PhD Proposal

Noam Barda

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1 Abstract

1.1 Background

Since the early 1990s, and more so in the last few years, multivariate risk models have been created to estimate patients' risk for different diseases over different time spans (e.g. [76, 13, 19]). These models are used to identify patients at risk and are capable of exact risk quantification over time[25]. Through their many variations, these risk models are included in different guidelines and occupy an important place in both primary prevention and diagnosis of different diseases[29, 25].

Such multivariate risk models have several characteristics:

- Their development has traditionally required extensive input from domain experts (clinicians) for the choice of predictors.
- Their performance is highest in the population used to develop them and is reduced on populations that are genetically or otherwise different[18, 3, 20].
- They are traditionally based on classic biostatistical models, usually logistic and Cox regression.

Such risk models have been particularly used for the diagnosis and prevention of cardiovascular disease (CVD), which despite reduced incidence in the developed world in recent years[43, 71], remains a significant cause of morbidity and mortality[53].

1.2 Goals

We intend to pursue three goals in this thesis:

- Recent advances in machine learning allow for a new approach to medical risk modeling[52]. Contrary to the classic approach that emphasizes domain knowledge for the pre-specification of risk factors, novel methods rely instead on sophisticated algorithms being presented with thousands of candidate variables and selecting the relevant ones by themselves. These variables are then used for the actual model building[74]. Such technologies allow a more standardized "one-size fits all" approach to risk modeling, utilizing a single comprehensive database with different outcomes[58]. We intend to establish a generic prediction framework allowing the standardized construction of validated predictive models for any outcome.
- Being ethnically distinct from the US and European populations used to develop existing models, CVD risk models are expected to perform sub-optimally in the Israeli population, but such external validation has yet to be performed on a population-wide scale[45]. We intend to perform external validation of CVD predictive models on a wide sample of the Israeli population.
- Once the comparison has been performed, we will use the different models to simulate a wide-scale population-wide intervention on the Clalit's population using EHR data based on current guidelines[25].

1.3 Methods

The generic prediction framework will make use of a sparsity inducing algorithm fed with the majority of the variables in the Clalit's electronic health record. The algorithm will then choose the appropriate variables and construct a model. The model will first be tuned on a validation set and then evaluated on a test set.

To perform external validation and comparison, the three leading CVD models will be selected and recreated on the Clalit's database. The models will be compared in their original population composition and on a common sample corresponding to the population on which we intend to simulate our intervention.

The simulated CVD intervention will examine a retrospective cohort of patients, and will utilize existing knowledge regarding the mortality reduction attributed to statin and aspirin use to simulate the 10-year-outcomes of this cohort had existing guidelines been adhered to.

1.4 Importance

A generic prediction framework will allow easy construction of validated predictive models of high quality, with the variable selection portion affording possible biological insight.

External validation of CVD and mortality risk models, currently in wide use and integrated into guidelines, is of vital importance[48].

Simulating the intervention will allow us to gauge the potential effectiveness of interventions based on such risk models. Such interventions are becoming more and more possible with widespread electronic health record availability.

2 Hebrew Abstract

מתחילת שנות ה-90 החלה, ובשנים האחרונות גברה, יצירתם של מודלים רב-משתניים לחישוב סיכון למחלות שונות(לדוגמה [76, 13, 19]). מודלים אלו משמשים לזיהוי חולים בסיכון, ומאפשרים כימות מדויק של הסיכון לאורך שנים רבות[25]. כיום, בצורותיהן השונות, מודלים אלו כלולים בקווים המנחים של ארגונים מקצועיים רבים, ולהם מקום חשוב הן במניעה הראשונית והן באבחנה של מחלות [29, 25].

למודלים אלו מספר מאפיינים:

- פיתוחם דרש באופן מסורתי התייצעות נרחבת עם מומחי תוכן (קלינאים), על מנת שאלו יספקו את המידע הנדרש בנוגע למשתנים הנדרשים לחיזוי התוצא.
- ביצועיהם של מודלים אלו מיטבי כאשר משתמשים בהם באוכלוסיות עליהם פותחו, ופוחת באוכלוסיות השונות מאוכלוסיות אלו מבחינה גנטית או אחרת[18, 3, 20].
- המודלים מבוססים ככלל על שיטות ביוסטטיסטיות מסורתיות, בפרט על רגרסיה לוגיסטית ורגרסיית קוקס.

במודלים אלו נעשו שימוש בייחוד לחיזוי ומניעה של מחלה קרדיו-וסקולרית, אשר חרף הירידה בהיארעותה בעולם המפותח בשנים האחרונות[43, 71], נותרה סיבה חשובה לתחלואה ולתמותה[53].

כוונתנו להשיג שלוש מטרות בתזה זו:

- חידושים מודרניים בלמידה חישובית מאפשרים גישות חדשות למידול סיכון רפואי[52]. בניגוד לגישה הקיימת, המבוססת על שימוש בידע תחומי לפירוט-מראש של גורמי הסיכון, גישות מודרניות מתירות לאלגוריתם החישובי, המוזן עם מאות משתנים אפשריים, לברור מביניהם את המשתנים הרלוונטיים בכחות עצמו[74]. לאחר מכן, משתנים אלו משמשים לבניית המודל עצמו. טכנולוגיות אלו מאפשרות גישה יותר אחידה למידול סיכון, המשתמשת בבסיס נתונים נרחב יחיד עם תוצאים שונים[58].
- בהיותה מובחנת אתנית מהאוכלוסיות האמריקאיות והאירופאיות עליהן פותחו, ביצועיהם של מודלי חיזוי קרדיו-וסקולריים באוכלוסיה הישראלית צפויים להיות ירודים. השערה זו טרם נבדקה על אוכלוסיה גדולה, המייצגת את האוכלוסיה הישראלית כולה[45]. אנו מתכוונים לבדוק השערה זו על מדגם נרחב של האוכלוסיה הישראלית, בהקשר של חיזוי מחלה קרדיווסקולרית.
- אנו נשתמש במודלים השונים (הן הקיימים והן המודל שיפותח כחלק מעבודה זו) על מנת לבצע סימולציה של התערבות אוכלוסייתית רחבה המבוססת על מידע מהתיק הרפואי הממוחשב, וזאת לפי הקווים המנחים הקיימים[25].

השלד לחיזוי גנרי יעשה שימוש באלגוריתם המבצע בחירת משתנים כחלק מפעולתו. אלגוריתם זה יוזן עם מרבית המשתנים הזמינים בבסיס הנתונים של קופ"ח כללית, מהם יבחר המשתנים הרלוונטיים בהם יעשה שימוש לבניית מודל. המודל יכוונן על גבי אוכלוסיית פיתוח וייבדק מול אוכלוסיית בדיקה.

על מנת לבצע תיקוף חיצוני והשוואה, שלושת המודלים המובילים לחיזוי CVD ייבחרו מהספרות וייבנו מחדש על גבי בסיס הנתונים של הכללית. המודלים יושוו הן בהרכב האוכלוסיה המקורי בו נבנו והן בהרכב האוכלוסיה בו אנו עתידים לדמות התערבות.

סימולציית ההתערבות תבחן עקבה רטרוספקטיבית , ובאמצעות ידע קיים בנוגע להפחתת התמותה המיוחסת לשימוש בסטטינים ובאספירין, תדמה התוצאים ל-10 שנים של עקבה זו באם הקוים המנחים הקיימים היו מקויימים כלשונם, לפי המודלים הקיימים ולפי המודל החדש.

מסגרת לחיזוי גנרי תאפשר בניית מודלים מתוקפים ובאיכות גבוהה לחיזוי מחלות שונות, ועצם תהליך בחירת המשתנים יכול שיאפשר תובנות ביולוגיות.

תיקוף חיצוני של מודלים לחיזוי מחלה קרדיווסקולרית, המצויים בשימוש רחב ומשולבים בקווים המנחים, הוא בעל חשיבות מכרעת[12].

ביצוע והערכת ההתערבות המתוכננת יאפשר לנו לשפוט את היעילות של התערבויות שכאלה, להם חשיבות מיוחדות במניעת מחלות קרדיווסקולריות[62], ואשר הופכות אפשריות יותר ויותר עם הזמינות הגוברת של תיקים רפואיים ממוחשבים.

3 Aim of the Thesis

The main aim of this thesis is to design, implement and evaluate an algorithm to develop multivariate predictive models based on Clalit Health Services' (CHS) electronic health record based database; to use it to generate a risk model for cardiovascular disease; to compare this model to existing risk models, externally validating them in the process; and to simulate an intervention on the Israeli population based on these risk models.

The aforementioned goal will require three steps:

Model Development A modern and novel approach to develop risk models based on Electronic Health Record (EHR) data will be developed. The full details of this approach will be detailed below, under "Research Methodology", but briefly, it will require no preliminary domain expertise, instead utilizing modern methods to simultaneously choose variables and create the model based on them.

Model Evaluation The above-mentioned approach will be used to construct a risk model for 10-year prediction of Cardiovascular Disease (CVD). The merits of this model will be tested by comparing it to the leading existing models from the literature. This evaluation will comprise a comprehensive test of these models' performance in both their original population composition and in a shared population with the characteristics we intend to use in our intervention.

Simulated Intervention The CVD models will be used to simulate an intervention based on a historic cohort of patients from the CHS' database. The true outcomes, the predicted outcomes based on existing models and the predicted outcomes based on our models will be compared.

Based on these aims, we hypothesize that:

1. That using less pre-specification of risk factors, and allowing a computerized algorithm to select risk factors in an autonomous fashion, will enable detection of novel risk factors, whose inclusion in future risk models will improve their performance.
2. That a model developed in such fashion will outperform traditional risk models.
3. That the advantages of such a model will have the potential to improve patient outcomes if used in a population-wide intervention based on EHR data.

4 Importance and Background

We will survey the pertinent background for each step in turn, highlighting the gap in existing knowledge to which we seek to contribute.

4.1 Part I

4.1.1 Methodology of Traditional Risk Models

For traditional medical risk models, two design decisions are ubiquitous[74]:

1. They are based on traditional biostatistical methodology such as generalized linear and cox models.
2. They rely heavily on the use of domain expertise to identify relevant risk factors.

Informally described, we could say that the model is tasked to estimate the relative weights of risk factors, themselves independently pre-identified by domain experts.

4.1.2 Generalized Linear Models

Generalized linear models (GLMs) are parametric models that are generalizations of ordinary linear regression, allowing outcome variables to have non-normal error distributions[50].

While classic linear regression follows the form:

$$E[Y] = x^t\beta$$

GLMs have the form:

$$E[Y] = g^{-1}(x^t\beta)$$

With g being the link function connecting the linear predictor space with the outcome space.

For example, logistic regression uses the logit function as the link, $\mu = \frac{\exp(x^t\beta)}{1+\exp(x^t\beta)}$, while linear regression uses the identity function.

The model then uses a loss function, usually maximum likelihood, to estimate the coefficients of the model. Under certain assumptions, these coefficients can have epidemiological interpretations, such as the coefficients of logistic regression being interpreted as odds ratio of an exposure for a given outcome. The model can also be used for prediction, disregarding all such assumptions.

4.1.3 Cox Proportional Hazards

The cox model is a survival analysis model (that is, it uses a compound outcome of time-to-event data) that is semi-parametric. A baseline hazard (λ_0) is estimated non-parametrically from the data, while a parametric linear hazard model is estimated in parallel[15].

The overall hazard model is thus $\lambda(t) = \lambda_0(t) \cdot x^t\beta$. The hazard itself is a somewhat elusive term rooted in calculus, representing the probability of death at a certain infinitesimal time window assuming survival up to that point. Survival is then one minus the integral of the hazard over time.

Similar to GLMs, the coefficients are estimated using a process of maximum likelihood (dubbed partial likelihood in the context of Cox regression), and under strict assumptions have the interpretation of hazard ratios, similar to odd ratios.

The assumptions for cox regression warrant special mention. While the assumption of linearity is similar to GLMs, cox proportional hazards also assumes proportionality - that is, that the hazard ratio between risk factors remains constant over time. This is a very strong assumption that does not always hold. It should be mentioned that some models circumvent this assumption at the cost of complexity and loss of interpretability. Just as before, the model can also be used for prediction, disregarding all assumptions.

4.1.4 Parametric Vs. Non-Parametric Models

Parametric models, such as those described above, summarize the data with a set of parameters of fixed size that is independent of the number of training examples. This has the advantage of simplicity, interpretability and speed, but also leads to biases in prediction if the "true" population model is different than the chosen model.

Non-parametric models make no such assumptions about the structure of the target function they seek to learn. This requires far more data for accurate training, and does not allow interpretation of coefficients using terms such as odd ratios, but does afford more predictive accuracy when sufficient data exists[64].

4.1.5 The Rise of AI and Machine Learning

In recent years the fields of machine and statistical learning have seen a tremendous rise[52]. this growth in machine learning, including predictive modeling, has occurred thanks to three main factors[65]:

- A large increase in the amount of accessible data.
- The development of new algorithms and methods.
- An increase in computation power.

These new methods have several defining characteristics, including:

- The use of a wider range of algorithms, not limited to generalized linear models.
- Less reliance on domain expertise, in essence allowing the algorithm to both find the main risk factors and to estimate their respective weights.
- The need for larger sample sizes, to allow the more complex modeling to occur successfully.

To date, these methods have yet to gain wide-acceptance in medical practice[52, 21].

4.1.6 Black-Box Vs. White-Box Models

While there are obstacles from many different domains to the integration of machine learning approaches in medicine: psychological, legal, regulatory and others, one overarching concern is the preeminence of black-box models in machine learning[57].

Broadly defined, black-box models are models whose results cannot be readily explained. For example, a logistic regression result can be fairly easily reasoned about: baseline risk was x%, and a certain combination of variables increased the risk by y% more. The same cannot be said for most models used in modern machine learning, including neural networks and tree-ensemble models. These models generate a result that is a complex non-linear function of their inputs, and one cannot easily explain why a specific patient got a risk of x%, while another got y%.

Beyond the legal and psychological difficulty this creates (how does one explain, to oneself and others, a decision based on unclear reasoning?), it also introduces the possibility of discrimination. The algorithm could choose to optimize for one (majority) population, while neglecting other (minority) populations[37]. This fascinating area of research falls under the more general notion of algorithmic fairness, more widely studied in other non-medical fields[14], and is beyond the scope of this thesis.

4.1.7 Electronic Health Record based Observational Studies

Most medical risk models in wide-use were developed based on specialized cohort studies[26]. This has the known advantages of cohort studies, most notably the accurate definition of exposures and outcomes, but is expensive and time-consuming, and by definition only allows inclusion of risk factors that were decided on in advance and measured as part of the study. On the other hand, with the larger availability of EHR data, risk models developed on such data have risen in amount. These models have the known disadvantages of EHR data (first of which are the non-standardized definitions), but offer a wealth of information that in certain cases, including the case in Israel[45], encompasses the full extent of a patient's encounters with the health system[27].

4.1.8 The Gap and our Thesis

We suggest using the unique availability of widely encompassing EHR data with large historic depth, coupled with modern statistical learning methods, to develop a generic method for generation of risk models based on the Clalit's EHR.

This method will make use of most available EHR data, and will require no pre-specification of risk factors, instead allowing the algorithm to ascertain the relative importance of the different factors by itself. Not only will this allow the creation of accurate risk models, it will also provide a way to automatically identify associations that exist in the EHR and could represent novel risk factors and biological pathways.

We will then use this method to develop a specific model to predict cardiovascular disease. As this model will make use of large portions of the EHR data and will be purposely built on the Clalit's population, it is likely to perform well.

4.2 Part II

4.2.1 Epidemiology of Cardiovascular Disease and Stroke

In its usual definition, cardiovascular disease (CVD) includes several disease categories[75]:

1. Coronary Heart Disease
    (a) Myocardial Infarction
    (b) Angina Pectoris
    (c) Heart Failure
    (d) Coronary death
2. Cerebrovascular Disease
    (a) Stroke (Thrombotic and Hemorrhagic)
    (b) Transient Ischemic Attack
3. Peripheral Artery Disease
4. Aortic Disease
    (a) Atherosclerosis
    (b) Aneurysm
5. Rheumatic Heart Disease
6. Congenital Heart Disease
7. Venous Thromboembolism
    (a) Pulmonary Embolism
    (b) Deep Vein Thrombosis

CVD is very common. Lifetime risk for people aged 30 with no prior cardiovascular disease approaches 50 percent[59], with coronary heart disease being the most common specific diagnosis[4].

While the rates of cardiovascular disease have declined in developed countries over the last 30 years[43, 71], they remain significant public health problems, being the second most common cause of mortality and third most common cause of disability worldwide[46]. The statistics in Israel are similar[22].

Among diseases with such a significant public health impact, cardiovascular disease stands out in two ways. First, its risk factors are well understood, with 90% of its population-attributable-risk caused by nine risk factors. It's also a very preventable disease, as these risk factors are mostly preventable[78, 53]: Smoking, dyslipidemia, hypertension, diabetes, etc.

4.2.2 History of Multivariate Risk Models

These unique characteristics have made CVD the main outcome in risk models, when such models began to enter clinical practice in the 1990s[76, 49, 13, 33, 19, 34, 25]. Still the most notable of said risk models is the Framingham risk model family, developed on a US population in Massachusetts, Boston[76], and the SCORE risk model, developed in 2003 on a European population[13].

Perhaps more important that their mere existence, is that these models have made their way into widely-accepted international guidelines, with their use mandated in routine clinical care. Two examples we'll cite are the use of these risk models in deciding on Statin therapy[25] and their use in deciding on anti-platelet therapy[6], both for primary prevention of CVD.

While CVD prediction was the bedrock for clinical risk models, they have since spread to encompass a large variety of diseases categories[40, 41], and have found use not only in prediction, but also in diagnosis[70]. This increasingly important place taken by risk models has brought about the publication of guidelines designed to regulate and improve their creation[12]. As estimating the probability for existing and future disease is a significant portion of the clinical process[47], and as this task can in large parts be automated, it seems likely that risk models will gain an increasingly important place in the medical practice.

4.2.3 Limitations of Risk Models

Naturally, risk models are developed on a specific population, whose data is available to the researchers developing the model. As patients differ in a variety of ways (both genetic and environmental), and even such basic things as lab methods and disease definitions differ in different areas, models tend to function better when used on the population on which they were developed[18, 3].

Recent models have tried to deal with this problem by including more ethnically varied populations[20] or recalibrating the model for each new population[40], but such efforts are limited to specific risk models, and even then have only been partially successful[16]. As one specific Israeli example, this phenomenon was observed in a recent publication that illustrated significant miscalibration for osteoporosis prediction models that are in wide clinical use and incorporated into guidelines[16]. As the probabilities generated by the model eventually help determine the proper interventions to perform, according to respective guidelines, such mis-calibration could invalidate the use of the model, making external validation an important endeavor[48].

4.2.4 The Gap and our Thesis

Though the risk scores are currently used in common medical practice, external validation of international CVD risk models for the Israeli population has yet to be performed, and recommen-

dations on which model to use are based on expert opinion[7].

We suggest, as a first effort, to externally validate widely used risk models for the prediction of CVD risk on the Israeli population. This could help decide which model has the best performance, and if all such models' performance is deemed unsatisfactory, this will have significant consequences for guidelines and practices based on said models. These models will then be compared to the internally developed model in part I.

4.3 Part III

4.3.1 Traditional Aim of Risk Models

Outside of the realm of medicine, risk models are used for great many purposes: deciding which customers are likely to default on loans, deciding which credit card deals are fraudulent, deciding which customers are likely to churn, etc.

Within the realm of medicine, the use of risk models is fairly consistent. When deciding on some intervention to lower some risk (e.g. statins for CVD), one has to always remember that interventions have risks themselves (e.g. rhabdomyolysis from statins). For any utility one mentally assigns lower CVD risk and higher rhabdomyolysis risk (in our example), the prescription of statins is more warranted if the baseline risk for CVD is higher. This is intuitive and simple - one does not walk around wearing a Hazmat suit if one is not in the immediate vicinity of hazardous materials (presumably because its hot within such suits).

With this logic in mind, risk models are constantly used, consciously and subconsciously, when deciding on diagnostic and therapeutic interventions. Consciously, for example, when deciding on aspirin and statins for CVD risk[25, 6], bisphosphonates for osteoporosis risk [39] or CT angiogram for pulmonary thromboembolism risk[73]. Subconsciously, for example, when deciding whether to refer a patient suspected of pneumonia to a chest x-ray.

4.3.2 The Way Risk Models are Used

For several reasons, utilizing risk models for these aims requires the direct involvement of a treating physician:

1. The different risk models require knowledge of a wide variety of clinical factors, including lab results that most patients are not expected to know themselves.
2. The decisions to be made can only be made by a physician. A patient cannot prescribe statins to himself.

And so the use of such model has mostly been limited to physicians. To make use of these risk models, the physician, usually the primary care physician, is required to the fill in the different covariates based on the patient's health record, communicate the results to the patient, and advise on whatever intervention is mandated to mitigate the risk.

It should be said that this entire time consuming act is expected to occur in an already time-strained primary care encounter[42].

4.3.3 The Gap and our Thesis

We suggest that the structure of the Israeli health care system is ideal for performing and evaluating an intervention based EHR based prediction of cardiovascular risk.

Instead of the usual methodology, by which patients are identified as high-risk when they enter the physician's office, usually for other concerns and in severe time constraints, we will predict the risk at once for all patients in the database.

We will then use this prediction to simulate an intervention by which all patients with a sufficient risk are prescribed statins and aspirin, and the relative yield of this intervention is measured and compared to the actual outcomes observed and among the different models.

5 The Novelty of the Thesis

All aforementioned aspects of the thesis contain measures of novelty to them:

- We propose that the methodology by which the model will be developed, and specifically its wide applicability, requiring little human intervention and pre-processing, offers significant advantages. The ability to identify risk factors and construct models for a wide variety of pathologies, some of which "unmapped" in regard to their primary risk factors, offers a promise of better understanding and more focused interventions to prevent these diseases.
- External validation of existing risk models is of utmost importance[48], as these models are used constantly as part of existing guidelines (e.g. the American Heart Association's pooled risk model and Statin treatment[25], FRAX and Osteoporosis treatment[40]). This is especially true, as previous external validation studies have at times documented significant mis-calibration[3, 16], that would make treatment decisions based on the models problematic.
- Population wide EHR-data based interventions using predictive risk models have yet to be implemented, to the best of our information. Illustrating the advantages of such interventions, specifically with the rising availability of EHR data, is of significant importance.

6 Published Work

The epidemiological characteristics of CVD in general and of stroke in particular are well understood[43, 71], and the dominant risk factors in the population well mapped[78, 53]. This is true both in the developed and in the developing world[46]. It is also true in Israel[22].

The increasingly central role filled out by risk prediction models in medicine has been observed[47], as have the challenges of developing such models based on Electronic Health Record (EHR) data[26, 27]. This rapid rise in the number of risk prediction models has led to the writing of specific guidelines on how to develop such risk models and report their results[12].

Many CVD risk models have been developed in the last 30 years, most prominent of which are the Framingham[76, 49, 19, 25], SCORE[13] and Qrisk[33, 34] families of models. Two of these model families also offer a stroke-specific model[77, 17, 32].

Risk models have been incorporated into guidelines for the prevention, diagnosis and treatment of varying conditions. Specifically for CVD prediction, these risks help decide on cholesterol lowering treatment, anti-platelet treatment and more generally, the intensity of follow-up[49, 29, 25, 6].

Models' tendency to under-perform when the target population is changed is widely recognized[18, 3, 20] and accordingly, the importance of external validation of models prior to their use in new population is recommended[48]. External validation of CVD models has been performed in several populations[18, 3, 20], though not in the Israeli population[7]. This is in contrary to, for example, Osteoporosis[16].

Much has been written on the advent of AI in general and machine learning in particular. In a relatively short time span, these technologies have penetrated large parts of the domains of modern life, and continue to do so in increasing force[51].

That this process has been relatively slow in medicine is also widely recognized, and many efforts now exist to better incorporate such technologies in health-care[52]. Specifically for risk prediction models, recent literature has emerged that details attempts at developing more generic risk models, though different than the idea proposed here both in method and in goal[58].

Attempts to more proactively involve patients in their own care have existed for a long time[1]. As AI and machine learning advance, it is only natural that these technologies will take part in such interventions. These attempts have taken varied forms: general diagnostic models based on provider statistics[2], smartphone apps designed to ease communications between providers and patients[68], wearable devices designed to encourage lifestyle change[28], etc.

More similar to this thesis are calculators presented directly to patients. These are many, and some deal directly with CVD and stroke[55]. But none of these calculators are based on locally developed models and none are able to access the patient's EHR, instead relying on him being knowledgeable about his risk factors. Also, being disconnected from the patient's EHR, these models cannot follow up on a patient's risk and health behavior, and accordingly cannot evaluate their own performance.

7 Research Methodology

We will elaborate on the following for each of the three parts:

- Planning, including population definition and variables.
- Data extraction.
- Descriptive statistics.
- Modeling and inferential statistics.

7.1 Planning

7.1.1 Part I

Our model will be developed on the following population.

Inclusion:

- Ages 30-90.
- At least 1 year of continuous membership in the Clalit prior to the index date.
- Continuous membership until the study end date or until death.

Exclusion:

- Past CVD event.

As is the standard for cardiovascular disease risk models, our model will predict disease for 10 years after the index date. The index date will be set at 1/6/2007, and follow up will persist until 1/6/2017, as illustrated in the following design diagram.

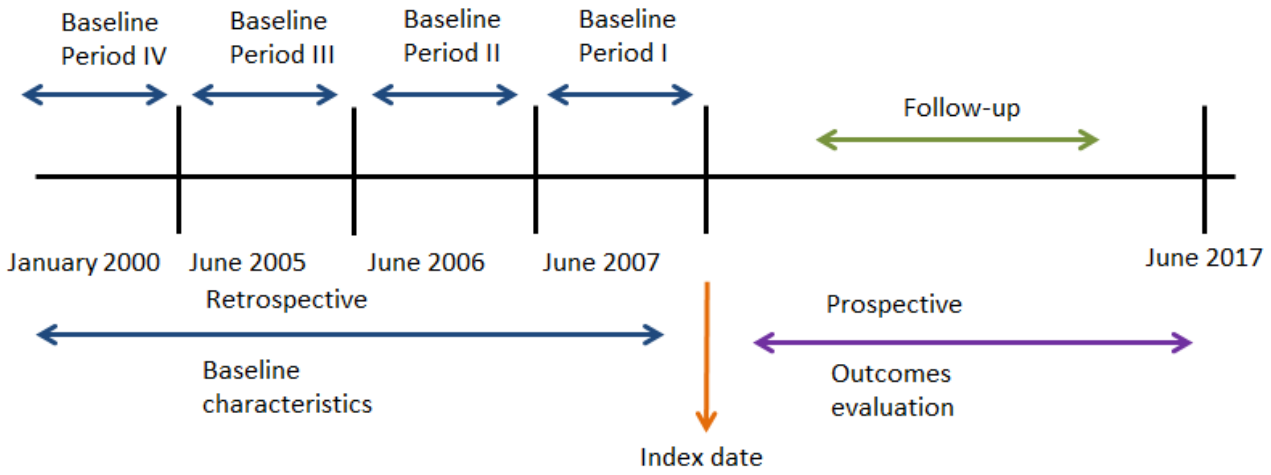

Figure 1: Study Design Timeline

Logically, model construction will encompass two steps: Using a sparsity inducing model to select among hundreds of variables, then building a model using the selected variables. In effect, algorithms will be chosen that perform both stages at once. See more details in the modeling section ahead.

The covariates supplied to the first step will be:

- Full demographic information, including age, sex, socioeconomic status, sector (arab/jew), ethnicity, etc.
- Clinical covariates, including blood pressure, height, weight, smoking status, etc. The data used will be the last result for each patient in the two years prior to the index date.
- Lab data, including all labs performed for each patient. Data will be extracted separately for the year before the index date, the year before that and the year before that.
- Chronic diagnoses, as defined by the Clalit's chronic registry[61], up to the index date.
- Drug dispensings, including all drug dispensed to the patient in ATC4 granularity[23]. Data will be extracted separately for the 3 years before the index date and all the years before that.

A full list can be found in appendix C.

7.1.2 Part II

We will externally validate three models that are the most significant and widely used existing models designed to assess risk for cardiovascular disease (CVD).

The models with their respective populations and outcomes are:

Name	Age	Model	Outcome
American Heart Association 2013 pooled risk model[25]	40-79	Cox proportional hazards	Myocardial infarction, coronary heart disease death, stroke and stroke death
SCORE[13]	45-64	Cox proportional hazards	Fatal cardiovascular disease
Qrisk[34]	35-74	Cox proportional hazards	coronary heart disease, stroke

Table 1: Models to be Externally Validated

Each model uses its own variables, see appendix A for full model variable lists.

7.1.3 Part III

The population for the application simulation will include all members of the Clalit's insured population as of 1/6/2007 that were members of the test set for the CVD prediction model. Inclusion and exclusion criteria will be the same as for the model (as mentioned above). The patients will be followed up for 10 years and their CVD outcomes recorded (as per the CVD outcomes in appendix A).

7.2 Data Extraction

The general population for all different parts of the study is the population of patients insured by Clalit Health Services (CHS). CHS is the largest sick fund in Israel, with an insured population of 4.4 active members. Clalit is both an insurer and a provider, directly providing primary care, specialist care, lab, imaging and pharamacy services. Additionally, clalit directly operates several large hospitals. The "attrition rate" (the percentage of patients leaving the sick fund each year) stands on a low 1%, allowing long term follow-up of patients.

The data will be collected using the CHS's electronic health record (EHR). CHS has maintained a comprehensive electronic health record since the year 2000, and has continued to improve it with time. This EHR contains, among others, demographic data, medical data (including clinical covariates, lab results, imaging studies, etc.) and claims data for both services rendered as part of the mandatory health insurance and for services rendered as part of the additive insurance ("Mashlim"). On top of the internal Clalit data, the database also contains external information such as the ministry of interior's causes of death listings and the ministry of health's cancer registry. This comprehensive database, combining both medical and claims data, covers large facets of a person's health.

The difficulties that arise in conducting observational studies on EHR data are many and well documented: Data inaccuracy, missing data, cohort effects, selection biases, myriad ontologies, etc[36, 38, 27]. Some of these issues, such as missing data, can be partially dealt with using statistical methods (see ahead), while some require in-depth expertise and know-how regarding

the data's structure and collection methods, knowledge that can only be acquired through rigorous analysis of it. The Clalit's research institute's (CRI) is the research body for Clalit Health Services, and is thus the main consumer of the clalit's EHR data. This grants the CRI intimate knowledge of the data, as is evidenced by the many studies published in major journals based on the Clalit's database and on the CRI's methods in extracting its information (e.g. [60, 16]).

Data extraction principles for these studies are:

- Demographic characteristics will be extracted from the Clalit's demographic database. Those that are time-dependent (e.g. age) will be extracted current to the index dates, those that are constantly overridden will be extracted to their latest value (e.g. SES).
- Cause of death will be collected directly from the ministry of interior's causes of death table.
- Clinical covariates will be extracted from their dedicated database. The latest value prior to the index date will be used. Tests that can be used as-is (e.g. systolic blood pressure) will be used as-is. Weights and heights measured within a 3-month span will be joined for the calculation of BMI. Smoking status will be "flattened" to never/present/past to account for partial "pack-years" reporting.
- Lab data will be extracted from the dedicated lab results database, using the latest lab values prior to the index date.
- Diagnoses will be collected from the community (both session and permanent diagnoses), from hospitalizations and from the Clalit's chronic registry[61]. Diagnoses will be extracted based on ICD9 codes, ICPC codes and chronic registry codes. Community diagnoses will be corroborated using free text validation so as to exclude suspicions, etc.
- Drug dispensings will be evaluated using the dedicated pharmacy database. Actual dispensings will be counted (as opposed to prescriptions). Drug adherence will be calculated using drug prescriptions and drug dispensings, with PDC and MPR as the actual statistics[44].
- Health care utilization will be calculated by simply counting and summing the patient's encounters and actual cost, both in the community and in hospitals.

In part II, where external validation of international models is to take part, special care will be required to handle variables that are not perfect "fits" for the Clalit's database, for example:

- UK socioeconomic status ("Townsend Deprivation Score"), which has different levels and is directed in the opposite direction (more means lower SES) than the Clalit's socioeconomic status.
- Diagnoses, that are collected based on dedicated physician visits in cohort studies and on ICD codes in EHR based studies, will be collected using a mixture of ICD codes, free text validation and validation using lab measurements (e.g glucose for diabetes) and drug dispensings (e.g. diuretics, ACE inhibitors, beta blockers and calcium channel blockers for hypertension).

CVD definitions, that are used as the outcome in the different models, will be based on those defined by a consensus committee organized by the CRI and headed by a cardiology and neurology specialists. These definitions similar to those used outside the CRI, such as by the Israeli acute stroke registry[22] (active within the ICDC).

7.3 Descriptive Statistics

The specific population for each of the models will be described in a dedicated population table ("Table 1") with appropriate statistics for each variable: proportions for categorical variables, means and standard deviations for continuous variables.

The common population to be used for comparing the external models and to construct the internal model will also be described in a population table. This table will include separate columns for the train and test populations (see ahead for modeling details), with the same appropriate statistics for each variable. Statistical tests will be used to compare these populations for differences in baseline variables that could affect model generalizability. The statistical tests to be used are Student's t-test for continuous variables and the Chi square goodness-of-fit test for categorical variables, once the basic assumptions (e.g. normality) are tested.

Missing data will be multiply imputed using chained equations. Specifically, continuous variables will be imputed using predictive mean matching, while categorical variables will utilize logistic regression[9]. Five datasets will be imputed, with the results combined as per Rubin's law[63].

7.4 Modeling and Inferential Statistics

7.4.1 Part I

To develop the new model, we will create a generic framework capable of generating models for any disease, given a fitting definition of the outcome.

The framework will serve two consecutive tasks. The first is to choose the relevant covariates from the long list of candidate covariates supplied to it. The second is to actually build the model.

It should be specifically noted that both parts carry independent significance. The covariate selection awards biological insight into the risk factors for a disease, while the model is the actual tool used for risk prediction.

The first step will involve applying a model to the training data that employs sparsity. That is, we will opt for models that include variable selection as a part of the fitting process. The hyperparameters for these models will be tuned using the validation set.

The three sparsity inducing models we intend to fit are:

1. LASSO[69]
2. Gradient Boosting[24]
3. Random Forest[8]

least absolute shrinkage and selection operator (LASSO) is a variant of regression that adds a regularization term based on the L_1 norm of the coefficients to the normal loss function to be optimized. Namely, the model minimizes:

$$\arg\min_{w} L(w) + \lambda \sum_{i} |\beta|_i$$

L being the likelihood function and lambda being a regularization parameter. Owing to the geometric structure of the L_1 norm, this has the effect of setting many covariates to 0, inducing

sparsity. The parameter lambda is selected using cross-validation on the validation set, with predictive performance (e.g. AUROC) as the goal.

As the regularization portion of the loss is dependent on variable scales, we will normalize the variables to have equal mean and standard deviation prior to model fitting.

Gradient boosting is an ensemble method that combines several weak learners (e.g. shallow trees) together using a weighted majority vote. Each consecutive learning phase focuses on those samples in the training set that were predicted wrong by the previous phases.

Random forest is also an ensemble method employing decision trees as the weak learners. It strives to induce variance among the trees by using bootstrapping to select the training set for each tree, and only using a randomly selected subset of features at each split in the tree.

Both gradient boosting and random forest induce sparsity by deciding on the important features at each split in each tree. The rules for these decisions are themselves parameters to the models, but all generally employ a version of Claude Shannon's information entropy:

For a given variable x, the entropy is defined as $H(x) = -\sum_{i=1}^{n} P(x_i) \log P(x_i)$. This entropy is maximized when the "doubt" about the value of a variable is maximal, and the different tree models strive to minimize it by choosing maximally informative variables for each split.

Hyper-parameter tuning, per each model's hyper-parameter lists, will be conducted on the validation set using random search[5]. The best performing model with regard to area under the ROC curve will be selected.

The model as produced by the sparsity inducing algorithm will be compared to the existing models examined in phase I using the above mentioned performance measures. For the sake of demonstrating clinical utility, we will also compare the best model from phase I to our model for net reclassification improvement[56] and decision curves[72].

We will include a learning curve for our model so as to demonstrate lack of over-fitting.

While in essence we could use the models from phase I or the model as produced by our sparsity inducing algorithm as is, the requirement of using the model in a web application, including tight memory and responsiveness constrains, forces us to fit a simpler final model.

To account for this, we will take the covariates from the best model and use them construct a simple logistic regression model. This will be our final model to be used in the application.

7.4.2 Part II

All models will be evaluated twice:

1. Once on a population that exactly mirrors the population they were originally defined on.
2. Once on a common shared population that represents the population for which we intend to use the model in our thesis.

This design is similar to previously published work[16].

The first phase will employ the full population matching the model's inclusion and exclusion criteria, so as to mirror their development population as much as possible.

For the second phase we'll use only the inclusion and exclusion criteria detailed above. This will be a common, shared population so as to allow comparison of model's performance on a joint dataset.

The population will be separated into three sets for the sake of model development: Train, Validation and Test in a 72%/8%/20% ratio. The training and validation sets will be discussed in subsection "part II" ahead. The test set will be used for comparing model's performance.

The following performance statistics will be computed and reported for each model[67, 30]:

- Area under the receiver operating characteristics (AUROC) curve, or c-statistic, as a measure of discrimination.
- Calibration slope as a measure of calibration.
- Brier score, as a combined measure of prediction accuracy.
- Sensitivity, Specificity, PPV and NPV for the 7.5% and 10% risk threshold. These thresholds are chosen for their importance in existing guidelines[25, 6].

To calculate the risk scores, the exact coefficients as published by the model's authors will be used. If dedicated software is available, it will be used instead.

Prior to comparing the model's to our own model, we will allow them linear recalibration, so as to "even the playing field" between a model being internally validated (our model) and models being externally validated. This recalibration will be done using the framework suggested by Van Houwlingen et al[35]. Specifically, the model's linear predictor will be fit again as a sole predictor in a logistic regression model and the ensuing slope and intercept recorded. These will then be used to adjust all model predictions.

Mathematically:

$$\forall_i \mathrm{LP}_i = \sum_{j=1}^{p} \beta_j x_j$$

$$\hat{y}_i = \gamma \mathrm{LP}_i + \delta$$

Where LP_i is the linear predictor, β_{ij} is the coefficient for covariate j in patient i, x_{ij} is the covariate j in patient i, $\hat{y}$ is the recalibrated prediction, for which γ is the slope and δ the intercept.

Or in words: We take the linear predictor from the original model, but allow it a new slope and intercept, thus preserving the relative importance of each covariate in the model, with the freedom to reset the global risk.

7.4.3 Part III

We will use the both external CVD models and the internal CVD model to generate recommendations for statin and aspirin use for all patients in the test set of the CVD algorithm. We will illustrate that the internal model is more accurate when deciding on the population to treat, and its use would have prevented more CVD events.

8 Preliminary Results

We will present preliminary results for the first two parts.

8.1 Part 1

Population Table for the AHA/ACC 2013 model[25]:

Variables	Categories	0	1	pval
Individuals	n	1758405	38356	
Age	Mean (SD)	51.8 (15.0)	66.6 (12.8)	<0.01
Age	Median (IQR)	50.0 (39.0-62.0)	68.0 (57.0-77.0)	
SES	Mean (SD)	9.9 (4.1)	9.6 (3.9)	<0.01
SES	Median (IQR)	10.0 (6.0-13.0)	10.0 (6.0-12.0)	
BMI	Mean (SD)	27.7 (5.4)	28.8 (5.4)	<0.01
BMI	Median (IQR)	27.0 (24.0-30.7)	28.1 (25.1-31.7)	
SBP	Mean (SD)	124.9 (17.1)	135.9 (19.2)	<0.01
SBP	Median (IQR)	120.0 (113.0-134.0)	132.0 (120.0-146.0)	
DBP	Mean (SD)	76.3 (9.4)	78.3 (10.1)	<0.01
DBP	Median (IQR)	78.0 (70.0-80.0)	80.0 (70.0-83.0)	
GFR	Mean (SD)	92.3 (20.3)	78.2 (20.7)	<0.01
GFR	Median (IQR)	94.3 (79.6-107.2)	80.3 (64.3-93.1)	
Glucose	Mean (SD)	98.1 (24.9)	114.2 (35.9)	<0.01
Glucose	Median (IQR)	92.0 (84.0-103.0)	102.0 (90.0-128.0)	
LDL	Mean (SD)	117.6 (30.9)	116.6 (32.5)	<0.01
LDL	Median (IQR)	116.0 (96.0-138.0)	114.8 (93.0-138.6)	
HDL	Mean (SD)	47.9 (12.2)	46.5 (12.1)	<0.01
HDL	Median (IQR)	46.0 (39.0-55.0)	45.0 (38.0-53.0)	
Triglycerides	Mean (SD)	193.6 (38.5)	194.7 (41.0)	
Triglycerides	Median (IQR)	191.0 (167.0-217.0)	191.0 (166.0-220.0)	<0.01

ROC Curve for the AHA/ACC 2013 Risk Score model is presented in appendix D.

8.2 Part 2

The population flow chart for the predictor is presented in appendix D.

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Appendices

A Model Variable Lists

1. American Heart Association 2013 pooled risk model
    (a) Sex
    (b) Age
    (c) Total Cholesterol
    (d) HDL
    (e) Treated Systolic Blood Pressure
    (f) Untreated Systolic Blood Pressure
    (g) Smoking Status
    (h) Diabetes
2. SCORE
    (a) Sex
    (b) Age
    (c) Total Cholesterol
    (d) Treated Systolic Blood Pressure
    (e) Untreated Systolic Blood Pressure
    (f) Smoking Status
3. QRisk2
    (a) Ethnicity
    (b) Age
    (c) Sex
    (d) Smoking Status
    (e) Systolic Blood Pressure
    (f) Total Cholesterol / HDL Ratio
    (g) BMI
    (h) Family Hx of CHD
    (i) Townsend Deprivation Score
    (j) Treated Hypertension
    (k) RA
    (l) CKD
    (m) Type II Diabetes
    (n) AF

B Extraction Protocol

B.1 Outcome Diagnoses

1. **Name** Intra-Cranial Hemorrhage
   ICD9 Codes 431%
   ICPC Codes NA
   CHR Codes NA
   Sources Admissions
   Free-Text Inclusion NA
   Free-Text Exclusion NA
   Comments Primary diagnosis only, not from rehabilitation
2. **Name** Ischemic CVA
   ICD9 Codes 433, 433._, 433._1, 434%, 362.3[1-3], 362.4%
   ICPC Codes NA
   CHR Codes NA
   Sources Admissions
   Free-Text Inclusion NA
   Free-Text Exclusion NA
   Comments Primary diagnosis only, not from rehabilitation
3. **Name** CVA NOS
   ICD9 Codes 436%
   ICPC Codes NA
   CHR Codes NA
   Sources Admissions
   Free-Text Inclusion NA
   Free-Text Exclusion NA
   Comments Primary diagnosis only, not from rehabilitation
4. **Name** Transient Ischemic Event
   ICD9 Codes 435%
   ICPC Codes NA
   CHR Codes NA
   Sources admissions, community, permanent, hospitals
   Free-Text Inclusion %transient%ischemic%attack%, %ischemic%attack%transient%, %transient%cerebral%ischemia%, %vertebral%artery%syndrome%, %ischemic%attack%transient%
   Free-Text Exclusion NA
   Comments Primary diagnoses only, not from rehabilitation, only community neurologis
5. **Name** Subarachnoid Hemorrhage
   ICD9 Codes 430%

ICPC Codes NA

CHR Codes NA

Sources Admissions

Free-Text Inclusion NA

Free-Text Exclusion NA

Comments Primary diagnosis only, not from rehabilitation

6. **Name** Myocardial Infarction

   ICD9 Codes 410%

   ICPC Codes NA

   CHR Codes NA

   Sources Admissions

   Free-Text Inclusion NA

   Free-Text Exclusion NA

   Comments Primary diagnosis only, not from rehabilitation

7. **Name** Non-MI Coronary Heart Disease

   ICD9 Codes 41[01234]%

   ICPC Codes K75, K76

   CHR Codes 110.1, 110.9

   Sources admissions, permanent, diagnoses and hospitals

   Free-Text Inclusion %angina%, %prectoris%, %heart%attack%, %myocardial%inf%, %ischemic%heart%, %ischaemic%heart%, %coronary%atherosclerosis%, %arterioscl%cardiovascular %post%coronary%bypass%, %coronary%insuf%, %atheroscl%cardiovasc%, %acute%coronary%, %cardial%ischemia%, %intermediate%coronary%, %dyspnea%effort%, infarction%myocardial%, %infarction%subendocardial%, %subendocardial%infarction%

   Free-Text Exclusion %fear%, %gynecologic%, %no%disease%, %us%examination%, %normal%, %breast%, %medical%examination%, %herp%angina%, %hearing%

   Comments NA

8. **Name** Congestive Heart Failure

   ICD9 Codes 428%

   ICPC Codes NA

   CHR Codes 112%

   Sources community, admissions, permanent

   Free-Text Inclusion %congestive%heart%, %heart%failure%, %systolic%dysfunction%, %diastolic%dysfunction%, %ventricular%failure%, %CHF%, %ventricular%d[yi]sfunction%

   Free-Text Exclusion NA

   Comments NA

9. **Name** Peripheral Vascular Disease

   ICD9 Codes 443%, 440.[23489]%, 250.7%, 444.2%

   ICPC Codes K92

CHR Codes 126%

Sources community, permanent, chronic registry, hospitals

Free-Text Inclusion %peripheral%vascular%, %PVD%, %claudication%, %buerger%, %thromboangiitis%obliterans%

Free-Text Exclusion %neurogenic%, %spinal%, , %dissection%, %acute%, %vitreous%, %floater%, %eye%, %detachment%, %PVD%BE%, %BE%PVD%, %OD%PVD%, %PVD%OD%
%PVD%LE%, %LE%PVD%, %raynaud%

Comments Exclude ophtalmologist diagnoses

B.2 Causes of Death

1. **Name** Coronary Death

   ICD10 Codes (I11% OR I13% OR I21% OR I24% OR I25% OR I20% OR I44% OR I47% OR I50% OR I51%) AND (NOT I456%) AND (NOT I514%)

B.3 Background Diagnoses

1. **Name** Stroke (all kinds)

   ICD9 Codes 43[0-8]%

   ICPC Codes K90

   CHR Codes 95.2, 124

   Sources community, admissions, permanent, chronic registry

   Free-Text Inclusion %cerebrovascular%accident%, %transient%ischemic%attack%, %intracerebral%hemorrhage%, %CVA%, %cerebelar%hemorrhage%, %cerebral%hemorrhage%, %cerebral%vasospasm%, %cerebrovascular%disease%, %stroke%, %cerebral%ischemia%, %subarachnoid%hemorrhage%, %ischemic%attack%transient%, %aneurysm%berry%ruptured%
   %intracranial%hemorrhage%, %hemorrhage%brain%nontraumic%

   Free-Text Exclusion %extradural%

   Comments NA

2. **Name** Left Ventricular Hypertrophy

   ICD9 Codes 429.3%

   ICPC Codes NA

   CHR Codes NA

   Sources community, admissions, permanent

   Free-Text Inclusion %cardiomegaly%, %ventricular%, %hypertrophy%

   Free-Text Exclusion NA

   Comments Primary diagnosis NA

3. **Name** Congestive Heart Failure

   ICD9 Codes 428%

   ICPC Codes NA

   CHR Codes 112%

Sources community, admissions, permanent

Free-Text Inclusion %congestive%heart%, %heart%failure%, %systolic%dysfunction%, %diastolic%dysfunction%, %ventricular%failure%, %CHF%, %ventricular%d[yi]sfunction%

Free-Text Exclusion NA

Comments NA

4. **Name** Coronary Heart Disease

   ICD9 Codes 41[012-34]%

   ICPC Codes K75, K76

   CHR Codes 110.1, 110.9

   Sources community, permanent, chronic registry, hospitals

   Free-Text Inclusion %angina%, %prectoris%, %heart%attack%, %myocardial%inf%, %ischemic%heart%, %ischaemic%heart%, %coronary%atherosclerosis%, %arterioscl%cardiovascular %post%coronary%bypass%, %coronary%insuf%, %atheroscl%cardiovasc%, %acute%coronary%, %cardial%ischemia%, %intermediate%coronary%, %dyspnea%effort%, infarction%myocardial%, %infarction%subendocardial%, %subendocardial%infarction%

   Free-Text Exclusion %fear%, %gynecologic%, %no%disease%, %us%examination%, %normal%, %breast%, %medical%examination%, %herp%angina%, %hearing%

   Comments NA

5. **Name** Peripheral Vascular Disease

   ICD9 Codes 443%, 440.[23489]%, 250.7%, 444.2%

   ICPC Codes K92

   CHR Codes 126%

   Sources community, permanent, chronic registry, hospitals

   Free-Text Inclusion %peripheral%vascular%, %PVD%, %claudication%, %buerger%, %thromboangiitis%obliterans%

   Free-Text Exclusion %neurogenic%, %spinal%, , %dissection%, %acute%, %vitreous%, %floater%, %eye%, %detachment%, %PVD%BE%, %BE%PVD%, %OD%PVD%, %PVD%OD% %PVD%LE%, %LE%PVD%, %raynaud%

   Comments Exclude ophtalmologist diagnoses

6. **Name** Hypertension

   ICD9 Codes 40[12345]

   ICPC Codes K85, K86, K87

   CHR Codes 120%

   Sources community, permanent, chronic registry, hospitals

   Free-Text Inclusion %hypertension%, %hypertensive%, %hypert%with%, %nephrosclerosis%, %hypert%, %essential%hypert%, %hypertesion%, %hypertention%

   Free-Text Exclusion %low%, %w/o%, %pulmonary%, %pulmoanry%, %ocular%, %portal%, %holter%, %no%hypert%, %no%retino%, %pre%hyper%, %borderline%, %prostat%, %hyperthy%, %hypertrig%, %ventricular%, %tonsil%, %hypertroph%, %hypertg%, %hyperton%, %cranial%, %endomet%, %adenoid%

   Comments NA

7. **Name** Rheumatoid Arthritis

   ICD9 Codes 714.0%, 714.2%

   ICPC Codes L88%

   CHR Codes 231%

   Sources community, permanent, chronic registry, hospitals

   Free-Text Inclusion % rheumatoid% arthritis%, % arthritis% atrophic%

   Free-Text Exclusion NA

   Comments NA

8. **Name** Chronic Kidney Disease

   ICD9 Codes 585%

   ICPC Codes NA

   CHR Codes 177%

   Sources community, permanent, chronic registry, hospitals

   Free-Text Inclusion %chronic%kidney%, %chronic%renal%, %renal% failure%chronic%, %uremia%

   Free-Text Exclusion NA

   Comments NA

9. **Name** Valvular Heart Disease

   ICD9 Codes 424.0%, 424.1%, 424.2%, 424.3%, 394%, 395%, 396%, 397%, 093.2%, 746.0%, 746.1%, 746.2%, 746.3%, 746.4%, 746.5%, 746.6%

   ICPC Codes K83%

   CHR Codes 111%

   Sources community, permanent, chronic registry, hospitals

   Free-Text Inclusion %valv%, %stenosis%, %regurgitation%, %incompetence%, %insufficiency%, %ebstein%, %tricuspid%atresia%, %pulmonary%atresia%

   Free-Text Exclusion NA

   Comments NA

10. **Name** Diabetes Mellitus

    ICD9 Codes Use internal CRI registry

    ICPC Codes Use internal CRI registry

    CHR Codes Use internal CRI registry

    Sources NA

    Free-Text Inclusion NA

    Free-Text Exclusion NA

    Comments NA

11. **Name** Atrial Fibrillation

    ICD9 Codes Use internal CRI registry

    ICPC Codes Use internal CRI registry

CHR Codes Use internal CRI registry

Sources NA

Free-Text Inclusion NA

Free-Text Exclusion NA

Comments NA

B.4 Drugs

1. **Name** Hypertension

   ATC Codes C09%, C07AB03, C07FB03, C07CB03, C07CB53, C07BB03, C07DB01, C07DB01, C07AB02, C07FX03, C07FB13, C07FB02, C07FX05, C07CB02, C07BB02, C07BB52, C08C%, C08G%, C03A%, C02AC01

2. **Name** Diabetes Mellitus

   ATC Codes A10%

3. **Name** Anti-coagulants

   ATC Codes B01AA03, B01AA07, B01AA02, B01AE07, B01AF01, B01AF02

C Generic Predictor Variable List

1. age
2. birth_area_desc
3. bmi_last_v
4. charlson
5. DBP_last_v
6. date_of_birth
7. date_of_death
8. ethnicity
9. GFR
10. immigration_date
11. LEUCOCYTES-SED
12. ERYTHROCYTES-SED
13. EPITHELIAL-SED
14. BACTERIA-SED
15. ESTRADIOL (E-2)
16. PROGESTERONE
17. 17-OH-PROGESTERONE
18. LH
19. Throat culture p
20. FSH
21. WBC
22. PROLACTIN
23. TESTOSTERONE- TOTAL
24. Aerobic blood cult.
25. Anaerobic blood cult
26. Bacterial culture
27. Body fluid culture
28. Ear culture 1
29. Fungal culture
30. DHEA SULPHATE
31. MRSA culture
32. CORTISOL-BLOOD
33. Pediatric blood cul
34. Sputum culture
35. Stool culture
36. Throat culture
37. Urine dipsl culture

38. Urine culture
39. Urine plating cult.P
40. Wound culture
41. RBC
42. Wound and Sec.Aer+An
43. TSH
44. First isolate
45. Second isolate
46. PRELIMINARY
47. T3-TOTAL
48. T3- FREE
49. CPE culture result
50. T4- FREE
51. HB
52. PTH
53. HCT
54. PLT
55. MCV
56. MCH
57. MCHC
58. RDW
59. MPV
60. BAB- Blood agar base
61. MacConkey agar
62. Sabour dextrose agar
63. PCT
64. ESBL test
65. PDW
66. MID abs.
67. MID %
68. VAR-F
69. LI
70. HDW
71. MICRO-F
72. ABO conf final (ad)
73. Rh confirmation
74. RH
75. BLOOD TYPE

76. Antibody screen Fin
77. BLAST-F
78. LUC%
79. LUC abs
80. MPXI
81. LEFT SHIFT
82. MACRO%
83. MICRO %
84. HYPER%
85. HYPO %
86. ANISO-F
87. LYMP.abs
88. LYM%
89. NEUT.abs
90. NEUT%
91. MONO.abs
92. MONO%
93. EOS.abs
94. EOS %
95. BASO abs
96. BASO %
97. HCT/HGB Ratio
98. Gram stain direct
99. Parasites microscopy
100. RDW-SD
101. RDW-CV
102. RETICUL. COUNT abs
103. RETICULOCYTES COUNT%
104. ALY%
105. ALY
106. LIC%
107. LIC
108. P-LCR
109. CHr
110. CH
111. PLATLATE CLUMPS
112. MICRO%/HYPO%
113. NORMOBLAST.abs

114. NORMOBLAST.%
115. TRANSGLUTAMINASE_IgA
116. C13 UREA BREATH CALC
117. PT-INR
118. PT-SEC
119. PT %
120. APTT-sec
121. APTT-R
122. FIBRINOGEN CALCU
123. FIBRINOGEN
124. CONTROL PT
125. CONTROL PTT
126. OCCULT BLOOD STOOL
127. LYMPHOCYTES %-DIF
128. GLUCOSE
129. OCCULT BLOOD SCREEN
130. NEUTROPHILS%-DIF
131. UREA
132. MONOCYTES%-DIF
133. CREATININE
134. EOSINOPHILS%-DIF
135. URIC ACID
136. BASOPHILS%-DIF
137. SODIUM
138. POTASSIUM
139. CHLORIDE
140. CALCIUM
141. lab_208512
142. PHOSPHORUS
143. CHOCOLATE
144. STABS %-DIF
145. PROTEIN-TOTAL
146. ALBUMIN
147. ATYPICAL LYMPH.%-DIF
148. CHOLESTEROL
149. LYMPHOCYTES abs-DIF
150. TRIGLYCERIDES
151. NEUTROPHILS abs-DIF

152. CHOLESTEROL- HDL
153. MONOCYTES abs-DIF
154. CHOLESTEROL-LDL calc
155. EOSINOPHILS abs-DIF
156. BASOPHILS abs-DIF
157. ALK. PHOSPHATASE
158. GOT (AST)
159. GPT (ALT)
160. STABS abs-DIF
161. GGT
162. LDH
163. ATYPICAL LYMPH-DIF
164. CK-CREAT.KINASE(CPK)
165. ANISOCYTOSIS-DIF
166. AMYLASE
167. IRON
168. TRANSFERRIN
169. BILIRUBIN TOTAL
170. BILIRUBIN-DIRECT
171. ALBUMIN (BY EP)
172. GLOBULIN ALPHA-1
173. GLOBULIN ALPHA-2
174. GLOBULIN GAMA
175. REMARK-MANU-DIF
176. MAGNESIUM
177. HEMOGLOBIN A1C %
178. FRUCTOSAMINE
179. SODIUM
180. POTASSIUM
181. CHLORIDE
182. CALCIUM IONIZED
183. pH BLOOD
184. pCO2
185. TOTAL HEMOGLOBIN
186. HCO3
187. TCO2
188. pO2
189. O2 SATURATION

190. Hct- OXIMETRY
191. CARBOXYHEMOGLO-OXIME
192. DEOXYHEMOGLOBIN-OXIM
193. METHEMOGLOBIN-OXIMET
194. OXYHEMOGLOBIN-OXIMET
195. STD BASE EXC (SBE)
196. TOTAL OXYGEN CONTENT
197. O2 TEN. AT 50% SAT
198. ACTUAL BASE EXCBSS
199. STANDARD BICARBONATE
200. LACTATE
201. VITAMIN B12
202. VITAMIN D (25-OH)
203. LIPASE
204. BILIRUBIN-NEONATAL
205. ZINC
206. REMARK-MAN-DIF
207. TROPONIN I
208. TROPONIN T
209. FOLIC ACID
210. CHOLESTEROL/ HDL
211. TRANSFERRIN SATURATI
212. MICROALBUMIN/CREAT
213. GLUCOSE I
214. BILIRUBIN INDIRECT
215. IRON SATURATION
216. GLOBULIN
217. ICTERIC
218. HEMOLYTIC
219. LIPEMIC
220. VLDL
221. ESR
222. CREATININE- U 24h
223. PROTEIN- U SAMPLE
224. CREATININE- U SAMPLE
225. SODIUM-URINE SAMPLE
226. POTASSIUM- U SAMPLE
227. CALCIUM- URINE 24h

228. PROTEIN- URINE 24h
229. MICROALBUMIN- U 24h
230. CALCIUM- U SAMPLE
231. MICROALBUMIN-U SAMP
232. HbF
233. HbA2
234. CARBAMAZEPINE
235. DIGOXIN
236. VALPROIC ACID
237. GLUCOSE 50g
238. CREATININE ENZ.CHILD
239. GLOM.FILTR.RATE
240. NON-HDL_CHOLESTEROL
241. ANA PATTERN
242. ANA TITER
243. CELIAC SCREEN
244. ANTISTREPTOLYSIN O
245. C-REACTIVE PROTEIN
246. RHEUMATOID FACTOR
247. ANTINUCLEAR Ab_(ANA)
248. ANTI CARDIOLIPIN IgM
249. THYROGLOBULIN Ab
250. DNA (ds) Ab
251. RNP
252. Sm (anti Smith Ab)
253. COMPLEMENT C3
254. COMPLEMENT C4
255. TOXOPLASMA IgG
256. TOXOPLASMA IgM
257. HELICO PYLORI IgG
258. REMARKS (GENERAL)
259. REMARKS MICRO
260. HEPATITIS Bs Ag
261. HEPATITIS C Ab
262. HEPATITIS Bs Ab
263. HEPATITIS A IgM
264. CMV IgG
265. CMV IgM

266. EBV VCA_IgG
267. EBV IgG-EBNA
268. EBV VCA IgM
269. RUBELLA Ab IgG
270. Anti Jo-1 Ab
271. Scl-70 Ab
272. ANTI CARDIOLIPIN IgG
273. HEPATITIS Bc Ab TOT.
274. Ig-E TOTAL
275. ANTI THYROID PEROXID
276. COOMBS INDIRECT
277. IgG
278. IgM
279. IgA
280. ANTICENTROMERE Ab
281. ALPHA FETOPROTEIN TM
282. CA-125
283. CA-15-3
284. CA-19-9
285. CEA
286. FERRITIN
287. PSA
288. GLUCOSE - U STRIP
289. BILIRUBIN- U STRIP
290. KETONES- U STRIP
291. SPECIFIC GRAV-U STRI
292. PROTEIN- U STRIP
293. NITRITE- U STRIP
294. LEUCOCYTES - U STRIP
295. ERYTHROCYTES-U STRIP
296. UROBILINOGEN-U STRIP
297. PH- U STRIP
298. SBP_last_v
299. sector
300. SES
301. sex
302. smoking_last_v
303. sw_confined

304. sw_immigrant
305. sw_malig_active
306. sw_malig_ever
307. sw_nursing_care
308. Antiinfectives for Local Oral Treatment
309. Corticosteroids for Local Oral Treatment
310. Calcium Compounds
311. Combination of Complexes of Calcium, Magnesium and AluminumCompounds
312. H2 Receptor Antagonists
313. Proton Pump Inhibitors
314. Synthetic Anticholinergics, Esters with Tertiary Amino Groups
315. Papaverine and Derivatives
316. Other drugs for func. gastro. disorders
317. Other Antispasmodics in Combination with Analgesics
318. Propulsives
319. Serotonin (5HT3) Antagonists
320. Other Antiemetics
321. Bile Acid and derivatives
322. Softeners, Emollients
323. Contact Laxatives
324. Osmotically Acting Laxatives
325. Enemas
326. Other drugs for constipation
327. Charcoal Preparations
328. Bismuth Preparations
329. Oral Rehydrating Salt Formulations
330. Antipropulsives
331. Aminosalicylic Acid and Similar Agents
332. Antidiarrheal Microorganisms
333. Enzyme Preparations
334. Insulins and Analogues, for Injection, Fast Acting
335. Insulin and Analogues, for Injection, Long Acting
336. Biguanides
337. Sufonylureas
338. Combinations or Oral Blood Glucose Lowering Drugs
339. Alpha Glucosidase Inhibitors
340. Dipeptidyl peptidase 4 (DPP-4) Iinhibi.
341. Glucagon-like peptide-1(GLP-1) analogues

342. Sodium-glucose co-transfer 2(SGLT2) Inhibitors
343. Other Blood Glucose Lowering Agents, Excluding Insulins
344. Multiple Vitamins with Minerals
345. Vitamin D and Analogues
346. Vitamin B1, in Combination with Vitamin B6 and/or B12
347. Ascorbic Acid (Vitamin C), Plain
348. Ascorbic Acid (Vitamin C), Combinations
349. Other Plain Vitamin Combinations
350. Vitamins, Other Combinations
351. Calcium
352. Calc.,Comb.with vit.D and/or other drugs
353. Potassium
354. Magnesium
355. Varoius Alimentary Tract and Metabolism Products
356. Vitamin K Antagonists
357. Heparin Group
358. Platelet Aggregation Inhibitors, Excluding Heparin
359. Direct Thrombin Inhibitors
360. Direct factor Xa inhibitors
361. Iron Bivalent, Oral Preparations
362. Iron Trivalent, Oral Preparations
363. Iron , Parenteral Preparations
364. Iron in Combination with Folic Acid
365. Iron in Other Combinations
366. Vitamin B12 (Cyanocobalamine and Derivatives)
367. Folic Acid and Derivatives
368. Other Antianemic Preparations
369. Digitalis Glycosides
370. Antiarrhythmics, Class IC
371. Antiarrhythmics, Class III
372. Organic Nitrates
373. Imidazoline Receptor Agonists
374. Alpha Adrenergic Blocking Agents
375. Thiazides, Plain
376. Sulfonamides, Plain
377. Aldosterone Antagonists
378. Other Antihemorrhoidals for Topical Use
379. Beta Blocking Agents, Non Selective

380. Beta Blocking Agents, Selective
381. Alpha and Beta Blocking Agents
382. Dihydropyridine Derivatives
383. Phenylalkalylamine Derivatives
384. ACE Inhibitors, Plain
385. ACE Inhibitors and Diuretics
386. ACE Inhibitors and Calcium Channel Blockers
387. Angiotensin II Antagonists, Plain
388. Angiotensin II Antagonists and Diuretics
389. Angiotensin II Antagonists and Calcium Channel Blockers
390. HMG CoA Reductase Inhibitors
391. Fibrates
392. Other lipid modifying agents
393. Imidazole Derivatives
394. Other Antifungals for Topical Use
395. Antifungals for Systemic Use
396. Zinc Products
397. Soft Paraffin and Fat Products
398. Carbamide Products
399. Salicylic Acid Products
400. Other Emollients and Protectives
401. Protectives Against UV-Radiations for Topical Use
402. Cod Liver Oil Ointments
403. Other Cicatrizants
404. Antihistamines for Topical Use
405. Anesthetic for Topical Use
406. Other Antipsoriatics for Topical Use
407. Other Antibiotics for Topical Use
408. Sulfonamides
409. Antivirals
410. Corticosteroids, Potent (Group III)
411. Corticosteroids, Very Potent (Group IV)
412. CORTICOSTEROIDS, WEAK, COMBINATIONS WITH ANTIBIOTICS
413. CORTICOSTEROIDS, MODERATELY POTENT, COMBINATIONS WITH ANTIBITICS
414. Corticosteroids, Potent, Combinations with Antibiotics
415. Corticosteroids, Potent, Other Combinations
416. Biguanides and Amidines
417. Phenol and Derivatives

418. Iodine Products
419. Other Antiseptics and Disinfectants
420. Retinoids for Topical Use in Acne
421. Peroxides
422. Antiinfectives for Treatment of Acne
423. Retinoids for Treatment of Acne
424. Medicated Shampoos
425. Wart and Anti-Corn Preparations
426. Other Dermatologicals
427. Imidazole Derivatives
428. Progestogens and Estrogens, Fixed Combinations
429. Progestogens
430. 3-Oxoandrosten (3) Derivatives
431. Natural and Semisynthetic Estrogens, Plain
432. Pregnen (4) Derivatives
433. Estren Derivatives
434. Progestogedns and Estrogens in Fixed Combination
435. Gonadotrophins
436. Antiandrogens and Estrogens
437. Selective Estrogen Receptor Modulator
438. Acidifiers
439. Urinary Concrement Solvents
440. Drugs for urinary frequency and incontinence
441. Drugs Used in Erectile Dysfunction
442. Other Urologicals
443. Alpha-Adrenoreceptor Antagonists
444. Testerone-5 Alpha Reductase Inhibitors
445. Other Drugs Used to Treat Benign Prostatic Hypertrophy
446. Somatotrophin and Somatrophin Agonists
447. Vasopressin and Analogues
448. Glucocorticoids
449. Thyroid Hormones
450. Other anti-parathyroid agents
451. Tetracyclines
452. Penicillins with Extended Spectrum
453. Beta Lactamase Sensitive Penicillins
454. Combinations of Penicillins, Including Beta-Lactamase Inhibitors
455. First-Generation Cephalosporins

456. Second-Generation Cephalosporins
457. Combinations of Sulfonamides and Trimethoprim, Including Derivatives
458. Macrolides
459. LINCOSAMIDES
460. Fluoroquinolones
461. Nitrofuran Derivatives
462. Other Antibacterials
463. Triazole Derivatives
464. Nucleosides and Nucleotides (excl. Reverse Transcriptase Inhibitors)
465. Antivirals for treatment of HIV infections, combinations
466. Influenza Vaccines
467. Hepatitis Vaccines
468. Bacterial and Viral Vaccines, Combined
469. Pyrimidine Analogues
470. Monoclonal Antibodies
471. Other Antineoplastic Agents
472. Gonadotrophin Releasing Hormone Analogues
473. Antiestrogens
474. Aromatase inhibitors
475. SELECTIVE IMMUNOSUPPRESANTS
476. Tumor Necrosis Factor Alpha (TNBF-a) Inhibitors
477. Calcineurin Inhibitors
478. Other Immunosuppressants
479. Acetic Acid Derivatives and Related Substances
480. Oxicams
481. Propionic Acid Derivatives
482. Coxibs
483. Other Antiinflammatory and Antirheumatic Products, Non Steroids
484. Antiinflammatory Preparations, Non Steroid for Topical Use
485. Capsicum and Similar Agents
486. Preparations with Salicylic Acid Derivatives
487. Ethers, Chemically Close to Antihistamines
488. Other Centrally Acting Agents
489. Preparations Inhibiting Uric Acid Production
490. Preparations with No Effect on Uric Acid Metabolism
491. Biphosphonates
492. Biphosphonates and Calcium, Sequential Preparations
493. Amides

494. Natural Opium Alkaloids
495. Phenylpiperidine Derivatives
496. Oripavine Derivatives
497. Opioids in combin. with non-opioid analg.
498. Other Opioids
499. Pyrazolones
500. Anilides
501. SELECTIVE 5HT-RECEPTOR AGONISTS
502. Barbiturates and Derivatives
503. Hydantoins and Derivatives
504. Benzodiazepine Derivatives
505. Carboxamide Derivatives
506. Fatty Acid Derivatives
507. Other Antiepileptics
508. Tertiary Amines
509. DOPA and DOPA Derivatives
510. Amantane Derivatives
511. Dopamine Agonists
512. Monoamine Oxidase Type B Inhibitors
513. Phenothiazines with Aliphatic Side Chain
514. Phenothiazines with Piperazine Structure
515. Phenothiazines with Piperidine Structure
516. Butyrophenone Derivatives
517. Thioxanthine Derivatives
518. Dibenzepines, Oxazepines, thiazepines, and oxepines
519. Benzamides
520. Lithium
521. Other Antipsychotics
522. Benzodiazepine Derivatives
523. Benzodiazepine Derivatives
524. Benzodiazepine Related Drugs
525. Other Hypnotics and Sedatives
526. Nonselective Monoamine Reuptake Inhibitors
527. Selective Serotonin Reuptake Inhibitors
528. Other Antidepressants
529. Centrally Acting Sympathomimetics
530. Anticholinesterases
531. Other Anti-Dementia Drugs

532. Drugs Used in Nicoitine Dependence
533. Antivertigo Preparations
534. Nitroimidazole Derivatives
535. Aminoquinolines
536. Benzimidzole Derivatives
537. Other Ectoparasiticides, Including Scabies
538. Other Insecticides and Repellants
539. Sympathomimetics, Plain
540. Sympathomimetics, Combinations Excluding Corticosteroids
541. Corticosteroids
542. Other Nasal Preparations
543. Sympathomimetics
544. Antiseptics
545. Selective Beta-2 Adrenoreceptor Agonists
546. Adrenergics in combinations with corticosteroids or other drugs, excl. anticholinergics
547. Corticosteroids
548. Anticholinergics
549. Leukotriene Receptor Antagonists
550. Expectorants
551. Mucolytics
552. Opium Alkaloids and Derivatives
553. Other Cough Suppressants
554. Opium Derivatives and Expectorants
555. Substituted Alkylamines
556. Phenothiazine Derivatives
557. Piperazine Derivatives
558. Other Antihistamines for Systemic Use
559. ANTIBIOTICS
560. Fluoroquinolones
561. Corticosteroids, Plain
562. Corticosteroids and Antiinfectives in Combination
563. Sympathomimetics in Glaucoma Therapy
564. Carbonic Anhydrase Inhibitors
565. Beta Blocking Agents
566. Prostaglandin Analogues
567. Sympathomimetics Used as Decongestants
568. Other Antiallergics
569. Other Ophthalmologicals

570. Corticosteroids and Antiinfectives in Combination
571. Analgesics and Anesthetics
572. Indifferent Preparations
573. Antiinfectives
574. Drugs for Treatment of Hyperkalemia
575. Nutrients with Low Calcium Content
576. Other Infant Formulas
577. Fat/Carbohydrate/Protein/Minerals/Vitamins, Combinations
578. Solvents and Diluting Agents, Including Irrigating Solutions
579. Cosmetics-C
580. Cosmetics-E
581. Hearing loss and Deafness
582. S - IHD (s/p MI)
583. S - Ischemic Heart Disease
584. Valvular Cardiac Dis (excl. MVP)
585. CHF-systolic w/o selected medications
586. CHF-systolic with selected medications
587. CHF-non systolic
588. CHF NOS with diuretics
589. CHF NOS
590. Cardiomyopathy
591. IHSS
592. Atrial fibrilation
593. Arrhythmia other
594. S - Hypertension / Diet Treatment
595. S - Hypertension / Drug Treatment
596. S - Hypertension / Unknown Treatment
597. Pulmonary Hypertension
598. s/p CVA
599. Carotid Artery Disease
600. S - Diabetes PVD
601. S - PVD
602. Aortic Aneurism
603. S - Amputation of Limb (Diabetic)
604. Amputation of Limb (Non-Diabetic)
605. S - Amputation of Limb
606. COPD
607. S - Asthma

608. s/p Pulmonary Embolism
609. s/p Pneumothorax
610. Chronic Bronchitis
611. Bronchiectasis
612. Hepatitis B Carrier
613. Celiac Disease
614. Peptic Ulcer
615. Reflux Esophagitis / Gastritis / Deudenitis
616. Irritable Bowel Syndrome
617. Addisons Disease
618. Chronic Act/Per Hepatitis
619. Cirrhosis
620. Wilsons Disease
621. Other Liver Disease
622. Ulcerative Colitis
623. Crohns Disease
624. H - Dialysis
625. Kidney Transplant
626. Prostatic Hypertrophy
627. Liver Transplant
628. Heart Transplant
629. Pancreas Transplant
630. Lung Transplant
631. Bone Marrow Transplant
632. Other Transplant
633. Unknown Transplant
634. Chronic Renal Failure
635. s/p splenectomy
636. Infertility Male/Female
637. S - Diabetic Nephropathy
638. S - Other Kidney Disease
639. Hepatitis C Carrier
640. Pemphigus Vulgaris
641. Psoriasis
642. Hidradenitis Suppurativa
643. Arthropathy
644. SLE
645. Rheumatoid Arthritis

646. Osteoporosis
647. Joint Replacement
648. Sarcoidosis
649. Scleroderma
650. Behcets Disease
651. Other Rheumatic / Autoimmune
652. Polymyalgia Rheumatica
653. Gout
654. s/p Head of Femur Fracture
655. Congenital Anomalies
656. H - AIDS Patient
657. HIV Carrier
658. Familial Mediteranean Fever
659. G-6-P-D Deficiency
660. Amyloidosis
661. S - Breast Cancer
662. S - Malignancy of Colon or Rectum
663. S - Malignancy of Prostate
664. S - Malignancy of Lung
665. S - Malignancy of Bladder
666. S - Malignancy of Ovary
667. S - Malignancy of Uterus
668. S - Malignancy of Pancreas
669. S - Malignancy of Brain / CNS
670. S - Stomach Cancer
671. S - Melanoma
672. S - Hodgkins Lymphoma
673. S - Non Hodgkin Lymphoma / Mycosis Fungoides
674. S - Acute Leukemia
675. S - Chronic Leukemia
676. S - Malignancy of Kidney
677. S - Malignancy of Larynx
678. S - Malignancy of Cervix Uteri
679. S - Malignancy of Pharynx
680. S - Malignancy of Esophagus
681. S - Malignancy of Liver / Bile Ducts
682. S - Malignancy of Thyroid
683. S - Malignancy of Bone

684. S - Malignancy of Connective Tissue / Sarcoma
685. S - Malignancy of Other Male/Female Genital Organs
686. S - Multiple Myeloma
687. S - Polycytemia Vera
688. S - Myelodysplastic Syndrom
689. S - Myelo/Lymphoproliferative Syndrom
690. S - Neurofibromatosis
691. S - Malignancy of Other Sites
692. S - Malignancy of Unknown Site
693. Tuberculosis
694. Benign Brain Tumor
695. Disability / Bedbound
696. Disability / Homebound
697. Disability / Requires assistance with ambulation
698. Breast Family History
699. Colon Family History
700. Hyperthyroidism
701. Hypothyroidism
702. Tuberculosis s/p
703. S - Diabetes / Diet Treatment
704. S - Diabetes / Oral Treatment
705. S - Diabetes / Insulin Treatment
706. S - Diabetes / Insulin + Oral Treatment
707. S - Diabetes / Unknown Treatment
708. H - Gaucher Disease
709. Hypo/Hyperparathyroidism
710. Acromegaly
711. Obesity
712. S - Hyperlipidemia / No Treatment
713. S - Hyperlipidemia / Treatment
714. S - Hyperlipidemia / Unknown Treatment
715. Cystic Fibrosis
716. Hyperprolactinemia
717. Other Endocrine and Metabolic Disease
718. Syphilis / Gonorrhea
719. Cushings Disease
720. Diabetes Insipidus
721. Hypophysary Adenoma

722. H - Hemophilia
723. H - Thalassemia Minor
724. H - Thalassemia Intermedia
725. H - Thalassemia Major
726. H - Thalassemia NOS
727. Other Hematologic Dis (excl. Iron Def Anemia)
728. Sickle Cell Anemia
729. Pernicious Anemia
730. ITP
731. Psychoses
732. Schizophrenia
733. Bipolar Disease (Manic Depressive)
734. Autism
735. Neuroses
736. Depression
737. Anxiety
738. Eating Disorders
739. Alcohol Abuse
740. Current Smoker
741. Former Smoker
742. Smoker
743. Drug Abuse
744. Mental Retardation (incl. Down)
745. Dementia / Alzheimers / OMS
746. Myasthenia Gravis
747. Parkinsons Disease
748. Epilepsy
749. Multiple Sclerosis
750. Cerebral Palsy
751. Huntingtons Chorea
752. Familial Dysautonomia
753. Hereditary Neurological Disease
754. Muscular Dystrophy
755. Motor Neuron Disease
756. S - Diabetic Neuropathy
757. s/p TIA
758. S - Other Neurological Disease
759. S - Diabetic Retinopathy

760. Non-Diabetic Retinopathy
761. S - Retinopathy
762. Glaucoma
763. Blindness
764. Retinitis Pigmentosum
765. Chronic Medication User

D Preliminary Result Graphs and Drawings

D.1 AHA/ACC 2013 Risk Model Result Graph

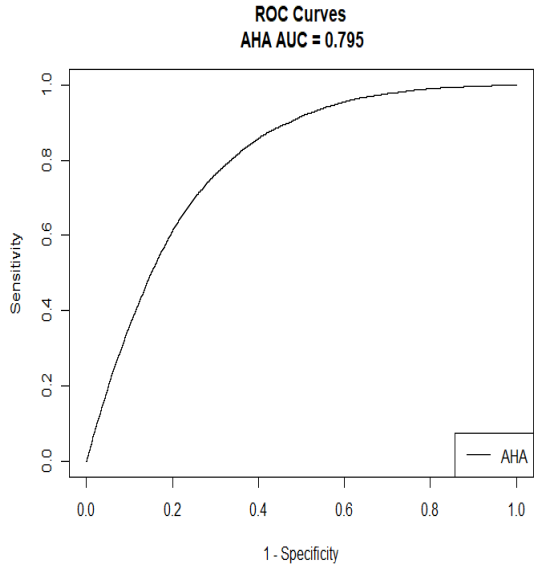

Figure 2: AHA/ACC 2013 ROC Curve

D.2 Clalit Model Population Flow Chart

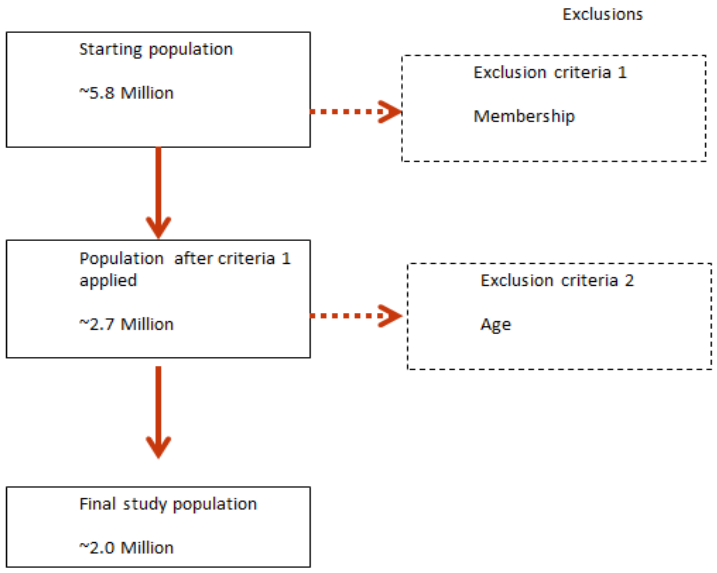

Figure 3: Population Flow Chart