

Improving Diabetes Prevention with Benefit-Based Tailored Treatment: Disseminating Individualized Risk Estimates Elizabeth L. Ciemins, PhD, MPH, MA,¹ Jason Nelson, MPH,^{2,3} Jill Powelson, RN, DrPH, MBA,¹ Carolyn Koenig, MD,⁴ Francis Colangelo, MD, MS-HQS, FACP,⁵ Anastassios Pittas, MD, MS,² John Cuddeback, MD, PhD,¹ David Kent, MD²

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Health System Reluctance to Screen

High rates of patients with prediabetes and few resources; if only we could prioritize... (AMGA's Together2Goal[®] Campaign)

Developing the Predictive Model

A risk-stratified analysis of individual patient data from 32 clinical trials including a reanalysis of Diabetes Prevention Program (DPP) Study (Figure 1)^{1,2,3} showed:

- Heterogeneity of treatment effect, i.e., not all patients will receive average absolute risk reduction.
- Wide and highly skewed distribution of risk for developing diabetes within 3 years.⁴

The predictive model was implemented in 2 health systems, Premier Medical Associates and Mercy Health, using Allscripts and Epic, respectively.

Methods

Design: Pre/post implementation study, 2018 – 2019.

Population studied: ~3,000 patients with prediabetes, 10 pilot primary care clinics, 40 providers, 2 health systems: (1) providers access model via EHR click, data elements auto-populate (2) manual data entry required.

Adaptations: Predictive model adapted for EHR use using Optum data:

- Removed variables like waist-to-hip ratio, see Table 1 for complete list of 11 variables and Figure 2 for patient prototype;
- Calculated coefficients for missing variables. Table 1 lists three required variables.
- **Surveys:** Pre-implementation focus groups and surveys with patients & providers

Evaluation: Measures for Reach, Adoption, Maintenance (RE-AIM)⁵ (Figure 3); Pre/post implementation surveys (Figure 4); and assessment of "balance" measures, e.g., preventive care screening rates.

Both have pre-diabetes. Who is at greatest risk for diabetes?

- 38-year-old female
- BMI: 34
- HbA1c: 5.8
- SBP: 153
- African American



HIGH RISK



LOW RISK

Add to Chart

- 58-year-old male
- BMI: 22
- HbA1c: 6.1
- SBP: 121
- HDL: 100
- Former Smoker

Figure 2. Predictive model results as displayed in EHR, high- and low-risk patients

Interpretation high-risk patient				
Predicted risk of T2DM at 3 years	Treatment	Relative Risk Reduction (RRR)	Number Needed to Treat (NNT)	
26.0%	Usual Care	Reference	na	
19.8%	Metformin	24%	17	
10.9%	DPP Lifestyle	58%	7	

	Inter
Predicted risk of T2DM at 3 years	Treatr
15.0%	Usual
15.0%	Metfo
6.3%	DPP Lif



Study Objective

Implement in an EHR a predictive model for people with prediabetes that provides individualized benefit estimates for taking metformin or participating in the Diabetes **Prevention Program**

Figure 1. Heterogeneity of Treatment Effect: DPP Study **Table 1. Diabetes Risk Calculator EHR Varia** Intensive Lifestyle Intervention 28.3 Age (25–7. Gender Race Average 14.2 13.6 Smoke Hypertens A1c (%) FPG (mg/o 4 (highest) 1 (lowest) Triglyceric Risk Group BMI (kg/n Systolic I Metformin Treatment HDL chole **SCORES** usual care DPP lifest metformir Average 7.1 4 (highest) 1 (lowest) Risk Group

pretation low-risk patient **Relative Risk** Number Needed Reduction (RRR) to Treat (NNT) Reference Care na rmin 0% 58% 12 festyle Add to Chart

Conclusions

- A predictive model, embedded in the EHR, that predicts individual patient risk for developing diabetes at the point of care improved treatment for patients with prediabetes.
- Use of individualized risk estimates resulted in prioritization of treatment for patients at greatest risk of developing type 2 diabetes.

Implications

- Only 3.7% of patients with prediabetes receive metformin; even fewer enroll in the DPP. Change is needed to engage patients and empower providers with tools to increase shared decision making around treatment choices.
- Providers and systems need tools to help prioritize limited resources to increase patient treatment, referral, and adherence through more targeted and tailored treatment recommendations.
- Potential to impact the \sim 86 million people in the US, one in three adults, with prediabetes. Most are undiagnosed and therefore untreated.
- Cost savings estimated at \$17,500 per patient averted or delayed diabetes for 5 years.

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ables	Value	Required
'5)	74	Yes
	F	Yes
	В	No
	Y	No
sion	Y	Yes
	6.4	No
dL)*	103	No
des (mg/dL)	263	No
า^2)	30	No
P (mmHg)	150	No
esterol (mg/dL)	32	No
2	56.0%	
yle	23.5%	
ן	25.1%	



Figure 3. Patients identified and treated,* by risk level



References

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Results

Table 2. Pre/Post-intervention referrals to DPP or metformin Rx among high-risk patients, by site

Organization	Pre-intervention	Post-intervention	
	DPP Lifestyle		
Premier	0%	44%	
Mercy	0%	12%	
	Metformin		
Premier	2%	19%	
Mercy	3%	17%	

Figure 4. Provider confidence survey question

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