditions	Discrete	CCC_061	Has back problems excluding fibromyalgia and arthritis
CCC : Chronic conditions	Discrete	CCC_071	Has high blood pressure
CCC : Chronic conditions	Discrete	CCC_072	Ever diagnosed with high blood pressure
CCC : Chronic conditions	Discrete	CCC_073	Medication - high blood pressure - past month
CCC : Chronic conditions	Discrete	CCC_073A	Pregnant when first diagnosed with high blood pressure
CCC : Chronic conditions	Discrete	CCC_073B	Other than during pregnancy - diag. with high blood pressure
CCC : Chronic conditions	Discrete	CCC_081	Has migraine headaches
CCC : Chronic conditions	Discrete	CCC_091	Has a COPD
CCC : Chronic conditions	Discrete	CCC_101	Has diabetes
CCC : Chronic conditions	Discrete	CCC_105	Diabetes - currently takes insulin
CCC : Chronic conditions	Discrete	CCC_106	Diabetes - takes pills to control blood sugar
CCC : Chronic conditions	Discrete	CCC_10A	Diabetes diagnosed when pregnant

CCC : Chronic conditions	Discrete	CCC_10B	Diabetes diagnosed - other than pregnant
CCC : Chronic conditions	Discrete	CCC_10C	Diabetes diagnosed - when started with insulin
CCC : Chronic conditions	Discrete	CCC_121	Has heart disease
CCC : Chronic conditions	Discrete	CCC_131	Has cancer
CCC : Chronic conditions	Discrete	CCC_141	Has stomach or intestinal ulcers
CCC : Chronic conditions	Discrete	CCC_151	Suffers from the effects of a stroke
CCC : Chronic conditions	Discrete	CCC_161	Has urinary incontinence
CCC : Chronic conditions	Discrete	CCC_171	Has a bowel disorder / Crohn's Disease or colitis
CCC : Chronic conditions	Discrete	CCC_173	Diagnosed with scoliosis
CCC : Chronic conditions	Discrete	CCC_17A	Type of bowel disease
CCC : Chronic conditions	Discrete	CCC_251	Has chronic fatigue syndrome
CCC : Chronic conditions	Discrete	CCC_261	Suffers multiple chemical sensitivities
CCC : Chronic conditions	Discrete	CCC_280	Has a mood disorder
CCC : Chronic conditions	Discrete	CCC_290	Has an anxiety disorder
CCC : Chronic conditions	Discrete	CCC_31A	Ever had cancer
CCC : Chronic conditions	Discrete	CCCDDIA	Diabetes type
CCC : Chronic conditions	Discrete	CCCG102	Diabetes - age first diagnosed - (G)
CCS : Colorectal cancer screening	Discrete	CCS_180	Had an FOBT test
CCS : Colorectal cancer screening	Discrete	CCS_182	Last time FOBT test done
CCS : Colorectal cancer screening	Discrete	CCS_184	Had colonoscopy or sigmoidoscopy
CCS : Colorectal cancer screening	Discrete	CCS_185	Last time had colonoscopy or sigmoidoscopy
CCS : Colorectal cancer screening	Discrete	CCS_187	Colonoscopy or sigmoidoscopy followed FOBT test
CCS : Colorectal cancer screening	Discrete	CCS_83A	Had FOBT - family history
CCS : Colorectal cancer screening	Discrete	CCS_83B	Had FOBT - regular check-up
CCS : Colorectal cancer screening	Discrete	CCS_83C	Had FOBT - age
CCS : Colorectal cancer screening	Discrete	CCS_83D	Had FOBT - follow-up of problem
CCS : Colorectal cancer screening	Discrete	CCS_83E	Had FOBT - follow-up of treatment
CCS : Colorectal cancer screening	Discrete	CCS_83F	Had FOBT - other
CCS : Colorectal cancer screening	Discrete	CCS_86A	Had colonoscopy/sigmoidoscopy - family history
CCS : Colorectal cancer screening	Discrete	CCS_86B	Had colonoscopy/sigmoidoscopy - regular check-up
CCS : Colorectal cancer screening	Discrete	CCS_86C	Had colonoscopy/sigmoidoscopy - age
CCS : Colorectal cancer screening	Discrete	CCS_86D	Had colonoscopy/sigmoidoscopy - follow-up of problem
CCS : Colorectal cancer screening	Discrete	CCS_86E	Had colonoscopy/sigmoidoscopy - follow-up of treatment
CCS : Colorectal cancer screening	Discrete	CCS_86F	Had colonoscopy/sigmoidoscopy - other

CHP : Contacts with health professionals	Discrete	CHP_01	Overnight patient
CHP : Contacts with health professionals	Discrete	CHP_03	Consulted with family doctor/general practitioner
CHP : Contacts with health professionals	Discrete	CHP_06	Consulted with eye specialist
CHP : Contacts with health professionals	Discrete	CHP_08	Consulted with other medical doctor
CHP : Contacts with health professionals	Discrete	CHP_11	Consulted with nurse
CHP : Contacts with health professionals	Discrete	CHP_14	Consulted with dentist or orthodontist
CHP : Contacts with health professionals	Discrete	CHP_16	Consulted with chiropractor
CHP : Contacts with health professionals	Discrete	CHP_18	Consulted with physiotherapist
CHP : Contacts with health professionals	Discrete	CHP_20	Consulted with psychologist
CHP : Contacts with health professionals	Discrete	CHP_22	Consulted with social worker or counsellor
CHP : Contacts with health professionals	Discrete	CHP_24	Consulted with speech/audiology/occ. therapist
CHP : Contacts with health professionals	Discrete	CHPG02	Number of nights as patient - (G)
CHP : Contacts with health professionals	Discrete	CHPG04	Num consultations - fam. doctor/general practitioner - (G)
CHP : Contacts with health professionals	Discrete	CHPG05	Where most recent cont-fam doctor/general practitioner-(G)
CHP : Contacts with health professionals	Discrete	CHPG07	Number of consultations - eye specialist - (G)
CHP : Contacts with health professionals	Discrete	CHPG09	Number consultations-other medical doctor - (G)
CHP : Contacts with health professionals	Discrete	CHPG10	Where most recent contact-other medical doctor - (G)
CHP : Contacts with health professionals	Discrete	CHPG12	Number of consultations - nurse - (G)
CHP : Contacts with health professionals	Discrete	CHPG13	Wheremost recent contact took place - nurse - (G)
CHP : Contacts with health professionals	Discrete	CHPG15	Number of consultations - dentist or orthodontist - (G)
CHP : Contacts with health professionals	Discrete	CHPG17	Number of consultations - chiropractor - (G)
CHP : Contacts with health professionals	Discrete	CHPG19	Number of consultations - physiotherapist - (G)
CHP : Contacts with health professionals	Discrete	CHPG21	Number of consultations - psychologist - (G)
CHP : Contacts with health professionals	Discrete	CHPG23	Number of consultations - social worker or counsellor - (G)
CHP : Contacts with health professionals	Discrete	CHPG25	No. of consultations - speech/audiology/occ. therap. - (G)
CHP : Contacts with health professionals	Discrete	CHPGMDC	Number of consultations with medical doctor - (D, G)
CIH : Changes made to improve health	Discrete	CIH_1	Did something to improve health
CIH : Changes made to improve health	Discrete	CIH_2	Most important change to improve health
CIH : Changes made to improve health	Discrete	CIH_3	Thinks should do something to improve health
CIH : Changes made to improve health	Discrete	CIH_4	Most important thing to improve health
CIH : Changes made to improve health	Discrete	CIH_5	Barrier to improving health
CIH : Changes made to improve health	Discrete	CIH_6A	Barrier to improving health - lack of will power
CIH : Changes made to improve health	Discrete	CIH_6B	Barrier to improving health - work schedule
CIH : Changes made to improve health	Discrete	CIH_6E	Barrier to improving health - too costly

CIH : Changes made to improve health	Discrete	CIH_6F	Barrier to improving health - too stressed
CIH : Changes made to improve health	Discrete	CIH_6G	Barrier to improving health - disability / health problem
CIH : Changes made to improve health	Discrete	CIH_6H	Barrier to improving health - other
CIH : Changes made to improve health	Discrete	CIH_6I	Barrier to improving health - family responsibilities
CIH : Changes made to improve health	Discrete	CIH_6J	Barrier to improving health - addiction to drugs / alcohol
CIH : Changes made to improve health	Discrete	CIH_6K	Barrier to improving health - physical condition
CIH : Changes made to improve health	Discrete	CIH_6L	Barrier to improving health - not available - in area
CIH : Changes made to improve health	Discrete	CIH_6M	Barrier to improving health - transportation problems
CIH : Changes made to improve health	Discrete	CIH_6N	Barrier to improving health - weather problems
CIH : Changes made to improve health	Discrete	CIH_7	Intending to improve health over next year
CIH : Changes made to improve health	Discrete	CIH_8A	Health improvement - more exercise
CIH : Changes made to improve health	Discrete	CIH_8B	Health improvement - lose weight
CIH : Changes made to improve health	Discrete	CIH_8C	Health improvement - improve eating habits
CIH : Changes made to improve health	Discrete	CIH_8G	Health improvement - reduce stress level
CIH : Changes made to improve health	Discrete	CIH_8H	Health improvement - take vitamins
CIH : Changes made to improve health	Discrete	CIH_8I	Health improvement - other
CIH : Changes made to improve health	Discrete	CIH_8J	Health improvement - quit smoking
CIH : Changes made to improve health	Discrete	CIH_8K	Health improvement - drink less alcohol
CIH : Changes made to improve health	Discrete	CIH_8L	Health improvement - receive medical treatment
CMH : Consultations about mental health	Discrete	CMH_01K	Consulted mental health professional
CMH : Consultations about mental health	Discrete	CMH_1MA	Consulted mental health professional - family doctor
CMH : Consultations about mental health	Discrete	CMH_1MB	Consulted mental health professional - psychiatrist
CMH : Consultations about mental health	Discrete	CMH_1MC	Consulted mental health professional - psychologist
CMH : Consultations about mental health	Discrete	CMH_1MD	Consulted mental health professional - nurse
CMH : Consultations about mental health	Discrete	CMH_1ME	Consulted mental hlth. professional - social worker
CMH : Consultations about mental health	Discrete	CMH_1MF	Consulted mental health professional - other
CMH : Consultations about mental health	Discrete	CMHG01L	Consulted mental health professional - number of times - (G)
CPG : Problem gambling	Continuous	CPGDACT	Number of different types of gambling activities - (D)
CPG : Problem gambling	Continuous	CPGDINT	Gambling interference - Mean - (D)
CPG : Problem gambling	Discrete	CPGDSEV	Problem gambling severity index - (D)
CPG : Problem gambling	Discrete	CPGDTYP	Type of gambler - (D)
CPG : Problem gambling	Discrete	CPGFGAM	Gambling activity - gambler vs. non-gambler - (F)
CPG : Problem gambling	Discrete	CPGFINT	Gambling Interference - (F)
DEN : Dental visits	Discrete	DEN_130	Visited dentist

DEN : Dental visits	Discrete	DEN_132	Last time visited dentist
DEN : Dental visits	Discrete	DEN_36A	No dental visit - have not gotten around to it
DEN : Dental visits	Discrete	DEN_36B	No dental visit - respondent didn't think necessary
DEN : Dental visits	Discrete	DEN_36C	No dental visit - dentist didn't think necessary
DEN : Dental visits	Discrete	DEN_36D	No dental visit - personal / family responsibilities
DEN : Dental visits	Discrete	DEN_36E	No dental visit - not available when required
DEN : Dental visits	Discrete	DEN_36F	No dental visit - not available in area
DEN : Dental visits	Discrete	DEN_36H	No dental visit - transportation problems
DEN : Dental visits	Discrete	DEN_36I	No dental visit - language problem
DEN : Dental visits	Discrete	DEN_36J	No dental visit - cost
DEN : Dental visits	Discrete	DEN_36K	No dental visit - did not know where to go
DEN : Dental visits	Discrete	DEN_36L	No dental visit - fear
DEN : Dental visits	Discrete	DEN_36M	No dental visit - wears dentures
DEN : Dental visits	Discrete	DENG36N	No dental visit - (G)
SDC : Socio-demographic characteristics	Discrete	DHH_OWN	Dwelling ownership - own or rent
DHH : Dwelling and household variables	Discrete	DHH_SEX	Sex
DHH : Dwelling and household variables	Discrete	DHHG611	Number of persons 6 to 11 years old in household - (D, G)
DHH : Dwelling and household variables	Discrete	DHHGAGE	Age - (G)
DHH : Dwelling and household variables	Discrete	DHHGHSZ	Household size - (D, G)
DHH : Dwelling and household variables	Discrete	DHHGL12	Number of persons less than 12 years old in household -(D,G)
DHH : Dwelling and household variables	Discrete	DHHGLE5	Number of persons 5 years old or less in household - (D, G)
DHH : Dwelling and household variables	Discrete	DHHGLVG	Living arrangement of selected respondent - (D, G)
DHH : Dwelling and household variables	Discrete	DHHGMS	Marital Status - (G)
DIA : Diabetes care	Discrete	DIA_01	Tested for "A-one-C" haemoglobin
DIA : Diabetes care	Continuous	DIA_02	Number of times - tested for haemoglobin "A-one-C"
DIA : Diabetes care	Discrete	DIA_03	Feet checked by health professional
DIA : Diabetes care	Continuous	DIA_04	Number of times - feet checked by health professional
DIA : Diabetes care	Discrete	DIA_05	Urine tested for protein by health professional
DIA : Diabetes care	Discrete	DIA_06	Ever had eye exam with pupils dilated
DIA : Diabetes care	Discrete	DIA_07	Eye exam with pupils dilated - last time
DIA : Diabetes care	Discrete	DIA_08	Checks glucose level / self - reporting unit
DIA : Diabetes care	Discrete	DIA_09	Checks feet / self - reporting unit
DIA : Diabetes care	Discrete	DIA_10	Medication - ASA - past month
DIA : Diabetes care	Discrete	DIA_11	Medication - blood cholesterol - past month

DIA : Diabetes care	Continuous	DIA_N8B	Checks glucose level/self - number of times per day
DIA : Diabetes care	Continuous	DIA_N8C	Checks glucose level/self - number of times per week
DIA : Diabetes care	Continuous	DIA_N8D	Checks glucose level/self - number of times per month
DIA : Diabetes care	Continuous	DIA_N8E	Checks glucose level/self - number of times per year
DIA : Diabetes care	Continuous	DIA_N9B	Checks feet / self - number of times per day
DIA : Diabetes care	Continuous	DIA_N9C	Checks feet / self - number of times per week
DIA : Diabetes care	Continuous	DIA_N9D	Checks feet / self - number of times per month
DIA : Diabetes care	Continuous	DIA_N9E	Checks feet / self - number of times per year
DIS : Distress	Discrete	DIS_10A	Frequency - distress: felt tired out - past month
DIS : Distress	Discrete	DIS_10B	Frequency - distress: felt nervous - past month
DIS : Distress	Discrete	DIS_10C	Freq./-distress: so nervous nothing calms down - past month
DIS : Distress	Discrete	DIS_10D	Frequency - distress: felt hopeless - past month
DIS : Distress	Discrete	DIS_10E	Frequency - distress: felt restless - past month
DIS : Distress	Discrete	DIS_10F	Frequency - distress: could not sit still - past month
DIS : Distress	Discrete	DIS_10G	Frequency - distress: felt sad / depressed - past month
DIS : Distress	Discrete	DIS_10H	Frequency - distress: depressed/nothing cheers - past month
DIS : Distress	Discrete	DIS_10I	Freq. - distress: felt everything was an effort - past month
DIS : Distress	Discrete	DIS_10J	Frequency - distress: felt worthless - past month
DIS : Distress	Discrete	DIS_10K	Frequency of distress feelings - past month
DIS : Distress	Discrete	DIS_10L	Frequency of distress feelings (more often)
DIS : Distress	Discrete	DIS_10M	Frequency of distress feelings (less often)
DIS : Distress	Discrete	DIS_10N	Frequency of dist. feelings interfere with life - past month
DIS : Distress	Discrete	DISDCHR	Chronicity of distress/impairment scale - past month - (D)
DIS : Distress	Continuous	DISDDSX	Distress scale - K10 - past month - (D)
DIS : Distress	Continuous	DISDK6	Distress scale - K6 - past month - (D)
ACC : Access to health care services	Discrete	DOACC	Access to health care services - Inclusion flag - (F)
ADL : Activities of Daily Living	Discrete	DOADL	Activities of daily living - Inclusion Flag - (F)
ALW : Alcohol use during the past week	Discrete	DOALW	Alcohol use - past week - Inlusion Flag - (F)
BPC : Blood pressure check	Discrete	DOBPC	Blood pressure check - Inclusion Flag - (F)
CCS : Colorectal cancer screening	Discrete	DOCCS	Colorectal cancer screening - Inclusion Flag - (F)
CIH : Changes made to improve health	Discrete	DOCIH	Changes made to improve health module - Inclusion Flag - (F)
CMH : Consultations about mental health	Discrete	DOCMH	Consultations - mental health module - Inclusion Flag - (F)
CPG : Problem gambling	Discrete	DOCPG	Problem gambling - Inclusion Flag - (F)
DEN : Dental visits	Discrete	DODEN	Dental visits - Inclusion Flag - (F)

DPS : Depression	Discrete	DODEP	Depression - Inclusion Flag - (F)
DIA : Diabetes care	Discrete	DODIA	Diabetes care - Inclusion Flag - (F)
DIS : Distress	Discrete	DODIS	Distress - Inclusion Flag - (F)
DRV : Driving and safety	Discrete	DODRV	Driving and safety - Inclusion Flag - (F)
EYX : Eye examinations	Discrete	DOEYX	Module: Eye examinations - Inclusion Flag - (F)
FDC : Food choices	Discrete	DOFDC	Food choices - Inclusion Flag - (F)
FSC : Food security	Discrete	DOFSC	Food security - Inclusion Flag - (F)
HCS : Health care system satisfaction	Discrete	DOHCS	Health care system satisfaction module- Inclusion Flag - (F)
HUI : Health utilities index	Discrete	DOHUI	Health utility index - Inclusion Flag - (F)
IDG : Illicit drug use	Discrete	DOIDG	Illicit drugs use - Inclusion Flag - (F)
INJ : Injuries	Discrete	DOINJ	Injuries - Inclusion Flag - (F)
INS : Insurance coverage	Discrete	DOINS	Insurance coverage - Inclusion Flag - (F)
LOP : Loss of productivity	Discrete	DOLOP	Loss of production - Inclusion Flag - (F)
MAM : Mammography	Discrete	DOMAM	Mammography - Inclusion Flag - (F)
MDB : Mood	Discrete	DOMDB	Mood (Bradburn affect balance scale) - Inclusion Flag - (F)
MEX : Maternal experiences - Breastfeeding	Discrete	DOMEX	Module flag: Maternal Experiences - (F)
MXA : Maternal experiences - Alcohol use duri	Discrete	DOMXA	Maternal exp.- Alcohol during preg. - Inclusion Flag - (F)
MXS : Maternal experiences - Smoking during	Discrete	DOMXS	Maternal exp.- Smoking during preg. - Inclusion Flag - (F)
OH1 : Oral health 1	Discrete	DOOH1	Theme module: Oral health 1 - (F)
OH2 : Oral health 2	Discrete	DOOH2	Oral health 2 - Inclusion Flag - (F)
PAP : PAP smear test	Discrete	DOPAP	PAP smear test module - Inclusion Flag - (F)
PAS : Patient satisfaction - Health care services	Discrete	DOPAS	Patient sat. - Health care service - Inclusion Flag -(F)
PSA : Prostate cancer screening	Discrete	DOPSA	Prostate cancer screening - Inclusion Flag - (F)
PSC : Patient satisfaction - Community-based c	Discrete	DOPSC	Patient sat. - Community-based care - Inclusion Flag - (F)
SAC : Sedentary activities	Discrete	DOSAC	Sedentary activities module - Inclusion Flag - (F)
SCA : Smoking cessation methods	Discrete	DOSCA	Smoking cessation methods - Inclusion Flag - (F)
SCH : Smoking - Stages of change	Discrete	DOSCH	Smoking - stages of change - Inclusion Flag - (F)
SCP : Physical activity - Stages of change	Discrete	DOSCP	Physical activity - Stages of change - Inclusion Flag - (F)
SLP : Sleep	Discrete	DOSLP	Optional module: Sleep - (F)
SPC : Smoking - Physician counselling	Discrete	DOSPC	Smoking - physician counselling - Inclusion Flag - (F)
SPS : Social Provisions Scale 10 Items	Discrete	DOSPS	Social Provisions - Inclusion Flag - (F)
SSB : Sun safety behaviours	Discrete	DOSSB	Sun safety behaviours - Inclusion Flag - (F)
SUI : Suicidal thoughts and attempts	Discrete	DOSUI	Suicidal thoughts & attempts - Inclusion Flag - (F)
SXB : Sexual behaviours	Discrete	DOSXB	Sexual behaviours - Inclusion Flag - (F)

TAL : Smoking - Other tobacco products	Discrete	DOTAL	Smoking - Other tobacco products - Inclusion Flag - (F)
UCN : Unmet health care needs	Discrete	DOUCN	Unmet health care needs - Inclusion Flag - (F)
UPE : Use of protective equipment	Discrete	DOUPE	Use of protective equipment - Inclusion Flag - (F)
WTM : Group Waiting Times	Continuous	DOWTM	Module: Waiting times - Inclusion Flag - (F)
YSM : Smoking - Youth smoking	Discrete	DOYSM	Optional module: Smoking - Youth smoking - (F)
CHP : Contacts with health professionals	Discrete	DPCP2	Module: Contacts with Health Professional - Part 2 - Inclusion Flag - (F)
DPS : Depression	Discrete	DPSDMT	Specific month last felt depressed - 2 weeks in a row - (D)
DPS : Depression	Discrete	DPSDPP	Depression scale - Predicted probability - (D)
DPS : Depression	Continuous	DPSDSF	Depression scale - short form score - (D)
DPS : Depression	Continuous	DPSDWK	Number of weeks felt depressed - (D)
DRV : Driving and safety	Discrete	DRV_01A	Drove a motor vehicle
DRV : Driving and safety	Discrete	DRV_01B	Drove a motorcycle
DRV : Driving and safety	Discrete	DRV_02	Frequency - used seat belt when driving
DRV : Driving and safety	Discrete	DRV_03A	Use of a cell phone while driving
DRV : Driving and safety	Discrete	DRV_03B	Use of a hands-free while driving
DRV : Driving and safety	Discrete	DRV_04	Frequency - felt tired when driving
DRV : Driving and safety	Discrete	DRV_05	Driving speed compared to others
DRV : Driving and safety	Discrete	DRV_06	Driving aggression compared to others
DRV : Driving and safety	Discrete	DRV_07	Number of times - drove after 2+ drinks
DRV : Driving and safety	Continuous	DRV_07A	Number of times - drove after 2+ drinks
DRV : Driving and safety	Discrete	DRV_08A	Frequency - uses seat belt - front seat passenger
DRV : Driving and safety	Discrete	DRV_08B	Frequency - uses seat belt - back seat passenger
DRV : Driving and safety	Discrete	DRV_09	Frequency - uses seat belt - in taxi
DRV : Driving and safety	Discrete	DRV_10	No. of times - passenger/driver had 2+ drinks
DRV : Driving and safety	Continuous	DRV_10A	No. of times - passenger/driver had 2+ drinks
DRV : Driving and safety	Discrete	DRV_11A	Driver or passenger - snowmobile, motor boat or seadoo
DRV : Driving and safety	Discrete	DRV_11B	Driver or passenger - ATV
DRV : Driving and safety	Discrete	DRV_12	Frequency wears helmet - ATV
DRV : Driving and safety	Discrete	DRV_13	No. of times - passenger/driver had 2+ drinks-ATV/snowmobile
DRV : Driving and safety	Continuous	DRV_13A	No. of times - passenger/driver had 2+ drinks-ATV/snowmobile
DRV : Driving and safety	Discrete	DRV_14	No. of times - drove snowmobile, ATV, etc after 2+ drinks
DRV : Driving and safety	Continuous	DRV_14A	No. of times - drove snowmobile, ATV, etc after 2+ drinks
DRV : Driving and safety	Discrete	DRVFSBU	Passenger seat belt use - motor vehicle - (F)
EDU : Education	Discrete	EDUDH04	Highest level of education – household, 4 levels - (D)

EDU : Education	Discrete	EDUDR04	Highest level of education - respondent, 4 levels - (D)
ETS : Exposure to second-hand smoke	Discrete	ETS_10	Someone smokes inside home
ETS : Exposure to second-hand smoke	Discrete	ETS_20	Exposed to second-hand smoke in private vehicle
ETS : Exposure to second-hand smoke	Discrete	ETS_20B	Exposed to second-hand smoke in public places
ETS : Exposure to second-hand smoke	Discrete	ETS_35	Smoking allowed - House
ETS : Exposure to second-hand smoke	Discrete	ETS_36	Smoking restrictions
ETS : Exposure to second-hand smoke	Discrete	ETS_37A	Type of restrictions -certain rooms only
ETS : Exposure to second-hand smoke	Discrete	ETS_37B	Type of restrictions - young children
ETS : Exposure to second-hand smoke	Discrete	ETS_37C	Type of restrictions - windows open
ETS : Exposure to second-hand smoke	Discrete	ETS_37D	Type of restrictions - Other
ETS : Exposure to second-hand smoke	Discrete	ETSG11	Number of people who smoke inside home - (G)
EYX : Eye examinations	Discrete	EYX_140	Visit eye doctor - 12 months
EYX : Eye examinations	Discrete	EYX_142	Last time eye examination
EYX : Eye examinations	Discrete	EYX_46A	No eye exam - haven't got around to it
EYX : Eye examinations	Discrete	EYX_46B	No eye exam - respondent think not necessary
EYX : Eye examinations	Discrete	EYX_46C	No eye exam - doctor. Think not necessary
EYX : Eye examinations	Discrete	EYX_46D	No eye exam - personal/ family responsibilities
EYX : Eye examinations	Discrete	EYX_46E	No eye exam - not available when require
EYX : Eye examinations	Discrete	EYX_46F	No eye exam - not available/area
EYX : Eye examinations	Discrete	EYX_46G	No eye exam - wait time too long
EYX : Eye examinations	Discrete	EYX_46H	No eye exam - transportation problems
EYX : Eye examinations	Discrete	EYX_46J	No eye exam - cost
EYX : Eye examinations	Discrete	EYX_46K	No eye exam - did not know where to go
EYX : Eye examinations	Discrete	EYX_46L	No eye exam - fear
EYX : Eye examinations	Discrete	EYX_46N	No eye exam - health problem
EYX : Eye examinations	Discrete	EYXG46M	No eye exam - other - (G)
FDC : Food choices	Discrete	FDC_1A	Chooses or avoids foods - concerned about body weight
FDC : Food choices	Discrete	FDC_1B	Chooses or avoids foods - concerned about heart disease
FDC : Food choices	Discrete	FDC_1C	Chooses or avoids foods - concerned about cancer
FDC : Food choices	Discrete	FDC_1D	Chooses or avoids foods - concerned about osteoporosis
FDC : Food choices	Discrete	FDC_2A	Reason to choose foods - lower fat content
FDC : Food choices	Discrete	FDC_2B	Reason to choose foods - fibre content
FDC : Food choices	Discrete	FDC_2C	Reason to choose foods - calcium content
FDC : Food choices	Discrete	FDC_3A	Reason to avoid foods - fat content

FDC : Food choices	Discrete	FDC_3B	Reason to avoid foods - type of fat
FDC : Food choices	Discrete	FDC_3C	Reason to avoid foods - salt content
FDC : Food choices	Discrete	FDC_3D	Reason to avoid foods - cholesterol content
FDC : Food choices	Discrete	FDC_3E	Reason to avoid foods - calorie content
FDC : Food choices	Discrete	FDCFAVD	Avoids foods for content reasons - (F)
FDC : Food choices	Discrete	FDCFCAH	Chooses/avoids foods b/c of certain health concerns - (F)
FDC : Food choices	Discrete	FDCFCHO	Chooses foods for content reasons - (F)
FLU : Flu shots	Discrete	FLU_160	Ever had a flu shot
FLU : Flu shots	Discrete	FLU_162	Had flu shot - last time
FLU : Flu shots	Discrete	FLU_164	Had flu shot - which month
FLU : Flu shots	Discrete	FLU_165	Had flu shot - current/last year
FLU : Flu shots	Discrete	FLU_66A	No flu shot - have not gotten around to it
FLU : Flu shots	Discrete	FLU_66B	No flu shot - respondent didn't think it was necessary
FLU : Flu shots	Discrete	FLU_66C	No flu shot - doctor didn't think it was necessary
FLU : Flu shots	Discrete	FLU_66D	No flu shot - personal or family responsibilities
FLU : Flu shots	Discrete	FLU_66E	No flu shot - not available at time required
FLU : Flu shots	Discrete	FLU_66F	No flu shot - not available at all in area
FLU : Flu shots	Discrete	FLU_66G	No flu shot - waiting time was too long
FLU : Flu shots	Discrete	FLU_66H	No flu shot - transportation problems
FLU : Flu shots	Discrete	FLU_66I	No flu shot - language problem
FLU : Flu shots	Discrete	FLU_66J	No flu shot - cost
FLU : Flu shots	Discrete	FLU_66K	No flu shot - did not know where to go
FLU : Flu shots	Discrete	FLU_66L	No flu shot - fear
FLU : Flu shots	Discrete	FLU_66M	No flu shot - bad reaction to previous shot
FLU : Flu shots	Discrete	FLU_66N	No flu shot - other
FLU : Flu shots	Discrete	FLU_66O	No flu shot - unable to leave house / health problem
FSC : Food security	Discrete	FSC_010	Food situation in household - 12 mo
FSC : Food security	Discrete	FSC_020	Worried food would run out - 12 mo
FSC : Food security	Discrete	FSC_030	Food bought just didn't last and no money to buy more -12 mo
FSC : Food security	Discrete	FSC_040	Could not afford to eat balanced meals - 12 mo
FSC : Food security	Discrete	FSC_050	Relied on few kinds of low-cost food for children - 12 mo
FSC : Food security	Discrete	FSC_060	Could not feed children a balanced meal - 12 mo
FSC : Food security	Discrete	FSC_070	Children were not eating enough - 12 mo
FSC : Food security	Discrete	FSC_080	Adults skipped or cut size of meals - 12 mo

FSC : Food security	Discrete	FSC_081	Adults skipped or cut size of meals - frequency - 12 mo
FSC : Food security	Discrete	FSC_090	Ate less than felt should - 12 mo
FSC : Food security	Discrete	FSC_100	Was hungry but could not afford to eat - 12 mo
FSC : Food security	Discrete	FSC_110	Lost weight no money to buy food- 12 mo
FSC : Food security	Discrete	FSC_120	Adults did not eat for whole day - 12 mo
FSC : Food security	Discrete	FSC_121	Adults did not eat whole day - frequency - 12 mo
FSC : Food security	Discrete	FSC_130	Adults cut size of children's meals - 12 mo
FSC : Food security	Discrete	FSC_140	Children skipped meals - 12 mo
FSC : Food security	Discrete	FSC_141	Children skipped meals - frequency - 12 mo
FSC : Food security	Discrete	FSC_150	Children were hungry - 12 mo
FSC : Food security	Discrete	FSC_160	Children did not eat for whole day - 12 mo
FSC : Food security	Discrete	FSCDAFS2	Food Security - Adult Status (D)
FSC : Food security	Discrete	FSCDCFS2	Food Security - Child Status (D)
FSC : Food security	Discrete	FSCDHFS2	Household Food Security Status - Modified version - (D)
FVC : Fruit and vegetable consumption	Discrete	FVCDCAR	Daily consumption - carrots - (D)
FVC : Fruit and vegetable consumption	Discrete	FVCDFRU	Daily consumption - fruit - (D)
FVC : Fruit and vegetable consumption	Discrete	FVCDJUI	Daily consumption - fruit juice - (D)
FVC : Fruit and vegetable consumption	Discrete	FVCDPOT	Daily consumption - potatoes - (D)
FVC : Fruit and vegetable consumption	Discrete	FVCDSAL	Daily consumption - green salad - (D)
FVC : Fruit and vegetable consumption	Discrete	FVCDTOT	Daily consumption - total fruits and vegetables - (D)
FVC : Fruit and vegetable consumption	Discrete	FVCDVEG	Daily consumption - other vegetables - (D)
FVC : Fruit and vegetable consumption	Continuous	FVCGTOT	Daily consumption - total fruits and vegetables - (D, G)
GEN : General health	Discrete	GEN_01	Self-perceived health
GEN : General health	Discrete	GEN_02	Self-perceived health compared to one year ago
GEN : General health	Discrete	GEN_02A2	Satisfaction with life in general
GEN : General health	Discrete	GEN_02B	Self-perceived mental health
GEN : General health	Discrete	GEN_07	Perceived life stress
GEN : General health	Discrete	GEN_08	Worked at job or business
GEN : General health	Discrete	GEN_09	Self-perceived work stress
GEN : General health	Discrete	GEN_10	Sense of belonging to local community
GEN : General health	Discrete	GENDHDI	Perceived Health
GEN : General health	Discrete	GENDMHI	Perceived Mental Health
GEN : General health	Discrete	GENGSWL	Satisfaction with life in general
GEO : Geography variables	Discrete	GEODBCHA	British Columbia Health Authority (BCHA) - (D)

GEO : Geography variables	Discrete	GEODPMF	Health Region - (G)
GEO : Geography variables	Discrete	GEOGPRV	Province of residence of respondent - (G)
HCS : Health care system satisfaction	Discrete	HCS_1	Rating of availability of health care - province
HCS : Health care system satisfaction	Discrete	HCS_2	Rating of quality of health care - province
HCS : Health care system satisfaction	Discrete	HCS_3	Rating of availability of health care - community
HCS : Health care system satisfaction	Discrete	HCS_4	Rating of quality of health care - community
HCU : Health care utilization	Discrete	HCU_1A1	Regular medical doctor
HCU : Health care utilization	Discrete	HCU_1A2	Kind of place
HCU : Health care utilization	Discrete	HCU_1AA	Has regular medical doctor
HCU : Health care utilization	Discrete	HCU_1BA	Reason has no regular doctor - no one available in area
HCU : Health care utilization	Discrete	HCU_1BB	Reason has no regular doctor - none taking new patients
HCU : Health care utilization	Discrete	HCU_1BC	Reason has no regular doctor - not tried to contact one
HCU : Health care utilization	Discrete	HCU_1BD	Reason has no regular doctor - has left or retired
HCU : Health care utilization	Discrete	HCU_1BE	Reason has no regular doctor - other
HUI : Health utilities index	Discrete	HUIDCOG	Cognition problems - function code - (D)
HUI : Health utilities index	Discrete	HUIDEMO	Emotion (function code) - (D)
HUI : Health utilities index	Continuous	HUIDHSI	Health utilities index - (D)
HUI : Health utilities index	Discrete	HUIGDEX	Dexterity (function code) - (D, G)
HUI : Health utilities index	Discrete	HUIGHER	Hearing (function code) - (D, G)
HUI : Health utilities index	Discrete	HUIGMOB	Ambulation (mobility) (function code) - (D, G)
HUI : Health utilities index	Discrete	HUIGSPE	Speech (function code) - (D, G)
HUI : Health utilities index	Discrete	HUIGVIS	Vision (function code) - (D, G)
HUI : Health utilities index	Discrete	HUPDPAD	Pain (function code) - (D)
HWT : Height and weight - Self-reported	Discrete	HWT_4	Respondent's opinion of own weight - self-reported
HWT : Height and weight - Self-reported	Discrete	HWTDCOL	BMI class. (12 to 17) / self-report - Cole system - (D)
HWT : Height and weight - Self-reported	Discrete	HWTDWHO	BMI of school-aged children & adolescents - self-report (D)
HWT : Height and weight - Self-reported	Continuous	HWTGBMI	Body Mass Index (BMI) / self-report - (D, G)
HWT : Height and weight - Self-reported	Discrete	HWTGHTM	Height (metres) / self-reported - (D, G)
HWT : Height and weight - Self-reported	Discrete	HWTGISW	BMI class. (18 +) / self-report - Intern. standard - (D, G)
HWT : Height and weight - Self-reported	Continuous	HWTGWTK	Weight (kilograms) / self-reported - (D, G)
IDG : Illicit drug use	Continuous	IDGDINT	Illicit drug interference - mean - 12 mo - (D)
IDG : Illicit drug use	Discrete	IDGFINT	Illicit drug interference - 12 mo - (F)
IDG : Illicit drug use	Discrete	IDGFLA	Illicit drug use - including one time cannabis - ever - (F)
IDG : Illicit drug use	Discrete	IDGFLAC	Illicit drug use - excluding one time cannabis - ever - (F)

IDG : Illicit drug use	Discrete	IDGFLCA	Cannabis drug use - including one time only - ever - (F)
IDG : Illicit drug use	Discrete	IDGFLCM	Cannabis drug use - excluding one time only - ever - (F)
IDG : Illicit drug use	Discrete	IDGFYA	Illicit drug use - including one time cannabis - 12 mo - (F)
IDG : Illicit drug use	Discrete	IDGFYAC	Illicit drug use - excluding one time cannabis - 12 mo - (F)
IDG : Illicit drug use	Discrete	IDGFYCM	Cannabis drug use - excluding one time only - 12 mo - (F)
INC : Income	Discrete	INCDRCA	Household income distribution - (D)
INC : Income	Discrete	INCDRPR	Household income distribution - provincial level - (D)
INC : Income	Discrete	INCDRRS	Household income distribution - health region level - (D)
INC : Income	Discrete	INCG2	Total household income - main source - (G)
INC : Income	Discrete	INCG7	Main source of personal income - (G)
INC : Income	Discrete	INCGHH	Total household income from all sources - (D, G)
INC : Income	Discrete	INCGPER	Total personal income from all sources - (D, G)
INJ : Injuries	Discrete	INJ_01	Injured in past 12 months
INJ : Injuries	Discrete	INJ_10	Most serious injury - result of a fall
INJ : Injuries	Discrete	INJ_13	Most serious injury - received treatment within 48 hours
INJ : Injuries	Discrete	INJ_14A	Treated doctor's office
INJ : Injuries	Discrete	INJ_14B	Treated emergency room
INJ : Injuries	Discrete	INJ_14O	Treated where injury happened
INJ : Injuries	Discrete	INJ_15	Follow-up care because of injury
INJ : Injuries	Discrete	INJ_15A	Follow-up care because of injury
INJ : Injuries	Discrete	INJ_16	Other injuries - treated but did not limit normal activities
INJ : Injuries	Discrete	INJDSTT	Injury Status - (D)
INJ : Injuries	Discrete	INJG02	Number of injuries in past 12 months - (G)
INJ : Injuries	Discrete	INJG05	Most serious injury - type - (G)
INJ : Injuries	Discrete	INJG06	Most serious injury - body part affected - (G)
INJ : Injuries	Discrete	INJG08	Most serious injury - place of occurrence - (G)
INJ : Injuries	Discrete	INJG092	Most serious injury - activity when injured - (G)
INJ : Injuries	Discrete	INJG11A	How did you fall - (G)
INJ : Injuries	Discrete	INJG14C	Most serious injury - (G) - treated in clinic/ CLSC
INJ : Injuries	Discrete	INJG14J2	Most serious inj. - treated physio/mass.ther/chiro/other (G)
INJ : Injuries	Discrete	INJG17	Other injuries - number - (G)
INJ : Injuries	Discrete	INJGCAU	Cause of injury - (D, G)
INS : Insurance coverage	Discrete	INS_1	Insurance - prescription medications
INS : Insurance coverage	Discrete	INS_1A	Type of insurance for prescription meds - government

INS : Insurance coverage	Discrete	INS_1B	Type of insurance for prescription meds - employer
INS : Insurance coverage	Discrete	INS_1C	Type of insurance for prescription meds - private plan
INS : Insurance coverage	Discrete	INS_2	Insurance - dental expenses
INS : Insurance coverage	Discrete	INS_2A	Type of dental insurance - government
INS : Insurance coverage	Discrete	INS_2B	Type of dental insurance - employer
INS : Insurance coverage	Discrete	INS_2C	Type of dental insurance - private plan
INS : Insurance coverage	Discrete	INS_3	Insurance - eye glasses / contact lenses
INS : Insurance coverage	Discrete	INS_3A	Type of insurance for eye glasses/contacts - government
INS : Insurance coverage	Discrete	INS_3B	Type of insurance for eye glasses/contacts - employer
INS : Insurance coverage	Discrete	INS_3C	Type of insurance for eye glasses/contacts - private plan
INS : Insurance coverage	Discrete	INS_4	Insurance - hospital charges
INS : Insurance coverage	Discrete	INS_4A	Type of insurance for hospital room charges - government
INS : Insurance coverage	Discrete	INS_4B	Type of insurance for hospital room charges - employer
INS : Insurance coverage	Discrete	INS_4C	Type of insurance for hospital room charges - private plan
INW : Workplace injury	Discrete	INW_01	Injury occured in current job
INW : Workplace injury	Discrete	INWGSOC	Occupation group (SOC) where injury occurred - (G)
LBS : Labour force	Discrete	LBSDPFT	Current - full-time / part-time status - (D)
LBS : Labour force	Discrete	LBSDWSS	Working status last week - 4 groups - (D)
LBS : Labour force	Discrete	LBSG31	Employment status - 12 months - (G)
LBS : Labour force	Discrete	LBSGHPW	Total usual hours worked - current jobs - (D, G)
LBS : Labour force	Discrete	LBSGSOC	Occupation group - (D,G)
LOP : Loss of productivity	Discrete	LOP_015	Were you employed in past three months?
LOP : Loss of productivity	Discrete	LOP_030	Missed work due to chronic condition
LOP : Loss of productivity	Discrete	LOP_060	Missed work due to injury
LOP : Loss of productivity	Discrete	LOP_080	Missed work due to infectious disease
LOP : Loss of productivity	Discrete	LOP_090	Missed work for any other reason related to ph. or m. health
LOP : Loss of productivity	Discrete	LOP_81A	Had a cold
LOP : Loss of productivity	Discrete	LOP_81B	Had the flu or influenza
LOP : Loss of productivity	Discrete	LOP_81C	Stomach Flu
LOP : Loss of productivity	Discrete	LOP_81D	Respiratory infection
LOP : Loss of productivity	Discrete	LOP_81E	Other
LOP : Loss of productivity	Discrete	LOPG020	Reason for not working - (G)
LOP : Loss of productivity	Discrete	LOPG040	Number of work days lost due to chronic condition - (G)
LOP : Loss of productivity	Discrete	LOPG050	Chronic condition - (G)

LOP : Loss of productivity	Discrete	LOPG070	Number of work days missed due to injury - (G)
LOP : Loss of productivity	Discrete	LOPG082	Number of work days missed due to cold - (G)
LOP : Loss of productivity	Discrete	LOPG083	Number of work days missed due to flu or influenza - (G)
LOP : Loss of productivity	Discrete	LOPG084	Number of work days missed due to stomach flu - (G)
LOP : Loss of productivity	Discrete	LOPG085	No. of work days missed due to respiratory infection - (G)
LOP : Loss of productivity	Discrete	LOPG086	No. of work days missed due to other infect. disease - (G)
LOP : Loss of productivity	Discrete	LOPG100	Work days missed related to physical or mental hlth - (G)
MAM : Mammography	Discrete	MAM_030	Ever had mammogram
MAM : Mammography	Discrete	MAM_032	Last time mammogram was done
MAM : Mammography	Discrete	MAM_038	Had a hysterectomy
MAM : Mammography	Discrete	MAM_31A	Had mammogram - family history
MAM : Mammography	Discrete	MAM_31B	Had mammogram - regular check-up
MAM : Mammography	Discrete	MAM_31C	Had mammogram - age
MAM : Mammography	Discrete	MAM_31D	Had mammogram - previously detected lump
MAM : Mammography	Discrete	MAM_31E	Had mammogram - follow-up of treatment
MAM : Mammography	Discrete	MAM_31G	Had mammogram - breast problem
MAM : Mammography	Discrete	MAM_36A	No mammogram - have not gotten around to it - past 2 yrs
MAM : Mammography	Discrete	MAM_36B	No mammogram - resp. did not think necessary - past 2 yrs
MAM : Mammography	Discrete	MAM_36C	No mammogram - doctor did not think necessary - past 2 yrs
MAM : Mammography	Discrete	MAM_36D	No mammogram - personal/family responsibilities - past 2 yrs
MAM : Mammography	Discrete	MAM_36H	No mammogram - transportation problems - past 2 yrs
MAM : Mammography	Discrete	MAM_36K	No mammogram - did not know where to go - past 2 yrs
MAM : Mammography	Discrete	MAM_36L	No mammogram - fear - past 2 yrs
MAM : Mammography	Discrete	MAM_36N	No mammogram - unable to leave house/hlth prob - past 2 yrs
MAM : Mammography	Discrete	MAM_36O	No mammogram - Breasts removed / Mastectomy
MAM : Mammography	Discrete	MAMG31H	Had mammogram - (G)
MAM : Mammography	Discrete	MAMG36F	No mammogram - past 2 yrs - (G)
MAM : Mammography	Discrete	MAMG36M	No mammogram - past 2 yrs - (G)
MDB : Mood	Discrete	MDB_1	Frequency - felt on top of the world
MDB : Mood	Discrete	MDB_10	Frequency - felt upset because someone criticized you
MDB : Mood	Discrete	MDB_11	Happiness - self-perceived
MDB : Mood	Discrete	MDB_2	Frequency - felt lonely or remote from other people
MDB : Mood	Discrete	MDB_3	Frequency - felt particularly excited or interested
MDB : Mood	Discrete	MDB_4	Frequency - felt depressed or very unhappy

MDB : Mood	Discrete	MDB_5	Frequency - felt pleased about having accomplished something
MDB : Mood	Discrete	MDB_6	Frequency - felt bored
MDB : Mood	Discrete	MDB_7	Frequency - felt proud
MDB : Mood	Discrete	MDB_8	Frequency - felt so restless could not sit
MDB : Mood	Discrete	MDB_9	Frequency - felt that things were going your way
MDB : Mood	Continuous	MDBDBA1	Balance affect- method A - (D)
MDB : Mood	Discrete	MDBDBA2	Balance affect- method B - (D)
MDB : Mood	Continuous	MDBDNEG	Balance affect- negative mood - (D)
MDB : Mood	Continuous	MDBDPOS	Balance affect- positive mood - (D)
MEX : Maternal experiences - Breastfeeding	Discrete	MEX_01	Given birth in the past 5 years
MEX : Maternal experiences - Breastfeeding	Discrete	MEX_02	Took folic acid - before last pregnancy
MEX : Maternal experiences - Breastfeeding	Discrete	MEX_03	Breastfed or tried to breastfeed last child
MEX : Maternal experiences - Breastfeeding	Discrete	MEX_05	Still breastfeeding last child
MEX : Maternal experiences - Breastfeeding	Discrete	MEX_06	Duration of breastfeeding last child
MEX : Maternal experiences - Breastfeeding	Discrete	MEX_06A	Other liquids have been introduced to the baby's feeds
MEX : Maternal experiences - Breastfeeding	Discrete	MEX_06B	Age of last baby when other liquds were first added to feeds
MEX : Maternal experiences - Breastfeeding	Discrete	MEX_08A	Age of last baby when solid food were first added to feeds
MEX : Maternal experiences - Breastfeeding	Discrete	MEX_09	Give a vitamin supplement containing Vitamin D to the baby
MEX : Maternal experiences - Breastfeeding	Discrete	MEX_09B	Frequency of giving the Vitamin D supplementation to baby
MEX : Maternal experiences - Breastfeeding	Discrete	MEXDEBF2	Length of exclusive breastfeeding (D)
MEX : Maternal experiences - Breastfeeding	Discrete	MEXFEB6	Exclusively breastfed for 6 months or more
MEX : Maternal experiences - Breastfeeding	Discrete	MEXG04	Main reason did not breastfeed last child - (G)
MEX : Maternal experiences - Breastfeeding	Discrete	MEXG08B	Main reason - other liquids/foods added - (G)
MEX : Maternal experiences - Breastfeeding	Discrete	MEXG10	Main reason why stopped breastfeeding - (G)
MXA : Maternal experiences - Alcohol use duri	Discrete	MXA_01	Drank alcohol - last pregnancy
MXA : Maternal experiences - Alcohol use duri	Discrete	MXA_03	Drank alcohol - while breastfeeding last baby
MXA : Maternal experiences - Alcohol use duri	Discrete	MXAG02	Frequency of drinking - last pregnancy - (G)
MXA : Maternal experiences - Alcohol use duri	Discrete	MXAG04	Frequency of drinking - while breastfeeding last baby - (G)
MXS : Maternal experiences - Smoking during	Discrete	MXS_01	Type of smoker - last pregnancy
MXS : Maternal experiences - Smoking during	Discrete	MXS_04	Smoked while breastfeeding last baby (occasional smoker)
MXS : Maternal experiences - Smoking during	Discrete	MXS_07	Second-hand smoke - during or after last pregnancy
MXS : Maternal experiences - Smoking during	Discrete	MXSG02	No. of cigarettes daily - last pregnancy (daily smoker) -(G)
MXS : Maternal experiences - Smoking during	Discrete	MXSG03	No. of cig. daily - last pregnancy (occasional smoker) - (G)
MXS : Maternal experiences - Smoking during	Discrete	MXSG05	No. of cig. daily - while breastfeeding (daily smoker) - (G)

MXS : Maternal experiences - Smoking during	Discrete	MXSG06	No. of cig. daily - while breastfeeding (occ. smoker) - (G)
OH1 : Oral health 1	Discrete	OH1_20	Self-perceived health of teeth and mouth
OH1 : Oral health 1	Discrete	OH1_21A	Ability to chew - firm foods
OH1 : Oral health 1	Discrete	OH1_21B	Ability to chew - fresh apple
OH1 : Oral health 1	Discrete	OH1_21C	Ability to chew - boiled vegetables
OH1 : Oral health 1	Discrete	OH1_22	Frequency of pain in teeth or gums - past month
OH2 : Oral health 2	Discrete	OH2_10	Frequency usually visits the dentist
OH2 : Oral health 2	Discrete	OH2_11	Insurance for dental expenses
OH2 : Oral health 2	Discrete	OH2_11A	Type of dental insurance plan - government-sponsored
OH2 : Oral health 2	Discrete	OH2_11B	Type of dental insurance plan - employer-sponsored
OH2 : Oral health 2	Discrete	OH2_11C	Type of dental insurance plan - private
OH2 : Oral health 2	Discrete	OH2_12	Teeth removed by dentist - 12 mo
OH2 : Oral health 2	Discrete	OH2_13	Teeth removed - decay or gum disease - 12 mo
OH2 : Oral health 2	Discrete	OH2_20	Has one or more of own teeth
OH2 : Oral health 2	Discrete	OH2_21	Wears dentures
OH2 : Oral health 2	Discrete	OH2_22	Condition of teeth/mouth - difficulty speaking clearly
OH2 : Oral health 2	Discrete	OH2_23	Condition of teeth/mouth - avoided conversation - 12 mo
OH2 : Oral health 2	Discrete	OH2_24	Condition of teeth/mouth - avoided laughing/smiling - 12 mo
OH2 : Oral health 2	Discrete	OH2_25A	Had a toothache - past mo.
OH2 : Oral health 2	Discrete	OH2_25B	Teeth sensitive to hot or cold - past mo.
OH2 : Oral health 2	Discrete	OH2_25C	Had pain - jaw joints - past mo.
OH2 : Oral health 2	Discrete	OH2_25D	Had pain - mouth or face - past mo.
OH2 : Oral health 2	Discrete	OH2_25E	Had bleeding gums - past mo.
OH2 : Oral health 2	Discrete	OH2_25F	Had dry mouth - past mo.
OH2 : Oral health 2	Discrete	OH2_25G	Had bad breath - past mo.
OH2 : Oral health 2	Discrete	OH2_30	Frequency of brushing teeth
OH2 : Oral health 2	Discrete	OH2FLIM	Limited socially due to oral health status - 12 mo - (F)
OH2 : Oral health 2	Discrete	OH2FOFP	Oral or facial pain - past mo. - (F)
PAC : Physical activities	Discrete	PAC_1A	Activity / last 3 months - walking
PAC : Physical activities	Discrete	PAC_1B	Activity / last 3 months - gardening or yard work
PAC : Physical activities	Discrete	PAC_1C	Activity / last 3 months - swimming
PAC : Physical activities	Discrete	PAC_1D	Activity / last 3 months - bicycling
PAC : Physical activities	Discrete	PAC_1E	Activity / last 3 months - popular or social dance
PAC : Physical activities	Discrete	PAC_1F	Activity / last 3 months - home exercises

PAC : Physical activities	Discrete	PAC_1G	Activity / last 3 months - ice hockey
PAC : Physical activities	Discrete	PAC_1H	Activity / last 3 months - ice skating
PAC : Physical activities	Discrete	PAC_1I	Activity / last 3 months - in-line skating or rollerblading
PAC : Physical activities	Discrete	PAC_1J	Activity / last 3 months - jogging or running
PAC : Physical activities	Discrete	PAC_1K	Activity / last 3 months - golfing
PAC : Physical activities	Discrete	PAC_1L	Activity / last 3 months - exercise class or aerobics
PAC : Physical activities	Discrete	PAC_1M	Activity / last 3 months - downhill skiing or snowboarding
PAC : Physical activities	Discrete	PAC_1N	Activity / last 3 months - bowling
PAC : Physical activities	Discrete	PAC_1O	Activity / last 3 months - baseball or softball
PAC : Physical activities	Discrete	PAC_1P	Activity / last 3 months - tennis
PAC : Physical activities	Discrete	PAC_1Q	Activity / last 3 months - weight-training
PAC : Physical activities	Discrete	PAC_1R	Activity / last 3 months - fishing
PAC : Physical activities	Discrete	PAC_1S	Activity / last 3 months - volleyball
PAC : Physical activities	Discrete	PAC_1T	Activity / last 3 months - basketball
PAC : Physical activities	Discrete	PAC_1U	Activity / last 3 months - Any other
PAC : Physical activities	Discrete	PAC_1V	Activity / last 3 months - No physical activity
PAC : Physical activities	Discrete	PAC_1W	Activity / last 3 months - other (#2)
PAC : Physical activities	Discrete	PAC_1X	Activity / last 3 months - other (#3)
PAC : Physical activities	Discrete	PAC_1Z	Activity / last 3 months - Soccer
PAC : Physical activities	Continuous	PAC_2A	Number of times / 3 months - walking for exercise
PAC : Physical activities	Continuous	PAC_2B	Number of times / 3 months - gardening/yard work
PAC : Physical activities	Continuous	PAC_2C	Number of times / 3 months - swimming
PAC : Physical activities	Continuous	PAC_2D	Number of times / 3 months - bicycling
PAC : Physical activities	Continuous	PAC_2E	Number of times / 3 months - popular or social dance
PAC : Physical activities	Continuous	PAC_2F	Number of times / 3 months - home exercises
PAC : Physical activities	Continuous	PAC_2H	Number of times / 3 months - ice skating
PAC : Physical activities	Continuous	PAC_2I	Number of times / 3 months- in-line skating or rollerblading
PAC : Physical activities	Continuous	PAC_2J	Number of times / 3 months - jogging or running
PAC : Physical activities	Continuous	PAC_2K	Number of times / 3 months - golfing
PAC : Physical activities	Continuous	PAC_2L	Number of times / 3 months - exercise class or aerobics
PAC : Physical activities	Continuous	PAC_2M	Number of times / 3 months - downhill skiing or snowboarding
PAC : Physical activities	Continuous	PAC_2N	Number of times / 3 months - bowling
PAC : Physical activities	Continuous	PAC_2O	Number of times / 3 months - baseball or softball
PAC : Physical activities	Continuous	PAC_2P	Number of times / 3 months - tennis

PAC : Physical activities	Continuous	PAC_2Q	Number of times / 3 months - weight-training
PAC : Physical activities	Continuous	PAC_2R	Number of times / 3 months - fishing
PAC : Physical activities	Continuous	PAC_2S	Number of times / 3 months - volleyball
PAC : Physical activities	Continuous	PAC_2T	Number of times / 3 months - basketball
PAC : Physical activities	Continuous	PAC_2U	Number of times / 3 months - other activity (#1)
PAC : Physical activities	Continuous	PAC_2W	Number of times / 3 months - other activity (#2)
PAC : Physical activities	Continuous	PAC_2X	Number of times - other activity (#3)
PAC : Physical activities	Continuous	PAC_2Z	Number of times / 3 months - soccer
PAC : Physical activities	Discrete	PAC_3A	Time spent - walking for exercise
PAC : Physical activities	Discrete	PAC_3B	Time spent - gardening or yard work
PAC : Physical activities	Discrete	PAC_3C	Time spent - swimming
PAC : Physical activities	Discrete	PAC_3D	Time spent - bicycling
PAC : Physical activities	Discrete	PAC_3E	Time spent - popular or social dance
PAC : Physical activities	Discrete	PAC_3F	Time spent - home exercises
PAC : Physical activities	Discrete	PAC_3G	Time spent - ice hockey
PAC : Physical activities	Discrete	PAC_3H	Time spent - ice skating
PAC : Physical activities	Discrete	PAC_3I	Time spent - in-line skating or rollerblading
PAC : Physical activities	Discrete	PAC_3J	Time spent - jogging or running
PAC : Physical activities	Discrete	PAC_3K	Time spent - golfing
PAC : Physical activities	Discrete	PAC_3L	Time spent - exercise class or aerobics
PAC : Physical activities	Discrete	PAC_3M	Time spent - downhill skiing or snowboarding
PAC : Physical activities	Discrete	PAC_3N	Time spent - bowling
PAC : Physical activities	Discrete	PAC_3O	Time spent - baseball or softball
PAC : Physical activities	Discrete	PAC_3P	Time spent - tennis
PAC : Physical activities	Discrete	PAC_3Q	Time spent - weight-training
PAC : Physical activities	Discrete	PAC_3R	Time spent - fishing
PAC : Physical activities	Discrete	PAC_3S	Time spent - volleyball
PAC : Physical activities	Discrete	PAC_3T	Time spent - basketball
PAC : Physical activities	Discrete	PAC_3U	Time spent - other activity (#1)
PAC : Physical activities	Discrete	PAC_3W	Time spent - other activity (#2)
PAC : Physical activities	Discrete	PAC_3X	Time spent - other activity (#3)
PAC : Physical activities	Discrete	PAC_3Z	Time spent - soccer
PAC : Physical activities	Discrete	PAC_7	Walked to work or school / last 3 months
PAC : Physical activities	Continuous	PAC_7A	Number of times / 3 months - walking to go work or school

PAC : Physical activities	Discrete	PAC_7B	Time spent - walking to / from work or school
PAC : Physical activities	Discrete	PAC_8	Bicycled to work or school / last 3 months
PAC : Physical activities	Continuous	PAC_8A	# times / 3 months - bicycling to and from work or school
PAC : Physical activities	Discrete	PAC_8B	Time spent - bicycling to go work or school
PAC : Physical activities	Continuous	PACDEE	Daily energy expenditure - Leisure physical activities - (D)
PAC : Physical activities	Continuous	PACDFM	Month. freq. - Leisure phys. activity lasting >15 min. - (D)
PAC : Physical activities	Discrete	PACDFR	Frequency of all leisure physical activity > 15 min. - (D)
PAC : Physical activities	Discrete	PACDLTI	Leisure and transportation physical activity index - (D)
PAC : Physical activities	Discrete	PACDPAI	Leisure physical activity index - (D)
PAC : Physical activities	Discrete	PACDTLE	Daily ener. expend. - Transport. and leisure phy. act. - (D)
PAC : Physical activities	Discrete	PACFD	Participant in daily leisure phys. activity > 15 min. - (F)
PAC : Physical activities	Discrete	PACFLEI	Participant in leisure physical activity - (F)
PAC : Physical activities	Discrete	PACFLTI	Participant in leisure or transportation phys. activ. - (F)
PAC : Physical activities	Discrete	PACG2G	Number of times / 3 months - ice hockey - (G)
PAP : PAP smear test	Discrete	PAP_020	Ever had PAP smear test
PAP : PAP smear test	Discrete	PAP_022	Last time had PAP smear test
PAP : PAP smear test	Discrete	PAP_26A	No PAP smear - have not gotten around to it
PAP : PAP smear test	Discrete	PAP_26B	No PAP smear - respondent didn't think necessary
PAP : PAP smear test	Discrete	PAP_26C	No PAP smear - doctor didn't think necessary
PAP : PAP smear test	Discrete	PAP_26K	No PAP smear - did not know where to go
PAP : PAP smear test	Discrete	PAP_26L	No PAP smear - fear
PAP : PAP smear test	Discrete	PAP_26M	No PAP smear - hysterectomy
PAP : PAP smear test	Discrete	PAP_26N	No PAP smear - hate / dislike having one done
PAP : PAP smear test	Discrete	PAPG26G	No PAP smear - (G) - Not avail. /Wait time
PAP : PAP smear test	Discrete	PAPG26O	No PAP smear - other - (G)
PAS : Patient satisfaction - Health care services	Discrete	PAS_11	Received health care services
PAS : Patient satisfaction - Health care services	Discrete	PAS_12	Rating of quality of care received
PAS : Patient satisfaction - Health care services	Discrete	PAS_13	Satisfaction with way care provided
PAS : Patient satisfaction - Health care services	Discrete	PAS_21A	Received health care services at hospital
PAS : Patient satisfaction - Health care services	Discrete	PAS_21B	Type of patient - most recent visit
PAS : Patient satisfaction - Health care services	Discrete	PAS_22	Rating of quality of care received - hospital
PAS : Patient satisfaction - Health care services	Discrete	PAS_23	Satisfaction with way care provided - hospital
PAS : Patient satisfaction - Health care services	Discrete	PAS_31A	Received physician care
PAS : Patient satisfaction - Health care services	Discrete	PAS_31B	Type of physician - most recent care

PAS : Patient satisfaction - Health care services	Discrete	PAS_32	Rating of quality of care received - physician
PAS : Patient satisfaction - Health care services	Discrete	PAS_33	Satisfaction with way care provided - physician
ADM : Administration information	Discrete	PMKPROXY	Person most knowledgeable
PSA : Prostate cancer screening	Discrete	PSA_170	Ever had a PSA blood test (prostate cancer)
PSA : Prostate cancer screening	Discrete	PSA_172	Last time had PSA blood test
PSA : Prostate cancer screening	Discrete	PSA_174	Had a digital rectal exam
PSA : Prostate cancer screening	Discrete	PSA_175	Last time had digital rectal exam
PSA : Prostate cancer screening	Discrete	PSA_73A	Had PSA test - family history of prostate cancer
PSA : Prostate cancer screening	Discrete	PSA_73B	Had PSA test - regular check-up
PSA : Prostate cancer screening	Discrete	PSA_73C	Had PSA test - age
PSA : Prostate cancer screening	Discrete	PSA_73D	Had PSA test - follow-up of problem
PSA : Prostate cancer screening	Discrete	PSA_73E	Had PSA test - follow-up of prostate cancer treatment
PSA : Prostate cancer screening	Discrete	PSA_73F	Had PSA test - other
PSC : Patient satisfaction - Community-based c	Discrete	PSC_1	Received any community-based care
PSC : Patient satisfaction - Community-based c	Discrete	PSC_2	How rate quality of the community-based received
PSC : Patient satisfaction - Community-based c	Discrete	PSC_3	How satisfied with the way community-based care provided
RAC : Restriction of activities	Discrete	RAC_1	Has dificulty with activities
RAC : Restriction of activities	Discrete	RAC_2A	Reduction in kind/amount of activities - at home
RAC : Restriction of activities	Discrete	RAC_2B1	Reduction in kind/amount of activities - at school
RAC : Restriction of activities	Discrete	RAC_2B2	Reduction in kind/amount of activities - at work
RAC : Restriction of activities	Discrete	RAC_2C	Reduction in kind/amount of activities - other activities
RAC : Restriction of activities	Discrete	RACDIMP	Impact of health problems - (D)
RAC : Restriction of activities	Discrete	RACDPAL	Participation and activity limitation - (D)
RAC : Restriction of activities	Discrete	RACG5	Cause of health problem - (G)
INJ : Injuries	Discrete	REP_1A	Repetitive strain injury
INJ : Injuries	Discrete	REP_2	Repetitive strain injury - normal activities limited
INJ : Injuries	Discrete	REP_3A	Repetitive strain- activity causing injury
INJ : Injuries	Discrete	REP_4	Repetitive strain- working at a job or business
INJ : Injuries	Discrete	REP_5A	Repetitive strain - Activity - walking
INJ : Injuries	Discrete	REP_5B	Repetitive strain - Activity - sports
INJ : Injuries	Discrete	REP_5C	Repetitive strain - Activity - leisure
INJ : Injuries	Discrete	REP_5D	Repetitive strain - Activity - household chores
INJ : Injuries	Discrete	REP_5F	Repetitive strain - Activity - computer
INJ : Injuries	Discrete	REP_5G	Repetitive strain - Activity - driving motor vehicle

INJ : Injuries	Discrete	REP_5H	Repetitive strain - Activity - lifting or carrying
INJ : Injuries	Discrete	REP_5I	Repetitive strain - Activity - other
INJ : Injuries	Discrete	REPG3	Repetitive strain - body part affected - (G)
SAC : Sedentary activities	Discrete	SACDTER	Total no. hrs / week (excl. reading) - sedentary act. - (D)
SAC : Sedentary activities	Discrete	SACDTOT	Total number hours - sedentary activities - past 3 mo - (D)
SAC : Sedentary activities	Discrete	SACG1	Number of hours - on a computer - past 3 mo - (G)
SAC : Sedentary activities	Discrete	SACG2	Number of hours - playing video games - past 3 mo - (G)
SAC : Sedentary activities	Discrete	SACG3	Number hours-watching television/videos - past 3 mo - (G)
SAC : Sedentary activities	Discrete	SACG4	Number of hours - reading - past 3 mo - (G)
SCA : Smoking cessation methods	Discrete	SCA_10	Used nicotine patch
SCA : Smoking cessation methods	Discrete	SCA_11	Used nicotine gum or candy
SCA : Smoking cessation methods	Discrete	SCA_11A	Usefulness of nicotine gum or candy
SCA : Smoking cessation methods	Discrete	SCA_12	Used medication such as Zyban
SCA : Smoking cessation methods	Discrete	SCA_50	Stopped smoking for at least 24 hours
SCA : Smoking cessation methods	Discrete	SCA_60	Tried to quit smoking - nicotine patch
SCA : Smoking cessation methods	Discrete	SCA_61	Tried to quit smoking - nicotine gum or candy - past 12 mo
SCA : Smoking cessation methods	Discrete	SCA_62	Tried to quit smoking - medication such as Zyban
SCA : Smoking cessation methods	Discrete	SCADQUI	Attempted to stop smoking - (D)
SCA : Smoking cessation methods	Discrete	SCAG10A	Usefulness of nicotine patch - (G)
SCA : Smoking cessation methods	Discrete	SCAG12A	Usefulness of medication such as Zyban - (G)
SCH : Smoking - Stages of change	Discrete	SCH_1	Quitting smoking - next 6 months
SCH : Smoking - Stages of change	Discrete	SCH_2	Quitting smoking - next 30 days
SCH : Smoking - Stages of change	Discrete	SCH_3	Stopped smoking for at least 24 hours - 12 mo
SCH : Smoking - Stages of change	Continuous	SCH_4	Number of times stopped for at least 24 hours - 12 mo
SCH : Smoking - Stages of change	Discrete	SCHDSTG	Smoking stages of change - (D)
SCP : Physical activity - Stages of change	Discrete	SCP_01	level of physical activity for every week
SCP : Physical activity - Stages of change	Discrete	SCP_02	Increase of physical activity level
SCP : Physical activity - Stages of change	Discrete	SCP_03	Intend to increase of physical activity level/next 30 days
SCP : Physical activity - Stages of change	Discrete	SCP_04	Intend to increase of physical activity level/next 6 months
SCP : Physical activity - Stages of change	Discrete	SCPDSTG	Stages of changes - physical activity
SDC : Socio-demographic characteristics	Discrete	SDC_5A_1	Knowledge of official languages
EDU : Education	Discrete	SDC_8	Current student
SDC : Socio-demographic characteristics	Discrete	SDCDFOLS	First official language spoken - (D)
SDC : Socio-demographic characteristics	Discrete	SDCFIMM	Immigrant - (F)

EDU : Education	Discrete	SDCG9	Full-time student or part-time student
SDC : Socio-demographic characteristics	Discrete	SDCG9	Full-time student or part-time student - (Grouped)
SDC : Socio-demographic characteristics	Discrete	SDCGCB13	Country of birth - Canada/other - (G)
SDC : Socio-demographic characteristics	Discrete	SDCGCGT	Cultural or racial origin - (D, G)
SDC : Socio-demographic characteristics	Discrete	SDCGLHM	Language(s) spoken at home - (D, G)
SDC : Socio-demographic characteristics	Discrete	SDCGRES	Length of time in Canada since immigration - (D, G)
SLP : Sleep	Discrete	SLP_02	Frequency - trouble sleeping
SLP : Sleep	Discrete	SLP_03	Frequency - find sleep refreshing
SLP : Sleep	Discrete	SLP_04	Frequency - find it difficult to stay awake
SLP : Sleep	Discrete	SLPG01	Number of hours spent sleeping per night - (G)
SMK : Smoking	Discrete	SMK_01A	Smoked 100 or more cigarettes - life
SMK : Smoking	Discrete	SMK_01B	Ever smoked whole cigarette
SMK : Smoking	Continuous	SMK_05B	Number of cigarettes smoked per day (occasional smoker)
SMK : Smoking	Continuous	SMK_05C	Number of days - smoked 1 cigarette or more (occ. smoker)
SMK : Smoking	Discrete	SMK_05D	Ever smoked cigarettes daily
SMK : Smoking	Discrete	SMK_06A	Stopped smoking - when (was never a daily smoker)
SMK : Smoking	Discrete	SMK_09A	Stopped smoking daily - when stopped (former daily smoker)
SMK : Smoking	Discrete	SMK_10	Quit smoking completely (former daily smoker)
SMK : Smoking	Discrete	SMK_10A	Stopped smoking completely - when (former daily smoker)
SMK : Smoking	Discrete	SMK_202	Type of smoker
SMK : Smoking	Continuous	SMK_204	Number of cigarettes smoked per day (daily smoker)
SMK : Smoking	Continuous	SMK_208	Number of cigarettes smoked per day (former daily smoker)
SMK : Smoking	Discrete	SMKDSTY	Type of smoker - (D)
SMK : Smoking	Continuous	SMKDYCS	Number of years smoked (current daily smokers) - (D)
SMK : Smoking	Discrete	SMKG01C	Age - smoked first whole cigarette - (G)
SMK : Smoking	Discrete	SMKG06C	Number of years since stopped smoking - (G)
SMK : Smoking	Discrete	SMKG09C	Yrs since stopped smoking daily (former daily smoker) - (G)
SMK : Smoking	Discrete	SMKG10C	Number of years since stopped smoking (daily) - (G)
SMK : Smoking	Discrete	SMKG203	Age - started smoking daily (daily smoker) - (G)
SMK : Smoking	Discrete	SMKG207	Age - started smoking daily (former daily smoker) - (G)
SMK : Smoking	Discrete	SMKGSTP	Number of years since stopping smoking completely - (D, G)
SPC : Smoking - Physician counselling	Discrete	SPC_10	Visited regular medical doctor
SPC : Smoking - Physician counselling	Discrete	SPC_11	Doctor - knows smokes/smoked
SPC : Smoking - Physician counselling	Discrete	SPC_12	Doctor - advised to quit

SPC : Smoking - Physician counselling	Discrete	SPC_13	Doctor - gave specific help
SPC : Smoking - Physician counselling	Discrete	SPC_14C	Type of help - recommended nicotine patch or gum
SPC : Smoking - Physician counselling	Discrete	SPC_14D	Type of help - recommended Zyban or other medication
SPC : Smoking - Physician counselling	Discrete	SPC_14E	Type of help - provided self-help information
SPC : Smoking - Physician counselling	Discrete	SPC_20	Visited dentist
SPC : Smoking - Physician counselling	Discrete	SPC_21	Dentist/hygienist - knows smokes/smoked
SPC : Smoking - Physician counselling	Discrete	SPC_22	Dentist/hygienist - advised to quit
SPC : Smoking - Physician counselling	Discrete	SPCG14G	Type of help - (G)
SPS : Social Provisions Scale 10 Items	Discrete	SPS_01	Relationships - people who can be count on to have help
SPS : Social Provisions Scale 10 Items	Discrete	SPS_02	Relationships - enjoy the same social activities
SPS : Social Provisions Scale 10 Items	Discrete	SPS_03	Relationships - sense of emotional security and wellbeing
SPS : Social Provisions Scale 10 Items	Discrete	SPS_04	Relationships - Talk about important decisions in life
SPS : Social Provisions Scale 10 Items	Discrete	SPS_05	Relationships - Competence and skill are recognized
SPS : Social Provisions Scale 10 Items	Discrete	SPS_06	Relationships - trustworthy person for advice
SPS : Social Provisions Scale 10 Items	Discrete	SPS_07	Relationships - share attitudes and beliefs
SPS : Social Provisions Scale 10 Items	Discrete	SPS_08	Relationships - strong emotional bond
SPS : Social Provisions Scale 10 Items	Discrete	SPS_09	Relationships - admire talents and abilities
SPS : Social Provisions Scale 10 Items	Discrete	SPS_10	Relationships - people to count on in an emergency
SPS : Social Provisions Scale 10 Items	Continuous	SPSDALL	Social Provisions Scale -Reliable alliance
SPS : Social Provisions Scale 10 Items	Continuous	SPSDATT	Social Provisions Scale - Attachment
SPS : Social Provisions Scale 10 Items	Continuous	SPSDCON	Social Provisions Overall Scale
SPS : Social Provisions Scale 10 Items	Continuous	SPSDGUI	Social Provisions Scale - Guidance
SPS : Social Provisions Scale 10 Items	Continuous	SPSDINT	Social Provisions Scale - Social Integration
SPS : Social Provisions Scale 10 Items	Continuous	SPSDWOR	Social Provisions Scale - Reassurance of Worth
SSB : Sun safety behaviours	Discrete	SSB_01	Been sunburnt - past 12 months
SSB : Sun safety behaviours	Discrete	SSB_02	Sunburn involved blistering
SSB : Sun safety behaviours	Discrete	SSB_03	Sunburns involved pain - lasting more than 1 day
SSB : Sun safety behaviours	Discrete	SSB_06	Amount of time in the sun - 11 am to 4 pm
SSB : Sun safety behaviours	Discrete	SSB_07	Frequency - seek shade
SSB : Sun safety behaviours	Discrete	SSB_08	Frequency - wear hat in the sun
SSB : Sun safety behaviours	Discrete	SSB_09A	Frequency - wear long pants or skirt in the sun
SSB : Sun safety behaviours	Discrete	SSB_09B	Frequency - use sunscreen on your face
SSB : Sun safety behaviours	Discrete	SSB_10	Sun Proctection factor (SPF) usually use - face
SSB : Sun safety behaviours	Discrete	SSB_11	Frequency - use sunscreen on your body

SSB : Sun safety behaviours	Discrete	SSB_12	Sun Proctection factor (SPF) usually use on body
SUI : Suicidal thoughts and attempts	Discrete	SUI_1	Seriously considered suicide - lifetime
SUI : Suicidal thoughts and attempts	Discrete	SUI_2	Seriously considered suicide - past 12 months
SXB : Sexual behaviours	Discrete	SXB_07	Ever diagnosed with STI
SXB : Sexual behaviours	Discrete	SXB_09	Important to avoid getting pregnant
SXB : Sexual behaviours	Discrete	SXB_1	Ever had sexual intercourse
SXB : Sexual behaviours	Discrete	SXB_10	Important to avoid getting partner pregnant
SXB : Sexual behaviours	Discrete	SXB_11	Usually use birth control - past 12 months
SXB : Sexual behaviours	Discrete	SXB_12A	Usual birth control method - condom
SXB : Sexual behaviours	Discrete	SXB_12B	Usual birth control method - Birth control pill
SXB : Sexual behaviours	Discrete	SXB_12C	Usual birth control method - diaphragm
SXB : Sexual behaviours	Discrete	SXB_12D	Usual birth control method - spermicide
SXB : Sexual behaviours	Discrete	SXB_12E	Usual birth control method - other
SXB : Sexual behaviours	Discrete	SXB_12F	Usual birth control method - birth control injection
SXB : Sexual behaviours	Discrete	SXB_13A	Birth control method used last time - condom
SXB : Sexual behaviours	Discrete	SXB_13B	Birth control method used last time - birth control pill
SXB : Sexual behaviours	Discrete	SXB_13C	Birth control method used last time - diaphragm
SXB : Sexual behaviours	Discrete	SXB_13D	Birth control method used last time - spermicide
SXB : Sexual behaviours	Discrete	SXB_13E	Birth control method used last time - other
SXB : Sexual behaviours	Discrete	SXB_13F	Birth control method used last time - birth control injection
SXB : Sexual behaviours	Discrete	SXB_13G	Method used last time - nothing
SXB : Sexual behaviours	Discrete	SXB_3	Had sexual intercourse - past 12 months
SXB : Sexual behaviours	Discrete	SXB_7A	Condom use - last time
TAL : Smoking - Other tobacco products	Discrete	TAL_1	Smoked cigars - last month
TAL : Smoking - Other tobacco products	Discrete	TAL_2	Smoked a pipe - past month
TAL : Smoking - Other tobacco products	Discrete	TAL_3	Used snuff - past month
TAL : Smoking - Other tobacco products	Discrete	TAL_4	Used chewing tobacco - past month
UCN : Unmet health care needs	Discrete	UCN_010	Unmet health care needs - self-perceived
UCN : Unmet health care needs	Discrete	UCN_020A	Care not received - not available in area
UCN : Unmet health care needs	Discrete	UCN_020B	Care not received - not available at time required
UCN : Unmet health care needs	Discrete	UCN_020C	Care not received - waiting time too long
UCN : Unmet health care needs	Discrete	UCN_020D	Care not received - felt would be inadequate
UCN : Unmet health care needs	Discrete	UCN_020E	Care not received - cost
UCN : Unmet health care needs	Discrete	UCN_020F	Care not received - too busy

UCN : Unmet health care needs	Discrete	UCN_020G	Care not received - didn't get around to it
UCN : Unmet health care needs	Discrete	UCN_020H	Care not received - decided not to seek care
UCN : Unmet health care needs	Discrete	UCN_020I	Care not received - dr didn't think it was necessary
UCN : Unmet health care needs	Discrete	UCN_020J	Care not received - other
UCN : Unmet health care needs	Discrete	UCN_030A	Type of care not received - treatment phys. health problem
UCN : Unmet health care needs	Discrete	UCN_030B	Type of care not received - treatment emotional problem
UCN : Unmet health care needs	Discrete	UCN_030C	Type of care not received - regular check-up
UCN : Unmet health care needs	Discrete	UCN_030D	Type of care not received - care of injury
UCN : Unmet health care needs	Discrete	UCN_030E	Type of care not received - other
UCN : Unmet health care needs	Discrete	UCN_040A	Location tried to get service - doctor's office
UCN : Unmet health care needs	Discrete	UCN_040B	Location tried to get service - community health centre/CLSC
UCN : Unmet health care needs	Discrete	UCN_040C	Location tried to get service - walk-in clinic
UCN : Unmet health care needs	Discrete	UCN_040D	Location tried to get service - appointment clinic
UCN : Unmet health care needs	Discrete	UCN_040E	Location tried to get service - hospital emergency room
UCN : Unmet health care needs	Discrete	UCN_040F	Location tried to get service - hosp. outpatient clinic
UCN : Unmet health care needs	Discrete	UCN_040G	Location tried to get service - other
UPE : Use of protective equipment	Discrete	UPE_01	Frequency - wears helmet - bicycling
UPE : Use of protective equipment	Discrete	UPE_01A	Done any bicycling in past 12 months
UPE : Use of protective equipment	Discrete	UPE_02	Done any in-line skating in past 12 months
UPE : Use of protective equipment	Discrete	UPE_02A	Frequency - wears helmet - in-line skating
UPE : Use of protective equipment	Discrete	UPE_02B	Frequency - wears wrist guards - in-line skating
UPE : Use of protective equipment	Discrete	UPE_02C	Frequency - wears elbow pads - in-line skating
UPE : Use of protective equipment	Discrete	UPE_02D	Frequency - wears knee pads - in-line skating
UPE : Use of protective equipment	Discrete	UPE_03A	Downhill skiing or snowboarding - past 3 mo.
UPE : Use of protective equipment	Discrete	UPE_03B	Downhill skiing or snowboarding - past 12 mo
UPE : Use of protective equipment	Discrete	UPE_04A	Frequency - wears helmet - downhill skiing
UPE : Use of protective equipment	Discrete	UPE_05A	Frequency - wears helmet - snowboarding
UPE : Use of protective equipment	Discrete	UPE_05B	Frequency - wears wrist guards - snowboarding
UPE : Use of protective equipment	Discrete	UPE_06	Has done skateboarding - past 12 mo
UPE : Use of protective equipment	Discrete	UPE_06A	Frequency - wears helmet - skateboarding
UPE : Use of protective equipment	Discrete	UPE_06B	Frequency - wears wrist guards/protectors - skateboarding
UPE : Use of protective equipment	Discrete	UPE_06C	Frequency - wears elbow pads - skateboarding
UPE : Use of protective equipment	Discrete	UPE_07	Played ice hockey past 12 months
UPE : Use of protective equipment	Discrete	UPE_07A	Wear a mouth guard

UPE : Use of protective equipment	Discrete	UPEFILS	Wears all protective equipment - in-line skating - (F)
UPE : Use of protective equipment	Discrete	UPEFSKB	Wears all protective equipment - skateboarding - (F)
UPE : Use of protective equipment	Discrete	UPEFSNB	Wears all protective equipment - snowboarding - (F)
SAM : Sample variables	Discrete	VERDATE	Date of file creation
WTM : Group Waiting Times	Discrete	WTM_01	Required visit to medical specialist
WTM : Group Waiting Times	Discrete	WTM_02	Required visit medical specialist - type of condition
WTM : Group Waiting Times	Discrete	WTM_03	Person who referred respondent to medical specialist
WTM : Group Waiting Times	Discrete	WTM_04	Already visited the medical specialist
WTM : Group Waiting Times	Discrete	WTM_05	Difficulty seeing medical specialist
WTM : Group Waiting Times	Discrete	WTM_06D	Difficulties - waited too long for appointment
WTM : Group Waiting Times	Discrete	WTM_06E	Difficulties - waited too long to see doctor
WTM : Group Waiting Times	Discrete	WTM_06F	Difficulties - transportation
WTM : Group Waiting Times	Discrete	WTM_06G	Difficulties - language
WTM : Group Waiting Times	Discrete	WTM_06H	Difficulties - cost
WTM : Group Waiting Times	Discrete	WTM_06I	Difficulties - personal/family responsibilities
WTM : Group Waiting Times	Discrete	WTM_06J	Difficulties - deterioration of health
WTM : Group Waiting Times	Discrete	WTM_06L	Difficulties - unable leave house/health
WTM : Group Waiting Times	Continuous	WTM_07A	Length of wait to see specialist
WTM : Group Waiting Times	Discrete	WTM_07B	Length of wait to see specialist - unit
WTM : Group Waiting Times	Continuous	WTM_08A	Length of time been waiting to see specialist
WTM : Group Waiting Times	Discrete	WTM_08B	Length of time waiting/see specialist - unit
WTM : Group Waiting Times	Continuous	WTM_11A	Acceptable waiting time
WTM : Group Waiting Times	Discrete	WTM_11B	Acceptable waiting time - unit
WTM : Group Waiting Times	Discrete	WTM_12	Visit to specialist cancelled/ postponed
WTM : Group Waiting Times	Discrete	WTM_13B	Visit cancelled/postponed - by specialist
WTM : Group Waiting Times	Discrete	WTM_14	Life affected by wait for visit to specialist
WTM : Group Waiting Times	Discrete	WTM_15A	Life affected by wait - worry
WTM : Group Waiting Times	Discrete	WTM_15B	Life affected by wait - worry for family
WTM : Group Waiting Times	Discrete	WTM_15C	Life affected by wait - pain
WTM : Group Waiting Times	Discrete	WTM_15D	Life affected by wait - problems with daily activities
WTM : Group Waiting Times	Discrete	WTM_15G	Life affected by wait - increase dependence
WTM : Group Waiting Times	Discrete	WTM_15H	Life affected by wait - increase use of medications
WTM : Group Waiting Times	Discrete	WTM_15I	Life affected by wait - health deteriorated
WTM : Group Waiting Times	Discrete	WTM_15L	Life affected by wait - other

WTM : Group Waiting Times	Discrete	WTM_17	Already had the surgery
WTM : Group Waiting Times	Discrete	WTM_18	Surgery required overnight hospital stay
WTM : Group Waiting Times	Discrete	WTM_19	Difficulties getting this surgery
WTM : Group Waiting Times	Discrete	WTM_20E	Difficulties - waited too long/surgery
WTM : Group Waiting Times	Discrete	WTM_20H	Difficulties - language
WTM : Group Waiting Times	Discrete	WTM_20J	Difficulties - personal/family responsibilities
WTM : Group Waiting Times	Discrete	WTM_20K	Difficulties - deterioration of health
WTM : Group Waiting Times	Discrete	WTM_20M	Difficulties - unable leave house/health
WTM : Group Waiting Times	Continuous	WTM_21A	Length of wait/surgery
WTM : Group Waiting Times	Discrete	WTM_21B	Length of wait/surgery - unit
WTM : Group Waiting Times	Discrete	WTM_22	Surgery will require overnight hospital stay
WTM : Group Waiting Times	Continuous	WTM_23A	Time since decision to have surgery
WTM : Group Waiting Times	Discrete	WTM_23B	Time since decision to have surgery - unit
WTM : Group Waiting Times	Continuous	WTM_25A	Acceptable waiting time
WTM : Group Waiting Times	Discrete	WTM_25B	Acceptable waiting time - unit
WTM : Group Waiting Times	Discrete	WTM_26	Surgery cancelled or postponed
WTM : Group Waiting Times	Discrete	WTM_28	Life affected by wait for surgery
WTM : Group Waiting Times	Discrete	WTM_29C	Life affected by wait - pain
WTM : Group Waiting Times	Discrete	WTM_29D	Life affected by wait - problems with daily activities
WTM : Group Waiting Times	Discrete	WTM_29F	Life affected by wait - loss of income
WTM : Group Waiting Times	Discrete	WTM_29I	Life affected by wait - health deteriorated
WTM : Group Waiting Times	Discrete	WTM_29J	Life affected by wait - health improved
WTM : Group Waiting Times	Discrete	WTM_30	Type of diagnostic test required
WTM : Group Waiting Times	Discrete	WTM_31	Required diagnosed test - type of condition
WTM : Group Waiting Times	Discrete	WTM_32	Already had diagnostic test
WTM : Group Waiting Times	Discrete	WTM_33	Location of test
WTM : Group Waiting Times	Discrete	WTM_35	Patient in hospital at time of test
WTM : Group Waiting Times	Discrete	WTM_36	Difficulties getting diagnostic test
WTM : Group Waiting Times	Discrete	WTM_37A	Difficulties - getting referral
WTM : Group Waiting Times	Discrete	WTM_37C	Difficulties - waited too long to get an appointment
WTM : Group Waiting Times	Discrete	WTM_37E	Difficulties - service not available at time required
WTM : Group Waiting Times	Discrete	WTM_37G	Difficulties - transportation
WTM : Group Waiting Times	Discrete	WTM_37H	Difficulties - language
WTM : Group Waiting Times	Discrete	WTM_37I	Difficulties - cost

WTM : Group Waiting Times	Discrete	WTM_37J	Difficulties - deterioration of health
WTM : Group Waiting Times	Discrete	WTM_37K	Difficulties - did not know where to go
WTM : Group Waiting Times	Discrete	WTM_37L	Difficulties - unable leave house/health
WTM : Group Waiting Times	Continuous	WTM_38A	Length of wait between decision and test
WTM : Group Waiting Times	Discrete	WTM_38B	Length wait decision and test - unit
WTM : Group Waiting Times	Continuous	WTM_39A	Length of time been waiting/diagnosed test
WTM : Group Waiting Times	Discrete	WTM_39B	Length time been waiting for test - unit
WTM : Group Waiting Times	Continuous	WTM_41A	Acceptable waiting time
WTM : Group Waiting Times	Discrete	WTM_41B	Acceptable waiting time - unit
WTM : Group Waiting Times	Discrete	WTM_42	Test cancelled or postponed
WTM : Group Waiting Times	Discrete	WTM_44	Life affected by wait/test
WTM : Group Waiting Times	Discrete	WTM_45A	Life affected by wait - worry
WTM : Group Waiting Times	Discrete	WTM_45B	Life affected by wait - worry for family
WTM : Group Waiting Times	Discrete	WTM_45C	Life affected by wait - pain
WTM : Group Waiting Times	Discrete	WTM_45D	Life affected by wait - problems with daily activities
WTM : Group Waiting Times	Discrete	WTM_45I	Life affected by wait - health deteriorated
WTM : Group Waiting Times	Continuous	WTMDCA	# days acceptable to wait - non-emergency surgery - (D)
WTM : Group Waiting Times	Continuous	WTMDCN	# days wait - non-urgent surgery - not done(D)
WTM : Group Waiting Times	Continuous	WTMDCO	# days wait - non-urgent surgery - surgery done (D)
WTM : Group Waiting Times	Continuous	WTMDSA	# days acceptable to wait - medical specialist (D)
WTM : Group Waiting Times	Continuous	WTMDSN	# days wait/medical specialist - not seen - (D)
WTM : Group Waiting Times	Continuous	WTMDSO	# days wait/medical specialist -seen specialist - (D)
WTM : Group Waiting Times	Continuous	WTMDTA	# days acceptable to wait - diagnosed test -(D)
WTM : Group Waiting Times	Continuous	WTMDTN	# days wait - diagnosed test - not done -(D)
WTM : Group Waiting Times	Continuous	WTMDTO	# days wait - diagnosed test - done - (D)
WTM : Group Waiting Times	Discrete	WTMG06B	Difficulties - getting referral/appointment - (G)
WTM : Group Waiting Times	Discrete	WTMG06M	Difficulties - other - (G)
WTM : Group Waiting Times	Discrete	WTMG10	Respondent's opinion of waiting time - (G)
WTM : Group Waiting Times	Discrete	WTMG13C	Visit cancelled/postponed - by respondent / other (G)
WTM : Group Waiting Times	Discrete	WTMG15F	Life affected by wait - loss of work / income
WTM : Group Waiting Times	Discrete	WTMG15K	Life affected by wait - health improved
WTM : Group Waiting Times	Discrete	WTMG20N	Difficulties - other - (G)
WTM : Group Waiting Times	Discrete	WTMG24	Respondent's opinion of waiting time - (G)
WTM : Group Waiting Times	Discrete	WTMG27C	Surgery cancelled/postponed - by surgeon / hospital (G)

WTM : Group Waiting Times	Discrete	WTMG27D	Surgery cancelled/postponed - respondent / other (G)
WTM : Group Waiting Times	Discrete	WTMG29B	Life affected by wait - worry / worry for family
WTM : Group Waiting Times	Discrete	WTMG29L	Life affected by wait - other - (G)
WTM : Group Waiting Times	Discrete	WTMG37M	What type of difficulties did you experience
WTM : Group Waiting Times	Discrete	WTMG40	Respondent's opinion of waiting time - (G)
WTM : Group Waiting Times	Discrete	WTMG43	Test cancelled or postponed by - (G)
WTM : Group Waiting Times	Discrete	WTMG45F	Life affected by wait - lost work/income
WTM : Group Waiting Times	Discrete	WTMG45L	Life affected by wait - other - (G)
WTS : Weights	Continuous	WTS_M	Weights - Master
YSM : Smoking - Youth smoking	Discrete	YSM_3	Age asked when buying cigarettes in store
YSM : Smoking - Youth smoking	Discrete	YSM_5	Asked a stranger to buy cigarettes
YSM : Smoking - Youth smoking	Discrete	YSMG1	Source of cigarettes - (G)

Appendix C

Chapter 3 Supplement: Data Summary

The table that follows on the next page is a summary of all the variables in the CCHS dataset, grouped by the cause of injury. The statistical summaries include the mean, standard deviation(SD), median, minimum, maximum, range, skew and kurtosis measures.

Appendix C Summary Statistics

Median ≥ 96

	Group	Mean	SD	Median	Min	Max	Skew
VERDATE1	0	20150326	0	20150326	20150326	20150326	NA
VERDATE2	1	20150326	0	20150326	20150326	20150326	NA
ADM_RNO1	0	31812.47	18428.07	32049	6	63521	-0.01
ADM_RNO2	1	31759.25	18286.86	31669.5	2	63520	0
GEOGPRV1	0	37.47	14.73	35	10	60	-0.12
GEOGPRV2	1	36.87	14.63	35	10	60	-0.1
GEODPMF1	0	38396.1	14732.82	35960	10911	60901	-0.13
GEODPMF2	1	37793.76	14635.4	35957	10911	60901	-0.1
GEODBCHA1	0	9403.01	1435.87	9996	5910	9996	-2.01
GEODBCHA2	1	9456.75	1379.67	9996	5910	9996	-2.17
ADM_PRX1	0	1.99	0.1	2	1	2	-10.07
ADM_PRX2	1	1.97	0.17	2	1	2	-5.59
ADM_N091	0	4.27	2.13	6	1	9	-0.39
ADM_N092	1	4.4	2.1	6	1	9	-0.5
ADM_N101	0	1.25	1.05	1	1	9	6.53
ADM_N102	1	1.33	1.31	1	1	9	5.35
ADM_N111	0	5.57	1.4	6	1	9	-1.89
ADM_N112	1	5.63	1.41	6	1	9	-1.74
DHHGAGE1	0	7.91	4.07	8	1	16	0
DHHGAGE2	1	8.93	4.86	10	1	16	-0.23
DHH_SEX1	0	1.48	0.5	1	1	2	0.07
DHH_SEX2	1	1.57	0.49	2	1	2	-0.29
DHHGLE51	0	0.12	0.32	0	0	1	2.37
DHHGLE52	1	0.08	0.27	0	0	1	3.17
DHHG6111	0	0.15	0.35	0	0	1	1.99
DHHG6112	1	0.13	0.33	0	0	1	2.26
DHHGL121	0	0.22	0.41	0	0	1	1.36
DHHGL122	1	0.17	0.38	0	0	1	1.75
DHHGMS1	0	2.59	1.36	3	1	9	0.14
DHHGMS2	1	2.66	1.3	3	1	9	-0.09
DHHGLVG1	0	4.41	7.8	3	1	99	11.05
DHHGLVG2	1	4.1	7.29	3	1	99	11.61
DHHGHSZ1	0	2.57	1.27	2	1	9	0.55
DHHGHSZ2	1	2.38	1.28	2	1	9	0.74
GEN_011	0	2.42	1.01	2	1	7	0.54
GEN_012	1	2.58	1.07	2	1	7	0.47
GEN_021	0	2.81	0.87	3	1	7	-0.21
GEN_022	1	2.89	0.91	3	1	7	-0.15
GEN_02A21	0	9.28	11.33	8	0	99	7.56
GEN_02A22	1	11.4	17.83	8	0	99	4.63

GEN_02B1	0	2.23	1.2	2	1	9	2.08
GEN_02B2	1	2.41	1.53	2	1	9	2.39
GEN_071	0	2.88	1	3	1	8	0.13
GEN_072	1	2.82	1.05	3	1	8	0.32
GEN_081	0	1.75	1.6	1	1	9	2.42
GEN_082	1	2.43	2.08	1	1	9	1.24
GEN_091	0	3.97	1.72	4	1	9	0.3
GEN_092	1	4.45	1.78	5	1	9	-0.22
GEN_101	0	2.32	1.14	2	1	9	2.57
GEN_102	1	2.44	1.51	2	1	9	2.75
GENDHDI1	0	2.59	1.02	3	0	9	-0.23
GENDHDI2	1	2.43	1.08	3	0	9	-0.21
GENDMHI1	0	2.91	1.17	3	0	9	1.1
GENDMHI2	1	3	1.47	3	0	9	1.8
GENGSWL1	0	1.9	1.15	2	1	9	3.85
GENGSWL2	1	2.11	1.6	2	1	9	3.2
DOSLP1	0	1.82	0.38	2	1	2	-1.67
DOSLP2	1	1.83	0.38	2	1	2	-1.71
SLPG011	0	79.98	34.52	96	1	99	-1.69
SLPG012	1	80.79	33.82	96	1	99	-1.77
SLP_021	0	5.4	1.41	6	1	9	-2.08
SLP_022	1	5.45	1.38	6	1	9	-2.03
SLP_031	0	5.54	1.11	6	1	9	-2.27
SLP_032	1	5.59	1.08	6	1	9	-2.1
SLP_041	0	5.31	1.58	6	1	9	-1.93
SLP_042	1	5.35	1.58	6	1	9	-1.91
DOCIH1	0	1.73	0.44	2	1	2	-1.06
DOCIH2	1	1.75	0.43	2	1	2	-1.14
CIH_11	0	4.78	2.07	6	1	9	-1.09
CIH_12	1	4.9	2.04	6	1	9	-1.15
CIH_21	0	80.15	35.07	96	1	99	-1.76
CIH_22	1	81.46	33.88	96	1	99	-1.9
CIH_31	0	4.76	2.11	6	1	9	-1.09
CIH_32	1	4.9	2.06	6	1	9	-1.15
CIH_41	0	77.56	37.22	96	1	99	-1.52
CIH_42	1	80.42	34.91	96	1	99	-1.79
CIH_51	0	5.11	1.84	6	1	9	-1.52
CIH_52	1	5.28	1.75	6	1	9	-1.64
CIH_6A1	0	5.54	1.37	6	1	9	-2.42
CIH_6A2	1	5.65	1.31	6	1	9	-2.4
CIH_6I1	0	5.56	1.31	6	1	9	-2.38
CIH_6I2	1	5.67	1.24	6	1	9	-2.3
CIH_6B1	0	5.55	1.34	6	1	9	-2.4
CIH_6B2	1	5.66	1.26	6	1	9	-2.34
CIH_6J1	0	5.57	1.27	6	1	9	-2.33
CIH_6J2	1	5.67	1.22	6	1	9	-2.25
CIH_6K1	0	5.57	1.3	6	1	9	-2.36

CIH_6K2	1	5.67	1.25	6	1	9	-2.31
CIH_6G1	0	5.56	1.3	6	1	9	-2.37
CIH_6G2	1	5.66	1.26	6	1	9	-2.34
CIH_6F1	0	5.57	1.29	6	1	9	-2.35
CIH_6F2	1	5.67	1.23	6	1	9	-2.28
CIH_6E1	0	5.57	1.29	6	1	9	-2.36
CIH_6E2	1	5.67	1.24	6	1	9	-2.31
CIH_6L1	0	5.57	1.27	6	1	9	-2.33
CIH_6L2	1	5.67	1.22	6	1	9	-2.26
CIH_6M1	0	5.57	1.27	6	1	9	-2.33
CIH_6M2	1	5.67	1.22	6	1	9	-2.25
CIH_6N1	0	5.57	1.29	6	1	9	-2.35
CIH_6N2	1	5.67	1.22	6	1	9	-2.26
CIH_6H1	0	5.55	1.33	6	1	9	-2.39
CIH_6H2	1	5.66	1.26	6	1	9	-2.34
CIH_71	0	5.07	1.93	6	1	9	-1.51
CIH_72	1	5.25	1.84	6	1	9	-1.65
CIH_8A1	0	5.27	1.76	6	1	9	-1.8
CIH_8A2	1	5.43	1.64	6	1	9	-1.93
CIH_8B1	0	5.36	1.54	6	1	9	-1.75
CIH_8B2	1	5.51	1.45	6	1	9	-1.82
CIH_8C1	0	5.34	1.59	6	1	9	-1.78
CIH_8C2	1	5.49	1.49	6	1	9	-1.86
CIH_8J1	0	5.37	1.52	6	1	9	-1.74
CIH_8J2	1	5.51	1.44	6	1	9	-1.8
CIH_8K1	0	5.38	1.49	6	1	9	-1.71
CIH_8K2	1	5.52	1.42	6	1	9	-1.77
CIH_8G1	0	5.37	1.51	6	1	9	-1.73
CIH_8G2	1	5.51	1.43	6	1	9	-1.79
CIH_8L1	0	5.37	1.51	6	1	9	-1.73
CIH_8L2	1	5.51	1.44	6	1	9	-1.8
CIH_8H1	0	5.38	1.49	6	1	9	-1.71
CIH_8H2	1	5.52	1.42	6	1	9	-1.77
CIH_8I1	0	5.37	1.51	6	1	9	-1.73
CIH_8I2	1	5.51	1.45	6	1	9	-1.81
DOOH11	0	1.69	0.46	2	1	2	-0.8
DOOH12	1	1.67	0.47	2	1	2	-0.74
OH1_201	0	4.91	1.76	6	1	9	-1.09
OH1_202	1	4.93	1.79	6	1	9	-0.98
OH1_21A1	0	4.46	2.32	6	1	9	-0.79
OH1_21A2	1	4.47	2.36	6	1	9	-0.72
OH1_21B1	0	4.48	2.3	6	1	9	-0.8
OH1_21B2	1	4.5	2.33	6	1	9	-0.73
OH1_21C1	0	4.46	2.33	6	1	9	-0.79
OH1_21C2	1	4.47	2.37	6	1	9	-0.72
OH1_221	0	5.15	1.4	6	1	9	-1.22
OH1_222	1	5.18	1.42	6	1	9	-0.98

DOHCS1	0	1.9	0.3	2	1	2	-2.61
DOHCS2	1	1.9	0.3	2	1	2	-2.66
HCS_11	0	5.66	1.1	6	1	9	-3.02
HCS_12	1	5.68	1.09	6	1	9	-2.99
HCS_21	0	5.65	1.17	6	1	9	-2.86
HCS_22	1	5.66	1.15	6	1	9	-2.9
HCS_31	0	5.68	1.09	6	1	9	-2.93
HCS_32	1	5.69	1.09	6	1	9	-2.99
HCS_41	0	5.66	1.14	6	1	9	-2.89
HCS_42	1	5.68	1.12	6	1	9	-2.93
HWT_41	0	2.35	1.54	3	1	9	2.25
HWT_42	1	2.57	1.91	3	1	9	2.16
HWTGHTM1	0	1.9	1.25	1.7	1.27	10	6.28
HWTGHTM2	1	2.05	1.72	1.68	1.27	10	4.4
HWTGWTK1	0	109.39	172.26	76.5	30.6	999.99	4.92
HWTGWTK2	1	133.96	228.5	74.25	31.5	999.99	3.5
HWTGBMI1	0	66.55	194.33	25.62	12.34	999.99	4.59
HWTGBMI2	1	95.43	250.52	25.75	13.56	999.99	3.33
HWTGISW1	0	3.39	1.66	3	1	9	1.5
HWTGISW2	1	3.67	1.88	3	1	9	1.26
HWTDCOL1	0	5.51	1.54	6	1	9	-2.23
HWTDCOL2	1	5.39	1.74	6	1	9	-1.72
HWTDWHO1	0	5.53	1.51	6	1	9	-2.28
HWTDWHO2	1	5.41	1.71	6	1	9	-1.76
CCC_0311	0	1.9	0.38	2	1	7	2.99
CCC_0312	1	1.9	0.4	2	1	8	3.77
CCC_0351	0	5.5	1.45	6	1	9	-2.48
CCC_0352	1	5.48	1.47	6	1	9	-2.41
CCC_0361	0	5.47	1.52	6	1	9	-2.46
CCC_0362	1	5.46	1.54	6	1	9	-2.39
CCC_0411	0	1.98	0.22	2	1	7	9.39
CCC_0412	1	1.97	0.33	2	1	9	10.3
CCC_0511	0	2.1	1.37	2	1	9	3.5
CCC_0512	1	2.16	1.63	2	1	9	2.91
CCC_0611	0	1.74	0.48	2	1	7	0.86
CCC_0612	1	1.76	0.54	2	1	9	3.09
CCC_0711	0	1.85	0.46	2	1	7	2.73
CCC_0712	1	1.79	0.58	2	1	9	3.83
CCC_0721	0	2.64	1.54	2	1	7	1.68
CCC_0722	1	2.92	1.78	2	1	9	1.14
CCC_0731	0	5.01	1.95	6	1	9	-1.42
CCC_0732	1	4.59	2.21	6	1	9	-0.89
CCC_073A1	0	5.66	1.15	6	1	9	-2.91
CCC_073A2	1	5.37	1.5	6	1	9	-1.8
CCC_073B1	0	5.98	0.4	6	1	9	-8.89
CCC_073B2	1	5.98	0.56	6	1	9	-5.54
CCC_0811	0	1.87	0.37	2	1	7	0.78

CCC_0812	1	1.89	0.41	2	1	9	3.95
CCC_0911	0	3.55	2	2	1	7	0.39
CCC_0912	1	3.33	1.97	2	1	9	0.61
CCC_1011	0	1.94	0.26	2	1	7	1.26
CCC_1012	1	1.91	0.4	2	1	9	4.97
CCCG1021	0	90.93	20.47	96	1	99	-3.79
CCCG1022	1	87.38	26.05	96	1	99	-2.69
CCC_10A1	0	5.95	0.44	6	1	9	-9.3
CCC_10A2	1	5.92	0.62	6	1	9	-6
CCC_10B1	0	5.99	0.23	6	1	9	-19.78
CCC_10B2	1	5.99	0.32	6	1	9	-10.17
CCC_10C1	0	90.69	21.32	96	1	99	-3.76
CCC_10C2	1	86.92	27.25	96	1	99	-2.66
CCC_1051	0	5.75	1.01	6	1	9	-3.78
CCC_1052	1	5.57	1.32	6	1	9	-2.62
CCC_1061	0	5.72	1.12	6	1	9	-3.77
CCC_1062	1	5.53	1.44	6	1	9	-2.62
CCC_1211	0	1.96	0.3	2	1	7	7.07
CCC_1212	1	1.93	0.44	2	1	9	6.45
CCC_1311	0	1.99	0.27	2	1	7	13.08
CCC_1312	1	1.99	0.3	2	1	9	13.08
CCC_31A1	0	2.03	0.6	2	1	7	5.5
CCC_31A2	1	2.02	0.72	2	1	9	4.56
CCC_1411	0	1.98	0.3	2	1	8	10.61
CCC_1412	1	1.97	0.31	2	1	9	10.1
CCC_1511	0	1.99	0.13	2	1	7	6.36
CCC_1512	1	1.98	0.24	2	1	9	12.52
CCC_1611	0	2.96	1.77	2	1	7	1.11
CCC_1612	1	2.94	1.82	2	1	9	1.05
CCC_1711	0	1.94	0.29	2	1	7	2.64
CCC_1712	1	1.94	0.42	2	1	9	7.09
CCC_17A1	0	5.81	0.79	6	1	9	-4.04
CCC_17A2	1	5.8	0.83	6	1	9	-3.44
CCC_1731	0	1.96	0.24	2	1	7	2.38
CCC_1732	1	1.97	0.33	2	1	9	9.87
CCC_2511	0	1.99	0.26	2	1	7	12.52
CCC_2512	1	2	0.39	2	1	9	10.83
CCC_2611	0	1.96	0.32	2	1	7	7.23
CCC_2612	1	1.98	0.41	2	1	9	9.53
CCC_2801	0	1.89	0.39	2	1	7	2.89
CCC_2802	1	1.88	0.43	2	1	9	3.86
CCC_2901	0	1.92	0.41	2	1	7	4.81
CCC_2902	1	1.9	0.42	2	1	9	4.82
CCCDDIA1	0	5.77	0.95	6	1	9	-3.64
CCCDDIA2	1	5.62	1.23	6	1	9	-2.45
DODIA1	0	1.94	0.24	2	1	2	-3.71
DODIA2	1	1.93	0.25	2	1	2	-3.44

DIA_011	0	5.98	0.32	6	1	7	-15.22
DIA_012	1	5.97	0.38	6	1	6	-12.66
DIA_021	0	993.02	54.37	996	1	999	-18.16
DIA_022	1	991.25	68.51	996	1	997	-14.33
DIA_031	0	5.98	0.31	6	1	6	-15.04
DIA_032	1	5.97	0.36	6	1	6	-12.78
DIA_041	0	993.39	50.87	996	1	996	-19.42
DIA_042	1	992.91	55.32	996	1	996	-17.82
DIA_051	0	5.98	0.3	6	1	7	-15.85
DIA_052	1	5.97	0.35	6	1	7	-13.4
DIA_061	0	5.98	0.31	6	1	6	-15.01
DIA_062	1	5.97	0.38	6	1	6	-12.66
DIA_071	0	5.99	0.21	6	1	6	-19
DIA_072	1	5.98	0.26	6	2	6	-14.65
DIA_081	0	5.98	0.28	6	1	6	-16.28
DIA_082	1	5.97	0.35	6	1	6	-13.46
DIA_N8B1	0	993.95	45.09	996	1	996	-21.93
DIA_N8B2	1	991.71	65.14	996	1	996	-15.12
DIA_N8C1	0	994.51	38.53	996	1	996	-25.73
DIA_N8C2	1	995.28	26.67	996	1	996	-37.24
DIA_N8D1	0	995.81	13.62	996	2	996	-72.93
DIA_N8D2	1	995.52	21.76	996	1	996	-45.62
DIA_N8E1	0	995.81	13.57	996	6	996	-72.93
DIA_N8E2	1	995.76	15.36	996	4	996	-64.54
DIA_091	0	5.98	0.25	6	1	6	-17.32
DIA_092	1	5.98	0.31	6	1	7	-14.42
DIA_N9B1	0	994.69	36.06	996	1	996	-27.52
DIA_N9B2	1	993.38	51.03	996	1	999	-19.39
DIA_N9C1	0	994.13	43.03	996	1	996	-23
DIA_N9C2	1	994.81	34.37	996	1	996	-28.82
DIA_N9D1	0	996	0	996	996	996	NA
DIA_N9D2	1	994.81	34.42	996	1	996	-28.82
DIA_N9E1	0	995.81	13.64	996	1	996	-72.93
DIA_N9E2	1	996	0	996	996	996	NA
DIA_101	0	5.98	0.3	6	1	6	-15.39
DIA_102	1	5.97	0.36	6	1	6	-12.99
DIA_111	0	5.98	0.3	6	1	6	-15.36
DIA_112	1	5.97	0.36	6	1	6	-12.98
DOHUI1	0	1	0	1	1	1	NA
DOHUI2	1	1	0	1	1	1	NA
HUIGVIS1	0	1.59	0.86	2	1	9	5.06
HUIGVIS2	1	1.73	1.06	2	1	9	4.67
HUIGHER1	0	1.17	1	1	1	9	7.28
HUIGHER2	1	1.23	1.11	1	1	9	6.27
HUIGSPE1	0	1.02	0.32	1	1	9	23.15
HUIGSPE2	1	1.03	0.37	1	1	9	19.47
HUIGMOB1	0	1.12	0.57	1	1	9	7.1

HUIGMOB2	1	1.3	0.9	1	1	9	4.18
HUIGDEX1	0	1.02	0.26	1	1	9	24.12
HUIGDEX2	1	1.03	0.38	1	1	9	16.93
HUIDEMO1	0	1.36	0.81	1	1	9	4.89
HUIDEMO2	1	1.39	0.86	1	1	9	4.72
HUIDCOG1	0	2.1	4.77	1	1	99	18.96
HUIDCOG2	1	2.28	5.75	1	1	99	15.95
HUIDHSI1	0	3.73	16.73	0.93	-0.32	100	5.58
HUIDHSI2	1	4.69	19.28	0.9	-0.34	100	4.74
HUPDPAD1	0	1.68	1.23	1	1	9	1.81
HUPDPAD2	1	1.81	1.36	1	1	9	1.67
HCU_1AA1	0	1.16	0.41	1	1	7	4.54
HCU_1AA2	1	1.14	0.44	1	1	7	6.72
HCU_1BA1	0	5.39	1.5	6	1	9	-1.99
HCU_1BA2	1	5.51	1.38	6	1	9	-2.31
HCU_1BB1	0	5.38	1.51	6	1	9	-1.99
HCU_1BB2	1	5.51	1.38	6	1	9	-2.31
HCU_1BC1	0	5.36	1.57	6	1	9	-2.01
HCU_1BC2	1	5.49	1.44	6	1	9	-2.33
HCU_1BD1	0	5.38	1.54	6	1	9	-2
HCU_1BD2	1	5.5	1.41	6	1	9	-2.32
HCU_1BE1	0	5.4	1.48	6	1	9	-1.98
HCU_1BE2	1	5.52	1.35	6	1	9	-2.29
HCU_1A11	0	5.27	1.75	6	1	9	-1.94
HCU_1A12	1	5.41	1.6	6	1	9	-2.27
HCU_1A21	0	84.21	30.76	96	1	99	-2.22
HCU_1A22	1	86.71	27.75	96	1	99	-2.65
CHP_011	0	1.9	0.33	2	1	8	0.51
CHP_012	1	1.83	0.41	2	1	8	0.39
CHPG021	0	0.85	6.1	0	0	99	13.28
CHPG022	1	2.3	10.58	0	0	99	7.43
CHP_031	0	1.2	0.44	1	1	9	3.88
CHP_032	1	1.18	0.45	1	1	9	5.29
CHPG041	0	3.82	9.01	2	0	99	8.67
CHPG042	1	4.6	10.74	2	0	99	7.47
CHPG051	0	20.2	37.41	1	1	99	1.53
CHPG052	1	18.02	35.64	1	1	99	1.73
CHP_061	0	1.58	0.57	2	1	9	2.26
CHP_062	1	1.53	0.59	2	1	9	2.68
CHPG071	0	0.94	5.66	0	0	99	16.66
CHPG072	1	1.1	6	0	0	99	15.61
CHP_081	0	1.64	0.51	2	1	9	0.93
CHP_082	1	1.61	0.56	2	1	9	2.13
CHPG091	0	1.29	4.79	0	0	99	16.2
CHPG092	1	1.84	7.63	0	0	99	11.44
CHPG101	0	61.46	45.23	96	1	99	-0.55
CHPG102	1	58.24	45.96	96	1	99	-0.4

CHP_111	0	1.8	0.46	2	1	9	1.81
CHP_112	1	1.81	0.53	2	1	9	3.58
CHPG121	0	1.04	6.33	0	0	99	14.03
CHPG122	1	1.76	10.06	0	0	99	9.11
CHPG131	0	77.03	37.14	96	1	99	-1.45
CHPG132	1	76.99	37.1	96	1	99	-1.44
CHP_141	0	1.31	0.51	1	1	9	2.8
CHP_142	1	1.35	0.54	1	1	9	3.04
CHPG151	0	1.93	5.84	1	0	99	14.76
CHPG152	1	2.33	8.62	1	0	99	10.51
CHPGMDC1	0	5.04	9.85	3	0	99	7.17
CHPGMDC2	1	6.34	12.74	3	0	99	5.94
DOCP21	0	1	0	1	1	1	NA
DOCP22	1	1	0	1	1	1	NA
CHP_161	0	1.81	0.43	2	1	8	0.88
CHP_162	1	1.85	0.37	2	1	7	-1.15
CHPG171	0	1.94	7.28	0	0	99	8.33
CHPG172	1	1.33	5.66	0	0	99	10.3
CHP_181	0	1.77	0.45	2	1	8	0.31
CHP_182	1	1.77	0.46	2	1	8	0.97
CHPG191	0	2.31	7.48	0	0	99	7.15
CHPG192	1	2.43	8.89	0	0	99	7.78
CHP_201	0	1.95	0.27	2	1	8	3.56
CHP_202	1	1.96	0.29	2	1	8	6.35
CHPG211	0	0.39	3.4	0	0	99	23.54
CHPG212	1	0.49	5.05	0	0	99	17.95
CHP_221	0	1.91	0.32	2	1	8	1.4
CHP_222	1	1.9	0.38	2	1	8	3.49
CHPG231	0	0.68	4.71	0	0	99	17.46
CHPG232	1	0.96	6.92	0	0	99	13.07
CHP_241	0	1.95	0.26	2	1	8	3.97
CHP_242	1	1.94	0.29	2	1	8	3.88
CHPG251	0	0.2	3.12	0	0	99	29.96
CHPG252	1	0.24	3.18	0	0	99	28.8
DOUCN1	0	1	0	1	1	1	NA
DOUCN2	1	1	0	1	1	1	NA
UCN_0101	0	1.84	0.43	2	1	7	1.66
UCN_0102	1	1.85	0.46	2	1	8	3.18
UCN_020A1	0	5.3	1.57	6	1	9	-1.72
UCN_020A2	1	5.35	1.53	6	1	9	-1.81
UCN_020B1	0	5.29	1.58	6	1	9	-1.73
UCN_020B2	1	5.34	1.54	6	1	9	-1.82
UCN_020C1	0	5.26	1.64	6	1	9	-1.75
UCN_020C2	1	5.32	1.6	6	1	9	-1.84
UCN_020D1	0	5.31	1.54	6	1	9	-1.71
UCN_020D2	1	5.35	1.51	6	1	9	-1.8
UCN_020E1	0	5.3	1.56	6	1	9	-1.72

UCN_020E2	1	5.35	1.53	6	1	9	-1.81
UCN_020F1	0	5.3	1.55	6	1	9	-1.71
UCN_020F2	1	5.35	1.51	6	1	9	-1.8
UCN_020G1	0	5.3	1.55	6	1	9	-1.71
UCN_020G2	1	5.36	1.5	6	1	9	-1.79
UCN_020H1	0	5.3	1.57	6	1	9	-1.72
UCN_020H2	1	5.35	1.52	6	1	9	-1.81
UCN_020I1	0	5.3	1.55	6	1	9	-1.72
UCN_020I2	1	5.35	1.52	6	1	9	-1.8
UCN_020J1	0	5.27	1.63	6	1	9	-1.75
UCN_020J2	1	5.32	1.59	6	1	9	-1.84
UCN_030A1	0	5.2	1.77	6	1	9	-1.75
UCN_030A2	1	5.26	1.72	6	1	9	-1.84
UCN_030B1	0	5.29	1.58	6	1	9	-1.73
UCN_030B2	1	5.35	1.53	6	1	9	-1.81
UCN_030C1	0	5.3	1.55	6	1	9	-1.71
UCN_030C2	1	5.35	1.51	6	1	9	-1.8
UCN_030D1	0	5.29	1.59	6	1	9	-1.73
UCN_030D2	1	5.33	1.56	6	1	9	-1.83
UCN_030E1	0	5.29	1.57	6	1	9	-1.72
UCN_030E2	1	5.35	1.53	6	1	9	-1.81
UCN_040A1	0	5.27	1.66	6	1	9	-1.78
UCN_040A2	1	5.33	1.61	6	1	9	-1.89
UCN_040B1	0	5.32	1.53	6	1	9	-1.73
UCN_040B2	1	5.38	1.5	6	1	9	-1.83
UCN_040C1	0	5.31	1.56	6	1	9	-1.74
UCN_040C2	1	5.38	1.51	6	1	9	-1.84
UCN_040D1	0	5.32	1.54	6	1	9	-1.73
UCN_040D2	1	5.38	1.49	6	1	9	-1.83
UCN_040E1	0	5.31	1.57	6	1	9	-1.75
UCN_040E2	1	5.36	1.55	6	1	9	-1.87
UCN_040F1	0	5.32	1.56	6	1	9	-1.74
UCN_040F2	1	5.38	1.5	6	1	9	-1.84
UCN_040G1	0	5.29	1.62	6	1	9	-1.77
UCN_040G2	1	5.35	1.57	6	1	9	-1.88
DOPAS1	0	1.84	0.37	2	1	2	-1.83
DOPAS2	1	1.84	0.37	2	1	2	-1.86
PAS_111	0	5.25	1.79	6	1	9	-1.93
PAS_112	1	5.3	1.76	6	1	9	-1.97
PAS_121	0	5.38	1.53	6	1	9	-2.11
PAS_122	1	5.42	1.51	6	1	9	-2.11
PAS_131	0	5.39	1.53	6	1	9	-2.17
PAS_132	1	5.43	1.52	6	1	9	-2.16
PAS_21A1	0	5.33	1.61	6	1	9	-2.01
PAS_21A2	1	5.37	1.61	6	1	9	-2.04
PAS_21B1	0	5.74	0.96	6	1	9	-3.45
PAS_21B2	1	5.73	1.02	6	1	9	-3.04

PAS_221	0	5.7	1.12	6	1	9	-3.47
PAS_222	1	5.68	1.19	6	1	9	-3.1
PAS_231	0	5.71	1.1	6	1	9	-3.57
PAS_232	1	5.68	1.19	6	1	9	-3.17
PAS_31A1	0	5.3	1.68	6	1	9	-2
PAS_31A2	1	5.36	1.65	6	1	9	-2.04
PAS_31B1	0	5.51	1.47	6	1	9	-2.65
PAS_31B2	1	5.55	1.44	6	1	9	-2.65
PAS_321	0	5.56	1.37	6	1	9	-2.72
PAS_322	1	5.59	1.35	6	1	9	-2.72
PAS_331	0	5.56	1.38	6	1	9	-2.75
PAS_332	1	5.59	1.36	6	1	9	-2.73
DOPSC1	0	1.57	0.5	2	1	2	-0.27
DOPSC2	1	1.56	0.5	2	1	2	-0.24
PSC_11	0	4.33	2.12	6	1	9	-0.46
PSC_12	1	4.42	2.14	6	1	9	-0.42
PSC_21	0	5.57	1.31	6	1	9	-2.57
PSC_22	1	5.65	1.32	6	1	9	-2.42
PSC_31	0	5.57	1.35	6	1	9	-2.62
PSC_32	1	5.65	1.33	6	1	9	-2.48
RAC_11	0	2.43	0.84	3	1	8	-0.73
RAC_12	1	2.38	0.84	3	1	8	-0.48
RAC_2A1	0	2.53	0.82	3	1	9	-0.76
RAC_2A2	1	2.47	0.83	3	1	9	-0.61
RAC_2B11	0	3.65	0.65	4	1	9	-1.79
RAC_2B12	1	3.65	0.66	4	1	9	-1.8
RAC_2B21	0	3.01	0.93	3	1	9	-0.79
RAC_2B22	1	3.26	0.88	3	1	9	-1.09
RAC_2C1	0	2.55	0.81	3	1	9	-0.77
RAC_2C2	1	2.53	0.83	3	1	9	-0.18
RACG51	0	54.91	46.34	96	1	99	-0.24
RACG52	1	50.5	46.72	96	1	99	-0.05
RACDIMP1	0	2.4	0.88	3	1	9	0.05
RACDIMP2	1	2.38	0.91	3	1	9	0.7
RACDPAL1	0	2.32	0.93	3	1	9	0.73
RACDPAL2	1	2.3	0.99	3	1	9	1.63
DOADL1	0	1	0	1	1	1	NA
DOADL2	1	1	0	1	1	1	NA
ADL_011	0	1.97	0.19	2	1	7	-0.77
ADL_012	1	1.94	0.25	2	1	2	-3.55
ADL_021	0	1.94	0.3	2	1	7	3.22
ADL_022	1	1.87	0.35	2	1	7	-1.25
ADL_031	0	1.93	0.32	2	1	8	3.8
ADL_032	1	1.87	0.35	2	1	7	-0.45
ADL_041	0	1.98	0.14	2	1	2	-6.84
ADL_042	1	1.95	0.21	2	1	2	-4.22
ADL_051	0	1.99	0.16	2	1	8	12.93

ADL_052	1	1.97	0.16	2	1	2	-5.97
ADL_061	0	1.98	0.26	2	1	7	9.38
ADL_062	1	1.95	0.33	2	1	7	5.56
ADLF6R1	0	1.9	0.48	2	1	9	7.6
ADLF6R2	1	1.82	0.49	2	1	9	4.4
FLU_1601	0	1.46	1	1	1	9	5.31
FLU_1602	1	1.59	1.47	1	1	9	4.2
FLU_1621	0	3.39	2.24	3	1	9	0.39
FLU_1622	1	3.3	2.39	3	1	9	0.61
FLU_1641	0	68.36	40.37	96	1	99	-0.77
FLU_1642	1	64.63	41.63	96	1	99	-0.56
FLU_1651	0	5.96	1.02	6	1	9	-1.97
FLU_1652	1	6.06	1.14	6	1	9	-1.02
FLU_66A1	0	3.44	2.17	2	1	9	0.64
FLU_66A2	1	3.88	2.35	2	1	9	0.39
FLU_66B1	0	3.12	2.42	2	1	9	0.6
FLU_66B2	1	3.62	2.59	2	1	9	0.33
FLU_66C1	0	3.54	2.08	2	1	9	0.71
FLU_66C2	1	3.97	2.26	2	1	9	0.45
FLU_66D1	0	3.54	2.07	2	1	9	0.72
FLU_66D2	1	3.98	2.25	2	1	9	0.46
FLU_66E1	0	3.54	2.08	2	1	9	0.71
FLU_66E2	1	3.97	2.25	2	1	9	0.46
FLU_66F1	0	3.55	2.07	2	1	9	0.72
FLU_66F2	1	3.97	2.25	2	1	9	0.46
FLU_66G1	0	3.55	2.07	2	1	9	0.72
FLU_66G2	1	3.98	2.25	2	1	9	0.46
FLU_66H1	0	3.55	2.07	2	1	9	0.72
FLU_66H2	1	3.98	2.25	2	1	9	0.46
FLU_66I1	0	3.55	2.07	2	2	9	0.72
FLU_66I2	1	3.98	2.25	2	2	9	0.46
FLU_66J1	0	3.55	2.07	2	1	9	0.72
FLU_66J2	1	3.98	2.25	2	1	9	0.46
FLU_66K1	0	3.54	2.07	2	1	9	0.72
FLU_66K2	1	3.97	2.25	2	1	9	0.46
FLU_66L1	0	3.51	2.1	2	1	9	0.69
FLU_66L2	1	3.95	2.27	2	1	9	0.44
FLU_66M1	0	3.5	2.12	2	1	9	0.67
FLU_66M2	1	3.93	2.3	2	1	9	0.42
FLU_66O1	0	3.55	2.07	2	1	9	0.72
FLU_66O2	1	3.98	2.25	2	1	9	0.46
FLU_66N1	0	3.53	2.08	2	1	9	0.71
FLU_66N2	1	3.97	2.26	2	1	9	0.45
DOBPC1	0	1.94	0.24	2	1	2	-3.71
DOBPC2	1	1.94	0.24	2	1	2	-3.73
BPC_0101	0	5.71	1.17	6	1	9	-3.73
BPC_0102	1	5.73	1.16	6	1	9	-3.69

BPC_0121	0	5.75	1.05	6	1	9	-4.01
BPC_0122	1	5.77	1.04	6	1	9	-3.97
BPC_0131	0	5.94	0.47	6	1	6	-8.58
BPC_0132	1	5.97	0.37	6	2	6	-10.62
BPC_16A1	0	5.99	0.2	6	1	9	-17.37
BPC_16A2	1	6	0.23	6	1	9	-9.01
BPC_16B1	0	5.99	0.23	6	1	9	-18.48
BPC_16B2	1	6	0.24	6	1	9	-10.08
BPC_16C1	0	5.99	0.2	6	1	9	-17.37
BPC_16C2	1	6	0.22	6	1	9	-7.6
BPC_16H1	0	5.99	0.2	6	2	9	-17.04
BPC_16H2	1	6	0.22	6	2	9	-6.73
BPC_16I1	0	5.99	0.2	6	2	9	-17.04
BPC_16I2	1	6	0.22	6	2	9	-6.73
BPC_16N1	0	5.99	0.2	6	2	9	-17.04
BPC_16N2	1	6	0.22	6	2	9	-6.73
BPCG16M1	0	5.99	0.21	6	1	9	-17.64
BPCG16M2	1	6	0.22	6	2	9	-6.73
DOPAP1	0	1.95	0.22	2	1	2	-4.06
DOPAP2	1	1.95	0.22	2	1	2	-4.08
PAP_0201	0	5.89	0.74	6	1	9	-6.33
PAP_0202	1	5.89	0.73	6	1	9	-6.27
PAP_0221	0	5.93	0.49	6	1	9	-7.65
PAP_0222	1	5.95	0.45	6	1	9	-7.45
PAP_26A1	0	5.97	0.34	6	1	9	-11.95
PAP_26A2	1	5.97	0.39	6	1	9	-8.96
PAP_26B1	0	5.97	0.35	6	1	9	-12.04
PAP_26B2	1	5.97	0.4	6	1	9	-9.18
PAP_26C1	0	5.97	0.35	6	1	9	-12.02
PAP_26C2	1	5.97	0.4	6	1	9	-9.18
PAPG26G1	0	5.97	0.33	6	2	9	-11.77
PAPG26G2	1	5.97	0.38	6	2	9	-8.43
PAP_26K1	0	5.97	0.33	6	2	9	-11.77
PAP_26K2	1	5.97	0.38	6	2	9	-8.72
PAP_26L1	0	5.97	0.33	6	2	9	-11.77
PAP_26L2	1	5.97	0.38	6	2	9	-8.72
PAP_26M1	0	5.97	0.35	6	1	9	-12.05
PAP_26M2	1	5.97	0.41	6	1	9	-9.22
PAP_26N1	0	5.97	0.33	6	1	9	-11.81
PAP_26N2	1	5.97	0.38	6	2	9	-8.72
PAPG26O1	0	5.97	0.34	6	1	9	-11.98
PAPG26O2	1	5.97	0.39	6	1	9	-8.63
DOMAM1	0	1.82	0.39	2	1	2	-1.65
DOMAM2	1	1.82	0.39	2	1	2	-1.65
MAM_0301	0	5.75	1.07	6	1	7	-4.06
MAM_0302	1	5.66	1.26	6	1	9	-3.28
MAM_31A1	0	5.83	0.83	6	1	9	-4.59

MAM_31A2	1	5.75	0.99	6	1	9	-3.59
MAM_31B1	0	5.8	0.95	6	1	9	-4.61
MAM_31B2	1	5.72	1.14	6	1	9	-3.64
MAM_31C1	0	5.83	0.83	6	1	9	-4.59
MAM_31C2	1	5.76	0.99	6	1	9	-3.58
MAM_31D1	0	5.83	0.83	6	1	9	-4.59
MAM_31D2	1	5.75	0.99	6	1	9	-3.59
MAM_31E1	0	5.83	0.81	6	1	9	-4.55
MAM_31E2	1	5.76	0.98	6	1	9	-3.56
MAM_31G1	0	5.83	0.81	6	1	9	-4.56
MAM_31G2	1	5.76	0.98	6	1	9	-3.56
MAMG31H1	0	5.83	0.81	6	1	9	-4.55
MAMG31H2	1	5.76	0.97	6	1	9	-3.51
MAM_0321	0	5.86	0.71	6	1	9	-5.48
MAM_0322	1	5.82	0.81	6	1	9	-4.43
MAM_36A1	0	5.97	0.39	6	1	7	-11.16
MAM_36A2	1	5.94	0.51	6	1	9	-8.22
MAM_36B1	0	5.97	0.39	6	1	7	-11.17
MAM_36B2	1	5.94	0.51	6	1	9	-8.22
MAM_36C1	0	5.97	0.37	6	1	7	-11.09
MAM_36C2	1	5.94	0.49	6	1	9	-8.15
MAM_36D1	0	5.97	0.37	6	1	7	-11.04
MAM_36D2	1	5.95	0.47	6	2	9	-8
MAMG36F1	0	5.97	0.37	6	1	9	-10.75
MAMG36F2	1	5.95	0.47	6	1	9	-8.04
MAM_36H1	0	5.97	0.36	6	1	7	-10.99
MAM_36H2	1	5.95	0.47	6	2	9	-8
MAM_36K1	0	5.97	0.36	6	2	7	-10.96
MAM_36K2	1	5.95	0.47	6	1	9	-8.04
MAM_36L1	0	5.97	0.37	6	1	7	-11.06
MAM_36L2	1	5.95	0.48	6	1	9	-8.06
MAM_36N1	0	5.97	0.36	6	2	7	-10.96
MAM_36N2	1	5.95	0.47	6	1	9	-8.02
MAM_36O1	0	5.97	0.36	6	1	7	-10.99
MAM_36O2	1	5.95	0.47	6	1	9	-8.02
MAMG36M1	0	5.97	0.37	6	1	9	-10.75
MAMG36M2	1	5.95	0.48	6	1	9	-8.07
MAM_0381	0	5.69	1.1	6	1	9	-3.33
MAM_0382	1	5.62	1.23	6	1	9	-2.89
DOPSA1	0	1.84	0.37	2	1	2	-1.81
DOPSA2	1	1.84	0.37	2	1	2	-1.81
PSA_1701	0	5.79	0.96	6	1	9	-4.32
PSA_1702	1	5.81	0.94	6	1	9	-4.37
PSA_1721	0	5.91	0.67	6	1	9	-5.99
PSA_1722	1	5.92	0.69	6	1	9	-5.32
PSA_73A1	0	5.91	0.65	6	1	9	-5.34
PSA_73A2	1	5.92	0.65	6	1	9	-4.71

PSA_73B1	0	5.89	0.76	6	1	9	-5.61
PSA_73B2	1	5.91	0.74	6	1	9	-5.18
PSA_73C1	0	5.91	0.65	6	1	9	-5.34
PSA_73C2	1	5.92	0.67	6	1	9	-4.82
PSA_73D1	0	5.91	0.65	6	1	9	-5.34
PSA_73D2	1	5.92	0.66	6	1	9	-4.8
PSA_73E1	0	5.91	0.64	6	1	9	-5.29
PSA_73E2	1	5.92	0.65	6	1	9	-4.71
PSA_73F1	0	5.91	0.65	6	1	9	-5.3
PSA_73F2	1	5.92	0.65	6	1	9	-4.68
PSA_1741	0	5.78	1	6	1	9	-4.23
PSA_1742	1	5.78	1.02	6	1	9	-4.17
PSA_1751	0	5.9	0.65	6	1	9	-6.41
PSA_1752	1	5.88	0.71	6	1	9	-5.8
DOCCS1	0	1.6	0.49	2	1	2	-0.39
DOCCS2	1	1.59	0.49	2	1	2	-0.38
CCS_1801	0	4.98	1.88	6	1	9	-1.3
CCS_1802	1	4.9	1.98	6	1	9	-1.08
CCS_1821	0	87.69	26.58	96	1	99	-2.88
CCS_1822	1	86.09	28.81	96	1	99	-2.55
CCS_83A1	0	5.65	1.17	6	1	9	-2.76
CCS_83A2	1	5.61	1.31	6	1	9	-2.16
CCS_83B1	0	5.6	1.34	6	1	9	-2.83
CCS_83B2	1	5.55	1.47	6	1	9	-2.29
CCS_83C1	0	5.65	1.17	6	1	9	-2.75
CCS_83C2	1	5.61	1.3	6	1	9	-2.14
CCS_83D1	0	5.62	1.25	6	1	9	-2.82
CCS_83D2	1	5.59	1.37	6	1	9	-2.24
CCS_83E1	0	5.65	1.16	6	1	9	-2.74
CCS_83E2	1	5.62	1.29	6	1	9	-2.12
CCS_83F1	0	5.65	1.17	6	1	9	-2.75
CCS_83F2	1	5.61	1.3	6	1	9	-2.14
CCS_1841	0	4.98	1.88	6	1	9	-1.3
CCS_1842	1	4.9	1.99	6	1	9	-1.07
CCS_1851	0	87.57	26.66	96	1	99	-2.84
CCS_1852	1	85.94	28.89	96	1	99	-2.51
CCS_86A1	0	5.63	1.21	6	1	9	-2.78
CCS_86A2	1	5.59	1.36	6	1	9	-2.18
CCS_86B1	0	5.62	1.26	6	1	9	-2.82
CCS_86B2	1	5.57	1.4	6	1	9	-2.22
CCS_86C1	0	5.65	1.18	6	1	9	-2.75
CCS_86C2	1	5.6	1.31	6	1	9	-2.11
CCS_86D1	0	5.6	1.31	6	1	9	-2.82
CCS_86D2	1	5.55	1.46	6	1	9	-2.25
CCS_86E1	0	5.65	1.17	6	1	9	-2.74
CCS_86E2	1	5.6	1.3	6	1	9	-2.1
CCS_86F1	0	5.65	1.17	6	1	9	-2.74

CCS_86F2	1	5.6	1.31	6	1	9	-2.12
CCS_1871	0	5.8	0.93	6	1	9	-3.93
CCS_1872	1	5.79	1.06	6	1	9	-2.91
DOEYX1	0	1.69	0.46	2	1	2	-0.8
DOEYX2	1	1.67	0.47	2	1	2	-0.74
EYX_1401	0	5.32	1.73	6	1	9	-2.06
EYX_1402	1	5.2	1.87	6	1	9	-1.71
EYX_1421	0	4.83	1.93	6	1	9	-1.14
EYX_1422	1	4.76	2.06	6	1	9	-0.96
EYX_46A1	0	5.56	1.36	6	1	9	-2.34
EYX_46A2	1	5.72	1.22	6	1	9	-2.42
EYX_46B1	0	5.52	1.47	6	1	9	-2.38
EYX_46B2	1	5.69	1.31	6	1	9	-2.53
EYX_46C1	0	5.58	1.28	6	1	9	-2.25
EYX_46C2	1	5.73	1.16	6	1	9	-2.28
EYX_46D1	0	5.58	1.28	6	1	9	-2.25
EYX_46D2	1	5.74	1.16	6	1	9	-2.27
EYX_46E1	0	5.58	1.28	6	1	9	-2.25
EYX_46E2	1	5.74	1.16	6	1	9	-2.27
EYX_46F1	0	5.58	1.28	6	1	9	-2.25
EYX_46F2	1	5.74	1.16	6	2	9	-2.27
EYX_46G1	0	5.58	1.28	6	1	9	-2.25
EYX_46G2	1	5.74	1.16	6	1	9	-2.27
EYX_46H1	0	5.58	1.28	6	1	9	-2.25
EYX_46H2	1	5.74	1.16	6	2	9	-2.27
EYX_46J1	0	5.57	1.33	6	1	9	-2.31
EYX_46J2	1	5.72	1.2	6	1	9	-2.39
EYX_46K1	0	5.58	1.28	6	1	9	-2.25
EYX_46K2	1	5.74	1.16	6	1	9	-2.27
EYX_46L1	0	5.58	1.28	6	1	9	-2.25
EYX_46L2	1	5.74	1.16	6	1	9	-2.27
EYX_46N1	0	5.58	1.28	6	1	9	-2.25
EYX_46N2	1	5.73	1.16	6	1	9	-2.28
EYXG46M1	0	5.58	1.29	6	1	9	-2.25
EYXG46M2	1	5.73	1.17	6	1	9	-2.29
DODEN1	0	1.69	0.46	2	1	2	-0.8
DODEN2	1	1.67	0.47	2	1	2	-0.74
DEN_1301	0	4.85	2.12	6	1	9	-1.25
DEN_1302	1	4.84	2.14	6	1	9	-1.19
DEN_1321	0	66.82	43.62	96	1	99	-0.83
DEN_1322	1	66.45	43.76	96	1	99	-0.8
DEN_36A1	0	5.88	0.77	6	1	9	-4.36
DEN_36A2	1	5.86	0.91	6	1	9	-3.13
DEN_36B1	0	5.87	0.8	6	1	9	-4.45
DEN_36B2	1	5.85	0.94	6	1	9	-3.25
DEN_36C1	0	5.88	0.75	6	1	9	-4.26
DEN_36C2	1	5.86	0.89	6	1	9	-3.02

DEN_36D1	0	5.88	0.75	6	2	9	-4.25
DEN_36D2	1	5.86	0.89	6	1	9	-3.03
DEN_36E1	0	5.88	0.75	6	2	9	-4.25
DEN_36E2	1	5.86	0.89	6	1	9	-3.02
DEN_36F1	0	5.88	0.75	6	2	9	-4.25
DEN_36F2	1	5.86	0.89	6	1	9	-3.02
DEN_36H1	0	5.88	0.75	6	1	9	-4.26
DEN_36H2	1	5.86	0.89	6	2	9	-3.02
DEN_36I1	0	5.88	0.75	6	2	9	-4.25
DEN_36I2	1	5.86	0.89	6	2	9	-3.02
DEN_36J1	0	5.87	0.83	6	1	9	-4.53
DEN_36J2	1	5.85	0.96	6	1	9	-3.3
DEN_36K1	0	5.88	0.75	6	2	9	-4.25
DEN_36K2	1	5.86	0.89	6	1	9	-3.02
DEN_36L1	0	5.88	0.77	6	1	9	-4.34
DEN_36L2	1	5.86	0.9	6	1	9	-3.07
DEN_36M1	0	5.87	0.79	6	1	9	-4.42
DEN_36M2	1	5.85	0.96	6	1	9	-3.3
DENG36N1	0	5.88	0.76	6	1	9	-4.28
DENG36N2	1	5.86	0.9	6	1	9	-3.09
DOOH21	0	1.57	0.5	2	1	2	-0.27
DOOH22	1	1.56	0.5	2	1	2	-0.22
OH2_101	0	4.34	2.1	6	1	9	-0.54
OH2_102	1	4.39	2.14	6	1	9	-0.47
OH2_111	0	4.06	2.38	6	1	9	-0.32
OH2_112	1	4.15	2.41	6	1	9	-0.27
OH2_11A1	0	4.86	1.95	6	1	9	-0.79
OH2_11A2	1	5.05	1.95	6	1	9	-0.81
OH2_11B1	0	4.66	2.26	6	1	9	-0.83
OH2_11B2	1	4.89	2.22	6	1	9	-0.89
OH2_11C1	0	4.87	1.93	6	1	9	-0.78
OH2_11C2	1	5.06	1.93	6	1	9	-0.79
OH2_121	0	4.59	1.99	6	1	9	-0.61
OH2_122	1	4.61	2.04	6	1	9	-0.51
OH2_131	0	5.85	0.88	6	1	9	-4.14
OH2_132	1	5.87	0.96	6	1	9	-3.1
OH2_201	0	3.91	2.49	6	1	9	-0.27
OH2_202	1	3.97	2.53	6	1	9	-0.21
OH2_211	0	4.25	2.09	6	1	9	-0.28
OH2_212	1	4.27	2.2	6	1	9	-0.2
OH2_221	0	4.3	2.03	6	1	9	-0.25
OH2_222	1	4.35	2.09	6	1	9	-0.15
OH2_231	0	5.13	1.11	6	1	9	-0.28
OH2_232	1	5.17	1.2	6	1	9	0.09
OH2_241	0	5.11	1.16	6	1	9	-0.45
OH2_242	1	5.15	1.25	6	1	9	-0.11
OH2_25A1	0	4.32	2.09	6	1	9	-0.35

OH2_25A2	1	4.44	2.12	6	1	9	-0.31
OH2_25B1	0	4.23	2.2	6	1	9	-0.38
OH2_25B2	1	4.36	2.23	6	1	9	-0.34
OH2_25C1	0	4.27	2.08	6	1	9	-0.28
OH2_25C2	1	4.32	2.14	6	1	9	-0.17
OH2_25D1	0	4.27	2.07	6	1	9	-0.27
OH2_25D2	1	4.32	2.13	6	1	9	-0.17
OH2_25E1	0	4.25	2.1	6	1	9	-0.28
OH2_25E2	1	4.31	2.15	6	1	9	-0.18
OH2_25F1	0	4.23	2.12	6	1	9	-0.29
OH2_25F2	1	4.27	2.2	6	1	9	-0.2
OH2_25G1	0	4.27	2.13	6	1	9	-0.31
OH2_25G2	1	4.33	2.18	6	1	9	-0.22
OH2_301	0	57.65	46.18	96	1	99	-0.37
OH2_302	1	59.24	45.9	96	1	99	-0.44
OH2FLIM1	0	4.29	2.05	6	1	9	-0.25
OH2FLIM2	1	4.35	2.11	6	1	9	-0.15
OH2FOFP1	0	4.07	2.35	6	1	9	-0.3
OH2FOFP2	1	4.13	2.4	6	1	9	-0.22
DOFDC1	0	1.67	0.47	2	1	2	-0.73
DOFDC2	1	1.69	0.46	2	1	2	-0.8
FDC_1A1	0	4.55	2.15	6	1	9	-0.78
FDC_1A2	1	4.68	2.12	6	1	9	-0.83
FDC_1B1	0	4.6	2.09	6	1	9	-0.77
FDC_1B2	1	4.72	2.08	6	1	9	-0.8
FDC_1C1	0	4.62	2.06	6	1	9	-0.77
FDC_1C2	1	4.74	2.04	6	1	9	-0.79
FDC_1D1	0	4.66	2	6	1	9	-0.75
FDC_1D2	1	4.76	2.01	6	1	9	-0.78
FDC_2A1	0	4.52	2.2	6	1	9	-0.76
FDC_2A2	1	4.64	2.19	6	1	9	-0.8
FDC_2B1	0	4.54	2.19	6	1	9	-0.77
FDC_2B2	1	4.65	2.17	6	1	9	-0.81
FDC_2C1	0	4.59	2.1	6	1	9	-0.77
FDC_2C2	1	4.7	2.1	6	1	9	-0.8
FDC_3A1	0	4.52	2.21	6	1	9	-0.76
FDC_3A2	1	4.64	2.2	6	1	9	-0.81
FDC_3B1	0	4.53	2.19	6	1	9	-0.77
FDC_3B2	1	4.66	2.18	6	1	9	-0.81
FDC_3C1	0	4.53	2.19	6	1	9	-0.76
FDC_3C2	1	4.65	2.18	6	1	9	-0.8
FDC_3D1	0	4.58	2.12	6	1	9	-0.77
FDC_3D2	1	4.7	2.11	6	1	9	-0.81
FDC_3E1	0	4.56	2.15	6	1	9	-0.77
FDC_3E2	1	4.67	2.14	6	1	9	-0.81
FDCFAVD1	0	4.46	2.28	6	1	9	-0.75
FDCFAVD2	1	4.59	2.27	6	1	9	-0.79

FDCFCAH1	0	4.51	2.22	6	1	9	-0.76
FDCFCAH2	1	4.65	2.19	6	1	9	-0.8
FDCFCHO1	0	4.48	2.26	6	1	9	-0.75
FDCFCHO2	1	4.61	2.24	6	1	9	-0.79
FVCDJUI1	0	21.85	144.03	0.4	0	999.9	6.64
FVCDJUI2	1	43.09	201.42	0.4	0	999.9	4.54
FVCDFRU1	0	26.72	156.97	1	0	999.9	6.04
FVCDFRU2	1	48.83	212.32	1	0	999.9	4.26
FVCDSAL1	0	25.87	157.11	0.4	0	999.9	6.04
FVCDSAL2	1	49.38	215.55	0.4	0	999.9	4.18
FVCDPOT1	0	23.97	151.94	0.3	0	999.9	6.27
FVCDPOT2	1	42.52	200.95	0.3	0	999.9	4.55
FVCDCAR1	0	29.28	167.52	0.3	0	999.9	5.62
FVCDCAR2	1	50.21	217.57	0.3	0	999.9	4.13
FVCDVEG1	0	36.02	182.37	1	0	999.9	5.09
FVCDVEG2	1	59.12	232.97	1	0	999.9	3.79
FVCDTOT1	0	60.31	228.39	4.5	0	999.9	3.87
FVCDTOT2	1	86.43	273.01	4.7	0	999.9	3.05
FVCGTOT1	0	1.88	1.82	1	1	9	3.3
FVCGTOT2	1	2.08	2.14	1	1	9	2.7
PAC_1A1	0	1.34	0.88	1	1	9	6.56
PAC_1A2	1	1.5	1.39	1	1	9	4.69
PAC_1B1	0	1.48	0.9	1	1	9	5.81
PAC_1B2	1	1.72	1.37	2	1	9	4.42
PAC_1C1	0	1.77	0.85	2	1	9	5.75
PAC_1C2	1	1.94	1.31	2	1	9	4.52
PAC_1D1	0	1.81	0.84	2	1	9	5.92
PAC_1D2	1	1.98	1.3	2	1	9	4.58
PAC_1E1	0	1.88	0.81	2	1	9	6.39
PAC_1E2	1	2.03	1.28	2	1	9	4.7
PAC_1F1	0	1.6	0.89	2	1	9	5.55
PAC_1F2	1	1.78	1.36	2	1	9	4.4
PAC_1G1	0	1.98	0.76	2	1	9	7.64
PAC_1G2	1	2.13	1.24	2	1	9	5.05
PAC_1H1	0	1.97	0.77	2	1	9	7.42
PAC_1H2	1	2.11	1.24	2	1	9	4.99
PAC_1I1	0	2.04	0.72	2	1	9	8.87
PAC_1I2	1	2.18	1.21	2	1	9	5.31
PAC_1J1	0	1.75	0.86	2	1	9	5.69
PAC_1J2	1	1.94	1.32	2	1	9	4.51
PAC_1K1	0	1.97	0.77	2	1	9	7.42
PAC_1K2	1	2.12	1.24	2	1	9	5.03
PAC_1L1	0	1.93	0.79	2	1	9	6.9
PAC_1L2	1	2.07	1.26	2	1	9	4.84
PAC_1M1	0	2	0.74	2	1	9	8.14
PAC_1M2	1	2.14	1.23	2	1	9	5.12
PAC_1N1	0	1.95	0.77	2	1	9	7.23

PAC_1N2	1	2.11	1.25	2	1	9	4.96
PAC_1O1	0	1.99	0.75	2	1	9	7.87
PAC_1O2	1	2.14	1.23	2	1	9	5.11
PAC_1P1	0	2.02	0.73	2	1	9	8.49
PAC_1P2	1	2.17	1.21	2	1	9	5.29
PAC_1Q1	0	1.8	0.84	2	1	9	5.89
PAC_1Q2	1	2	1.29	2	1	9	4.63
PAC_1R1	0	1.91	0.8	2	1	9	6.7
PAC_1R2	1	2.07	1.26	2	1	9	4.83
PAC_1S1	0	1.98	0.75	2	1	9	7.72
PAC_1S2	1	2.11	1.24	2	1	9	5
PAC_1T1	0	1.95	0.77	2	1	9	7.24
PAC_1T2	1	2.1	1.25	2	1	9	4.92
PAC_1Z1	0	1.93	0.78	2	1	9	6.96
PAC_1Z2	1	2.09	1.25	2	1	9	4.9
PAC_1U1	0	1.86	0.82	2	1	9	6.27
PAC_1U2	1	2.04	1.28	2	1	9	4.74
PAC_1V1	0	2.03	0.72	2	1	9	8.63
PAC_1V2	1	2.14	1.23	2	1	9	5.11
PAC_1W1	0	5.16	1.76	6	1	9	-1.35
PAC_1W2	1	5.38	1.7	6	1	9	-1.32
PAC_1X1	0	5.83	0.97	6	1	9	-3.34
PAC_1X2	1	5.94	0.96	6	1	9	-2.11
PAC_2A1	0	303.26	424.13	60	1	999	1.01
PAC_2A2	1	338.17	437.07	90	1	999	0.83
PAC_3A1	0	3.55	1.79	3	1	9	0.72
PAC_3A2	1	3.72	2	3	1	9	0.76
PAC_2B1	0	431.63	481	45	1	999	0.32
PAC_2B2	1	529.58	486.41	996	1	999	-0.09
PAC_3B1	0	4.38	1.7	4	1	9	0.04
PAC_3B2	1	4.71	1.81	6	1	9	-0.07
PAC_2C1	0	701.56	450.68	996	1	999	-0.88
PAC_2C2	1	736.33	433.5	996	1	999	-1.07
PAC_3C1	0	5.14	1.52	6	1	9	-1
PAC_3C2	1	5.33	1.51	6	1	9	-0.78
PAC_2D1	0	741.61	429.14	996	1	999	-1.1
PAC_2D2	1	770.34	411.29	996	1	999	-1.27
PAC_3D1	0	5.21	1.53	6	1	9	-1.16
PAC_3D2	1	5.37	1.55	6	1	9	-0.97
PAC_2E1	0	808.74	387.22	996	1	999	-1.58
PAC_2E2	1	816.88	380.48	996	1	999	-1.65
PAC_3E1	0	5.56	1.12	6	1	9	-1.59
PAC_3E2	1	5.61	1.25	6	1	9	-1.11
PAC_2F1	0	547.32	478.96	996	1	999	-0.13
PAC_2F2	1	594.24	472.19	996	1	999	-0.33
PAC_3F1	0	4.31	2	6	1	9	-0.23
PAC_3F2	1	4.52	2.11	6	1	9	-0.24

PACG2G1	0	907.99	279.82	996	1	999	-2.86
PACG2G2	1	914.72	269.87	996	1	999	-3.01
PAC_3G1	0	5.82	0.77	6	1	9	-1.73
PAC_3G2	1	5.89	0.87	6	2	9	-0.37
PAC_2H1	0	893.28	301.88	996	1	999	-2.6
PAC_2H2	1	901.87	290.22	996	1	999	-2.75
PAC_3H1	0	5.74	0.93	6	1	9	-2.02
PAC_3H2	1	5.84	0.99	6	1	9	-0.92
PAC_2I1	0	963.02	177.57	996	1	999	-5.19
PAC_2I2	1	963.65	176.09	996	1	999	-5.24
PAC_3I1	0	5.93	0.66	6	1	9	-3.05
PAC_3I2	1	5.99	0.76	6	1	9	-0.58
PAC_2J1	0	686	453.55	996	1	999	-0.78
PAC_2J2	1	735.22	430.93	996	1	999	-1.05
PAC_3J1	0	4.88	1.81	6	1	9	-0.82
PAC_3J2	1	5.12	1.81	6	1	9	-0.82
PAC_2K1	0	893.87	300.77	996	1	999	-2.6
PAC_2K2	1	909.63	279.3	996	1	999	-2.92
PAC_3K1	0	5.82	0.71	6	1	9	-1.13
PAC_3K2	1	5.91	0.8	6	1	9	0.27
PAC_2L1	0	858.66	339.41	996	1	999	-2.07
PAC_2L2	1	864.19	334.11	996	1	999	-2.14
PAC_3L1	0	5.63	1.08	6	1	9	-1.72
PAC_3L2	1	5.69	1.19	6	1	9	-1.06
PAC_2M1	0	932.28	243	996	1	999	-3.55
PAC_2M2	1	928.75	249.24	996	1	999	-3.43
PAC_3M1	0	5.9	0.6	6	1	9	-1.1
PAC_3M2	1	5.95	0.75	6	1	9	0.6
PAC_2N1	0	879.88	319.13	996	1	999	-2.38
PAC_2N2	1	893.56	302.14	996	1	999	-2.61
PAC_3N1	0	5.76	0.83	6	1	9	-1.61
PAC_3N2	1	5.85	0.92	6	1	9	-0.45
PAC_2O1	0	918.75	265.18	996	1	999	-3.14
PAC_2O2	1	927.58	250.75	996	1	999	-3.39
PAC_3O1	0	5.84	0.74	6	1	9	-2.06
PAC_3O2	1	5.92	0.85	6	1	9	-0.56
PAC_2P1	0	947.77	213.07	996	1	999	-4.19
PAC_2P2	1	959.84	185.84	996	1	999	-4.93
PAC_3P1	0	5.9	0.68	6	1	9	-2.55
PAC_3P2	1	5.99	0.75	6	1	9	-0.18
PAC_2Q1	0	737.43	427.65	996	1	999	-1.05
PAC_2Q2	1	794.13	393.13	996	1	999	-1.43
PAC_3Q1	0	5.14	1.6	6	1	9	-1.16
PAC_3Q2	1	5.39	1.57	6	1	9	-1.1
PAC_2R1	0	838.55	361.9	996	1	999	-1.86
PAC_2R2	1	860.02	340.78	996	1	999	-2.1
PAC_3R1	0	5.69	0.88	6	1	9	-1.27

PAC_3R2	1	5.8	0.94	6	1	9	-0.24
PAC_2S1	0	911.08	276.65	996	1	999	-2.95
PAC_2S2	1	903.56	287.03	996	1	999	-2.78
PAC_3S1	0	5.8	0.86	6	1	9	-2.27
PAC_3S2	1	5.83	1.01	6	1	9	-1.08
PAC_2T1	0	882.64	313.9	996	1	999	-2.41
PAC_2T2	1	885.84	309.57	996	1	999	-2.45
PAC_3T1	0	5.7	1	6	1	9	-2.09
PAC_3T2	1	5.77	1.1	6	1	9	-1.19
PAC_2Z1	0	862.46	336.82	996	1	999	-2.13
PAC_2Z2	1	879.09	318.29	996	1	999	-2.35
PAC_3Z1	0	5.65	1.07	6	1	9	-1.91
PAC_3Z2	1	5.76	1.1	6	1	9	-1.12
PAC_2U1	0	795.92	393.95	996	1	999	-1.46
PAC_2U2	1	832.76	364	996	1	999	-1.78
PAC_3U1	0	5.51	1.14	6	1	9	-1.45
PAC_3U2	1	5.66	1.17	6	1	9	-0.95
PAC_2W1	0	949.14	209.17	996	1	999	-4.24
PAC_2W2	1	960.43	183.48	996	1	999	-4.95
PAC_3W1	0	5.91	0.67	6	1	9	-2.59
PAC_3W2	1	6	0.73	6	1	9	0
PAC_2X1	0	984.41	106.27	996	1	999	-9.03
PAC_2X2	1	987.36	92.29	996	1	999	-10.48
PAC_3X1	0	6	0.43	6	1	9	-0.61
PAC_3X2	1	6.07	0.58	6	2	9	2.76
PAC_71	0	2.1	0.95	2	1	9	3.73
PAC_72	1	2.37	1.36	2	1	9	3.3
PAC_7A1	0	814.29	374.56	996	1	999	-1.58
PAC_7A2	1	827.91	363.33	996	1	999	-1.7
PAC_7B1	0	5.26	1.7	6	1	9	-1.54
PAC_7B2	1	5.37	1.73	6	1	9	-1.36
PAC_81	0	2.26	0.84	2	1	9	5.21
PAC_82	1	2.51	1.26	2	1	9	3.99
PAC_8A1	0	954.66	196.64	996	1	999	-4.54
PAC_8A2	1	955.34	194.88	996	1	999	-4.57
PAC_8B1	0	5.86	0.9	6	1	9	-3.51
PAC_8B2	1	5.92	1.01	6	1	9	-2.29
PACDEE1	0	3.93	10.16	2.2	0	99.9	8.58
PACDEE2	1	5.75	16.83	2	0	99.9	5.24
PACFLEI1	0	1.12	0.82	1	1	9	9.02
PACFLEI2	1	1.31	1.38	1	1	9	5.23
PACDFM1	0	42.54	100.91	28	0	999	8.64
PACDFM2	1	60.79	167.55	27	0	999	5.25
PACDFR1	0	1.45	1.03	1	1	9	4.35
PACDFR2	1	1.68	1.49	1	1	9	3.59
PACFD1	0	1.6	0.9	2	1	9	5.56
PACFD2	1	1.76	1.36	2	1	9	4.4

PACDPAI1	0	2.07	1.1	2	1	9	2.35
PACDPAI2	1	2.27	1.47	2	1	9	2.73
PACDLTI1	0	2.1	1.3	2	1	9	2.85
PACDLTI2	1	2.29	1.59	2	1	9	2.71
PACDTLE1	0	4.95	13.85	2.3	0	99.9	6.41
PACDTLE2	1	6.61	18.77	2.2	0	99.9	4.63
PACFLTI1	0	1.12	0.82	1	1	9	9.05
PACFLTI2	1	1.31	1.38	1	1	9	5.24
DOSCP1	0	1.85	0.35	2	1	2	-2.01
DOSCP2	1	1.87	0.34	2	1	2	-2.17
SCP_011	0	5.46	1.38	6	1	9	-2.18
SCP_012	1	5.53	1.35	6	1	9	-2.29
SCP_021	0	5.57	1.35	6	1	9	-2.71
SCP_022	1	5.6	1.35	6	1	9	-2.65
SCP_031	0	5.8	0.98	6	1	9	-4.25
SCP_032	1	5.87	0.84	6	1	9	-4.52
SCP_041	0	5.94	0.6	6	1	9	-6.54
SCP_042	1	5.96	0.59	6	1	9	-5.47
SCPDSTG1	0	5.71	0.87	6	1	9	-2.79
SCPDSTG2	1	5.76	0.83	6	1	9	-2.75
DOSAC1	0	1.98	0.13	2	1	2	-7.72
DOSAC2	1	1.99	0.12	2	1	2	-8.23
SACG11	0	94.54	11.51	96	1	99	-7.77
SACG12	1	94.85	10.29	96	1	99	-8.79
SACG21	0	94.53	11.69	96	1	99	-7.82
SACG22	1	94.83	10.46	96	1	99	-8.79
SACG31	0	94.56	11.39	96	1	99	-7.78
SACG32	1	94.89	10.01	96	1	99	-8.88
SACG41	0	94.54	11.54	96	1	99	-7.77
SACG42	1	94.85	10.31	96	1	99	-8.79
SACDTOT1	0	94.6	11.15	96	2	99	-7.83
SACDTOT2	1	94.91	9.86	96	2	99	-8.89
SACDTER1	0	94.58	11.28	96	1	99	-7.83
SACDTER2	1	94.9	9.98	96	1	99	-8.89
DOUPE1	0	1	0	1	1	1	NA
DOUPE2	1	1	0	1	1	1	NA
UPE_01A1	0	2.96	2.02	2	1	9	0.95
UPE_01A2	1	3	2.11	2	1	9	1.16
UPE_011	0	4.38	2.05	6	1	9	-0.59
UPE_012	1	4.61	2.11	6	1	9	-0.56
UPE_021	0	2.16	1.02	2	1	9	4.71
UPE_022	1	2.29	1.39	2	1	9	3.9
UPE_02A1	0	5.78	0.99	6	1	9	-3.21
UPE_02A2	1	5.81	1.18	6	1	9	-2.23
UPE_02B1	0	5.82	0.85	6	1	9	-3.07
UPE_02B2	1	5.88	0.97	6	1	9	-1.68
UPE_02C1	0	5.84	0.75	6	1	9	-2.6

UPE_02C2	1	5.88	0.95	6	1	9	-1.52
UPE_02D1	0	5.84	0.78	6	1	9	-2.75
UPE_02D2	1	5.88	0.96	6	1	9	-1.59
UPE_03A1	0	5.74	1.16	6	1	9	-3.09
UPE_03A2	1	5.79	1.26	6	1	9	-2.22
UPE_03B1	0	3.96	1.05	4	1	9	0.2
UPE_03B2	1	4.08	1.25	4	1	9	1.21
UPE_04A1	0	5.58	1.41	6	1	9	-2.57
UPE_04A2	1	5.66	1.47	6	1	9	-2.11
UPE_05A1	0	5.76	1.13	6	1	9	-3.3
UPE_05A2	1	5.8	1.25	6	1	9	-2.37
UPE_05B1	0	5.89	0.63	6	1	9	-1.91
UPE_05B2	1	5.93	0.8	6	1	9	-0.38
UPE_061	0	5.32	1.58	6	1	9	-1.85
UPE_062	1	5.18	1.73	6	1	9	-1.52
UPE_06A1	0	5.88	0.66	6	1	9	-5.28
UPE_06A2	1	5.84	0.79	6	1	9	-4.14
UPE_06B1	0	5.92	0.47	6	1	9	-4.23
UPE_06B2	1	5.89	0.57	6	1	9	-3.2
UPE_06C1	0	5.92	0.47	6	1	9	-4.21
UPE_06C2	1	5.89	0.56	6	1	9	-3.09
UPE_071	0	2.38	1.35	2	1	9	2.8
UPE_072	1	2.49	1.61	2	1	9	2.75
UPE_07A1	0	5.63	1.14	6	1	9	-2.39
UPE_07A2	1	5.7	1.23	6	1	9	-1.69
UPEFILS1	0	5.71	1.14	6	1	9	-2.64
UPEFILS2	1	5.77	1.24	6	1	9	-1.93
UPEFSKB1	0	5.84	0.8	6	1	9	-4.37
UPEFSKB2	1	5.79	0.94	6	1	9	-3.51
UPEFSNB1	0	5.77	1.04	6	1	9	-2.89
UPEFSNB2	1	5.81	1.17	6	1	9	-1.93
DOSSB1	0	1.94	0.23	2	1	2	-3.77
DOSSB2	1	1.94	0.23	2	1	2	-3.77
SSB_011	0	5.74	1.07	6	1	9	-3.82
SSB_012	1	5.76	1.03	6	1	9	-3.78
SSB_021	0	5.87	0.74	6	1	9	-5.03
SSB_022	1	5.92	0.63	6	1	9	-5.71
SSB_031	0	5.86	0.8	6	1	9	-5.13
SSB_032	1	5.91	0.67	6	1	9	-5.9
SSB_061	0	90.87	20.99	96	1	99	-3.84
SSB_062	1	91.08	20.63	96	1	99	-3.94
SSB_071	0	5.85	0.73	6	1	9	-4.47
SSB_072	1	5.88	0.72	6	1	9	-4.34
SSB_081	0	5.85	0.79	6	1	9	-4.96
SSB_082	1	5.88	0.73	6	1	9	-4.86
SSB_09A1	0	5.87	0.69	6	1	9	-5.26
SSB_09A2	1	5.9	0.63	6	1	9	-5.08

SSB_09B1	0	5.86	0.73	6	1	9	-5.17
SSB_09B2	1	5.88	0.72	6	1	9	-4.92
SSB_101	0	5.92	0.54	6	1	9	-5.28
SSB_102	1	5.94	0.54	6	1	9	-4.58
SSB_111	0	5.87	0.7	6	1	9	-5.14
SSB_112	1	5.9	0.66	6	1	9	-4.96
SSB_121	0	5.93	0.52	6	1	9	-5.21
SSB_122	1	5.95	0.51	6	2	9	-4.55
DOINJ1	0	1	0	1	1	1	NA
DOINJ2	1	1	0	1	1	1	NA
REP_1A1	0	1.81	0.51	2	1	7	2.85
REP_1A2	1	1.85	0.47	2	1	7	3.1
REP_21	0	5.05	1.9	6	1	9	-1.45
REP_22	1	5.24	1.75	6	1	9	-1.77
REPG31	0	84.31	30.59	96	1	99	-2.23
REPG32	1	86.73	27.64	96	1	99	-2.64
REP_3A1	0	5.38	1.65	6	1	9	-2.18
REP_3A2	1	5.52	1.49	6	1	9	-2.57
REP_41	0	5.49	1.47	6	1	9	-2.35
REP_42	1	5.63	1.29	6	1	9	-2.77
REP_5A1	0	5.54	1.31	6	1	9	-2.27
REP_5A2	1	5.66	1.18	6	1	9	-2.71
REP_5B1	0	5.52	1.39	6	1	9	-2.33
REP_5B2	1	5.64	1.24	6	1	9	-2.77
REP_5C1	0	5.54	1.31	6	1	9	-2.27
REP_5C2	1	5.66	1.17	6	1	9	-2.69
REP_5D1	0	5.53	1.35	6	1	9	-2.3
REP_5D2	1	5.65	1.19	6	1	9	-2.73
REP_5F1	0	5.54	1.34	6	1	9	-2.29
REP_5F2	1	5.65	1.19	6	1	9	-2.72
REP_5G1	0	5.55	1.31	6	1	9	-2.26
REP_5G2	1	5.66	1.16	6	1	9	-2.68
REP_5H1	0	5.52	1.38	6	1	9	-2.33
REP_5H2	1	5.65	1.21	6	1	9	-2.75
REP_5I1	0	5.52	1.38	6	1	9	-2.32
REP_5I2	1	5.64	1.23	6	1	9	-2.77
INJ_011	0	1	0	1	1	1	NA
INJ_012	1	1	0	1	1	1	NA
INJG021	0	1.41	0.75	1	1	4	1.79
INJG022	1	1.38	0.73	1	1	4	1.91
INJG051	0	5.61	7.02	5	1	99	12.36
INJG052	1	5.09	6.98	5	1	99	12.24
INJG061	0	9.17	15.84	7	1	99	5.19
INJG062	1	10.34	19.01	7	1	99	4.22
INJG081	0	4.3	8.93	3	1	99	9.63
INJG082	1	3.41	4.39	2	1	99	14.92
INJG0921	0	4.65	10.19	3	1	99	8.77

INJG0922	1	4.25	5.95	5	1	99	13.55
INW_011	0	5.28	1.85	6	1	9	-1.63
INW_012	1	5.73	1.16	6	1	9	-3.57
INWGSOC1	0	5.63	1.18	6	1	9	-2.33
INWGSOC2	1	5.87	0.72	6	1	9	-4.49
INJ_101	0	2.01	0.25	2	2	7	20.16
INJ_102	1	1	0	1	1	1	NA
INJG11A1	0	96.01	0.15	96	96	99	20.16
INJG11A2	1	4.15	6.24	4	1	99	14.31
INJ_131	0	1.52	0.56	2	1	8	1.86
INJ_132	1	1.43	0.51	1	1	7	0.88
INJ_14A1	0	3.95	2.11	6	1	9	-0.06
INJ_14A2	1	3.63	2.07	2	1	9	0.25
INJ_14B1	0	3.78	2.3	6	1	9	-0.08
INJ_14B2	1	3.33	2.34	2	1	9	0.23
INJG14C1	0	3.95	2.12	6	1	9	-0.06
INJG14C2	1	3.63	2.07	2	1	9	0.25
INJ_14O1	0	4.02	2.03	6	1	9	-0.03
INJ_14O2	1	3.7	2	2	1	9	0.29
INJG14J21	0	3.97	2.1	6	1	9	-0.05
INJG14J22	1	3.67	2.03	2	1	9	0.27
INJ_151	0	4.01	2.04	6	1	9	-0.03
INJ_152	1	3.63	2.07	2	1	9	0.25
INJ_15A1	0	1.81	0.42	2	1	8	0.57
INJ_15A2	1	1.8	0.4	2	1	2	-1.47
INJ_161	0	1.94	0.36	2	1	8	5.83
INJ_162	1	1.93	0.31	2	1	7	2.29
INJG171	0	5.68	1.23	6	1	9	-3.25
INJG172	1	5.66	1.24	6	1	9	-3.25
INJGCAU*1	0	1	0	1	1	1	NA
INJGCAU*2	1	2	0	2	2	2	NA
INJDSTT1	0	1.16	0.64	1	1	9	5.94
INJDSTT2	1	1.16	0.58	1	1	9	4.79
SMK_01A1	0	1.55	0.52	2	1	8	0.95
SMK_01A2	1	1.56	0.56	2	1	8	2.04
SMK_01B1	0	3.7	2.15	2	1	9	0.1
SMK_01B2	1	3.68	2.14	2	1	9	0.14
SMKG01C1	0	41.27	45.85	4	1	99	0.36
SMKG01C2	1	43.66	46.14	5	1	99	0.26
SMK_2021	0	2.64	0.82	3	1	9	0.09
SMK_2022	1	2.7	0.82	3	1	9	0.65
SMKG2031	0	81.29	33.87	96	1	99	-1.86
SMKG2032	1	83	32.17	96	1	99	-2.06
SMK_2041	0	839.11	359.56	996	1	999	-1.85
SMK_2042	1	855.91	343.24	996	1	999	-2.04
SMK_05B1	0	943.25	222.73	996	1	999	-3.98
SMK_05B2	1	955.08	197.44	996	1	999	-4.61

SMK_05C1	0	91.44	19.58	96	0	99	-4.08
SMK_05C2	1	92.45	17.4	96	0	99	-4.7
SMK_05D1	0	4.56	2.25	6	1	9	-0.9
SMK_05D2	1	4.53	2.27	6	1	9	-0.85
SMK_06A1	0	5.96	0.35	6	1	9	-4.73
SMK_06A2	1	5.96	0.4	6	1	9	-3.46
SMKG06C1	0	5.95	0.49	6	1	9	-5.72
SMKG06C2	1	5.95	0.51	6	1	9	-4.08
SMKG2071	0	71.99	40.55	96	1	99	-1.09
SMKG2072	1	71.81	40.61	96	1	99	-1.08
SMK_2081	0	746.92	426.69	996	1	999	-1.13
SMK_2082	1	743.16	428.5	996	1	999	-1.1
SMK_09A1	0	5.35	1.23	6	1	9	-1.78
SMK_09A2	1	5.38	1.16	6	1	9	-1.62
SMKG09C1	0	5.31	1.43	6	1	9	-1.53
SMKG09C2	1	5.27	1.46	6	1	9	-1.31
SMK_101	0	4.86	2.1	6	1	9	-1.25
SMK_102	1	4.79	2.15	6	1	9	-1.15
SMK_10A1	0	5.98	0.33	6	1	9	-7.49
SMK_10A2	1	5.99	0.37	6	1	9	-6.3
SMKG10C1	0	5.98	0.36	6	1	9	-7.46
SMKG10C2	1	6	0.31	6	1	9	-2.9
SMKDSTY1	0	4.81	6.59	5	1	99	13.15
SMKDSTY2	1	5.17	8.17	5	1	99	10.87
SMKGSTP1	0	5.55	1.09	6	1	9	-2.32
SMKGSTP2	1	5.59	1.04	6	1	9	-2.07
SMKDYCS1	0	841.55	355.26	996	0	999	-1.87
SMKDYCS2	1	859.81	336.4	996	0	999	-2.06
DOSCH1	0	1.69	0.46	2	1	2	-0.8
DOSCH2	1	1.67	0.47	2	1	2	-0.74
SCH_11	0	5.71	1.16	6	1	9	-3.48
SCH_12	1	5.77	1.07	6	1	9	-3.69
SCH_21	0	5.82	0.92	6	1	9	-4.27
SCH_22	1	5.87	0.84	6	1	9	-4.57
SCH_31	0	5.72	1.12	6	1	9	-3.47
SCH_32	1	5.78	1.03	6	1	9	-3.68
SCH_41	0	93.39	15.27	96	1	99	-5.68
SCH_42	1	94.14	12.97	96	1	99	-6.79
SCHDSTG1	0	5.69	1.07	6	1	9	-2.93
SCHDSTG2	1	5.74	1.02	6	1	9	-2.75
DOSCA1	0	1.69	0.46	2	1	2	-0.8
DOSCA2	1	1.67	0.47	2	1	2	-0.74
SCA_101	0	5.99	0.31	6	1	9	-8.29
SCA_102	1	5.99	0.35	6	1	9	-5.63
SCAG10A1	0	6	0.19	6	1	9	-1.37
SCAG10A2	1	6.01	0.24	6	1	9	2.46
SCA_111	0	5.99	0.32	6	1	9	-8.44

SCA_112	1	5.99	0.35	6	1	9	-5.63
SCA_11A1	0	6	0.19	6	1	9	-1.09
SCA_11A2	1	6.01	0.24	6	1	9	2.89
SCA_121	0	5.99	0.31	6	1	9	-8.29
SCA_122	1	5.99	0.34	6	2	9	-4.79
SCAG12A1	0	6	0.19	6	1	9	1.29
SCAG12A2	1	6.01	0.2	6	6	9	15.12
SCA_501	0	5.72	1.12	6	1	9	-3.44
SCA_502	1	5.78	1.03	6	1	9	-3.64
SCA_601	0	5.88	0.76	6	1	9	-4.9
SCA_602	1	5.92	0.68	6	1	9	-4.94
SCA_611	0	5.87	0.77	6	1	9	-4.94
SCA_612	1	5.92	0.68	6	1	9	-4.93
SCA_621	0	5.88	0.74	6	1	9	-4.85
SCA_622	1	5.92	0.67	6	1	9	-4.88
SCADQUI1	0	5.57	1.23	6	1	9	-2.55
SCADQUI2	1	5.62	1.19	6	1	9	-2.39
DOSPC1	0	1.98	0.13	2	1	2	-7.72
DOSPC2	1	1.99	0.12	2	1	2	-8.23
SPC_101	0	5.98	0.3	6	1	6	-16
SPC_102	1	5.99	0.22	6	1	9	-18.84
SPC_111	0	5.99	0.28	6	1	9	-14.32
SPC_112	1	5.99	0.22	6	1	9	-17.79
SPC_121	0	5.99	0.26	6	1	9	-14.62
SPC_122	1	5.99	0.22	6	1	9	-17.59
SPC_131	0	5.99	0.25	6	1	9	-14.25
SPC_132	1	5.99	0.2	6	1	9	-16.98
SPC_14C1	0	6	0.18	6	1	9	-12.72
SPC_14C2	1	6	0.16	6	1	9	-16.82
SPC_14D1	0	6	0.19	6	1	9	-14.45
SPC_14D2	1	6	0.15	6	1	9	-15.2
SPC_14E1	0	6	0.19	6	1	9	-14.45
SPC_14E2	1	6	0.16	6	1	9	-16.82
SPCG14G1	0	6	0.18	6	1	9	-12.72
SPCG14G2	1	6	0.15	6	1	9	-15.2
SPC_201	0	5.99	0.27	6	1	6	-18.76
SPC_202	1	6	0.19	6	1	9	-21.51
SPC_211	0	5.99	0.26	6	1	6	-18.93
SPC_212	1	6	0.17	6	1	9	-22.09
SPC_221	0	5.99	0.2	6	1	6	-21.34
SPC_222	1	6	0.17	6	1	9	-18
DOYSM1	0	1.94	0.23	2	1	2	-3.77
DOYSM2	1	1.94	0.23	2	1	2	-3.77
YSMG11	0	6	0.14	6	1	6	-33.95
YSMG12	1	6	0.14	6	1	9	-26.29
YSM_31	0	6	0.12	6	1	6	-37.1
YSM_32	1	6	0.13	6	1	9	-28.49

YSM_51	0	6	0.14	6	1	6	-33.19
YSM_52	1	6	0.14	6	1	9	-25.17
ETS_101	0	2.2	1.11	2	1	9	3.3
ETS_102	1	2.28	1.24	2	1	9	3.13
ETSG111	0	5.68	1.2	6	1	9	-3.14
ETSG112	1	5.72	1.17	6	1	9	-3.1
ETS_201	0	2.83	1.73	2	1	9	1.35
ETS_202	1	2.75	1.69	2	1	9	1.6
ETS_20B1	0	2.76	1.79	2	1	9	1.28
ETS_20B2	1	2.68	1.75	2	1	9	1.51
ETS_351	0	2.27	1.2	2	1	9	2.98
ETS_352	1	2.26	1.26	2	1	9	3.12
ETS_361	0	5.38	1.59	6	1	9	-1.94
ETS_362	1	5.36	1.63	6	1	9	-1.78
ETS_37A1	0	5.74	1.13	6	1	9	-3.34
ETS_37A2	1	5.76	1.14	6	1	9	-3.14
ETS_37B1	0	5.76	1.07	6	1	9	-3.28
ETS_37B2	1	5.78	1.07	6	1	9	-3.02
ETS_37C1	0	5.75	1.09	6	1	9	-3.31
ETS_37C2	1	5.78	1.09	6	1	9	-3.07
ETS_37D1	0	5.77	1.03	6	1	9	-3.22
ETS_37D2	1	5.79	1.05	6	1	9	-2.98
DOTAL1	0	1.63	0.48	2	1	2	-0.53
DOTAL2	1	1.62	0.49	2	1	2	-0.47
TAL_11	0	4.5	1.98	6	1	9	-0.53
TAL_12	1	4.48	1.99	6	1	9	-0.46
TAL_21	0	4.52	1.95	6	1	9	-0.51
TAL_22	1	4.49	1.97	6	1	9	-0.45
TAL_31	0	4.53	1.95	6	1	9	-0.51
TAL_32	1	4.5	1.97	6	1	9	-0.44
TAL_41	0	4.52	1.95	6	1	9	-0.51
TAL_42	1	4.49	1.97	6	1	9	-0.45
ALC_11	0	1.26	0.8	1	1	9	7.28
ALC_12	1	1.4	1.04	1	1	9	5.75
ALC_21	0	22.99	37.71	5	1	99	1.42
ALC_22	1	31.06	42.37	5	1	99	0.88
ALC_31	0	22.18	38.46	2	1	99	1.4
ALC_32	1	30.31	43.14	2	1	99	0.87
ALCDTTM1	0	1.66	1.12	1	1	9	3.4
ALCDTTM2	1	1.89	1.33	1	1	9	3.05
DOALW1	0	1.22	0.41	1	1	2	1.38
DOALW2	1	1.21	0.41	1	1	2	1.4
ALW_11	0	3.12	2.32	2	1	9	0.49
ALW_12	1	3.46	2.4	2	1	9	0.27
ALW_2A11	0	600.18	486.97	996	0	999	-0.42
ALW_2A12	1	651.26	473.5	996	0	999	-0.64
ALW_2A21	0	600.89	486.86	996	0	999	-0.42

ALW_2A22	1	653.36	472.87	996	0	999	-0.65
ALW_2A31	0	601.04	486.86	996	0	999	-0.42
ALW_2A32	1	654.81	472.38	996	0	999	-0.66
ALW_2A41	0	603.13	486.39	996	0	999	-0.43
ALW_2A42	1	655.53	472.13	996	0	999	-0.66
ALW_2A51	0	605.72	485.85	996	0	999	-0.44
ALW_2A52	1	658.15	471.27	996	0	999	-0.68
ALW_2A61	0	606.24	485.78	996	0	999	-0.44
ALW_2A62	1	660.22	470.64	996	0	999	-0.69
ALW_2A71	0	609.75	485.04	996	0	999	-0.46
ALW_2A72	1	661.15	470.34	996	0	999	-0.69
ALWDWKY1	0	393.68	484.19	8	0	999	0.44
ALWDWKY2	1	458.51	494.2	14	0	999	0.17
ALWDDLY1	0	391.19	486.14	1	0	999	0.44
ALWDDLY2	1	456.41	496.1	2	0	999	0.17
DODRV1	0	1.52	0.5	2	1	2	-0.09
DODRV2	1	1.51	0.5	2	1	2	-0.05
DRV_01A1	0	3.76	2.46	6	1	9	-0.1
DRV_01A2	1	3.86	2.48	6	1	9	-0.06
DRV_01B1	0	4.12	2.08	6	1	9	-0.07
DRV_01B2	1	4.19	2.13	6	1	9	0.02
DRV_021	0	4.11	2.44	6	1	9	-0.42
DRV_022	1	4.36	2.44	6	1	9	-0.53
DRV_03A1	0	5.07	1.34	6	1	9	-0.74
DRV_03A2	1	5.25	1.31	6	1	9	-0.5
DRV_03B1	0	4.91	1.63	6	1	9	-1
DRV_03B2	1	5.12	1.56	6	1	9	-0.92
DRV_041	0	4.78	1.71	6	1	9	-0.68
DRV_042	1	5	1.67	6	1	9	-0.67
DRV_051	0	4.81	1.64	6	1	9	-0.52
DRV_052	1	5.02	1.62	6	1	9	-0.49
DRV_061	0	5.01	1.46	6	1	9	-0.73
DRV_062	1	5.2	1.44	6	1	9	-0.63
DRV_071	0	4.66	1.96	6	1	9	-0.65
DRV_072	1	4.91	1.89	6	1	9	-0.79
DRV_07A1	0	94.04	13.28	96	1	99	-6.61
DRV_07A2	1	95.06	9.47	96	1	99	-9.5
DRV_08A1	0	3.74	2.5	6	1	9	-0.11
DRV_08A2	1	3.79	2.56	6	1	9	-0.06
DRV_08B1	0	3.91	2.42	6	1	9	-0.24
DRV_08B2	1	4	2.47	6	1	9	-0.21
DRV_091	0	4.55	2.04	6	1	9	-0.86
DRV_092	1	4.62	2.1	6	1	9	-0.78
DRV_101	0	4.11	2.12	6	1	9	-0.1
DRV_102	1	4.19	2.16	6	1	9	-0.01
DRV_10A1	0	90.9	21.18	96	1	99	-3.89
DRV_10A2	1	92.52	17.8	96	1	99	-4.8

DRV_11A1	0	4.01	2.22	6	1	9	-0.12
DRV_11A2	1	4.09	2.25	6	1	9	-0.04
DRV_11B1	0	4.05	2.17	6	1	9	-0.11
DRV_11B2	1	4.13	2.2	6	1	9	-0.02
DRV_121	0	5.61	1.33	6	1	9	-2.61
DRV_122	1	5.74	1.27	6	1	9	-2.46
DRV_131	0	5.3	1.6	6	1	9	-1.51
DRV_132	1	5.46	1.55	6	1	9	-1.53
DRV_13A1	0	94.96	9.87	96	1	99	-9.1
DRV_13A2	1	94.86	10.54	96	1	99	-8.57
DRV_141	0	5.4	1.5	6	1	9	-1.78
DRV_142	1	5.58	1.36	6	1	9	-1.94
DRV_14A1	0	95.04	9.45	96	1	99	-9.58
DRV_14A2	1	95.47	7.25	96	1	99	-12.52
DRVFSBU1	0	3.77	2.47	6	1	9	-0.11
DRVFSBU2	1	3.83	2.53	6	1	9	-0.06
ALDGSF1	0	82.24	33.61	96	0	99	-2.03
ALDGSF2	1	83.56	32.22	96	0	99	-2.2
ALDDPP1	0	8.53	3.48	9.96	0	9.99	-2.03
ALDDPP2	1	8.67	3.34	9.96	0	9.99	-2.2
ALDDINT1	0	98.15	11.88	99.6	0	99.9	-8.08
ALDDINT2	1	98.35	11.06	99.6	0	99.9	-8.7
ALDFINT1	0	5.94	0.51	6	1	9	-7.95
ALDFINT2	1	5.95	0.48	6	1	9	-8.47
DOMEX1	0	1.34	0.47	1	1	2	0.68
DOMEX2	1	1.33	0.47	1	1	2	0.74
MEX_011	0	5.37	1.57	6	1	9	-1.78
MEX_012	1	5.53	1.4	6	1	9	-2.18
MEX_021	0	5.89	0.75	6	1	9	-5.36
MEX_022	1	5.92	0.64	6	1	9	-6.6
MEX_031	0	5.88	0.8	6	1	9	-5.38
MEX_032	1	5.92	0.66	6	1	9	-6.61
MEXG041	0	95.73	5.1	96	1	99	-18.14
MEXG042	1	95.65	5.68	96	1	99	-16.04
MEX_051	0	5.91	0.66	6	1	9	-5.47
MEX_052	1	5.95	0.52	6	1	9	-7
MEX_061	0	94.37	11.9	96	1	99	-7.14
MEX_062	1	94.88	9.96	96	1	99	-8.72
MEX_06A1	0	5.99	0.36	6	1	9	-8.38
MEX_06A2	1	6	0.25	6	1	9	-10.52
MEX_06B1	0	94.12	12.87	96	1	99	-6.66
MEX_06B2	1	94.78	10.41	96	1	99	-8.39
MEX_08A1	0	94.05	12.96	96	4	99	-6.43
MEX_08A2	1	94.79	10.25	96	4	99	-8.3
MEXG08B1	0	94.02	13.46	96	1	99	-6.62
MEXG08B2	1	94.76	10.7	96	1	99	-8.46
MEX_091	0	5.91	0.71	6	1	9	-5.94

MEX_092	1	5.95	0.55	6	1	9	-7.75
MEX_09B1	0	5.94	0.59	6	1	9	-6.5
MEX_09B2	1	5.96	0.47	6	1	9	-8.45
MEXG101	0	94.31	12.32	96	1	99	-7.14
MEXG102	1	94.88	10.11	96	1	99	-8.89
MEXDEBF21	0	93.77	14.2	96	0	99	-6.17
MEXDEBF22	1	94.39	12.15	96	0	99	-7.37
MEXFEB61	0	5.91	0.69	6	1	9	-5.23
MEXFEB62	1	5.93	0.57	6	1	9	-6.26
DOMXA1	0	1.9	0.3	2	1	2	-2.61
DOMXA2	1	1.9	0.3	2	1	2	-2.66
MXA_011	0	5.99	0.25	6	1	9	-14.84
MXA_012	1	5.98	0.26	6	2	8	-14.7
MXAG021	0	6	0.1	6	2	9	-15.26
MXAG022	1	6	0.05	6	6	9	64.54
MXA_031	0	5.99	0.25	6	1	9	-16.32
MXA_032	1	5.99	0.26	6	1	9	-15.7
MXAG041	0	6	0.16	6	1	9	-23.83
MXAG042	1	6	0.13	6	1	9	-28.02
DOMXS1	0	1.9	0.3	2	1	2	-2.61
DOMXS2	1	1.9	0.3	2	1	2	-2.66
MXS_011	0	5.99	0.16	6	3	9	-13.73
MXS_012	1	5.99	0.21	6	1	6	-20.85
MXSG021	0	96	0.06	96	96	99	51.56
MXSG022	1	95.91	2.87	96	1	96	-32.26
MXSG031	0	96	0.06	96	96	99	51.56
MXSG032	1	95.98	1.39	96	6	99	-64.43
MXS_041	0	5.99	0.15	6	2	9	-14.72
MXS_042	1	5.99	0.18	6	1	6	-24.29
MXSG051	0	96	0.06	96	96	99	51.56
MXSG052	1	95.91	2.77	96	4	96	-32.25
MXSG061	0	95.98	1.3	96	1	99	-72.71
MXSG062	1	96	0.05	96	96	99	64.54
MXS_071	0	5.99	0.21	6	1	9	-17.15
MXS_072	1	5.99	0.23	6	1	6	-19.75
DOIDG1	0	1.83	0.38	2	1	2	-1.76
DOIDG2	1	1.84	0.37	2	1	2	-1.82
IDGFLCA1	0	5.25	1.74	6	1	9	-1.78
IDGFLCA2	1	5.32	1.66	6	1	9	-1.82
IDGFLCM1	0	5.26	1.7	6	1	9	-1.78
IDGFLCM2	1	5.34	1.63	6	1	9	-1.81
IDGFYCM1	0	5.31	1.59	6	1	9	-1.76
IDGFYCM2	1	5.37	1.55	6	1	9	-1.77
IDGFLA1	0	5.25	1.74	6	1	9	-1.78
IDGFLA2	1	5.32	1.66	6	1	9	-1.82
IDGFLAC1	0	5.26	1.71	6	1	9	-1.78
IDGFLAC2	1	5.33	1.64	6	1	9	-1.81

IDGFYA1	0	5.31	1.59	6	1	9	-1.76
IDGFYA2	1	5.37	1.55	6	1	9	-1.78
IDGFYAC1	0	5.31	1.59	6	1	9	-1.76
IDGFYAC2	1	5.37	1.55	6	1	9	-1.77
IDGDINT1	0	97.76	13.38	99.6	0	99.9	-7.13
IDGDINT2	1	97.99	12.54	99.6	0	99.9	-7.64
IDGFINT1	0	5.94	0.6	6	1	9	-5.12
IDGFINT2	1	5.96	0.59	6	1	9	-4.43
DOCPG1	0	1.57	0.49	2	1	2	-0.29
DOCPG2	1	1.59	0.49	2	1	2	-0.35
CPGFGAM1	0	4.07	2.37	6	1	9	-0.31
CPGFGAM2	1	4.29	2.38	6	1	9	-0.34
CPGDSEV1	0	76.32	38.66	96	0	99	-1.46
CPGDSEV2	1	80.05	35.72	96	0	99	-1.79
CPGDTYP1	0	63.72	44.72	96	1	99	-0.67
CPGDTYP2	1	66.14	43.93	96	1	99	-0.79
CPGDACT1	0	56.56	46.67	96	0	99	-0.34
CPGDACT2	1	59.41	46.22	96	0	99	-0.46
CPGDINT1	0	98.91	8.24	99.6	0	99.9	-11.87
CPGDINT2	1	99.25	5.89	99.6	0	99.9	-16.6
CPGFINT1	0	5.99	0.4	6	1	9	-5.25
CPGFINT2	1	6.03	0.44	6	1	9	1.36
DOSXB1	0	1	0	1	1	1	NA
DOSXB2	1	1	0	1	1	1	NA
SXB_11	0	3.5	2.51	2	1	9	0.14
SXB_12	1	4.25	2.38	6	1	9	-0.49
SXB_31	0	3.91	2.58	6	1	9	-0.09
SXB_32	1	4.65	2.31	6	1	9	-0.77
SXB_071	0	4.28	2.19	6	1	9	-0.04
SXB_072	1	4.88	1.97	6	1	9	-0.7
SXB_7A1	0	5.18	1.95	6	1	9	-1.19
SXB_7A2	1	5.42	1.71	6	1	9	-1.68
SXB_091	0	5.8	0.98	6	1	9	-4.3
SXB_092	1	5.84	0.91	6	1	9	-4.5
SXB_101	0	89.88	23.29	96	1	99	-3.53
SXB_102	1	91.63	19.88	96	1	99	-4.32
SXB_111	0	5.49	1.54	6	1	9	-2.34
SXB_112	1	5.62	1.38	6	1	9	-2.76
SXB_12A1	0	5.62	1.35	6	1	9	-2.67
SXB_12A2	1	5.72	1.2	6	1	9	-3.07
SXB_12B1	0	5.62	1.36	6	1	9	-2.67
SXB_12B2	1	5.72	1.2	6	1	9	-3.07
SXB_12C1	0	5.68	1.18	6	1	9	-2.51
SXB_12C2	1	5.76	1.05	6	1	9	-2.85
SXB_12D1	0	5.68	1.17	6	1	9	-2.5
SXB_12D2	1	5.76	1.05	6	1	9	-2.84
SXB_12F1	0	5.68	1.18	6	1	9	-2.51

SXB_12F2	1	5.76	1.06	6	1	9	-2.87
SXB_12E1	0	5.67	1.19	6	1	9	-2.54
SXB_12E2	1	5.76	1.07	6	1	9	-2.92
SXB_13A1	0	5.64	1.36	6	1	9	-2.6
SXB_13A2	1	5.73	1.21	6	1	9	-2.92
SXB_13B1	0	5.64	1.34	6	1	9	-2.59
SXB_13B2	1	5.73	1.21	6	1	9	-2.92
SXB_13C1	0	5.69	1.18	6	1	9	-2.4
SXB_13C2	1	5.77	1.06	6	1	9	-2.64
SXB_13D1	0	5.69	1.18	6	1	9	-2.39
SXB_13D2	1	5.77	1.06	6	2	9	-2.64
SXB_13F1	0	5.69	1.18	6	1	9	-2.41
SXB_13F2	1	5.77	1.07	6	1	9	-2.66
SXB_13G1	0	5.69	1.18	6	1	9	-2.4
SXB_13G2	1	5.77	1.07	6	1	9	-2.66
SXB_13E1	0	5.69	1.2	6	1	9	-2.43
SXB_13E2	1	5.77	1.08	6	1	9	-2.71
DOSPS1	0	1.79	0.41	2	1	2	-1.44
DOSPS2	1	1.79	0.41	2	1	2	-1.43
SPS_011	0	5.07	1.91	6	1	9	-1.47
SPS_012	1	5.14	1.89	6	1	9	-1.43
SPS_021	0	5.11	1.87	6	1	9	-1.48
SPS_022	1	5.18	1.85	6	1	9	-1.45
SPS_031	0	5.08	1.9	6	1	9	-1.46
SPS_032	1	5.16	1.88	6	1	9	-1.42
SPS_041	0	5.08	1.91	6	1	9	-1.47
SPS_042	1	5.15	1.89	6	1	9	-1.42
SPS_051	0	5.1	1.87	6	1	9	-1.47
SPS_052	1	5.19	1.84	6	1	9	-1.44
SPS_061	0	5.07	1.91	6	1	9	-1.46
SPS_062	1	5.14	1.9	6	1	9	-1.41
SPS_071	0	5.13	1.82	6	1	9	-1.5
SPS_072	1	5.19	1.82	6	1	9	-1.44
SPS_081	0	5.08	1.9	6	1	9	-1.47
SPS_082	1	5.15	1.89	6	1	9	-1.42
SPS_091	0	5.12	1.84	6	1	9	-1.48
SPS_092	1	5.19	1.83	6	1	9	-1.44
SPS_101	0	5.07	1.92	6	1	9	-1.45
SPS_102	1	5.13	1.91	6	1	9	-1.41
SPSDCON1	0	84.25	23.9	96	13	99	-1.55
SPSDCON2	1	84.78	23.68	96	13	99	-1.64
SPSDATT1	0	77.65	35.94	96	2	99	-1.45
SPSDATT2	1	77.84	35.83	96	2	99	-1.46
SPSDGUI1	0	78.14	35.59	96	2	99	-1.49
SPSDGUI2	1	78.81	35.15	96	2	99	-1.55
SPSDALL1	0	78.09	35.61	96	2	99	-1.48
SPSDALL2	1	78.75	35.18	96	2	99	-1.54

SPSDINT1	0	78.33	35.54	96	2	99	-1.51
SPSDINT2	1	78.94	35.14	96	2	99	-1.56
SPSDWOR1	0	78.22	35.6	96	4	99	-1.5
SPSDWOR2	1	79.15	34.96	96	2	99	-1.58
DOCMH1	0	1.29	0.45	1	1	2	0.92
DOCMH2	1	1.29	0.45	1	1	2	0.95
CMH_01K1	0	3.17	2.06	2	1	9	0.9
CMH_01K2	1	3.32	2.23	2	1	9	0.93
CMHG01L1	0	85.7	28.94	96	1	99	-2.44
CMHG01L2	1	86.03	28.61	96	1	99	-2.48
CMH_1MA1	0	5.53	1.53	6	1	9	-2.05
CMH_1MA2	1	5.61	1.61	6	1	9	-1.65
CMH_1MB1	0	5.57	1.42	6	1	9	-1.97
CMH_1MB2	1	5.65	1.51	6	1	9	-1.51
CMH_1MC1	0	5.57	1.43	6	1	9	-1.97
CMH_1MC2	1	5.65	1.51	6	1	9	-1.51
CMH_1MD1	0	5.58	1.37	6	1	9	-1.9
CMH_1MD2	1	5.67	1.46	6	1	9	-1.4
CMH_1ME1	0	5.56	1.45	6	1	9	-1.99
CMH_1ME2	1	5.64	1.53	6	1	9	-1.55
CMH_1MF1	0	5.59	1.37	6	1	9	-1.88
CMH_1MF2	1	5.67	1.45	6	1	9	-1.4
DOMDB1	0	1.94	0.23	2	1	2	-3.77
DOMDB2	1	1.94	0.23	2	1	2	-3.77
MDB_11	0	5.77	0.97	6	1	9	-3.9
MDB_12	1	5.78	0.96	6	1	9	-3.9
MDB_21	0	5.81	0.83	6	1	9	-3.85
MDB_22	1	5.82	0.83	6	1	9	-3.64
MDB_31	0	5.76	1.02	6	1	9	-3.84
MDB_32	1	5.78	1	6	1	9	-3.77
MDB_41	0	5.81	0.82	6	1	9	-3.84
MDB_42	1	5.83	0.8	6	1	9	-3.6
MDB_51	0	5.75	1.04	6	1	9	-3.82
MDB_52	1	5.77	1.04	6	1	9	-3.75
MDB_61	0	5.79	0.88	6	1	9	-3.88
MDB_62	1	5.8	0.9	6	1	9	-3.81
MDB_71	0	5.77	0.99	6	1	9	-3.83
MDB_72	1	5.78	0.98	6	1	9	-3.72
MDB_81	0	5.79	0.89	6	1	9	-3.94
MDB_82	1	5.81	0.88	6	1	9	-3.81
MDB_91	0	5.76	1.02	6	1	9	-3.83
MDB_92	1	5.78	1.01	6	1	9	-3.74
MDB_101	0	5.81	0.81	6	1	9	-3.81
MDB_102	1	5.83	0.8	6	1	9	-3.61
MDB_111	0	5.77	0.99	6	1	9	-3.82
MDB_112	1	5.78	1	6	1	9	-3.72
MDBDPOS1	0	91.26	19.49	96	5	99	-3.86

MDBDPOS2	1	91.4	19.23	96	6	99	-3.93
MDBDNEG1	0	91.02	20.38	96	5	99	-3.84
MDBDNEG2	1	91.27	19.91	96	5	99	-3.96
MDBDBA11	0	940.47	228.13	996	-6	999	-3.86
MDBDBA12	1	942.73	223.72	996	-5	999	-3.96
MDBDBA21	0	5.82	0.82	6	1	9	-3.71
MDBDBA22	1	5.83	0.81	6	1	9	-3.53
DODIS1	0	1.84	0.37	2	1	2	-1.81
DODIS2	1	1.84	0.37	2	1	2	-1.81
DIS_10A1	0	5.69	0.89	6	1	9	-2.39
DIS_10A2	1	5.72	0.93	6	1	9	-1.86
DIS_10B1	0	5.64	0.99	6	1	9	-2.16
DIS_10B2	1	5.69	1	6	1	9	-1.83
DIS_10C1	0	5.81	0.59	6	1	9	-1.86
DIS_10C2	1	5.84	0.66	6	1	9	-0.92
DIS_10D1	0	5.81	0.6	6	1	9	-1.92
DIS_10D2	1	5.84	0.65	6	1	9	-0.75
DIS_10E1	0	5.74	0.78	6	1	9	-2.54
DIS_10E2	1	5.78	0.81	6	1	9	-1.84
DIS_10F1	0	5.81	0.62	6	1	9	-2.28
DIS_10F2	1	5.84	0.67	6	1	9	-1.03
DIS_10G1	0	5.73	0.79	6	1	9	-2.27
DIS_10G2	1	5.76	0.83	6	1	9	-1.61
DIS_10H1	0	5.82	0.56	6	1	9	-1.71
DIS_10H2	1	5.85	0.63	6	1	9	-0.63
DIS_10I1	0	5.77	0.73	6	1	9	-2.66
DIS_10I2	1	5.8	0.79	6	1	9	-2
DIS_10J1	0	5.81	0.59	6	1	9	-2.06
DIS_10J2	1	5.84	0.66	6	1	9	-1.25
DIS_10K1	0	5.55	1.26	6	1	9	-2.24
DIS_10K2	1	5.61	1.24	6	1	9	-2.04
DIS_10L1	0	5.91	0.73	6	1	9	-4.53
DIS_10L2	1	5.95	0.71	6	1	9	-3.21
DIS_10M1	0	5.97	0.5	6	1	9	-4.92
DIS_10M2	1	6	0.54	6	1	9	-2.13
DIS_10N1	0	5.67	1	6	1	9	-2.28
DIS_10N2	1	5.72	1.02	6	1	9	-1.93
DISDK61	0	81.35	33.83	96	0	99	-1.88
DISDK62	1	82.15	33.11	96	0	99	-1.97
DISDCHR1	0	83.66	31.41	96	1	99	-2.15
DISDCHR2	1	84.7	30.29	96	1	99	-2.29
DISDDSX1	0	81.81	32.92	96	0	99	-1.89
DISDDSX2	1	82.58	32.21	96	0	99	-1.98
DODEP1	0	1.69	0.46	2	1	2	-0.83
DODEP2	1	1.69	0.46	2	1	2	-0.8
DPSDSF1	0	67.59	43.63	96	0	99	-0.88
DPSDSF2	1	68.34	43.37	96	0	99	-0.92

DPSDPP1	0	7.02	4.51	9.96	0	9.99	-0.88
DPSDPP2	1	7.09	4.48	9.96	0	9.99	-0.92
DPSDWK1	0	92.9	16.01	96	2	99	-5.01
DPSDWK2	1	93.46	14.69	96	2	99	-5.53
DPSDMT1	0	92.87	16.55	96	1	99	-5.03
DPSDMT2	1	93.46	15.1	96	1	99	-5.59
DOSUI1	0	1.78	0.42	2	1	2	-1.34
DOSUI2	1	1.79	0.41	2	1	2	-1.39
SUI_11	0	5.16	1.7	6	1	9	-1.42
SUI_12	1	5.26	1.65	6	1	9	-1.5
SUI_21	0	5.89	0.76	6	1	9	-4.62
SUI_22	1	5.91	0.75	6	1	9	-4.07
DOACC1	0	1.9	0.3	2	1	2	-2.6
DOACC2	1	1.89	0.32	2	1	2	-2.45
ACC_101	0	5.58	1.31	6	1	9	-2.75
ACC_102	1	5.56	1.35	6	1	9	-2.64
ACC_111	0	5.84	0.84	6	1	9	-4.67
ACC_112	1	5.83	0.87	6	1	9	-4.25
ACC_12A1	0	5.96	0.44	6	1	9	-8.24
ACC_12A2	1	5.97	0.43	6	1	9	-7.44
ACC_12B1	0	5.96	0.46	6	1	9	-8.45
ACC_12B2	1	5.97	0.44	6	1	9	-7.71
ACC_12C1	0	5.96	0.43	6	1	9	-8.14
ACC_12C2	1	5.97	0.43	6	1	9	-7.44
ACC_12D1	0	5.96	0.46	6	1	9	-8.44
ACC_12D2	1	5.97	0.46	6	1	9	-7.98
ACC_12E1	0	5.96	0.45	6	1	9	-8.31
ACC_12E2	1	5.97	0.42	6	1	9	-7.33
ACC_12F1	0	5.96	0.43	6	1	9	-8.08
ACC_12F2	1	5.97	0.42	6	1	9	-7.21
ACC_12J1	0	5.96	0.43	6	1	9	-8.02
ACC_12J2	1	5.97	0.42	6	2	9	-7.15
ACC_12K1	0	5.96	0.43	6	1	9	-8.08
ACC_12K2	1	5.97	0.42	6	1	9	-7.21
ACC_12L1	0	5.96	0.44	6	1	9	-8.24
ACC_12L2	1	5.97	0.44	6	1	9	-7.63
ACCG12N1	0	5.96	0.45	6	1	9	-8.29
ACCG12N2	1	5.97	0.44	6	1	9	-7.63
ACC_201	0	5.61	1.22	6	1	9	-2.7
ACC_202	1	5.59	1.25	6	1	9	-2.59
ACC_211	0	5.97	0.41	6	1	9	-8.98
ACC_212	1	5.96	0.48	6	1	9	-7.37
ACCG22B1	0	6	0.19	6	1	9	-9.87
ACCG22B2	1	5.99	0.28	6	1	9	-8.71
ACCG22D1	0	6	0.2	6	1	9	-10.71
ACCG22D2	1	5.99	0.27	6	1	9	-8.04
ACC_22E1	0	6	0.2	6	1	9	-11.43

ACC_22E2	1	5.99	0.28	6	1	9	-9
ACC_22H1	0	6	0.19	6	2	9	-8.9
ACC_22H2	1	6	0.26	6	2	9	-6.74
ACC_22J1	0	6	0.19	6	2	9	-8.9
ACC_22J2	1	6	0.26	6	2	9	-6.74
ACC_22L1	0	6	0.19	6	1	9	-9.87
ACC_22L2	1	6	0.26	6	1	9	-7.22
ACC_22M1	0	6	0.19	6	1	9	-9.87
ACC_22M2	1	5.99	0.27	6	1	9	-8.04
ACCG22O1	0	6	0.21	6	1	9	-12.06
ACCG22O2	1	5.99	0.28	6	1	9	-9
ACC_301	0	5.6	1.25	6	1	9	-2.73
ACC_302	1	5.58	1.3	6	1	9	-2.62
ACC_311	0	5.93	0.58	6	1	9	-6.47
ACC_312	1	5.9	0.67	6	1	9	-5.42
ACC_32A1	0	6	0.23	6	2	9	-8.63
ACC_32A2	1	5.99	0.27	6	2	9	-7
ACC_32B1	0	6	0.24	6	1	9	-9.53
ACC_32B2	1	5.99	0.27	6	1	9	-7.42
ACC_32C1	0	5.99	0.26	6	1	9	-11.34
ACC_32C2	1	5.99	0.3	6	1	9	-9.46
ACC_32D1	0	5.99	0.24	6	1	9	-9.91
ACC_32D2	1	5.99	0.28	6	1	9	-8.15
ACCG32F1	0	6	0.24	6	2	9	-7.92
ACCG32F2	1	5.99	0.28	6	1	9	-8.47
ACC_32H1	0	6	0.23	6	2	9	-8.63
ACC_32H2	1	5.99	0.27	6	2	9	-7
ACC_32J1	0	6	0.23	6	2	9	-8.63
ACC_32J2	1	5.99	0.27	6	2	9	-7
ACC_32K1	0	6	0.23	6	2	9	-8.63
ACC_32K2	1	5.99	0.27	6	2	9	-7
ACC_32L1	0	6	0.23	6	2	9	-8.63
ACC_32L2	1	5.99	0.27	6	1	9	-7.42
ACC_32M1	0	6	0.23	6	2	9	-8.63
ACC_32M2	1	5.99	0.27	6	2	9	-7
ACCG32N1	0	6	0.24	6	1	9	-8.83
ACCG32N2	1	5.99	0.28	6	1	9	-8.47
ACC_401	0	5.57	1.36	6	1	9	-2.75
ACC_402	1	5.56	1.37	6	1	9	-2.64
ACC_40A1	0	5.75	1.07	6	1	9	-3.94
ACC_40A2	1	5.78	1.04	6	1	9	-4.04
ACC_40B1	0	5.79	0.91	6	1	9	-3.85
ACC_40B2	1	5.81	0.9	6	1	9	-3.94
ACC_40C1	0	5.78	0.96	6	1	9	-3.92
ACC_40C2	1	5.81	0.91	6	1	9	-3.97
ACC_40D1	0	5.78	0.95	6	1	9	-3.91
ACC_40D2	1	5.8	0.93	6	1	9	-4

ACC_40E1	0	5.78	0.96	6	1	9	-3.92
ACC_40E2	1	5.8	0.94	6	1	9	-4.02
ACC_40F1	0	5.79	0.94	6	1	9	-3.89
ACC_40F2	1	5.81	0.89	6	1	9	-3.93
ACC_40G1	0	5.78	0.95	6	1	9	-3.91
ACC_40G2	1	5.81	0.92	6	1	9	-3.98
ACC_411	0	5.78	0.94	6	1	9	-3.91
ACC_412	1	5.81	0.91	6	1	9	-3.96
ACC_421	0	5.96	0.46	6	1	9	-9.17
ACC_422	1	5.98	0.42	6	1	9	-8.64
ACCG43B1	0	5.98	0.38	6	1	9	-9.5
ACCG43B2	1	5.99	0.34	6	1	9	-7.66
ACC_43C1	0	5.98	0.37	6	1	9	-9.36
ACC_43C2	1	5.99	0.34	6	1	9	-7.51
ACC_43D1	0	5.98	0.38	6	1	9	-9.61
ACC_43D2	1	5.99	0.34	6	1	9	-7.66
ACC_43E1	0	5.98	0.39	6	1	9	-9.64
ACC_43E2	1	5.98	0.37	6	1	9	-8.64
ACC_43G1	0	5.98	0.35	6	1	9	-8.87
ACC_43G2	1	5.99	0.33	6	2	9	-7
ACCG43I1	0	5.98	0.38	6	1	9	-9.54
ACCG43I2	1	5.99	0.36	6	1	9	-8.28
ACC_441	0	5.97	0.4	6	1	9	-9.03
ACC_442	1	5.98	0.36	6	1	9	-7.49
ACCG45B1	0	5.99	0.28	6	1	9	-10.24
ACCG45B2	1	6	0.25	6	1	9	-4.95
ACC_45C1	0	5.99	0.27	6	1	9	-9.8
ACC_45C2	1	6	0.25	6	1	9	-4.95
ACC_45D1	0	5.99	0.29	6	1	9	-10.92
ACC_45D2	1	6	0.26	6	1	9	-6.76
ACC_45E1	0	5.99	0.28	6	1	9	-10.77
ACC_45E2	1	6	0.25	6	1	9	-5.62
ACCG45I1	0	5.99	0.29	6	1	9	-10.92
ACCG45I2	1	6	0.24	6	1	9	-4.2
ACC_461	0	5.98	0.34	6	1	9	-7.92
ACC_462	1	5.99	0.33	6	1	9	-6.37
ACCG47C1	0	6	0.16	6	1	9	-0.5
ACCG47C2	1	6.01	0.19	6	1	9	2.31
ACC_47D1	0	6	0.16	6	1	9	-0.5
ACC_47D2	1	6.01	0.19	6	1	9	4.7
ACC_47E1	0	6	0.16	6	2	9	2.49
ACC_47E2	1	6.01	0.18	6	2	9	7.55
ACC_47F1	0	6	0.16	6	2	9	2.49
ACC_47F2	1	6.01	0.18	6	2	9	7.55
ACCG47I1	0	6	0.16	6	1	9	-0.5
ACCG47I2	1	6.01	0.18	6	2	9	7.55
ACC_50A1	0	5.53	1.46	6	1	9	-2.71

ACC_50A2	1	5.51	1.49	6	1	9	-2.6
ACC_501	0	5.56	1.38	6	1	9	-2.75
ACC_502	1	5.54	1.41	6	1	9	-2.63
ACC_511	0	5.75	1	6	1	9	-3.57
ACC_512	1	5.75	1.02	6	1	9	-3.43
ACC_521	0	5.97	0.42	6	1	9	-9.78
ACC_522	1	5.97	0.43	6	1	9	-9
ACC_53A1	0	5.98	0.36	6	1	9	-9.36
ACC_53A2	1	5.98	0.35	6	1	9	-8.35
ACC_53B1	0	5.98	0.38	6	1	9	-9.79
ACC_53B2	1	5.98	0.36	6	1	9	-8.76
ACC_53D1	0	5.98	0.37	6	1	9	-9.63
ACC_53D2	1	5.98	0.36	6	1	9	-8.67
ACC_53E1	0	5.98	0.35	6	1	9	-9
ACC_53E2	1	5.98	0.34	6	1	9	-8.1
ACC_53F1	0	5.98	0.34	6	1	9	-8.83
ACC_53F2	1	5.98	0.34	6	1	9	-7.96
ACCG53G1	0	5.98	0.34	6	1	9	-8.44
ACCG53G2	1	5.98	0.35	6	1	9	-8.23
ACCG53J1	0	5.98	0.34	6	1	9	-8.44
ACCG53J2	1	5.98	0.34	6	2	9	-7.81
ACCG53M1	0	5.98	0.35	6	1	9	-8.8
ACCG53M2	1	5.98	0.36	6	1	9	-8.67
ACC_541	0	5.98	0.34	6	1	9	-9
ACC_542	1	5.98	0.34	6	1	9	-7.62
ACC_55A1	0	6	0.22	6	1	9	-8.15
ACC_55A2	1	6	0.2	6	2	9	-1.49
ACC_55B1	0	6	0.22	6	1	9	-7.52
ACC_55B2	1	6	0.21	6	1	9	-3.02
ACC_55D1	0	6	0.22	6	1	9	-7.52
ACC_55D2	1	6	0.21	6	1	9	-3.02
ACC_55E1	0	6	0.23	6	1	9	-9.23
ACC_55E2	1	6	0.21	6	1	9	-4.34
ACC_55F1	0	6	0.22	6	1	9	-8.15
ACC_55F2	1	6	0.21	6	1	9	-3.02
ACCG55G1	0	6	0.22	6	1	9	-7.52
ACCG55G2	1	6	0.21	6	1	9	-3.02
ACC_55I1	0	6	0.22	6	2	9	-6.8
ACC_55I2	1	6	0.2	6	2	9	-1.49
ACC_55L1	0	6	0.22	6	2	9	-6.8
ACC_55L2	1	6	0.2	6	2	9	-1.49
ACCG55M1	0	6	0.22	6	1	9	-8.15
ACCG55M2	1	6	0.21	6	1	9	-3.02
ACC_601	0	5.58	1.33	6	1	9	-2.75
ACC_602	1	5.56	1.35	6	1	9	-2.64
ACC_611	0	5.83	0.86	6	1	9	-4.45
ACC_612	1	5.84	0.84	6	1	9	-4.36

ACC_621	0	5.96	0.45	6	1	9	-9.27
ACC_622	1	5.97	0.42	6	1	9	-9.03
ACC_63A1	0	5.98	0.34	6	1	9	-10.2
ACC_63A2	1	5.99	0.32	6	2	9	-7.78
ACC_63B1	0	5.98	0.34	6	1	9	-10.33
ACC_63B2	1	5.99	0.33	6	1	9	-8.47
ACC_63D1	0	5.98	0.34	6	1	9	-10.26
ACC_63D2	1	5.99	0.33	6	1	9	-8.47
ACC_63E1	0	5.98	0.37	6	1	9	-10.8
ACC_63E2	1	5.98	0.36	6	1	9	-9.34
ACC_63F1	0	5.98	0.33	6	1	9	-10.05
ACC_63F2	1	5.99	0.32	6	2	9	-7.78
ACCG63G1	0	5.98	0.33	6	1	9	-10.05
ACCG63G2	1	5.99	0.32	6	1	9	-7.98
ACCG63L1	0	5.98	0.33	6	1	9	-9.96
ACCG63L2	1	5.99	0.32	6	2	9	-7.78
ACCG63M1	0	5.98	0.34	6	1	9	-10.33
ACCG63M2	1	5.99	0.33	6	1	9	-8.47
ACC_641	0	5.97	0.42	6	1	9	-9.28
ACC_642	1	5.98	0.38	6	1	9	-8.75
ACC_65A1	0	5.99	0.3	6	1	9	-10.93
ACC_65A2	1	5.99	0.28	6	1	9	-7.58
ACC_65B1	0	5.99	0.3	6	1	9	-11.05
ACC_65B2	1	5.99	0.28	6	1	9	-7.92
ACC_65D1	0	5.99	0.3	6	1	9	-11.16
ACC_65D2	1	5.99	0.28	6	1	9	-7.92
ACC_65E1	0	5.98	0.33	6	1	9	-11.85
ACC_65E2	1	5.99	0.31	6	1	9	-9.91
ACC_65F1	0	5.99	0.28	6	2	9	-10.35
ACC_65F2	1	5.99	0.27	6	2	9	-7.2
ACCG65G1	0	5.99	0.29	6	1	9	-10.52
ACCG65G2	1	5.99	0.27	6	2	9	-7.2
ACCG65M1	0	5.99	0.3	6	1	9	-11.26
ACCG65M2	1	5.99	0.27	6	2	9	-7.2
ACC_661	0	5.97	0.37	6	1	9	-8.83
ACC_662	1	5.98	0.34	6	1	9	-7.52
ACCG67E1	0	6	0.22	6	1	9	-12.98
ACCG67E2	1	6	0.21	6	1	9	-5.71
ACC_67I1	0	6	0.2	6	2	9	-9.44
ACC_67I2	1	6	0.19	6	2	9	0.42
ACC_67J1	0	6	0.2	6	2	9	-9.44
ACC_67J2	1	6	0.19	6	2	9	0.42
ACCG67M1	0	6	0.21	6	1	9	-12.11
ACCG67M2	1	6	0.19	6	2	9	0.42
DOWTM1	0	1.98	0.15	2	1	2	-6.16
DOWTM2	1	1.97	0.17	2	1	2	-5.42
WTM_011	0	5.97	0.38	6	1	9	-11.32

WTM_012	1	5.96	0.43	6	1	9	-9.43
WTM_021	0	95.74	4.83	96	5	99	-18.16
WTM_022	1	95.73	4.96	96	1	99	-17.84
WTM_031	0	5.99	0.27	6	1	9	-16.65
WTM_032	1	5.99	0.24	6	1	9	-13.94
WTM_041	0	5.99	0.27	6	1	9	-16.55
WTM_042	1	5.99	0.29	6	1	9	-14.09
WTM_051	0	5.99	0.21	6	1	9	-17.15
WTM_052	1	5.99	0.23	6	1	9	-12.83
WTMG06B1	0	6	0.11	6	1	9	-21.72
WTMG06B2	1	6	0.12	6	1	9	-2.35
WTM_06D1	0	6	0.11	6	1	9	-21.72
WTM_06D2	1	6	0.11	6	2	9	7.53
WTM_06E1	0	6	0.11	6	1	9	-21.72
WTM_06E2	1	6	0.11	6	2	9	7.53
WTM_06F1	0	6	0.1	6	2	9	-15.26
WTM_06F2	1	6	0.11	6	2	9	7.53
WTM_06G1	0	6	0.1	6	2	9	-15.26
WTM_06G2	1	6	0.11	6	2	9	7.53
WTM_06H1	0	6	0.1	6	2	9	-15.26
WTM_06H2	1	6	0.11	6	2	9	7.53
WTM_06I1	0	6	0.1	6	2	9	-15.26
WTM_06I2	1	6	0.11	6	2	9	7.53
WTM_06J1	0	6	0.1	6	2	9	-15.26
WTM_06J2	1	6	0.11	6	2	9	7.53
WTM_06L1	0	6	0.1	6	2	9	-15.26
WTM_06L2	1	6	0.11	6	2	9	7.53
WTMG06M1	0	6	0.11	6	1	9	-25.48
WTMG06M2	1	6	0.11	6	2	9	7.53
WTM_07A1	0	993.77	47.04	996	1	999	-20.99
WTM_07A2	1	993.62	48.56	996	1	999	-20.34
WTM_07B1	0	5.99	0.18	6	1	9	-14.82
WTM_07B2	1	6	0.2	6	1	9	-9.78
WTM_08A1	0	995.44	23.54	996	3	999	-42.08
WTM_08A2	1	995.53	21.75	996	1	999	-45.62
WTM_08B1	0	6	0.11	6	1	9	-19.12
WTM_08B2	1	6	0.11	6	3	9	8.75
WTMG101	0	5.99	0.26	6	1	9	-16.51
WTMG102	1	5.99	0.28	6	1	9	-14.02
WTM_11A1	0	994.88	33.34	996	1	999	-29.73
WTM_11A2	1	995.29	26.62	996	1	999	-37.24
WTM_11B1	0	6	0.13	6	2	9	-16.6
WTM_11B2	1	6	0.13	6	2	9	-1.11
WTM_121	0	5.99	0.25	6	1	9	-16.32
WTM_122	1	5.99	0.25	6	1	9	-12.51
WTM_13B1	0	6	0.17	6	1	9	-22.74
WTM_13B2	1	6	0.12	6	1	9	-2.35

WTMG13C1	0	6	0.16	6	1	9	-21.69
WTMG13C2	1	6	0.11	6	2	9	7.53
WTM_141	0	5.99	0.24	6	1	9	-16.24
WTM_142	1	5.99	0.25	6	1	9	-12.79
WTM_15A1	0	6	0.16	6	1	9	-24.31
WTM_15A2	1	6	0.14	6	1	9	-7.76
WTM_15B1	0	6	0.15	6	1	9	-23.39
WTM_15B2	1	6	0.13	6	2	9	-2.33
WTM_15C1	0	6	0.15	6	1	9	-22.61
WTM_15C2	1	6	0.13	6	2	9	-2.33
WTM_15D1	0	6	0.15	6	1	9	-22.61
WTM_15D2	1	6	0.14	6	1	9	-11.51
WTMG15F1	0	6	0.14	6	1	9	-21.51
WTMG15F2	1	6	0.13	6	2	9	-2.33
WTM_15G1	0	6	0.15	6	1	9	-22.61
WTM_15G2	1	6	0.13	6	2	9	-2.33
WTM_15H1	0	6	0.15	6	1	9	-22.61
WTM_15H2	1	6	0.13	6	2	9	-2.33
WTM_15I1	0	6	0.15	6	1	9	-22.61
WTM_15I2	1	6	0.13	6	2	9	-2.33
WTMG15K1	0	6	0.14	6	1	9	-21.51
WTMG15K2	1	6	0.13	6	2	9	-2.33
WTM_15L1	0	6	0.14	6	1	9	-21.51
WTM_15L2	1	6	0.13	6	2	9	-2.33
WTM_171	0	5.99	0.22	6	1	9	-21.38
WTM_172	1	5.99	0.28	6	1	9	-14.95
WTM_181	0	5.99	0.18	6	1	9	-21.83
WTM_182	1	5.99	0.25	6	1	9	-15.42
WTM_191	0	5.99	0.18	6	1	9	-21.83
WTM_192	1	5.99	0.24	6	1	9	-15.07
WTM_20E1	0	6	0.1	6	1	9	-33.4
WTM_20E2	1	6	0.17	6	1	9	-18
WTM_20H1	0	6	0.09	6	2	9	-28.04
WTM_20H2	1	6	0.15	6	2	9	-12.98
WTM_20J1	0	6	0.09	6	2	9	-28.04
WTM_20J2	1	6	0.15	6	2	9	-12.98
WTM_20K1	0	6	0.09	6	2	9	-28.04
WTM_20K2	1	6	0.15	6	2	9	-12.98
WTM_20M1	0	6	0.09	6	2	9	-28.04
WTM_20M2	1	6	0.15	6	2	9	-12.98
WTMG20N1	0	6	0.1	6	1	9	-33.4
WTMG20N2	1	6	0.17	6	1	9	-18
WTM_21A1	0	994.32	40.74	996	1	999	-24.26
WTM_21A2	1	993.63	48.38	996	1	999	-20.35
WTM_21B1	0	5.99	0.16	6	1	9	-22.79
WTM_21B2	1	5.99	0.19	6	2	9	-10.4
WTM_221	0	6	0.08	6	1	9	-36.05

WTM_222	1	6	0.14	6	1	9	-16.14
WTM_23A1	0	995.82	12.83	996	60	999	-72.93
WTM_23A2	1	995.53	21.51	996	3	999	-45.63
WTM_23B1	0	6	0.06	6	3	9	0
WTM_23B2	1	6	0.11	6	2	9	-1.73
WTMG241	0	5.99	0.21	6	1	9	-21.4
WTMG242	1	5.99	0.27	6	1	9	-14.78
WTM_25A1	0	995.63	19.04	996	3	999	-51.56
WTM_25A2	1	994.82	34.26	996	1	999	-28.83
WTM_25B1	0	6	0.07	6	3	9	-14.02
WTM_25B2	1	6	0.14	6	2	9	-10.33
WTM_261	0	5.99	0.19	6	1	9	-21.09
WTM_262	1	5.99	0.26	6	1	9	-14.59
WTMG27C1	0	6	0.12	6	1	9	-32.2
WTMG27C2	1	6	0.2	6	1	9	-16.3
WTMG27D1	0	6	0.11	6	1	9	-30.71
WTMG27D2	1	6	0.17	6	2	9	-10.92
WTM_281	0	5.99	0.19	6	1	9	-21.09
WTM_282	1	5.99	0.26	6	1	9	-14.46
WTMG29B1	0	6	0.11	6	1	9	-30.71
WTMG29B2	1	6	0.18	6	1	9	-17.52
WTM_29C1	0	6	0.13	6	1	9	-32.94
WTM_29C2	1	6	0.18	6	1	9	-17.52
WTM_29D1	0	6	0.13	6	1	9	-32.94
WTM_29D2	1	6	0.17	6	1	9	-16.63
WTM_29F1	0	6	0.1	6	2	9	-27.93
WTM_29F2	1	6	0.16	6	2	9	-13.9
WTM_29I1	0	6	0.11	6	1	9	-30.71
WTM_29I2	1	6	0.18	6	1	9	-17.52
WTM_29J1	0	6	0.1	6	2	9	-27.93
WTM_29J2	1	6	0.16	6	2	9	-13.9
WTMG29L1	0	6	0.11	6	1	9	-30.71
WTMG29L2	1	6	0.17	6	1	9	-16.63
WTM_301	0	5.98	0.29	6	1	9	-14.22
WTM_302	1	5.98	0.33	6	1	9	-11.98
WTM_311	0	5.99	0.16	6	1	9	-14.32
WTM_312	1	5.99	0.18	6	3	9	-8.31
WTM_321	0	5.98	0.33	6	1	9	-14.16
WTM_322	1	5.98	0.37	6	1	9	-12.11
WTM_331	0	5.98	0.33	6	1	9	-14.43
WTM_332	1	5.98	0.36	6	1	9	-12.55
WTM_351	0	5.98	0.28	6	1	9	-14.15
WTM_352	1	5.98	0.3	6	1	9	-11.8
WTM_361	0	5.98	0.27	6	1	9	-13.99
WTM_362	1	5.98	0.31	6	1	9	-12.01
WTM_37A1	0	6	0.1	6	2	9	-15.26
WTM_37A2	1	6	0.13	6	2	9	-11.02

WTM_37C1	0	6	0.11	6	1	9	-21.72
WTM_37C2	1	6	0.16	6	1	9	-18.4
WTM_37E1	0	6	0.1	6	2	9	-15.26
WTM_37E2	1	6	0.13	6	2	9	-11.02
WTM_37G1	0	6	0.1	6	2	9	-15.26
WTM_37G2	1	6	0.13	6	2	9	-11.02
WTM_37H1	0	6	0.1	6	2	9	-15.26
WTM_37H2	1	6	0.13	6	2	9	-11.02
WTM_37I1	0	6	0.1	6	2	9	-15.26
WTM_37I2	1	6	0.13	6	2	9	-11.02
WTM_37J1	0	6	0.1	6	2	9	-15.26
WTM_37J2	1	6	0.13	6	2	9	-11.02
WTM_37K1	0	6	0.1	6	2	9	-15.26
WTM_37K2	1	6	0.13	6	2	9	-11.02
WTM_37L1	0	6	0.1	6	2	9	-15.26
WTM_37L2	1	6	0.13	6	2	9	-11.02
WTMG37M1	0	6	0.11	6	1	9	-21.72
WTMG37M2	1	6	0.13	6	2	9	-11.02
WTM_38A1	0	992.27	60.75	996	1	999	-16.22
WTM_38A2	1	991.24	68.62	996	1	999	-14.33
WTM_38B1	0	5.99	0.25	6	1	9	-13.33
WTM_38B2	1	5.98	0.29	6	1	9	-11.93
WTM_39A1	0	995.82	13.47	996	13	999	-72.93
WTM_39A2	1	995.53	21.67	996	2	999	-45.62
WTM_39B1	0	6	0.09	6	1	9	-18.38
WTM_39B2	1	6	0.11	6	2	9	-1.73
WTMG401	0	5.98	0.32	6	1	9	-13.96
WTMG402	1	5.98	0.36	6	1	9	-12.1
WTM_41A1	0	995.44	23.6	996	1	999	-42.08
WTM_41A2	1	994.57	37.69	996	1	999	-26.3
WTM_41B1	0	6	0.11	6	1	9	-12.2
WTM_41B2	1	6	0.18	6	1	9	-16.1
WTM_421	0	5.98	0.28	6	1	9	-13.45
WTM_422	1	5.98	0.31	6	1	9	-11.42
WTMG431	0	6	0.15	6	1	9	-20.34
WTMG432	1	6	0.1	6	2	9	3.86
WTM_441	0	5.98	0.28	6	1	9	-13.36
WTM_442	1	5.98	0.32	6	1	9	-11.6
WTM_45A1	0	6	0.13	6	1	9	-18.93
WTM_45A2	1	6	0.14	6	1	9	-14.41
WTM_45B1	0	6	0.13	6	1	9	-18.93
WTM_45B2	1	6	0.13	6	2	9	-11.02
WTM_45C1	0	6	0.13	6	1	9	-18.93
WTM_45C2	1	6	0.15	6	1	9	-16.75
WTM_45D1	0	6	0.13	6	1	9	-18.93
WTM_45D2	1	6	0.15	6	1	9	-16.75
WTMG45F1	0	6	0.12	6	2	9	-12.45

WTMG45F2	1	6	0.15	6	1	9	-16.75
WTM_45I1	0	6	0.13	6	1	9	-18.93
WTM_45I2	1	6	0.14	6	1	9	-14.41
WTMG45L1	0	6	0.13	6	1	9	-18.93
WTMG45L2	1	6	0.15	6	1	9	-16.75
WTMDSO1	0	9973.68	469.76	9996	2	9999	-20.99
WTMDSO2	1	9972.24	484.92	9996	1	9999	-20.35
WTMDSN1	0	9990.42	235.06	9996	3	9999	-42.09
WTMDSN2	1	9991.25	217.2	9996	30	9999	-45.62
WTMDSA1	0	9967.98	527.25	9996	2	9999	-18.76
WTMDSA2	1	9967.4	532.67	9996	1	9999	-18.56
WTMDCO1	0	9979.23	407.56	9996	1	9999	-24.26
WTMDCO2	1	9972.41	481.56	9996	14	9999	-20.37
WTMDCN1	0	9994.46	112.32	9996	1800	9999	-72.93
WTMDCN2	1	9991.39	210.86	9996	21	9999	-45.71
WTMDCA1	0	9977.43	428.26	9996	1	9999	-23.02
WTMDCA2	1	9967.5	530.88	9996	7	9999	-18.56
WTMDTO1	0	9958.65	608.4	9996	1	9999	-16.22
WTMDTO2	1	9948.24	688.23	9996	1	9999	-14.33
WTMDTN1	0	9994.13	136.8	9996	13	9999	-72.93
WTMDTN2	1	9991.24	217.41	9996	60	9999	-45.62
WTMDTA1	0	9956.72	624.33	9996	1	9999	-15.83
WTMDTA2	1	9943.41	722.43	9996	1	9999	-13.66
LBSG311	0	3.07	2.44	1	1	9	0.5
LBSG312	1	3.9	2.49	6	1	9	-0.15
LBSGHPW1	0	415.59	467.75	50	1	999	0.43
LBSGHPW2	1	576.21	475.68	996	1	999	-0.25
LBSDPFT1	0	3.15	2.46	2	1	9	0.5
LBSDPFT2	1	3.98	2.48	6	1	9	-0.15
LBSDWSS1	0	2.22	1.73	1	1	9	1.55
LBSDWSS2	1	2.94	2.06	3	1	9	0.77
LBSGSOC1	0	3.9	2.09	4	1	9	-0.08
LBSGSOC2	1	4.47	2.05	6	1	9	-0.52
DOLOP1	0	1	0	1	1	1	NA
DOLOP2	1	1	0	1	1	1	NA
LOP_0151	0	2.67	2.4	1	1	9	0.89
LOP_0152	1	3.52	2.55	2	1	9	0.15
LOPG0201	0	72.96	39.53	96	1	99	-1.13
LOPG0202	1	68.96	41.6	96	1	99	-0.88
LOP_0301	0	3.5	2.11	2	1	9	0.68
LOP_0302	1	4.2	2.18	6	1	9	0.03
LOPG0401	0	91.67	19.42	96	1	99	-4.21
LOPG0402	1	92.7	17.08	96	1	99	-4.87
LOPG0501	0	88.35	24.89	96	1	99	-2.91
LOPG0502	1	88.36	24.93	96	1	99	-2.91
LOP_0601	0	3.45	2.14	2	1	9	0.62
LOP_0602	1	4.16	2.22	6	1	9	-0.02

LOPG0701	0	87.78	26.12	96	1	99	-2.86
LOPG0702	1	89.19	23.81	96	1	99	-3.2
LOP_0801	0	3.41	2.18	2	1	9	0.6
LOP_0802	1	4.15	2.23	6	1	9	-0.02
LOP_81A1	0	5.44	1.64	6	1	9	-1.77
LOP_81A2	1	5.69	1.38	6	1	9	-2.14
LOP_81B1	0	5.47	1.55	6	1	9	-1.71
LOP_81B2	1	5.71	1.31	6	1	9	-2.01
LOP_81C1	0	5.48	1.54	6	1	9	-1.69
LOP_81C2	1	5.71	1.31	6	1	9	-2.03
LOP_81D1	0	5.5	1.49	6	1	9	-1.63
LOP_81D2	1	5.73	1.27	6	1	9	-1.92
LOP_81E1	0	5.5	1.49	6	1	9	-1.63
LOP_81E2	1	5.73	1.26	6	1	9	-1.91
LOPG0821	0	89.44	24.1	96	1	99	-3.36
LOPG0822	1	92	19.17	96	1	99	-4.48
LOPG0831	0	92.86	17.02	96	1	99	-5.12
LOPG0832	1	94.35	12.6	96	1	99	-7.14
LOPG0841	0	93.48	15.38	96	1	99	-5.78
LOPG0842	1	94.11	13.5	96	1	99	-6.69
LOPG0851	0	95.35	8.14	96	1	99	-11.22
LOPG0852	1	95.48	7.49	96	1	99	-12.24
LOPG0861	0	95.22	8.85	96	1	99	-10.36
LOPG0862	1	95.59	6.76	96	1	99	-13.56
LOP_0901	0	3.47	2.12	2	1	9	0.64
LOP_0902	1	4.19	2.17	6	1	9	0.01
LOPG1001	0	89.27	24.22	96	1	99	-3.29
LOPG1002	1	91.99	19.08	96	1	99	-4.45
EDUDH041	0	3.73	1.29	4	1	9	1.3
EDUDH042	1	3.52	1.37	4	1	9	0.82
EDUDR041	0	3.05	1.44	4	1	9	0.54
EDUDR042	1	2.78	1.51	3	1	9	0.69
SDC_81	0	2.17	1.27	2	1	9	3.26
SDC_82	1	2.34	1.53	2	1	9	2.71
SDCG91	0	5.36	1.73	6	1	9	-1.87
SDCG92	1	5.42	1.75	6	1	9	-1.83
SDCGCB131	0	1.25	1.06	1	1	9	6.57
SDCGCB132	1	1.35	1.34	1	1	9	5.24
SDC_5A_11	0	1.6	1.19	1	1	9	3.48
SDC_5A_12	1	1.66	1.39	1	1	9	3.5
SDCDFOLS1	0	1.32	1.03	1	1	9	6.03
SDCDFOLS2	1	1.39	1.27	1	1	9	5.14
DHH_OWN1	0	1.34	1.01	1	1	9	6.08
DHH_OWN2	1	1.45	1.27	1	1	9	4.98
SDCGLHM1	0	1.41	1.09	1	1	9	4.78
SDCGLHM2	1	1.47	1.34	1	1	9	4.43
SDCFIMM1	0	2.02	0.98	2	1	9	6.22

SDCFIMM2	1	2.09	1.25	2	1	9	4.95
SDCGRES1	0	5.61	1.37	6	1	9	-2.05
SDCGRES2	1	5.61	1.45	6	1	9	-1.65
SDCGCGT1	0	1.33	1.24	1	1	9	5.58
SDCGCGT2	1	1.42	1.5	1	1	9	4.61
PMKPROXY1	0	5.4	1.64	6	1	9	-2.28
PMKPROXY2	1	5.21	1.84	6	1	9	-1.79
DOINS1	0	1.65	0.48	2	1	2	-0.63
DOINS2	1	1.64	0.48	2	1	2	-0.57
INS_11	0	4.39	2.31	6	1	9	-0.65
INS_12	1	4.35	2.35	6	1	9	-0.58
INS_1A1	0	4.89	1.92	6	1	9	-0.97
INS_1A2	1	4.83	2.01	6	1	9	-0.89
INS_1B1	0	4.75	2.15	6	1	9	-0.99
INS_1B2	1	4.73	2.16	6	1	9	-0.91
INS_1C1	0	4.92	1.86	6	1	9	-0.95
INS_1C2	1	4.89	1.89	6	1	9	-0.85
INS_21	0	5.83	0.91	6	1	9	-4.69
INS_22	1	5.8	0.98	6	1	9	-4.12
INS_2A1	0	5.89	0.68	6	1	9	-5.53
INS_2A2	1	5.91	0.68	6	1	9	-5.07
INS_2B1	0	5.88	0.77	6	1	9	-5.64
INS_2B2	1	5.89	0.78	6	1	9	-5.34
INS_2C1	0	5.89	0.68	6	1	9	-5.53
INS_2C2	1	5.91	0.67	6	1	9	-5
INS_31	0	4.46	2.26	6	1	9	-0.68
INS_32	1	4.45	2.27	6	1	9	-0.61
INS_3A1	0	5.12	1.79	6	1	9	-1.14
INS_3A2	1	5.18	1.78	6	1	9	-1.17
INS_3B1	0	4.96	2.07	6	1	9	-1.2
INS_3B2	1	5.04	2.03	6	1	9	-1.24
INS_3C1	0	5.12	1.77	6	1	9	-1.13
INS_3C2	1	5.19	1.75	6	1	9	-1.15
INS_41	0	4.6	2.22	6	1	9	-0.78
INS_42	1	4.58	2.23	6	1	9	-0.7
INS_4A1	0	5.31	1.77	6	1	9	-1.04
INS_4A2	1	5.35	1.77	6	1	9	-1.05
INS_4B1	0	5.17	2.05	6	1	9	-1.19
INS_4B2	1	5.22	2.03	6	1	9	-1.2
INS_4C1	0	5.31	1.78	6	1	9	-1.05
INS_4C2	1	5.36	1.76	6	1	9	-1.04
DOFSC1	0	1.26	0.44	1	1	2	1.07
DOFSC2	1	1.26	0.44	1	1	2	1.12
FSC_0101	0	2.54	2.29	1	1	9	1.01
FSC_0102	1	2.57	2.34	1	1	9	1.06
FSC_0201	0	3.79	1.55	3	1	9	1.04
FSC_0202	1	3.82	1.62	3	1	9	1.14

FSC_0301	0	3.81	1.52	3	1	9	1.09
FSC_0302	1	3.83	1.6	3	1	9	1.18
FSC_0401	0	3.8	1.54	3	1	9	1.06
FSC_0402	1	3.82	1.61	3	1	9	1.14
FSC_0501	0	5.27	1.36	6	1	9	-1.13
FSC_0502	1	5.37	1.31	6	1	9	-1.29
FSC_0601	0	5.28	1.34	6	1	9	-1.1
FSC_0602	1	5.38	1.29	6	1	9	-1.25
FSC_0701	0	5.9	0.65	6	1	9	-3.38
FSC_0702	1	5.91	0.64	6	1	9	-3.16
FSC_0801	0	5.6	1.4	6	1	9	-2.19
FSC_0802	1	5.63	1.42	6	1	9	-1.99
FSC_0811	0	5.9	0.87	6	1	9	-3.11
FSC_0812	1	5.92	0.94	6	1	9	-2.52
FSC_0901	0	5.6	1.4	6	1	9	-2.21
FSC_0902	1	5.64	1.42	6	1	9	-1.99
FSC_1001	0	5.62	1.35	6	1	9	-2.15
FSC_1002	1	5.65	1.37	6	1	9	-1.92
FSC_1101	0	5.63	1.33	6	1	9	-2.13
FSC_1102	1	5.66	1.35	6	1	9	-1.89
FSC_1201	0	5.85	0.98	6	1	9	-2.89
FSC_1202	1	5.88	1.02	6	1	9	-2.37
FSC_1211	0	6.01	0.56	6	1	9	-1.63
FSC_1212	1	6.03	0.64	6	1	9	-0.59
FSC_1301	0	5.96	0.55	6	1	9	-4.76
FSC_1302	1	5.97	0.55	6	1	9	-4.3
FSC_1401	0	5.96	0.55	6	1	9	-4.68
FSC_1402	1	5.97	0.55	6	1	9	-4.22
FSC_1411	0	6.02	0.27	6	1	9	6.9
FSC_1412	1	6.02	0.28	6	2	9	7.49
FSC_1501	0	5.96	0.55	6	1	9	-4.73
FSC_1502	1	5.97	0.55	6	1	9	-4.29
FSC_1601	0	5.96	0.54	6	1	9	-4.62
FSC_1602	1	5.97	0.54	6	1	9	-4.14
FSCDHFS21	0	1.85	2.79	0	0	9	1
FSCDHFS22	1	1.86	2.83	0	0	9	1.04
FSCDAFS21	0	1.85	2.79	0	0	9	1
FSCDAFS22	1	1.86	2.83	0	0	9	1.04
FSCDCFS21	0	4.59	2.57	6	0	9	-1.18
FSCDCFS22	1	4.79	2.44	6	0	9	-1.38
INCG21	0	1.88	1.9	1	1	9	2.82
INCG22	1	2.35	2.26	1	1	9	2.09
INCG71	0	3.66	2.68	3	1	9	0.4
INCG72	1	4.32	2.56	6	1	9	-0.03
INCGHH1	0	3.75	1.39	4	1	9	-0.51
INCGHH2	1	3.43	1.46	4	1	9	-0.21
INCGPER1	0	23.69	38.38	4	1	99	1.39

INCGPER2	1	28.37	41.42	4	1	99	1.06
INCDRCA1	0	9.28	17.03	6	1	99	4.76
INCDRCA2	1	8.44	16.35	6	1	99	5.01
INCDRPR1	0	9.22	17.04	6	1	99	4.76
INCDRPR2	1	8.37	16.36	6	1	99	5.01
INCDRRS1	0	17.91	31.34	7	1	99	2.15
INCDRRS2	1	17.08	31.13	6	1	99	2.2
WTS_M1	0	512.41	719.89	277.58	6.4	11454.5	4.48
WTS_M2	1	446.6	709.73	233.47	2.15	10825.12	5.65