Using a population-based risk tool to support health planning for diabetes in Canada

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- DLSPH, U of T: Paul Corey, Cam Mustard
- PHIAT-DM Study Team
- CIHR & PHAC
Learning Objectives

1. To introduce a population based risk algorithm for physician diagnosed diabetes

2. To demonstrate the use of risk algorithms for chronic disease planning at the population level

3. To discuss specific issues related to measurement
Diabetes

- Prevalence of obesity has doubled in Canada from 1985 – 1998 and continues to rise

- WHO: “Diabetes deaths will increase > 50% in the next 10 years without urgent action”

Population perspective

- Evaluation models look at high risk people with diabetes - but the characteristics of those people might be quite different from the actual (Canadian) target population.

- Furthermore estimates of the population size might be quite different.
Why prediction?

- Studies that predict or forecast what will happen in the future have contributed to our understanding of the world and the value of strategies modify the likely course of events in many other settings.

- Engineering, Economics, Environment
- Estimate the impact of policy changes such as tax hikes or tax changes
- Impact of average global temperature rise or rise on sea levels
- Education, justice, and medicine
IN OTHER POLICY MAKING SETTINGS

- Policy evaluation tool for resource management
  - Tools capable of evaluating policies on a large scale system to allow policy makers to evaluate several alternatives before deploying them
- Labour laws and tax programs
- To identify groups to target for government programs
- Changes in the environment
What is a risk algorithm?

- This method uses an approach that is widely used in the clinical setting - risk algorithm - and applies this to the population setting.

- A risk algorithm:
  - Predicts risk of an outcome – usually a disease state
  - Risk is expressed as a probability
  - Calculated for individuals, but can be summarized for groups
  - Typically used when there is multiple factors that contribute to risk
  - Primarily used as a **decision making tool**
## IN MEDICINE…

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Primary Endpoint</th>
<th>Use</th>
</tr>
</thead>
<tbody>
<tr>
<td>*Framingham</td>
<td>-Coronary Heart Disease</td>
<td>-Individual pharmacologic, lifestyle, or surgical interventions</td>
</tr>
<tr>
<td>FINNRRISK</td>
<td>-Incident Diabetes</td>
<td>-Individual pharmacologic or lifestyle interventions</td>
</tr>
<tr>
<td>Reynolds Risk Score</td>
<td>-Heart and Stroke Risk</td>
<td>-Decisions about hospitalizations for patients with pneumonia</td>
</tr>
<tr>
<td>Gail risk score</td>
<td>-Breast Cancer</td>
<td>-Used in research studies</td>
</tr>
<tr>
<td>Fine</td>
<td>-Death in Pneumonia patients</td>
<td>-Decisions about hospitalizations for patients with pneumonia</td>
</tr>
</tbody>
</table>
Risk algorithms in populations

- In the clinical setting, predictive studies have contributed to tremendous advances in individual patient treatment.

At the population level:

- Forecast future incidence of disease.
- Casts future needs for medical resources.
- Stratify the population by risk.
- Adjust for baseline risk in research studies.
- Estimate the impact of population based interventions.
Effectiveness and efficiency of different guidelines on statin treatment for preventing deaths from coronary heart disease: modelling study

Douglas G Manuel, Kelvin Kwong, Peter Tanuseputro, Jenny Lim, Cameron A Mustard, Geoffrey M Anderson, Sten Ardal, David A Alter and Andreas Laupacis

BMJ 2006;332;1419-; originally published online 31 May 2006; doi:10.1136/bmj.38849.487546.DE

• Using this approach, Manuel et al. showed that small changes to the Canadian lipid guidelines should lead to thousands of additional CVD deaths avoided while at the same time saving 100s of millions of health care dollars
Objective: To develop a population based risk tool for Diabetes Mellitus (DM) that is valid, reliable and accessible for all levels of health.

Validity in this context:

1. With the available factors is this the best model that can be found (statistical)
2. Does the model predict accurately for its intended purpose (policy relevant)
DIABETES POPULATION RISK TOOL (DPORT)

- Meaningful
- Policy relevant
- Simple
- Practical
- Validated (in 2 external population cohorts)
Vision

- Enable a health planner to take the characteristics from their population and estimate the number of new diabetes cases in their population for the purpose of:
  + Resource planning
  + Prevention
  + Understand distribution of risk in the population
  + To facilitate decision making and priority setting
Key challenge

Balancing accessibility with model performance
Data sources:

- **DEVELOPMENT COHORT:** Linked 1996/7 NPHS in ON (N=23,403)

- **VALIDATION COHORT 1:** Linked 2000/1 CCHS in ON (N=37,463)

- **VALIDATION COHORT 2:** Linked 1996/7 NPHS in MB (N=10,118)

- Risk attributes: only those that are routinely and publicly available (in the NPHS and CCHS)

- Outcome - physician-diagnosed diabetes (ODD & MB version)
Validation Process

Compare observed and predicted

Assess discrimination via ‘ROC-like’ measures (C statistic)

Calibrate (re-calibrate)
Calibration and Discrimination

George Diamond

- A prediction model cannot be both perfectly reliable and discriminating …
- Maximizing discrimination is done at the expense of reliability and vice versa

“At best they can be made to form a very unstable emulsion – akin to a Béarnaise”

- Balanced with additional variable constraints
### Attributes of DPoRT

<table>
<thead>
<tr>
<th>MALES</th>
<th>FEMALES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Body Mass Index (Kg/m²)</td>
<td>Body Mass Index (Kg/m²)</td>
</tr>
<tr>
<td>Age</td>
<td>Age</td>
</tr>
<tr>
<td>Non-white Ethnicity</td>
<td>Non-white Ethnicity</td>
</tr>
<tr>
<td>Prevalent hypertension</td>
<td>Prevalent hypertension</td>
</tr>
<tr>
<td>Smoking</td>
<td>Immigrant Status</td>
</tr>
<tr>
<td>Prevalent heart Disease</td>
<td>Post Secondary Education</td>
</tr>
<tr>
<td>Post Secondary Education</td>
<td></td>
</tr>
</tbody>
</table>
DPoRT Example: High Risk Male

Profile: Male; 55 years old; BMI = 29 kg/m2, hypertension, white, non-smoker; heart disease & hypertension, graduated secondary school

**Note all variables are centered

\[ \mu = 10.5971 + (-0.2624 \cdot \text{hypertension}) - 0.6316 \cdot \text{non-white ethnicity} - 0.5355 \cdot \text{heart disease} - 0.1765 \cdot \text{smoker} + 0.2344 \cdot \text{secondary school education} + 0.00 \cdot \text{BMI} < 23 \cdot \text{Age} < 45 - 1.2378 \cdot 23 \leq \text{BMI} < 25 \cdot \text{Age} < 45 - 1.5490 \cdot 25 \leq \text{BMI} < 30 \cdot \text{Age} < 45 - 2.5437 \cdot 30 \leq \text{BMI} < 35 \cdot \text{Age} < 45 - 3.4717 \cdot \text{BMI} \geq 35 \cdot \text{Age} < 45 - 2.4426 \cdot 23 \leq \text{BMI} < 25 \cdot \text{Age} \geq 45 - 2.8488 \cdot 25 \leq \text{BMI} < 30 \cdot \text{Age} \geq 45 - 3.3179 \cdot 30 \leq \text{BMI} < 35 \cdot \text{Age} \geq 45 - 3.5857 \cdot \text{BMI} \geq 35 \cdot \text{Age} \geq 45 \]

\[ \mu = 8.8816 \]

\[ m = \log(365.25 \cdot 9) - \mu / \sigma = 8.09781 - 8.8816 / 0.8049 \]

\[ m = -0.97374 \]

9-year predicted risk for developing diabetes is:

\[ P = 1 - \exp(-\exp(-0.97374)) \]

\[ P = 0.3145 \]

or 31.45%
Observed Predicted

Diabetes incidence rate (%)

Males Females Males Females

CCHS-ON validation cohort

NPHS-MB validation cohort
Calibrated Females in CCHS Population (5-year risk)

Calibrated Males in CCHS Population (5-year risk)

Observed and Predicted by Risk Categories in Two External Cohorts

Calibrated Females in Manitoba (9-year risk)

Calibrated Males in Manitoba (9-year risk)

C = 0.77 95% CI (0.76, 0.79)

C = 0.76 95% CI (0.75, 0.79)

C = 0.79 95% CI (0.77, 0.82)

C = 0.80 95% CI (0.77, 0.82)
Applying the risk tool
Predictions using public Canadian data:
By Geography
By Risk Groups
By Time
METHODS: ESTIMATING DIABETES RISK

- Sex-specific DPoRT models can be applied to any of the national health surveys in Canada (NPHS or CCHS) for those who are 20 year + and free of diabetes at baseline.

- The number of new cases is estimated by multiplying the diabetes risk (probability) by the population number.

- To examine age-specific risks were applied to a standard population.
In the next 10 years…

- 1.9 million new diabetes cases
- 1,010,882 males and 848,165 females
- 10-year cumulative incidence rate of 9.2%
### Male 5-year predicted incident rate and number of new cases in Ontario

<table>
<thead>
<tr>
<th>LHIN</th>
<th>5-year Incident Rate</th>
<th>Cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Erie St. Clair</td>
<td>5.0</td>
<td>25,000</td>
</tr>
<tr>
<td>South West</td>
<td>5.0</td>
<td>20,000</td>
</tr>
<tr>
<td>Waterloo</td>
<td>5.0</td>
<td>15,000</td>
</tr>
<tr>
<td>Hamilton-Niagara</td>
<td>5.0</td>
<td>10,000</td>
</tr>
<tr>
<td>Central West</td>
<td>5.0</td>
<td></td>
</tr>
<tr>
<td>Mississauga</td>
<td>5.0</td>
<td></td>
</tr>
<tr>
<td>Toronto Central</td>
<td>5.0</td>
<td></td>
</tr>
<tr>
<td>Central</td>
<td>5.0</td>
<td></td>
</tr>
<tr>
<td>Central East</td>
<td>5.0</td>
<td></td>
</tr>
<tr>
<td>South East</td>
<td>5.0</td>
<td></td>
</tr>
<tr>
<td>Champlain</td>
<td>5.0</td>
<td></td>
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<tr>
<td>North Simcoe</td>
<td>5.0</td>
<td></td>
</tr>
<tr>
<td>North East</td>
<td>5.0</td>
<td></td>
</tr>
<tr>
<td>North West</td>
<td>5.0</td>
<td></td>
</tr>
</tbody>
</table>
10-year risk (%) of DM by BMI category in Canada

BMI (kg/m²)

Male Risk (%)
Female Risk (%)

<23 23-25 25-30 30-35 >35
10-year risk (%) of DM by BMI category in Canada

<table>
<thead>
<tr>
<th>BMI (kg/m²)</th>
<th>Male Risk (%)</th>
<th>Female Risk (%)</th>
<th>Male # of Cases</th>
<th>Female # of Cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;23</td>
<td>60,114</td>
<td>116,537</td>
<td>60,114</td>
<td>116,537</td>
</tr>
<tr>
<td>23-25</td>
<td>90,849</td>
<td>129,266</td>
<td>90,849</td>
<td>129,266</td>
</tr>
<tr>
<td>25-30</td>
<td>202,369</td>
<td>242,132</td>
<td>202,369</td>
<td>242,132</td>
</tr>
<tr>
<td>30-35</td>
<td>112,897</td>
<td>164,997</td>
<td>112,897</td>
<td>164,997</td>
</tr>
<tr>
<td>&gt;35</td>
<td>0.0</td>
<td>600,000</td>
<td>0.0</td>
<td>600,000</td>
</tr>
</tbody>
</table>
10-year risk (%) of DM in Canada by Education

- Males
  - < than secondary: 13.6%
  - Secondary school grad.: 11.4%
  - Other post-secondary: 7.1%
  - Post secondary grad.: 7.3%

- Females
  - < than secondary: 9.5%
  - Secondary school grad.: 8.4%
  - Other post-secondary: 5.9%
  - Post secondary grad.: 5.8%
DPoRT & Interventions in SES groups

- Given the high baseline risk of diabetes in lower SES populations, this group has more to benefit from interventions to prevent diabetes.

- Use DPoRT to estimate the future risk of diabetes across socioeconomic strata and to assess how prevention interventions may influence social disparities in risk.

- Closely examine the impact of adherence to health interventions on this disparity in risk.
10-year risk (%) of DM in Canada by Ethnicity

**Males**
- White: 9.5%
- Non-White: 12.5%

**Females**
- White: 8.4%
- Non-White: 10.9%
Risk profile for diabetes in one Ontario LHIN (2005-2010)

Predicted 5-year incidence rate

- 2.0 4.0 6.0 8.0 10.0 12.0 14.0 16.0 18.0

Ethnicity
- White
- Black
- Asian
- South Asian
- Other

Education
- < Secondary
- Secondary Grad.
- Post-Secondary
- Post-Secondary Grad

Age
- <23
- 23-25
- 25-30
- 30-35
- >35

BMI (kg/m2)
- 25-30
- 30-35
- >35
Risk profile for diabetes in the Central West LHIN (2005-2010)

Predicted 5-year cases

Ethnicity
- <45
- 45-65
- >65
- White
- Black
- Asian
- South Asian
- Other

Education Age Group
- < Secondary
- Secondary Grad.
- Post-Secondary
- Post-Secondary Grad

BMI (kg/m²)
- <23
- 23-25
- 25-30
- 30-35
- >35
Why is prediction important to the health planner?

Because things are changing...
10-year DM risk by Province and Year in Females, 1994-2005

- MB & SK
- MAR
- ON
- Canada
- BC
- AB
- QC

10-year risk (%)

- 1994
- 1996
- 2000
- 2003
- 2005

10-year risk (%)
10-year DM risk by Province and Year in Females <35, 1994-2005
10-year risk over time in Canada by sex and age group

**Age ≤ 35**

- Males
- Females

**Age 35-55**

**Age 55-75**

**Age ≥ 75**
Interventions

- Quantifying the impact of changes in baseline risk gives important insight into the distribution of risk in the population
International Diabetes Federation (IDF) consensus on the prevention of type 2 diabetes

- IDF consensus reviewed available evidence on the major risk factors for diabetes and the benefits that can be achieved by interventions

- Based on their findings they developed recommendations for 2 groups: people at high risk and the entire population

- Recommends a 5-10% weight reduction in general population
Population

Current: 1,860,047
5% reduction in weight at the population: 1,618,974
10% reduction in weight at the population: 1,399,262
10% reduction in the obese population

Targeted: 1,860,047
Current: 1,643,365

20% reduction in the obese population

Targeted: 1,507,899

10% reduction in the overweight and 20% reduction in the obese

Targeted: 1,302,882
<table>
<thead>
<tr>
<th></th>
<th>Incident DM Cases in 10 years</th>
<th>Difference from Current</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Current</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1,860,047</td>
<td></td>
</tr>
<tr>
<td><strong>Intervention Population</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5% reduction in weight at the population</td>
<td>1,618,974</td>
<td>-241,073</td>
</tr>
<tr>
<td>10% reduction in weight at the population</td>
<td>1,399,262</td>
<td>-460,785</td>
</tr>
<tr>
<td><strong>Targeted</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10% reduction in the weight of the obese population</td>
<td>1,643,365</td>
<td>-216,682</td>
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Multilevel growth model for BMI

- Statistics Canada’s longitudinal National Population Health Survey: 17,276 persons from all ages in 1994/1995

- Using a multilevel growth model, modeled predictors of BMI and BMI change over time
Individual trajectories of BMI
Level 1
\[ \text{BMI}_{ij} = \pi_{0i} + \pi_{1i}(\text{WAVE}_{ij}) + \varepsilon_{ij} \]
Level 2 Systematic differences in growth trajectories

\[ \pi_{0i} = \gamma_{00} + \gamma_{01}X_i + \zeta_{0i} \] (predictors of initial status)
\[ \pi_{1i} = \gamma_{10} + \gamma_{11}X_i + \zeta_{1i} \] (predictors of rate of change)
BMI tends to increase with time for younger people; however BMI tends to decrease over time for older people.

Plotting of the influence of age on BMI.
Plotting the effect of baseline BMI

Those with high baseline BMI increase at a reduced rate
Plotting of the Income on BMI for males
Low income is associated with lower BMI in men compared whereas in women it is associated with increased BMI.
Measurement
Limitations of DPoRT

- Reliance on self-report measures
- Use of physician-diagnosed diabetes as an outcome
- Does not apply to those <19 years of age, institutionalized, or on reserve.
Measurement Issues

- Self-reported height and weight
- BMI
- Ethnicity
- Physician-diagnosed diabetes
Central Obesity and Diabetes


- From the clinical perspective central obesity generates “diabetogenic” substances thus is thought to be more informative for predicting incident DM
Meta analysis demonstrated that the relative risks associated with BMI, Waist circumference and waist/hip ratios were all similar: (RRs =1.87, 1.87, 1.88)

“Because of their high correlation, from the statistical perspective, body mass index and waist circumference are unlikely to yield different answers”

“Although from the clinical perspective focusing on central obesity is appealing, further research is needed to determine the usefulness of waist circumference or waist/hip over BMI”
Proportion of the Canadian population meeting the criteria for weight loss treatment according to the four algorithms.

- NIH algorithm: 23.9%
- BMI algorithm: 23.8%
- WC Algorithm (tiered cut-offs): 22.0%
- WC Algorithm (single cut-off): 6.7%

• Note that because only 0.1% of the population is captured by the NIH algorithm and is missed when using the BMI algorithm.
• The circle representing the NIH algorithm is almost completely eclipsed by the BMI circle.

(Mason and Katzmarzyk, 2005)
Limitations of variable constraints

- Additional clinical predictors (fasting blood glucose and family history) are not included in DPoRT because they are not consistently, accurately or systematically measured in populations.

- In a clinical setting it is feasible to capture this information from simple routine measurements and lab tests.

- How much of a problem does this pose?
• Clinical prediction rule from the Framingham study that included several physical measures and complex clinical variables for 7-year risk of T2DM in middle-aged adults

• Discrimination was slightly higher when using BMI as measure of obesity over waist circumference and discrimination BMI model stayed exactly the same when waist circumference

• Discrimination from complex clinical model (i.e. including C reactive protein, 2-hour OGTT, various insulin sensitivity indices, HOMA β-cell index ect..) versus simple clinical model did not improve discrimination, actually decreased slightly in some permutations
Limits to Discrimination

- As seen in other studies, simplified models perform as well or in some cases better than full models and improvements to discrimination with increasing predictors become negligible.

A Coronary Heart Disease Risk Score Based on Patient-Reported Information

Arch G. Mainous III, PhD<sup>a,b,*</sup>, Richelle J. Koopman, MD, MS<sup>a</sup>, Vanessa A. Diaz, MD, MS<sup>a</sup>, Charles J. Everett, PhD<sup>a</sup>, Peter W.F. Wilson, MD<sup>c</sup>, and Barbara C. Tilley, PhD<sup>b</sup>

- Self-report algorithm for CHD (Mainous et al, American Journal if Cardiology, 2007)
- 10-year CHD risk is similar in predictive ability to that of the Framingham Heart Score and to the European SCORE algorithms
Investigating error in height and weight

- Simulated data and outcome to match survey data

- Predicted risk, accuracy, and C statistic were calculated under various level of error

- Simulations were done 500 times with sample sizes typical of population-bases surveys (~10,000)
Self-reported height and weight

- Shields et al. (2008) examined agreement between self-report and measures BMI in a sub-sample of the CCHS population

- DPoRTs’ discrimination and calibration would be minimally affected at these levels
BIAS
• Predicted risk was biased downward due to the underestimation of weight and overestimation of height.
Difference in predicted risk (observed - true) under various levels of random error for females.

**Random Error**
- Predicted risk was biased upwards under random error.

Graph shows the difference in observed - true risk for different ICC heights (0.5 to 1.0) with varying random error levels (0% to 0.7%).
Ethnicity

- High risk ethnic groups outlined by diabetes screening guidelines are: people of Aboriginal, Hispanic, south Asian, Asian, or African descent)

- Currently DPoRT only examined ethnic grouping as “white/non-white”

- Compared DPoRT with a modified version which includes detailed ethnic information to determine its impact/relevance for estimating population diabetes risk
(1) DPoRT minus ethnicity – called “no ethnicity”

(2) DPoRT (white/non-white)

(3) DPoRT plus detailed ethnic information – called “Full model” (6 ethnic categories)
   □ All models produced similar C statistics (differing only at the 0.01 place)
   □ Accuracy achieved(defined by H-L) in a validation cohort using all algorithms except the one with full ethnicity in males
Physician-diagnosed diabetes

- Advocates argue that it is meaningful to both people with diabetes and health care system

- “True” prevalence of diabetes is estimated to be higher due to significant under-diagnosed population

- Risk tool can re-calibrated to predict “true” diabetes
Conclusions

- DPoRT was successful validated in two external validation cohorts and demonstrated good discrimination and calibration.

- Predictive tools allow us to empirically estimate the future risk and number of new cases of diabetes in a population.

- Tool can be applied to quantify impact that changes in risk factors will have on future diabetes incidence.
Future work

- Calibration/validation within minority populations
- Case ascertainment/testing between provinces
- Differential error in height and weight with respect to risk status
Future work

- Validating the growth model for predicting obesity in the Canadian population
- Putting DPoRT in the hands of health planners
- Collaboration with other models
Microsimulation Models

- Computer models that operate at the level of the individual behavioural entity

- Simulate large representative populations of these low-level entities in order to draw conclusions that apply to higher levels of aggregation such as an entire country

- DPoRT is currently being utilized within CVD microsimulation to predict transition states
THANK YOU
Questions? Comments?
The Ontario Diabetes Database

- The database is created using hospital discharge abstracts, physician service claims, and the National Ambulatory Care Reporting System (NACRS).
- A patient is said to have physician diagnosed diabetes if they have had one hospital admission with a diabetes diagnosis (International Classification of Diseases Clinical Modification code 250 (ICD9-CM) before 2002 or ICD-10 code E10 – E14 after 2002 or a physician services claim with a diabetes diagnosis (code 250) followed within 2 years by either physician services claim or a hospital admission with a diabetes diagnosis.
- Whenever there was a hospital record with a diagnosis of pregnancy care or delivery close to a diabetic record (i.e. a gestational admission date between 90 days before and 120 days after the diabetic record it was considered to be for gestational diabetes and excluded.
- The ODD has been validated against primary care health records for accurately determining incidence and prevalence of DM in Ontario with a sensitivity of 86% and a specificity of 97%.