Analyzing Chronic Diseases with Latent Growth Models: 
An Analysis of Multiple Sclerosis

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Abstract

Evidence based decision making in the context of chronic disease management requires long term tracking and analysis of patient data. This study demonstrates how disease data tracking can help in understanding underlying patterns in chronic disease progression. Latent Growth Modeling (LGM) is used as a tool to analyze the long term chronic data related to the progression of Multiple Sclerosis (MS). The survey data has been collected on a bi-annual basis by the North American Research Committee on Multiple Sclerosis (NARCOMS), a project of the Consortium of Multiple Sclerosis Centers for the purpose of clinical trial recruitment and epidemiological research. This data set allows for study of MS progression, by measuring three base models: Patient Determined Disease Steps (PDDS), Overall Health and Emotional Health. MS patient data are grouped as early, middle and late disease status. This study analyzes three temporal data points spanning three years and identifies patient traits that are both patient and physician controlled. Empirical evidence confirms many practitioner observations.

1. Introduction

Health Care and the medical profession have historically focused its attention and efforts toward the patient’s current conditions and what can immediately be accomplished to correct those conditions. The collection of data and information across a wider spectrum has prompted a shift to a greater emphasis on preventive measures that improve individual chances to forestall or even eliminate the emergence of adverse conditions. Chronic disease management can especially benefit from long term tracking and analysis of patient conditions. In this context, the application of analytic methods capable of assessing the long term nature of chronic disease progression is still an emerging area of research. While representation and measurement of change over time is a fundamental concern to practically all scientific disciplines [1], chronic disease tracking and analysis presents some unique challenges and requirements for analysis. Analysis of disease progression requires the incorporation of individual differences in conditions, disease history, treatment options and lifestyle choices. These conditions incorporate individual change over time and allow the identification of factors that make individuals perceive their health status as “better” or “worse”. The analysis time frame should be able to include time frames ranging from weeks to years between assessments.

The primary objective of this research is to demonstrate the application of Latent Growth Modeling (LGM) as a viable technique to analyze chronic disease data spanning multiple years. LGM is a technique used in longitudinal experiments when assessing a specific condition and factors that change those conditions. The specific condition is modeled as a linear function specifying the slope and intercept of the line (with other representations possible). The factors are considered covariates that modify the slope or intercept of the line. LGM has the benefit of incorporating individual differences in the analysis of a variety of conditions that historically could only be analyzed as a group. We use LGM as a valuable...
technique to investigate a large dataset of multiple sclerosis (MS) patients. MS fits well within this type of analysis due to the life-long nature of the disease. Our goal was to empirically analyze the impact of patient activity, treatments and other demographic variables such as age, race and gender, and associated life style choices on patient self reported health condition. Patient success at choosing certain life style and treatment programs through understanding the long term effects of MS can motivate patients with other diseases to search for guidance from similar studies of their own diseases.

The context of the multiple sclerosis study is first discussed in terms of the dataset and the patient participants. The basic application of LGM to multiple sclerosis is then discussed followed by the results of the LGM models. Finally, the implications of LGM use are addressed in the broader health care context along with the conclusions.

2. Multiple Sclerosis Context

Multiple sclerosis (MS) is a neurological disease that can be diagnosed in early childhood or infancy. The rate of disease progression for patients extends for many years and does not generally shorten an individual’s lifespan. While MS is not the cause of death, the quality of life for patients in terms of mobility is affected. Mobility is severely affected in the late stages of the disease and patients progress more rapidly to the final disease stages once reaching a certain stage of mobility [2].

The North American Research Committee on Multiple Sclerosis (NARCOMS) has tracked long-term disease progression over several years through a patient provided data set. The survey conducted by NARCOMS is administered every six months with a respondent population ranging from 8,000 to over 10,000 MS patients for the three year study period. The NARCOMS database includes patients as young as age 12 with 25% of the MS population below the age of 32. One of the key data points of the survey is a 9 point scale indicating the Patient Determined Disease Steps (PDDS), a proxy for progression of disease (Table 1). A significant sign of MS progression is the mobility of the patient and the PDDS scale measures decreased mobility through increasing scale item values.

The extended temporal nature of MS progression requires techniques that can incorporate patient self-reported disease status longitudinally. Latent Growth Modeling (LGM) provides the benefits of representing the disease progression in multiple time frames and the impact of life style, treatment and fixed effects in the model. The advantages to LGM include greater flexibility in specification, explicitness of all aspects of the model and the use of latent variable score estimates [3].

Our goal is to present LGM as a valuable technique to the investigation of MS and other long term illnesses. Three base models will be presented in which the basic disease progression marker, PDDS, is used for the 1st model. PDDS will be part of a latent variable termed Overall Health in the 2nd model. The final base model will evaluate another latent variable that represents the Emotional Health of patients. Each of these three base models can identify patient differences in fixed effects (age, sex, and race), life style (employment, income level) and treatment (on drug therapy).

3. Application of LGM for MS

Latent Growth Modeling is a technique used in longitudinal experiments when assessing a specific condition and factors that change those conditions. The use of LGM requires a dataset that has been collected consistently over the course of multiple assessments. These assessment periods can be over the course of a few months to multi-year assessments that span decades. Some examples of LGM application include a change in alcohol use that was assessed every six months for participants that were randomly assigned to three separate treatment
programs [4]. Adolescent substance use has been assessed yearly for seven years as an associative model of participant and participant peer groups [5]. Rates of autism identification in schools have been tracked over a seven year time period based on the districts available resources in school districts [6]. Psychologists have tracked the progression of adolescent Antisocial Behavior through the middle school years (4th thru 8th), assessed the covariates of Monitoring, Discipline, Wandering Change and Peer Change and their effect on the children as they progressed through their school years [7].

Latent Growth Models hypothesize a relationship across time periods that is represented by a linear equation (Figure 1 - Latent Growth Model). The following assumptions are the basis for testing the base LGM for the basic disease marker and the latent variables of interest. The measurement points are represented by Time 1 through Time 3. Data collection must include respondents from each time period. The linear equation is assumed to have the same intercept for all time periods and is represented in the model by the 1’s going from the intercept to each time period. Linear Growth, or Slope, in the case of MS is interpreted as disease progression. The initial assumption is that the disease progresses in a linear fashion, as opposed to a quadratic fashion. This assumption is represented by the path coefficients of 0, 1 and 2 leading from the Slope to each of the time periods 1, 2 and 3. The base models would have no Covariate included. When the Covariates are added to the model, the path coefficients leading from the Covariate would represent either positive or negative directional changes to the Intercept and Slope. Model fit statistics provide a measure of how good the assumptions are represented by the LGM.

The dataset provided by NARCOMS included 3,774 patient respondents across six survey time periods that included: 1) Fall 2004 (F04), 2) Spring 2005 (S05), 3) Fall 2005 (F05), 4) Spring 2006 (S06), 5) Fall 2006 (F06), and 6) Spring 2007 (S07). The population demographics are presented in Table 2. On average, the patient respondents have been living with MS for 15 years since diagnosis and 23 years since the onset of symptoms. Females in the population outnumber males three to one. MS seems to be racially discriminant with 93.6% of the study participants reporting their race as white.

The timeline for disease progression is known to be different for early vs. later stages of MS [2]. Since one of the goals of this study is to investigate these different disease progression stages, Table 2 also provides a division of the population that may be in either an early, middle or late stage of MS. The early stage is defined as anyone on the PDDS scale of 0, 1 or 2. The middle stage is defined as answers of 3, 4 or 5 and the late stage consists of answers of 6, 7 or 8. This division was based on the respondent answers to the PDDS question for the survey administered in Fall of 2005. The resulting three groups represent different sample sizes of the original 3,774 respondents. The three PDDS partitioned groups total 3,753 respondents. There were 21 respondents that had missing data for part of the LGMs tested. The

Table 2 - MS Patient Respondent Demographics

<table>
<thead>
<tr>
<th>N</th>
<th>% Female</th>
<th>% White</th>
<th>Employed</th>
</tr>
</thead>
<tbody>
<tr>
<td>3774</td>
<td>74.9%</td>
<td>93.6%</td>
<td>~ 35%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Age (@ Diag.</th>
<th>@ Onset</th>
<th>Health Ins</th>
<th>~ 98%</th>
</tr>
</thead>
<tbody>
<tr>
<td>53.21</td>
<td>38.74</td>
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</table>

<table>
<thead>
<tr>
<th>Early PDSS</th>
<th>Mid PDSS</th>
<th>Late PDSS</th>
<th>Drug Therapy</th>
</tr>
</thead>
<tbody>
<tr>
<td>~ 31%</td>
<td>~ 40%</td>
<td>~ 29%</td>
<td>~ 35%</td>
</tr>
</tbody>
</table>

Figure 1 - Latent Growth Model

data for these respondents was removed. Approximately 35% of the respondents are on some form of drug therapy. In addition, 35% of the population is employed with 98% of the population having some form of Health Insurance. The ~ symbol indicates that these percentages are approximated across the six survey timelines since the PDDS answers, as well as drug therapy, employment and health insurance, can change from survey to survey.

The latent variables, Overall Health and Emotional Health, each include four scale items. In addition to the 9 item PDDS scale, the remaining three scale items included were labeled mobility (Mobility), moderate activity (Mod Act) and climbing stairs (Climb Strs). Mobility is a 7 point
scale ranging from 0 – Normal to 6 – Bedridden. Moderate activity and climbing stairs are both a 3 point scale ranging from 1 – limited a lot to 3 – no limitations. The Emotional Health latent variable included: Accomplished Emotional (Acc Emot), Careful Emotional (C Emot), Calm (Calm) and Depression (Depress). All of the Emotional Health items are on a scale of 1 to 5 with 1 indicating “All of the time” and 5 indicating “None of the time”. Acc Emot asks if the patient “accomplished less than they would have liked” and C Emot asked if the patient “Didn’t do work as carefully as usual”. The Calm scale item asked if the patient felt “calm and peaceful” while the Depress item asked “Have you felt downhearted and depressed”. PDDS, Mobility, and Calm are all reverse coded with higher numbered responses indicating disease progression or negative effects.

To validate the increasing progression between the three groups, three LGMs were used to assess these changes. For the first LGM, only the scale item PDDS was used from the surveys of S05, S06 and S07. The same surveys were used to run the LGM for Overall Health and Emotional Health. The PDDS and OH base models both indicate a more rapid increase in disease progression in group 3 when compared to group 1. The Emotional Health base model provides a more stable picture of the patients (Figure 2 - LGM Base Models). The presentation of the fit statistics for the base models can be found in Table 3. The base models provide a baseline comparison when different covariates are included in the LGM.

### Table 3 - Base Model Fit

<table>
<thead>
<tr>
<th>LGM Type</th>
<th>Group</th>
<th>N</th>
<th>df</th>
<th>Chi²</th>
<th>RMSEA</th>
<th>NFI</th>
<th>NNFI</th>
<th>CFI</th>
<th>SRMR</th>
<th>GFI</th>
</tr>
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<tbody>
<tr>
<td>PDDS Base</td>
<td>1</td>
<td>1196</td>
<td>1</td>
<td>0.03</td>
<td>0.000</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>0.000</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1512</td>
<td>1</td>
<td>2.07</td>
<td>0.027</td>
<td>1.00</td>
<td>1.00</td>
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<td>1.00</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1045</td>
<td>1</td>
<td>0.98</td>
<td>0.000</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>0.000</td>
<td>1.00</td>
</tr>
<tr>
<td>Overall Health Base</td>
<td>1</td>
<td>1192</td>
<td>34</td>
<td>169</td>
<td>0.058</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.031</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1512</td>
<td>34</td>
<td>271</td>
<td>0.068</td>
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<tr>
<td></td>
<td>3</td>
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<td>34</td>
<td>110</td>
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<td>0.98</td>
<td>0.99</td>
<td>0.047</td>
<td>0.98</td>
</tr>
<tr>
<td>Emotional Health Base</td>
<td>1</td>
<td>1192</td>
<td>33</td>
<td>110</td>
<td>0.044</td>
<td>0.99</td>
<td>0.99</td>
<td>1.00</td>
<td>1.000</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
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<td>0.99</td>
<td>0.99</td>
<td>0.029</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td>3</td>
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<td>33</td>
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<td>0.080</td>
<td>0.98</td>
<td>0.97</td>
<td>0.99</td>
<td>0.047</td>
<td>0.96</td>
</tr>
</tbody>
</table>
4. Results - Covariate Modifications to Disease Progression

Examples of the covariates for this study include age, employment status and income. The inclusion of independent variables, and their effect on the dependent variable, is only assessed after the relationship between the covariates and dependent variables are removed [8]. Covariates are used in LGM to determine modifications to either intercept or slope.

Figure 3 – Covariate Modifications demonstrates the anticipated modifications to the linear progression of MS based on a single covariate. The Overall Health Base model discussed previously is represented by the decreasing line labeled OHbase. All modifications are premised from this base line. A covariate that adjusts the base model line may have the effect statistically of modifying the slope or disease development of Overall Health either positively or negatively. The covariate may also be associated with a change in intercept, or starting point, either positively or negatively. Note that these associations do not necessarily imply causation. The hypothesized representational changes in Figure 3 – Covariate Modifications indicate that, from the base linear disease progression line (OHbase), a negative intercept change, line OHİ, represents a lower Overall Health starting point with no slope change or rate of disease progression. A positive slope change, or reduced rate of disease progression, is represented by the line OHAS+.

When assessing the effects of covariates on MS disease progression, a consistent modification of either the disease starting level or disease progression advancement is searched for across the three groups of MS assessment respondents. Tables have been constructed to assist in the identification of the consistency of covariate associated adjustments to the base model characteristics. Tables 4 and 5 are constructed to present the results of covariates on the Emotional Health and Overall Health of each group. The consistency of the results is determined when a single covariate has the same effect across all three groups for either Overall or Emotional Health. These effects may be either a significant positive/negative slope change or a significant positive/negative intercept change.

Age Effects of MS

The expectations of disease progression may vary based on several views of a patient’s age. Since MS is not a curable disease, part of the goal is to provide MS patients with a life style that is as close to normal as possible. Three views of the patient’s age are used as covariates: Age, Age @ Diagnosis and Age @ Onset. For these LGMs, Age is simply defined as the patient’s birth age. The Age @ Diagnosis is the age at which a medical professional has confirmed that the patient does in fact have MS. Once this confirmation has occurred, life prior to the Age @ Diagnosis is reviewed. This review allows the patient to determine at which point in their life they can recognize the onset of symptoms of MS. This will then determine the covariate referred to as the Age @ Onset. Each of these covariates is used to assess their adjustment on the base LGM models.

An analysis of these covariates for all three groups is summarized in Table 4. The initial covariate (Age) indicates that, as an individual increases with Age, their Overall Health decreases as depicted by a positive increase in their Intercept. This covariate is the only one that indicates a consistent directional adjustment across all three groups. A graphical representation of this modification is provided in Figure 4 - Age Intercept Modification. The change over time or slope shows a positive increase only for Groups 1 and 2 which would be considered the healthiest MS patients. Disease progression is more rapid for older patients than for younger patients.

For the Age @ Diagnosis, the individuals for Group 1 and 2 that were diagnosed later in life exhibit a more advanced disease starting point. The starting point for Overall Health of these older patients is lower, indicating a more rapid disease progression. The Age @ Onset covariate is used to assess the effect of the age at which a patient recognizes the onset of symptoms of MS. This covariate is used to determine the disease starting level, or intercept, of Overall Health.

1 Only the fit statistics for the base model have been provided due to space constraints. Fit statistics for the Age Effect models and the remainder of the models outlined can be requested from the authors.
patients does not indicate any change in the rate of their disease progression. The only significant covariate for Age @ Onset was with Group 1 which indicated a reduction in the disease progression rate for the most capably active Group 1 patients. This specifies that the older patients are before “getting” the disease symptoms, the slower the disease progresses through the rest of their life.

With the Emotional Health assessment, positive increases in slope and intercept would indicate an improvement in the Emotional Health of the patient. None of the Age associated covariates exhibited consistent results across all three of the study groups. Group 1 had the most significant results indicating that: 1) the starting point of Emotional Health for the patient decreased with age; 2) Increase in Age @ Onset indicated both a positive increase of the starting point and positive slope improvement for Emotional Health. The group three Age model did not converge (DNC). In addition, patients in Group 3 showed a deteriorated Emotional Health in relation to Age @ diagnosis.

**Life Style and MS**

The early stages of MS are noted for how a patient is willing to continue to be active and productive in their lives. The activity and productivity of MS patients in these LGMs are indicated through their Income level where increasing selections of this categorical variable indicates higher levels of income. Employment Status is operationalized as a dichotomous variable of either Yes (0) or No (1).²

² The fit statistics for the models of these Life Style effects can be requested from the authors.
For Emotional Health, the starting point for MS was significantly related by both Employment status and Income for all three groups and in the same directions for all three groups. MS Patients who were employed had improved Emotional Health and were associated with additional Emotional Health benefits as their income increased (Figure 5 - Emotional Health). The rate of Emotional health change was significant only for Group 2 with the Income covariate. For this group, as their income increased their Emotional Health exhibited a reduction compared with those of lower Income levels.

### Drug Therapy Effectiveness

Whether a patient enters into a drug treatment therapy is a decision made under the consultation of a physician. There are multiple categories of drug therapies available. The data available for this investigation was a dichotomous variable indicating only whether the patient was participating in a drug treatment therapy or not. Generally, when a MS patient begins a drug treatment therapy, they continue for extended periods of time. Switching drugs during this time period is common. However, the drugs available during this analysis time period are equivalent in efficacy and therefore appropriate to compare patient status of either on or off drug therapy. The patient data used for these LGMs were checked to insure that patients included as on Drug Therapy for the target survey of spring 2006 were also on drug therapy for Spring 2005 and Spring 2007.

The significance of this covariate (Table 5) was inconsistent across the groups for Overall Health. However, for those significant relationships, the consistent message was that being on drug therapy was not associated with an improvement in the patient’s condition when compared to the base model. Group 2 and 3 both showed an association with improved Overall Health (intercept) when compared to those patients not on drug therapies. Group 1 showed an improved disease progression (slope) for those not on drug therapies. Emotional Health was consistent for all three groups in that being on Drug Therapy did not affect their Emotional Health stability. However, mixed results for each group resulted in their starting points of Emotional Health. For Group 1 and 3, being on drug therapy was positively related with improved Emotional Health. Group 2, in contrast, showed a negative relationship in Emotional Health when they were on drug therapy.

### Table 5 - Employment/Income & Drug Therapy Covariates

<table>
<thead>
<tr>
<th>Type</th>
<th>Group</th>
<th>Employment Status</th>
<th>Income</th>
<th>Drug Therapy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Intercept Adjust</td>
<td>Slope Adjust</td>
<td>Intercept Adjust</td>
</tr>
<tr>
<td>Overall Health</td>
<td>1</td>
<td>Pos ***</td>
<td>No Effect</td>
<td>Neg ***</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Pos ***</td>
<td>No Effect</td>
<td>Neg ***</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>Pos ***</td>
<td>Neg ***</td>
<td>No Effect</td>
</tr>
<tr>
<td>Emotional Health</td>
<td>1</td>
<td>Neg ***</td>
<td>No Effect</td>
<td>Pos ***</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Neg ***</td>
<td>No Effect</td>
<td>Pos ***</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>Neg ***</td>
<td>No Effect</td>
<td>Pos ***</td>
</tr>
</tbody>
</table>

For Emotional Health, the starting point (EHBase) and the change in Emotional Health (EH_{Δt}) are shown in Figure 5 - Emotional Health Income/Employed Covariate. Emotional Health was better for those who were employed.
5. Implications of LGM to Health Care

Context

The application of LGM to the NARCOMS dataset brings out the importance of this technique, not only for MS, but for multiple health care contexts. This initial analysis of MS growth factors highlight individual patient differences that are controllable (job status and drug therapy) and are not controllable (age). Each of the covariates explained individual differences within the three groups of patients analyzed. Specific improvements in Overall Health and Emotional Health could be anticipated with the patient’s determination of staying employed or seeking some form of drug therapy. These results were reached with an investigation using three data points across a three year time span of assessment and making a basic assumption of linearity in the dataset. The possible insights to be gained of the NARCOMS dataset, and other health care datasets, can be extended through the use of more complex specifically targeted LGM models.

The assumption of linearity for any disease context should always be questioned. There are often “triggers” that occur in a patients disease progression that hastens the advance of the disease. LGM allows the ability of the slope function to be determined by the dataset under investigation. A simple model determining the slope would allow the calculation of the third time periods slope function. Any result indicating a non-linear function would then more accurately be termed a shape function [1]. The determination of the true shape of the curve may require more data points for this unspecified growth function. Guidance on the number of data points required is available from Tisak and Meredith [9] and Burchinal and Applebaum [10]. The shape of growth over time can therefore be specified as either quadratic, cubic or left unspecified.

The change over time or shape of the curve, of any disease may vary between two multiple assessment periods. A Piece-wise LGM may be applied to determine a linear growth that exists in the first assessment period (three data points) while a quadratic growth may exist in the second assessment period (three data points) [11]. These periods may be separated by age, treatment or some other distinguishable variable. LGM also allows and Accelerated Design model in which cohorts can be sequentially modeled in order to form a common developmental trajectory of growth. This “cohort-sequential” design [12], in the case of MS and the NARCOMS dataset, can allow the three groups (early, middle and late disease progression) to be sequentially modeled to provide a clearer interpretation of the rapid advance of the late stages of the disease. This design is referred to as accelerated since the data from the different cohorts was collected during a shortened or identical time period.

The inclusion of additional covariates and application of models with greater complexity can provide even greater insights into the shape of MS progression and how predictors can modify that shape. The importance of treatment and life style interventions that improve the overall and emotional health of MS patients, as identified through the various LGM techniques, can allow patients to enact and their physicians to recommend positive life style changes.

6. Conclusions

The analysis of the NARCOMS dataset for MS patients included three cohorts at different disease stages and four covariates in the investigation of the linear progression of MS. Each covariate provided an indication of some linear modification of either overall or emotional health of the patient. The extended nature of the disease, an individual’s lifetime, would indicate that a three year assessment period is small compared to the length of time individuals live with the disease. However, even in the abbreviated time period of this study, LGM has demonstrated that controllable influences in an individual’s life can restrain progression of the disease. Though a control group of the normal population was not analyzed, it is safe to say that the health declines as individuals advance in age. Extending this study to assess the differences between MS patients and a normal population could bring greater understanding of the potential intervention effects for MS patients.

In a broader context, LGM can make use of existing datasets that allow the modeling of patients with long term diseases such as cancer, diabetes, heart disease and many more. LGM can model patients grouped as long term survivors of heart disease to analyze their life styles and treatments to inform new patients of the most effective steps to take to insure their continued life style. An accelerated LGM design, including a cohort of heart design “survivors” and a cohort of individuals “at risk”, can initially begin to investigate predictive covariates that further reduces the risk of heart disease for those individuals “at risk”. Diabetes research could be enhanced by an LGM investigation that analyzes the “trigger” events that place
individuals on insulin. Covariates that enhance the
life and life styles can provide better medical care
and reduce long term expenses for both the health
care sector and the private consumers.

Achieving these goals does require a long term
view for the collection of data. NARCOMS has a
dataset much larger than was currently available for
study. Recent efforts are underway to consolidate all
of the NARCOMS data in a central repository in
order to mine their data for up to a ten year period.
Improvements in the ability to assess additional
covariates would require the inclusion of specific
treatments. These treatments could be physical
therapy, drug therapy or social interventions. Data
cleansing techniques should be used when scales
have been adjusted for survey questions. Finally, care
must be taken to insure the privacy of all participants.
Yet, for LGM to be useful to health care research,
each assessment must continue to capture and link
the patient’s data in order to shape the progression of
any long term disease in order to assess beneficial
predictive variables.

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