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Screening for Impaired Fasting Glucose and Diabetes Using Available Health Plan Data

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Abstract

Aims—To develop and validate prediction equations to identify individuals at high-risk for type 2 diabetes using existing health plan data.

Methods—Health plan data from 2005–2009 from 18,527 members of a Midwestern HMO without diabetes, 6% who had fasting plasma glucose (FPG) 110 mg/dL , and health plan data from 2005–2006 from 368,025 members of a West Coast integrated delivery system without diabetes, 13% who had FPG $\,$ 110 mg/dL were analyzed. Within each health plan, we used multiple logistic regression to develop equations to predict FPG $\,$ 110 mg/dL for half of the population and validated the equations using the other half. We then externally validated the equations in the other health plan.

Results—Areas under the curve for the most parsimonious equations were 0.665 to 0.729 when validated internally. Positive predictive values were 14% to 32% when validated internally and 14% to 29% when validated externally.

Conclusion—Multivariate logistic regression equations can be applied to existing health plan data to efficiently identify persons at higher risk for dysglycemia who might benefit from definitive diagnostic testing and interventions to prevent or treat diabetes.

Competing interests: The authors declare that they have no competing interests.

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Authors' contributions: LMN participated in the design of the study, performed the statistical analysis, and drafted the manuscript. SRA performed the statistical analysis and helped draft the manuscript. JAS participated in the design of the study and helped to draft the manuscript. AF participated in the design of the study. JVS and WHH conceived of the study, and participated in its design and coordination. All authors read and approved the final manuscript.

Keywords

screening; impaired fasting glucose; diabetes; administrative data

BACKGROUND

Prediabetes may be defined by a fasting plasma glucose (FPG) 110 mg/dL and $\lt 126 \text{ mg/d}$ dL, or a hemoglobin A1c (HbA1c) 5.7 and $< 6.5\%$ (WHO 2006; Ryden, Standl et al. 2007). Prediabetes is associated with an increased risk of type 2 diabetes and cardiovascular disease (Gerstein, Santaguida et al. 2007; Ford, Zhao et al. 2010; ADA 2011). In 2001, the Hoorn Study found that over a six year period, persons with impaired fasting glucose (FPG

≥ 110 mg/dL) were nearly 8 times more likely to develop diabetes than those with normal tolerance at baseline (de Vegt, Dekker et al. 2001). The World Health Organization (WHO) predicts that the worldwide prevalence of diabetes among persons 20 years of age will increase from 4.0% measured in 1995 to 5.4% by the year 2025 (King, Aubert et al. 1998). To help curb this increase, it is essential to identify persons at high risk for developing diabetes and target them for primary prevention. Interventions are effective in delaying or preventing the development of type 2 diabetes and may reduce the risk of cardiovascular disease (Pan, Li et al. 1997; Tuomilehto, Lindstrom et al. 2001; Chiasson, Josse et al. 2002; Knowler, Barrett-Connor et al. 2002; Gerstein, Yusuf et al. 2006). Unfortunately, diabetes prevention has not been translated into routine clinical practice in part due to the difficulty in identifying individuals at risk.

We hypothesized that within organized systems of care, individuals at risk for type 2 diabetes may be identified without additional laboratory testing. Indeed, high risk individuals may be identified with existing health plan data and targeted laboratory testing may be performed only for those at risk. The goal of our study was to develop and to internally and externally validate equations to screen for prediabetes and previously undiagnosed diabetes using available health plan data. We believe that that the availability of such equations will facilitate the development and widespread implementation of costeffective interventions to prevent or treat diabetes.

SUBJECTS

To assess the likelihood of impaired fasting glucose (IFG) or previously undiagnosed diabetes, we developed a set of predictive equations using data from a Midwestern independent practice association model health maintenance organization (HMO) that requires primary care physicians to assess and report members' height, weight, blood pressure, FPG, lipids, and smoking status each year. Subjects were at least 18 years of age, not pregnant, had no history of diabetes, and were enrolled in the plan between January 2006 and March 2009. We obtained demographic, claims, and pharmacy data from the health plan, laboratory data from contracted laboratory providers and program enrollment forms, and clinical data from program enrollment forms. Demographic data included age, sex, and race. Claims data included CPT or ICD9 codes for obesity, hypertension, dyslipidemia, gestational diabetes mellitus (GDM), polycystic ovarian syndrome (PCOS), and cardiovascular disease in the 12 months before or after program enrollment (Appendix 1). Pharmacy data included evidence of one or more filled prescriptions for metformin, antihypertensive medications, or lipid-lowering medications in the 12 months before program enrollment (Appendix 1). Laboratory values were obtained for the date closest to enrollment from either the laboratory database or the program enrollment form. Laboratory data included total cholesterol, HDL, triglycerides, and calculated or direct LDL. Clinical

data were obtained from program enrollment forms and included body mass index (BMI), systolic blood pressure, smoking status, and FPG.

Predictive equations were also developed using data from a large West Coast staff model integrated delivery system. Subjects were at least 18 years of age, not pregnant, had no history of diabetes, and had a FPG performed in 2005 or 2006. The plan provided demographic, diagnoses, pharmacy, and laboratory data, as well as clinical data from electronic medical records.

Demographic data included age, sex, and race. Diagnoses included history of obesity, hypertension, dyslipidemia, GDM, PCOS, and cardiovascular disease in the 12 months preceding the date of the FPG test. Pharmacy data included evidence of one or more filled prescriptions for metformin, antihypertensive medications, or lipid-lowering medications in the 12 months before the FPG test date. Laboratory values were obtained from the laboratory database for the date closest to the FPG test and clinical data were obtained from electronic medical records.

For both health plans, we limited the study populations to those ≤ 40 years and $\lt 65$ years of age to increase the prevalence of IFG and undiagnosed diabetes and to account for the fact that few subjects 65 years of age were enrolled in these commercial health plans. We also excluded from the analyses any person with a filled prescription for a thiazolidinedione in the 12 months before the FPG date.

MATERIALS AND METHODS

Equation development

Data from each health plan were randomly divided into two equal parts, a development set and a validation set. Equations were developed using the development set and internally validated using the validation set.

Using a FPG cutpoint 110 mg/dL, we classified each subject as having normal glucose tolerance or IFG/diabetes. We then independently developed four equations to incorporate the available data from each health plan. The most simple equation used only demographic and claims or diagnoses data (Equation A). The second used demographic, claims/ diagnoses, and pharmacy data (Equation B). The third used demographic, claims/diagnoses, pharmacy, and laboratory data (Equation C). The final equation used demographic, claims/ diagnoses, pharmacy, laboratory, and clinical data (Equation D). In the Midwestern HMO, smoking status was available only through clinical data and was included only in Equation D. In the West Coast integrated delivery system, smoking status was available in claims/ diagnoses data and was included in Equations B, C, and D.

For each progressively more complex equation, we included only persons with non-missing data for the variables in the equation. For the Midwestern HMO, there were 9,264 individuals included in Equations A and B, 6,439 in Equation C, and 6,116 in Equation D. In the West Coast integrated delivery system, there were 184,197 individuals included in Equations A and B, 149,368 in Equation C, and 138,019 in Equation D. The same populations were used to construct the full and most parsimonious equations (Table 2).

The predictive equations were calculated with the following logistic regression parameters: $P = 1/(1 + e^{-X})$. The final mathematical equation provides an estimate of a subject's likelihood of previously undiagnosed IFG or diabetes expressed as a probability between 0.0 and 1.0. To obtain the most parsimonious equations, we removed variables with p-values $>$ 0.05 in the Midwestern HMO and > 0.01 in the West Coast integrated delivery system.

For each predictive equation, the significance of the variables was assessed by the Wald chisquare test, the estimated odds ratios, and 95% confidence intervals. Using the population with non-missing data for the most complex equation (Equation D), we assessed the fit of each equation by reporting the max-rescaled \mathbb{R}^2 , and the discrimination of each equation, defined as the ability of the equation to distinguish high-risk subjects as quantified by the area under the curve (C-statistic).

Equation validation

To internally validate the equations, we ran the most parsimonious equations in the health plan in which they were developed using the validation dataset and persons who had nonmissing data for each of the variables (Equation D, $N=8,682$ and $N=137,342$). To determine the positive predictive value (PPV) of Equations A-D, we used estimates from the most parsimonious equations (Table 2) and applied them to the corresponding validation populations of persons with non-missing data. From these analyses, we estimated the probabilities of IFG or diabetes for each person from each health plan. We then sorted these probabilities into deciles of predicted risk in order from low to high. For each decile of predicted risk, we calculated the percentage of persons with FPG $\,$ 110 mg/dL in that decile. This gave us estimates of the PPV for each of the equations.

We then externally validated the equations developed in each health plan using data from the other health plan. For these analyses, we used the same process to calculate PPV, using the entire datasets (development and validation combined) and members who had nonmissing data for each variable. The estimates for these equations are presented in Table 3. All analyses were performed using SAS version 9.1.3 or 9.2 (SAS Institute, Cary, NC).

RESULTS

Table 1 describes the characteristics of the populations. Six percent of the subjects in the Midwestern HMO had dysglycemia (N=919 (81%) IFG and N=219 (19%) previously undiagnosed diabetes) and 13% of the subjects in the West Coast integrated delivery system had dysglycemia (N=34,425 (71%) IFG and N=14,243 (29%) previously undiagnosed diabetes). The Midwestern HMO population was younger (mean age 50 years), 78% white, and more likely to be nonsmokers (94%). The West Coast integrated delivery system population was older (mean age 52 years) and more diverse (57% white). Diagnosis and treatment rates differed dramatically between plans but risk factors levels were similar. Substantial proportions of the Midwestern and West Coast populations had claims for hypertension (38% and 27% respectively) and had filled prescriptions for lipid-lowering medications (20% and 18%). In the West Coast integrated delivery system, more people had diagnoses of obesity (27% vs. 11%), however, the average BMI was the same (29 kg/m² vs. 29 kg/m²). In the Midwestern HMO, more people had claims for dyslipidemia (67% vs. 18%), however, the average LDL and HDL levels were similar (LDL: 118 mg/dL vs. 126 mg/dL, HDL: 51 mg/dL vs. 53 mg/dL). In the Midwestern HMO, more persons had claims for cardiovascular disease (21% vs. 5%).

The full equations derived in the development populations are presented in Appendix 2. We have indicated by an asterisk the variables that were included in the most parsimonious equations presented in Table 2 for both the Midwestern HMO and the West Coast integrated delivery system. In the Midwestern HMO, for the equation with the most limited data (Equation A), the most parsimonious equation included older age, male sex, and claims for obesity, hypertension, and dyslipidemia. For Equation B, which also included pharmacy data, the most parsimonious equation did not include dyslipidemia, but instead included lipid-lowering medications and metformin. For Equation C which also included laboratory values, the most parsimonious equation included older age, male sex, claims for obesity and

hypertension, metformin, and higher total cholesterol and lower HDL. For Equation D, which included clinical data, the most parsimonious equation included older age, male sex, race (higher risk for Asians compared to whites), metformin, lower HDL, higher BMI, and higher systolic blood pressure.

When we used the variables in Table 2 and the internal validation population that had nonmissing values for all variables in Equation D (N=8,682), the following R^2 and c-statistics were obtained: Equation A: R^2 =0.066, C-statistic=0.686, Equation B: R^2 =0.089, Cstatistic=0.706, Equation C: R^2 =0.088, C-statistic=0.706, Equation D: R^2 =0.109, Cstatistic=0.729 (data not shown in table). The equations explained 6.6% to 10.9%of the variance in the outcome and the areas under the curve were fair, 0.686 to 0.729.

In the West Coast integrated delivery system population, the most parsimonious equation, developed with the most limited data (Equation A) included older age, male sex, and diagnoses for obesity, hypertension, and cardiovascular disease (Table 2). For Equation B, the most parsimonious equation included older age, male sex, race (higher risk for Asian, Other, or missing compared to white), smoking, diagnoses for obesity, hypertension, dyslipidemia, and antihypertensive medications, lipid-lowering medications, and metformin. For Equation C, the most parsimonious equation included older age, male sex, race (higher risk for all groups compared to white), smoking, diagnoses for obesity, hypertension and dyslipidemia, antihypertensive medications, and lipid-lowering medications, lower HDL and higher triglycerides. For Equation D, the most parsimonious equation included older age, male sex, race (higher risk for all groups compared to white), smoking, diagnoses for obesity, hypertension and dyslipidemia, antihypertensive medications, lipid-lowering medications, lower HDL, higher triglycerides, higher BMI, and higher systolic blood pressure.

When using the variables presented in Table 2 and the internal validation population with non-missing values for all the variables in Equation D (N=137,342), the following \mathbb{R}^2 and cstatistics were obtained: Equation A: R^2 =0.069, C-statistic=0.665, Equation B: R^2 =0.083, Cstatistic=0.681, Equation C: R^2 =0.106, C-statistic=0.703, and Equation D: R^2 =0.123, Cstatistic=0.718 (data not shown in table).

For each validation population, to determine sensitivity, specificity, and PPV of the most parsimonious equations we sorted the probabilities into deciles of increasing risk and showed the number of persons with IFG or diabetes and the total number of persons in each decile (Table 3). For example, in the Midwestern HMO validation population, for Equation A, the total population was 9,263 and the prevalence of IFG or diabetes was 6% (N=558). In the highest decile of risk, 133 of the 964 persons had IFG or diabetes (PPV $= 14\%$). Sensitivity, the percent of true positives who are identified as such, was 133 / 588 or 24% and specificity, the percent of true negatives who are correctly identified, was 7,874 / 8,705 or 90%. PPV, sensitivity, and specificity were calculated for the remaining equations in a similar manner and Table 4 presents the sensitivity, specificity, and positive predictive values for the highest decide of risk for both the internal and external validation populations. Table 3 can also be used to determine the performance of the equations if one used, for example, the highest three deciles of risk to define a positive test. In the validation population of the Midwestern HMO, if the highest three decides of risk were used to define a positive test, the yield would be $(133 + 87 + 58 = 278)$, and the PPV 10%, the sensitivity 50%, and the specificity 71%.

CONCLUSION

We have demonstrated the feasibility of using existing health plan data to identify individuals at high risk for impaired fasting glucose and previously undiagnosed diabetes

and have documented the performance of equations according to the data available in each health plan. In general, performance improved with the availability of pharmacy, laboratory, and clinical data. Older age and male sex were consistent predictors of IFG or diabetes in all equations and in both health plans. All equations also included one or more indicators of larger body size (either a claim or diagnosis for obesity or a higher measured BMI), blood pressure (either a claim/diagnosis for hypertension, at least one filled prescription for an antihypertensive medication, or systolic blood pressure), and cholesterol (either a claim/ diagnosis for dyslipidemia, at least one filled prescription for a lipid-lowering medication, or lipid levels).

Non-white race, smoking, and metformin entered some but not all equations and the effect was plan specific. In the equations developed in the West Coast integrated delivery system, persons of white race had a lower risk of IFG or undiagnosed diabetes than others. In the Midwestern HMO, race entered 2 of 4 equations and persons of Asian race had a higher risk of IFG or undiagnosed diabetes. This may be because the Midwestern population was less diverse resulting in limited power to detect an effect. Smoking was a risk factor in all equations developed for the West Coast integrated delivery system and none of the equations developed for the Midwestern HMO. The West Coast population had a higher proportion of smokers. Since benefits were tied to nonsmoking status in the Midwestern HMO, it is possible that members did not accurately report their smoking status. The true prevalence of smoking in the Midwestern HMO was likely higher than 6%. Finally, metformin was a risk factor in all of the equations developed in the Midwestern HMO but not in Equations C and D developed in the West Coast integrated delivery system. We hypothesize that prescribing patterns for medications for the prevention of diabetes differ between the two health plans.

The equations we developed are similar to those reported by others. Each includes measures of age, obesity, and cardiovascular risk factors (Tabaei and Herman 2002; Tabaei, Engelgau et al. 2005; Kahn, Cheng et al. 2009; Schmid, Vollenweider et al. 2011). However, the previous studies all included patient-reported information available to a clinician such as family history of diabetes, eating, drinking, or physical activity habits. Our equations relied on administrative data available to health plans. Our two most complex equations also included laboratory and clinical data; however, with the increasing use of electronic medical records, these data may become more widely available.

A limitation of the reported equations is their low PPV. PPV is dependent on the prevalence of disease in the population and both of the populations had a low prevalence of IFG or diabetes (6% in the Midwestern HMO and 13% in the West Coast integrated delivery system). The National Health and Nutrition Examination Survey (NHANES) 1999–2002 found the prevalence of IFG or undiagnosed diabetes to be 35.3% in the United States. If 35% of the health plan populations had IFG or undiagnosed diabetes, the PPV for the highest decile of risk for Equation A in the Midwest population would increase from 14% to 56% and in the West Coast population from 26% to 55%. Applying our equations to the available health plan data of less thoroughly screened populations at will have a substantially higher yield.

Previous studies, including randomized controlled clinical trials, have demonstrated that lifestyle or medication interventions can delay or prevent the development of type 2 diabetes in high risk individuals (Pan, Li et al. 1997; Tuomilehto, Lindstrom et al. 2001; Chiasson, Josse et al. 2002; Knowler, Barrett-Connor et al. 2002; Gerstein, Yusuf et al. 2006). These interventions are both effective and cost-effective (Herman, Edelstein et al. 2012). Unfortunately they are not routinely implemented, in part because of the difficulty in identifying individuals at risk. The equations presented here have fairly low sensitivity (20–

25%) but high specificity (~90%). They represent appropriate population screening tests if implemented periodically to identify high risk individuals for definitive diagnostic testing. Screening results can be generated by health plans and reported to members or providers to facilitate diagnostic testing and to trigger interventions. Since these screening equations can be implemented using existing data and without patient or physician involvement, they may provide a low cost tool to improve detection of at-risk populations.

Our goal was to develop flexible equations that could be easily implemented by health systems using existing data in order to identify persons of high risk for IFG or diabetes so that cost-effective lifestyle or medication interventions could be implemented. We have presented eight such equations, each using progressively more complex levels of data that have been validated both internally and externally.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Table 1

Characteristics of the study populations stratified by glucose tolerance: normal glucose tolerance (NGT) vs impaired fasting glucose (IFG) or diabetes (DM) (defined as fasting plasma glucose [FPG] $\,$ 110 mg/dL).

GDM: gestational diabetes mellitus

PCOS: polycystic ovarian syndrome

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Table 2

Maximum likelihood estimates of logistic regression functions for the most parsimonious version of each equation.

 $\dot{\tau}$ for these variables the estimated odds ratio and 95% confidence interval for the odds ratio are per 10 unit increase

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Table 3

Positive predictive values of the most parsimonious equations given by number and percent of patients with IFG or diabetes in each decile of predicted risk.

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29%

8,611/29,669

28%

10 9,629/37,243 26% 9,628/37,104 26% 9,019/32,111 28% 8,611/29,669 29%

26%

26%

Percent with IFG/DM **IFG or DM / total Percent with IFG/DM IFG or DM / total Percent with IFG/DM IFG or DM / total Percent with IFG/DM IFG or DM / total Percent with IFG/DM** $2%$ $2%$ $2%$ 4% 6% $3%$ Total 1,138/18,527 6% 6% 1,138/18,527 6% 804/13,077 6% 6% 761/12,456 6% 6% $\frac{37}{1,690}$ 2% $\frac{39}{1,845}$ 2% 2% 2% 285 $2 \begin{array}{|c|c|c|c|c|}\n\hline\n49 / 1,997 & & 2\% \n\hline\n28 & & 44 / 1,814 & & 2\% \n\hline\n298 & & 296 & & 268\n\end{array}$ $\frac{3}{3}$ 65/1,845 4% 4% 50/1,876 3% 30/1,309 2% 22/1,246 2% 4 66/1,703 4% 80/1,871 4% 4% 40 41/1,307 3% 36/1,245 36% 36 5 | 85 | 1,883 | 5% | 99 | 1,851 | 5% | 59 | 59% | 59% | 4% | 4% | 4% **Equation D Decile Equation A Equation B Equation C Equation D** IFG or $DM /$ 761/12,456 19/1,246 36/1,245 $19/1,245$ 22/1,246 49/1,245 Percent with IFG/DM 6% $2%$ $2%$ $2%$ $3%$ $5%$ **Equation C** IFG or DM \prime total 804 / 13,077 $27/1,305$ 25/1,309 41/1,307 30/1,309 59/1,308 Percent with IFG/DM $2%$ $4%$ 6% $2%$ 3% $5%$ **Equation B** IFG or DM / total 1,138 / 18,527 $50 / 1,876$ $39/1,845$ $44/1,814$ $80/1,871$ 99/1,851 Percent with IFG/DM 6% $2%$ $4%$ $2%$ $4%$ $5%$ **Equation A** IFG or DM / total 1,138/18,527 $37/1,690$ $65/1,845$ 66/1,703 49 / 1,997 85/1,883 Decile Total \overline{c} $\tilde{3}$ 4 $\sqrt{2}$

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Table 4

Sensitivity, specificity, and positive predictive value (PPV) for the highest decile of risk for the most parsimonious equations using the internal and external validation populations.

