Multilevel Variation in Diabetes Screening Within an Integrated Health System

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EPIDEMIOLOGY/HEALTH SERVICES RESEARCH

OBJECTIVE

Variation in diabetes screening in clinical practice is poorly described. We examined the interplay of patient, provider, and clinic factors explaining variation in diabetes screening within an integrated health care system in the U.S.

RESEARCH DESIGN AND METHODS

We conducted a retrospective cohort study of primary care patients aged 18–64 years with two or more outpatient visits between 2010 and 2015 and no diagnosis of diabetes according to electronic health record (EHR) data. Hierarchical three-level models were used to evaluate multilevel variation in screening at the patient, provider, and clinic levels across 12 clinics. Diabetes screening was defined by a resulted gold standard screening test.

RESULTS

Of 56,818 patients, 70% completed diabetes screening with a nearly twofold variation across clinics (51–92%; $P < 0.001$). Of those meeting American Diabetes Association (ADA) (69%) and U.S. Preventive Services Task Force (USPSTF) (36%) screening criteria, three-quarters were screened with a nearly twofold variation across clinics (ADA 53–92%; USPSTF 49–93%). The yield of ADA and USPSTF screening was similar for diabetes (11% vs. 9%) and prediabetes (38% vs. 36%). Nearly 70% of patients not eligible for guideline-based screening were also tested. The USPSTF guideline missed more cases of diabetes (6% vs. 3%) and prediabetes (26% vs. 19%) than the ADA guideline. After adjustment for patient, provider, and clinic factors and accounting for clustering, twofold variation in screening by provider and clinic remained (median odds ratio 1.97; intraclass correlation 0.13).

CONCLUSIONS

Screening practices vary widely and are only partially explained by patient, provider, and clinic factors available in the EHR. Clinical decision support and system-level interventions are needed to optimize screening practices.

Diabetes screening identifies individuals with undiagnosed, asymptomatic type 2 diabetes or prediabetes who are eligible for evidence-based interventions to prevent or delay type 2 diabetes and its complications. National screening guidelines, such as the American Diabetes Association (ADA) (1) and U.S. Preventive Services Task Force (USPSTF) (2), help clinicians identify individuals at increased risk for type 2 diabetes and target screening tests in clinical practice. Despite screening recommendations, >7 million U.S. adults with type 2 diabetes and 74 million U.S. adults with prediabetes remain undiagnosed (3). Nationally representative data indicate significant gaps

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between screening eligibility and screening completion, with only half of individuals meeting ADA and USPSTF guidelines reporting a completed screening test (4,5).

The ADA and USPSTF recommend that diabetes screening occur in a health care setting where testing is "opportunistic," or obtained when patients present to the health care system for reasons unrelated to diabetes screening (1,2,6). Estimates of opportunistic screening rates in clinical practice vary from 6 to 24% and identify significant missed screening opportunities (6–10). Additionally, screening variation across clinical sites within integrated health systems is likely common but not well described. Importantly, there are currently no national quality metrics focused on diabetes screening or benchmarks for clinicians and health systems to strive for, which may contribute to underscreening and variation in patterns of screening.

As Accountable Care Organizations and health systems seek to manage the metabolic risk of patient populations to prevent type 2 diabetes and its complications, improved understanding of diabetes screening in clinical practice is critical for developing systematic screening approaches (11). In this study, we evaluate multilevel variation in diabetes screening across primary care clinics within a large, integrated safety-net health system and examine the contribution of patient, provider, and clinic characteristics to variation in diabetes screening within the health care system. We also describe adherence to and yield of the USPSTF and ADA diabetes screening guidelines across primary care clinics in the health system.

RESEARCH DESIGN AND METHODS

Study Design and Setting

We conducted a population-based retrospective cohort study using 2010–2015 electronic health record (EHR) data from the Parkland Health and Hospital System (Parkland) in Dallas, TX. Parkland is a publically funded, integrated health system, which is the sole safety-net provider in Dallas County. County residents who are poor and uninsured are eligible for county-funded medical assistance in any of the clinics in Parkland's extensive primary, specialty, and acute care clinic network. All sites use a common EHR (Epic, Verona, WI). Parkland operates 12 outpatient primary care clinics, including 8 community-based clinics, 2 academic teaching clinics that train resident physicians, an employee health clinic, and a women's health clinic.

Cohort Assembly

Eligible patients were nonpregnant adults aged 18–64 years without diagnosed diabetes who had at least two outpatient visits (i.e., one or more outpatient, primary care clinic visits and at least one laboratory visit after the index visit). The index visit was defined as the first outpatient, primary care clinic visit occurring between 2010 and 2014 for each participant. We excluded patients with diagnosed diabetes using *International Classification of Diseases*, 9th revision (ICD-9) codes from encounter diagnoses and problem lists available on or before the index visit. Patients aged 65 or older were excluded because Medicare eligibility increases the likelihood that they will receive health care in clinics outside of the safety-net health system, which prevents access to screening test results. Medicare is the U.S. health insurance program for people aged 65 or older and younger individuals with end-stage renal disease requiring dialysis and other disabilities (12).

At baseline, we examined the EHRs of 365,249 patients seen in the integrated, safety-net health system between 2010 and 2014. After excluding unqualified patients (i.e., no completed primary care visits [$n = 113{,}584$], outside the 18–64 age range [$n = 742$], prevalent diabetes [$n = 28{,}381$], pregnant patients [$n = 52{,}117$], pregnant patients with diabetes [$n = 1{,}834$], and patients with only one primary/index visit between 2010 and 2015 [$n = 111{,}773$]), we arrived at our study cohort of 56,818 patients.

Assignment of Patients to Clinical Sites and Providers

We assigned all patients to a primary clinic site according to the clinic they visited most frequently. If a patient visited two or more clinics an equal number of times, we assigned the clinic with the earliest visit. We subsequently assigned patients to providers by examining the number of times patients visited providers and assigned the "primary care provider" as the individual seen most frequently. If patients visited two or more providers an equal number of times, we assigned primary care providers based on the earliest visit. Primary care providers included attending physicians, physicians in training (resident and fellow physicians), and advanced practice providers (nurse practitioners and physician assistants). Patients were clustered within providers, which in turn were clustered within the clinics. Because analyses were conducted at the patient level, providers could be assigned to more than one primary care clinic.

Measures

Our primary outcome was diabetes screening using any of the three gold standard tests: hemoglobin A_{1c} (HbA_{1c}), fasting blood glucose (FBG), or oral glucose tolerance test (OGTT). Based on diabetes screening test results, we classified participants as having type 2 diabetes ($HbA_{1c} \geq 6.5\%$ [48 mmol/mol], FBG ≥ 126 mg/dL, or 2 h OGTT ≥ 200 mg/dL); prediabetes (HbA_{1c} 5.7–6.4% [39–46 mmol/mol], FBG 100–125 mg/dL, or 2 h OGTT 140–199 mg/dL); normal glycemic state ($HbA_{1c} < 5.7\%$ [39 mmol/mol], FBG < 100 mg/dL, or 2 h OGTT < 140 mg/dL) (1). FBG was identified by a specific EHR order for "fasting glucose." We did not include the glucose component of laboratory panels because the EHR does not allow clinicians to order "fasting panels." Because the frequency of confirmatory testing in clinical practice was unknown, we used a single test screening strategy in our primary analyses. We report the frequency and yield of confirmatory testing in the subgroup of patients completing a concurrent FBG and HbA_{1c} on the same day or a second, confirmatory test within 60 days of the initial screen (1).

Patient demographics (age, sex, race/ethnicity, insurance, marital status, smoking, and family history of diabetes) and comorbidities (prediabetes, hypertension, hyperlipidemia, cardiovascular disease, and history of gestational diabetes or infant weighing >9 lbs) were extracted from the EHR. Comorbidities were defined using ICD-9 codes in the 12 months preceding the index visit. We grouped providers into three groups for analyses: *1*) attending physicians; *2*) physicians in training; *3*) advanced practice providers. For clinical covariates, we classified clinics as teaching or nonteaching clinics.

Eligibility for diabetes screening was assessed using national, U.S. diabetes screening guidelines. The USPSTF guideline recommends diabetes screening for adults aged 40–70 with a BMI ≥ 25 kg/m^2 (2). The ADA recommends universal screening beginning at age 45 and targeted

screening for individuals <45 years old based on a combination of BMI and other diabetes risk factors, including race/ethnicity, family history, hypertension, high cholesterol, history of coronary artery disease or gestational diabetes, and physical inactivity (1). The EHR does not capture physical activity in a structured data field; therefore, this was not considered in our analysis.

Statistical Analysis

We used descriptive statistics to summarize patient-level demographics across the 12 clinics. We report the overall proportion of patients screened and the eligibility and yield of screening according to the ADA and USPSTF guidelines.

We fit the multilevel random logistic models using PROC GLIMMIX (13) in SAS 9.4 software (SAS Institute, Cary, NC). To quantify multilevel variation in diabetes screening across the clinics, we report the intraclass correlation (ICC) (14) and the median odds ratio (MOR) (15). The ICC reflects the proportion of total variance in diabetes screening due to influence from the providers and clinics, with the providers nested in clinics for the nested model. A higher ICC indicates that providers and clinics account for a higher proportion of the variance in diabetes screening under the assumption of the providers and clinics being random factors. The MOR ranges from 1 to infinity and reflects the unexplained cluster heterogeneity. An MOR value of 1 means there is no variation across the clinics, whereas larger values indicate greater variation.

Model Building and Selection

To confirm which model (two- or three-level) would be best in accounting for clustering at the provider and/or clinic level, we fit two separate unconditional (unadjusted) two-level random intercept logistic models (16), with one having provider as the random factor and the other having clinic as the random factor. We compared them to an unconditional, nested three-level random intercept logistic model (16) (a model that accounts for clustering at both the clinic and provider level simultaneously) using the log-likelihood ratio test (16). Because the log-likelihood ratio test was significant, we selected the three-level random intercept logistic model for our final analysis.

We examined the effects of patient-, provider-, and clinic-level covariates on diabetes screening in univariate analyses. The type I error rate was set at 0.05. All significant covariates and nonsignificant but clinically important covariates from univariate models were included in the three-level random intercept logistic models. For the model building, we specified five three-level nested logistic models: *1*) an unconditional model with no fixed level covariates, *2*) a conditional model including patient characteristics that were significant in univariate analyses, *3*) a conditional model with both significant patient and clinic level factors, *4*) a conditional model with significant patient-, clinic-, and provider-level factors, and *5*) a cross-classified random intercept logistic model to account for the possible movement of providers between clinics. We selected our final model (model 4) by comparing models 1–4 using log-likelihood ratio tests and by comparing the best nested model (model 4) to the cross-classified model (model 5) using minimization of Akaike information criterion (17) and Bayesian information criterion (18). The University of Texas Southwestern Institutional Review Board approved the study.

RESULTS

Patient and Clinic Characteristics

A total of 56,818 unique patients completed at least two outpatient visits in 1 of the 12 clinics during the 5-year study period. During the follow-up period, clinics differed in the number of unique patients served (n = 1,761–9,099) and number of primary care providers (n = 13–109), with teaching clinics having more providers than nonteaching clinics (Table 1). The distribution of age and race/ethnicity differed across clinics, with nine clinics serving mostly Hispanic patients and the remaining serving predominately non-Hispanic black patients. Sex and BMI were similar across clinics, with nearly 80% of patients being overweight or obese. Overall, 20% of the study population had a family history of diabetes documented in the EHR. Nearly 40% had diagnosed hypertension, with marked variation across clinic sites. Only 2–7% of all patients had a coded diagnosis of prediabetes. In 11 clinics, patients were mostly uninsured and covered by the county's indigent care system. Patients in clinic 6 had higher rates of commercial insurance, and those in clinics 2 and 12 had higher rates of Medicaid coverage, which is a jointly funded U.S. federal and state government program providing health insurance to low-income adults, pregnant women, and individuals with disabilities (19) (Table 1).

Overall Diabetes Screening Rates Across Clinics

Overall, 70.4% of the study population (n = 56,818) was screened for diabetes during an average follow-up of 3 years. Screening rates varied significantly across clinics, ranging from 50.8 to 91.5% of the total clinic population ($P \leq 0.0001$) (Table 2). Clinic 6 had the highest overall screening rate (92%), whereas a community-based clinic serving a predominately Hispanic population had the lowest screening rate (51%). Overall, HbA_{1c} was the most commonly used screening test (55%), followed by FBG (33%) and OGTT (2%). Clinics 4 and 7 preferentially screened patients with FBG instead of HbA_{1c}. Clinics 1 and 2 (teaching academic clinics) and clinic 6 (most with commercial insurance) were the highest users of HbA_{1c} for diabetes screening (Table 2).

Multilevel Clinic Variation in Diabetes Screening in Nested Models

The empty model (model 1: not adjusting for any covariate/fixed effect) showed significant variation in diabetes screening at both the clinic (P = 0.0162) and provider level ($P < 0.0001$) (Table 3). The ICC was 0.19 and the MOR was 2.26, indicating cluster heterogeneity and unexplained variability at both the clinic and provider level. Addition of fixed patient characteristics (model 2) reduced the ICC and MOR values slightly. Subsequent addition of fixed clinic factors (model 3) did not significantly change the ICC and MOR. Adding provider-level factors (model 4) provided the best model fit (ICC 0.13; MOR 1.97) and accounted for additional unexplained differences in diabetes screening across locations. However, even the final model had residual, unexplained heterogeneity at both the clinic and provider level after adjusting for covariates (MOR 1.97). After accounting for the correlation at the provider and clinic level, the overall probability that a patient was screened for diabetes in this integrated health system was 70.0%. We found similar results using a cross-classified model, which assumes providers are not nested in clinics (Table 3).

Table 1—Characteristics of patients eligible for diabetes screening who visited 1 of the 12 clinics in a safety-net health system from 2010 to 2015

		Teaching clinics		Nonteaching clinics									
	Total	Clinic 1	Clinic 2	Clinic 3	Clinic 4	Clinic 5	Clinic 6	Clinic 7	Clinic 8	Clinic 9	Clinic 10	Clinic 11	Clinic 12
Unique patients													
N	56,818	2,267	1,761	9,099	6,993	5,374	4,315	6,846	1,823	6,467	7,191	1,943	2,739
(%)	(100)	(4.0)	(3.1)	(16.0)	(12.3)	(9.5)	(7.6)	(12.1)	(3.2)	(11.4)	(12.7)	(3.4)	(4.8)
Age categories, %													
18–29	11.1	11.3	4.8	7.5	11.8	9.0	21.6	8.3	9.7	10.8	8.9	7.1	29.3
30–39	21.8	21.5	11.6	15.3	24.0	22.7	20.1	20.4	25.8	25.4	20.8	21.4	42.1
40–49	30.5	31.0	28.9	31.2	30.7	30.8	27.4	31.2	31.2	31.9	31.7	31.5	23.1
50–59	28.5	29.1	43.3	35.3	26.2	29.2	25.6	30.2	25.9	24.9	29.9	31.3	4.8
60–65	8.1	7.1	11.4	10.7	7.3	8.3	5.3	9.9	7.4	7.0	8.7	8.7	0.7
Age (years), median	46	45	51	49	45	46	43	47	45	44	47	47	35
Female sex, %	65.6	65.4	57.9	64.1	63.6	59.9	64.8	65.4	65.9	64.3	64.7	64.4	99.5
Race/ethnicity, %													
White	13.7	14.6	27.6	6.0	7.6	11.7	19.0	19.5	16.7	15.3	18.9	14.7	6.0
Black	32.1	20.9	41.6	76.8	15.2	21.4	34.6	20.1	15.5	11.1	36.8	33.9	23.2
Hispanic	47.7	58.6	24.8	16.0	75.6	63.1	23.6	44.9	64.6	64.3	42.5	44.2	68.5
Other	6.5	5.9	6.0	1.2	1.7	3.8	22.8	15.5	3.2	9.3	1.8	7.2	2.3
Marital status, %													
Married	43.9	46.1	25.3	22.3	52.0	46.8	52.2	50.5	49.2	51.9	42.6	43.2	47.5
Weight, %													
Normal	20.2	21.5	23.8	18.3	17.1	20.4	27.8	22.7	18.0	20.0	16.5	21.8	21.8
Overweight	32.1	32.7	31.3	27.1	32.8	34.2	33.5	34.8	30.0	36.1	30.4	35.0	30.5
Obese	47.7	45.8	44.9	54.6	50.1	45.4	38.7	42.5	52.0	43.9	53.1	43.2	47.7
BMI (kg/m^2), median	29.6	29.4	29.3	30.7	30.0	29.4	28.3	28.9	30.3	29.1	30.6	28.8	29.6
Insurance, %													
Commercial	7.1	2.3	2.6	1.8	0.8	0.9	79.6	0.5	1.0	0.9	1.1	0.9	1.1
Medicaid	13.8	16.4	28.2	17.5	10.5	13.4	3.1	8.0	10.5	9.0	13.9	11.3	45.1
Uninsured	75.5	80.1	64.2	76.9	85.5	83.3	16.3	88.3	84.0	86.1	77.9	85.9	50.9
Self-pay	3.6	1.2	5.0	3.8	3.2	2.4	1.0	3.2	4.5	4.0	7.1	1.9	2.9
Unemployed, %	58.9	57.9	73.3	71.6	58.4	57.7	29.3	56.7	60.3	55.0	65.0	54.5	58.7
Ever smoked, %	32.4	26.8	50.7	48.4	28.0	32.2	21.7	27.9	28.0	25.8	40.0	27.1	15.4
Family history,* %	20	19.9	17.9	22.3	25.0	20.5	16.4	14.8	22.6	16.2	24.2	14.2	19.3
Prediabetes,† %	3.1	6.5	4.2	2.0	2.1	3.7	1.7	3.6	1.5	3.6	4.4	3.2	2.7
Hypertension,† %	39.1	40.9	61.7	58.0	31.7	35.7	31.8	39.4	20.1	29.2	43.5	41.2	13.4
Hyperlipidemia,† %	22.0	31.2	37.0	10.1	18.0	24.0	23.8	26.4	16.5	19.3	22.4	28.5	7.6
Providers seen, %													
Attending/physician	81.3	8.8	4.3	80.1	85.2	97.7	99.9	98.2	92.3	82.2	97.1	99.5	17.7
NP/PA/MW	11.9	0.3	6.9	19.8	14.7	2.2	0.1	1.8	7.6	17.7	2.8	0.5	75.5
Physician in training§	6.8	91.1	88.8	0.1	0.1	0.1	NA	NA	0.1	0.1	0.1	NA	6.8
Unique providers, *n*	601	109	232	104	102	75	13	51	61	73	69	37	264

NA, not applicable; MW, midwife; NP, nurse practitioner, PA, physician assistant. *Family history of diabetes. †Based on ICD-9 codes. §Physician in training includes residents and fellows.

Fixed Effects of Patient-, Clinic-, and Provider-Level Factors

The results of our final model (model 4) showed age (odds ratio [OR] 1.01, 95% CI 1.01–1.02) and BMI (OR 1.03, 95% 1.02–1.04) were marginally significant but not clinically important drivers of screening. However, patients with prediabetes (OR 1.53, 95% CI 1.12–2.09), hyperlipidemia (OR 1.70, 95% CI 1.48–1.95), and hypertension (OR 1.22, 95% CI 1.07–1.39) were more likely to be screened for diabetes than those without these conditions. Unmarried patients were less likely to be screened (OR 0.81, 95% CI 0.70–0.92) than married patients (Table 3). Race/ethnicity, family history of diabetes, cardiovascular disease, gestational diabetes, and employment status had no significant fixed effect on screening.

Screening Variation by Clinic and Provider Type

Patients receiving care in teaching clinics (clinics 1 and 2) were more likely to be screened than those receiving care in nonteaching clinics (72.9% vs. 70.2%; $P = 0.0006$). However, no clinic effect was observed after accounting for clustering and other covariates in model 4 (OR 1.07, 95% CI 0.74–1.55) (Table 3).

Attending physicians and physicians in training had similar rates of overall screening (72.6% vs. 73.7%) and guideline-indicated screening. However, advanced practice providers had lower rates of overall screening (53.6%) and guideline-indicated screening. After controlling for patient-, provider-, and clinic-level factors (model 4), advanced practice providers were less likely to screen patients for diabetes compared with attending

Table 2—Diabetes screening practices and screening eligibility of patients who visited 1 of the 12 clinics in a safety-net health system from 2010 to 2015

		Teaching clinics		Nonteaching clinics									
	Total	Clinic 1	Clinic 2	Clinic 3	Clinic 4	Clinic 5	Clinic 6	Clinic 7	Clinic 8	Clinic 9	Clinic 10	Clinic 11	Clinic 12
Unique patients													
N	56,818	2,267	1,761	9,099	6,993	5,374	4,315	6,846	1,823	6,467	7,191	1,943	2,739
(%)	(100)	(4.0)	(3.1)	(16.0)	(12.3)	(9.5)	(7.6)	(12.1)	(3.2)	(11.4)	(12.7)	(3.4)	(4.8)
Ever screened	70.4	72.9	75.0	67.9	50.8	69.9	91.5	81.4	72.3	70.3	71.5	71.3	59.4
Diabetes screening tests completed													
HbA_{1c}	54.6	68.4	73.3	55.5	26.3	59.1	91.1	48.9	66.9	51.0	60.6	45.3	39.7
FBG	33.2	18.8	12.0	26.6	34.0	33.8	18.8	61.6	16.5	42.9	26.6	40.6	30.0
OGTT	2.1	0.8	0.3	4.1	0.9	4.9	0.6	0.8	0.8	2.2	1.8	0.8	4.1
USPSTF screening eligible (n = 20,595)													
Yes	36.3	44.9	60.7	38.0	26.0	31.8	26.0	36.0	35.3	36.0	50.3	42.0	19.4
USPSTF eligible and screened (n = 15,190)													
Yes	73.8	78.8	82.0	68.4	49.3	71.7	92.8	83.1	74.1	76.3	75.6	76.6	61.5
USPSTF ineligible but screened (n = 24,802)													
Yes	68.5	68.1	64.1	67.6	51.3	69.1	91.1	80.5	71.3	66.9	67.3	67.5	58.9
ADA screening eligible (n = 39,185)													
Yes	69.0	71.1	87.8	81.1	61.3	65.9	62.7	70.6	65.2	62.7	76.5	73.1	40.8
ADA eligible and screened (n = 28,579)													
Yes	72.9	76.0	77.7	69.0	53.3	71.9	92.2	83.4	74.4	73.6	74.2	74.6	62.3
ADA ineligible but screened (n = 11,413)													
Yes	64.7	65.2	55.4	63.2	46.8	66.2	90.4	76.6	68.5	64.6	62.7	62.3	57.4

Data are percentages unless otherwise indicated.

physicians (OR 0.66, 95% CI 0.47–0.93) (Table 3).

Screening Eligibility and Completion Rates According to Guidelines

Overall eligibility for screening was nearly twofold higher with the ADA screening guideline (69%) than with the USPSTF guideline (36%), and this pattern was consistent across clinics (Table 2). For both guidelines, patients seen at clinic 2 had the highest eligibility, whereas patients seen at clinic 12 had the lowest eligibility.

Among those eligible for guideline-indicated screening (USPSTF n = 20,595; ADA n = 39,185) the overall proportion (USPSTF 73.8% vs. ADA 72.9%) and proportion within each clinic completing guideline-indicated screening were similar (Table 2). However, across clinics, the proportion of patients completing guideline-indicated screening reflected the variation in overall screening with wide variation, ranging from 49.3 to 92.8% for USPSTF and 53.3 to 92.2% for ADA (Table 2).

Yield of Screening

Among all patients screened for diabetes, the overall yield (positive test result) was 10.6% for diabetes and 43.3% for prediabetes (Table 4). Across the clinics, the overall yield varied widely, from 3.5 to 13.4% for diabetes and from 27.7 to 52.4% for prediabetes (Table 4). The yield of guideline-indicated screening was numerically similar between USPSTF and ADA guidelines for diabetes (11% vs. 9%) as well as for prediabetes (38% vs. 36%) (Table 4). Among those ineligible for screening according to USPSTF and ADA guidelines, the USPSTF guideline missed more cases of diabetes (6% vs. 3%) and prediabetes (26% vs. 19%) than the ADA guideline (Table 4). However, the ADA guideline still missed up to 5% of diabetes cases and 25% of prediabetes cases across the clinics (Table 4). Participants with diabetes or prediabetes who were ineligible for screening based on the USPSTF guideline were more likely to be women, Hispanic, and have limited comorbid conditions. Participants with diabetes or prediabetes who were ineligible for screening according to the ADA guideline had similar characteristics but were younger (aged 30–39).

Frequency and Yield of Confirmatory Testing

Overall, only 17.6% of patients with an initial screening test in the diabetes range (n = 4,240) completed a second test to confirm the diagnosis of type 2 diabetes as recommended by the ADA guidelines (1). Among the 4,240 patients with an initial, gold standard test result in the diabetes range, only 14.2% had a second, confirmatory gold standard test result within 60 days. Of the 601 patients completing a confirmatory test, a diagnosis of diabetes was confirmed in 61.7%. As an alternative to having patients return on a separate day for confirmatory testing, the ADA recommends an alternate, one-step confirmatory testing strategy by obtaining a FBG and HbA_{1c} on a single blood sample (1,20). Clinicians used this one-step confirmatory testing strategy in 13.8% of all patients screened for diabetes (N = 39,992). Of the 5,531 patients completing both a FBG and HbA_{1c} on the same day, 6.8% of patients had a confirmed diagnosis of diabetes and 21.3% had a confirmed diagnosis of prediabetes based on concordant FBG and HbA_{1c} results in the respective diagnostic range.

CONCLUSIONS

In this large, retrospective EHR cohort of primary care patients in an integrated, safety-net health system, we found significant variation in diabetes screening at both the provider and clinic level. Although overall screening rates were higher than those reported in epidemiologic studies (4,21), one-quarter of those eligible for guideline-recommended screening were not screened, and nearly 70% of

Table 3—Fixed and random effects from three-level random intercept logistic regression models for diabetes screening (*N* = 56,818)

	Hierarchical nested three-level models				Cross-classified model
	Model 1 Unconditional model	Model 2 With patient-level factors only	Model 3 With patient- and clinic-level factors	Model 4 With patient-, clinic-, and provider-level factors	With patient-, clinic-, and provider-level factors
Random effects					
Variance (SE)					
Clinic	0.311 (0.15)	0.276 (0.14)	0.284 (0.15)	0.233 (0.13)	0.234 (0.13)
Provider in clinic	0.420 (0.04)	0.299 (0.06)	0.303 (0.06)	0.274 (0.06)	0.281 (0.06)
Intraclass correlation	0.185	0.149	0.151	0.134	0.135
MOR	2.261	2.061	2.08	1.97	1.98
AIC, BIC	61,919, 61,921	7,301, 7,312	7,303, 7,314	7,298, 7,310	7,301, 7,253
Fixed effects		AOR (95% CI)	AOR (95% CI)	AOR (95% CI)	AOR (95% CI)
Patient-level factors					
Age	—	**1.01 (1.01, 1.02)**	**1.01 (1.01, 1.02)**	**1.01 (1.01, 1.02)**	**1.01 (1.01, 1.02)**
BMI	—	**1.03 (1.02, 1.04)**	**1.03 (1.02, 1.04)**	**1.03 (1.02, 1.04)**	**1.03 (1.02, 1.04)**
Sex					
Male	—	Reference	Reference	Reference	Reference
Female	—	**1.26 (1.11, 1.42)**	**1.26 (1.11, 1.42)**	**1.26 (1.11, 1.42)**	**1.25 (1.11, 1.41)**
Race/ethnicity					
White	—	Reference	Reference	Reference	Reference
Black	—	1.01 (0.86, 1.18)	1.02 (0.87, 1.19)	1.02 (0.87, 1.20)	1.02 (0.87, 1.20)
Hispanic	—	1.03 (0.87, 1.23)	1.04 (0.88, 1.24)	1.05 (0.88, 1.24)	1.04 (0.88, 1.24)
Other	—	1.06 (0.76, 1.48)	1.09 (0.78, 1.53)	1.10 (0.79, 1.54)	1.10 (0.79, 1.54)
Prediabetes					
No	—	Reference	Reference	Reference	Reference
Yes	—	**1.55 (1.14, 2.12)**	**1.53 (1.12, 2.09)**	**1.53 (1.12, 2.09)**	**1.52 (1.12, 2.07)**
Family history of diabetes					
No	—	Reference	Reference	Reference	Reference
Yes	—	1.12 (0.97, 1.30)	1.12 (0.97, 1.30)	1.12 (0.97, 1.30)	1.13 (0.98, 1.30)
Hyperlipidemia					
No	—	Reference	Reference	Reference	Reference
Yes	—	**1.71 (1.49, 1.96)**	**1.71 (1.49, 1.96)**	**1.70 (1.48, 1.95)**	**1.70 (1.48, 1.95)**
Hypertension					
No	—	Reference	Reference	Reference	Reference
Yes	—	**1.23 (1.07, 1.40)**	**1.23 (1.07, 1.40)**	**1.22 (1.07, 1.39)**	**1.22 (1.07, 1.39)**
Gestational diabetes					
No	—	Reference	Reference	Reference	Reference
Yes	—	0.96 (0.27, 3.43)	1.01 (0.28, 3.61)	1.06 (0.29, 3.85)	1.09 (0.30, 3.95)
Infant >9 lbs					
No	—	Reference	Reference	Reference	Reference
Yes	—	1.91 (0.78, 4.68)	1.98 (0.80, 4.89)	1.92 (0.78, 4.73)	1.92 (0.78, 4.72)
Cardiovascular disease					
No	—	Reference	Reference	Reference	Reference
Yes	—	1.05 (0.84, 1.31)	1.05 (0.84, 1.32)	1.05 (0.84, 1.31)	1.05 (0.84, 1.32)
Employment status					
Employed	—	Reference	Reference	Reference	Reference
Not employed	—	0.92 (0.80, 1.05)	0.92 (0.80, 1.05)	0.92 (0.80, 1.05)	0.92 (0.80, 1.06)
Marital status					
Married	—	Reference	Reference	Reference	Reference
Not married	—	**0.80 (0.70, 0.92)**	**0.81 (0.70, 0.92)**	**0.81 (0.70, 0.92)**	**0.81 (0.70, 0.93)**
Insurance					
Uninsured	—	Reference	Reference	Reference	Reference
Insured*	—	**0.79 (0.69, 0.91)**	**0.79 (0.69, 0.91)**	**0.80 (0.69, 0.91)**	**0.79 (0.69, 0.91)**
Self-pay	—	0.73 (0.53, 1.01)	0.75 (0.54, 1.04)	0.74 (0.54, 1.03)	0.74 (0.54, 1.03)
Ever smoked					
No	—	Reference	Reference	Reference	Reference
Yes	—	**0.80 (0.70, 0.91)**	**0.80 (0.71, 0.91)**	**0.80 (0.71, 0.91)**	**0.80 (0.71, 0.91)**
Clinic-level factor					
Clinic type					
Teaching	—	Reference	Reference	Reference	Reference
Nonteaching	—	—	1.01 (0.71, 1.45)	1.07 (0.74, 1.55)	1.06 (0.74, 1.54)

Continued on p. 1022

Table 3—Continued

	Hierarchical nested three-level models				Cross-classified model
	Model 1 Unconditional model	Model 2 With patient-level factors only	Model 3 With patient- and clinic-level factors	Model 4 With patient-, clinic-, and provider-level factors	With patient-, clinic-, and provider-level factors
Provider-level factor					
Provider type					
Attending/physician	—	Reference	Reference	Reference	Reference
NP/PA/MW	—	—	—	**0.64 (0.46, 0.89)**	**0.66 (0.47, 0.93)**
Physician in training‡	—	—	—	1.23 (0.76, 1.99)	1.32 (0.81, 2.14)

Boldface type indicates statistical significance. AIC, Akaike information criterion; AOR, adjusted odds ratio; BIC, Bayesian information criterion; MW, midwife; NP, nurse pratitioner, PA, physician assistant. *Insured includes commercial and Medicaid. ‡Physician in training includes residents and fellows.

patients not eligible for guideline-indicated screening were tested. Our findings suggest that health care providers may not routinely use diabetes screening guidelines in clinical practice to guide testing or may not think of testing high-risk patients during routine clinical care. Improved understanding of variation in screening practices is critical to developing and implementing systems-based interventions such as EHR-driven clinical decision support to improve diabetes screening across the spectrum of providers and clinics within health systems.

We found substantial variation in screening practices across the 12 free-standing community clinics within Dallas County's integrated, safety-net health system. Although quality measures and benchmarks for diabetes screening have not been established, the heterogeneity in screening practices identified low-performing clinics in need of interventions to close gaps in guideline-indicated screening. Overall screening rates in our study were higher than those observed in a large, community health center network (22) and in a study of academic and federally qualified health centers (7), but were similar to a study of primary care patients cared for in a university setting, although this study included nonfasting glucose measures in its screening definition (23). The higher screening rates in our study may reflect the structure of the safety-net health system, which provides uninsured patients with subsidized care to cover preventive health screenings, including diabetes screening. Our findings reinforce that screening rates calculated using resulted screening tests from clinical practice are substantially higher than self-reported screening rates in nationally representative samples of community-dwelling U.S. adults (4,21).

Although patient characteristics and case-mix varied across clinics, these differences did not fully explain the observed variation in screening practices. We found that provider- and clinic-level factors accounted for additional variation in screening practices and significantly improved model fit. Residual variation in screening practices likely reflects unmeasured provider- and clinic-level factors not captured in EHR data, suggesting that system-level interventions are needed to close screening gaps. We did find that advanced practice providers were less likely to screen patients for diabetes than attending physicians. Advanced practice providers do provide longitudinal primary care in this health care system, but additional evaluation of encounter types (acute vs. longitudinal care) and awareness of diabetes risk are needed to better understand these differences in screening rates by provider type.

Although diabetes screening guidelines are designed to identify high-risk patients and help target diabetes screening, our findings suggest that guideline use in clinical practice is limited. For both ADA and USPSTF screening guidelines, the proportion of patients completing screening was nearly identical among those eligible for guideline-indicated screening and those for whom guidelines did not recommend screening. While providers may have knowledge of patient-level risk factors not captured in structured EHR fields, the similar rates of overall screening, guideline-indicated screening, and guideline-ineligible screening suggest that providers screen based on their clinical gestalt or as a routine part of clinical practice rather than using screening guidelines to identify patients in need of testing. The yield of guideline-indicated screening was higher than those screened without guideline indications, but nearly one-third of patients tested without a guideline-based indication for screening had newly diagnosed diabetes or prediabetes, which reflects the suboptimal performance of screening guidelines to identify high risk patients with undiagnosed dysglycemia (24). Additionally, rates of confirmatory testing for individuals with an initial test result in the diabetes range were low, suggesting that clinicians in real-world practice diagnose patients using a single test result. Nearly 40% patients with an initial test result in the diabetes range did not have diabetes on confirmatory testing. This has important implications for patients and clinicians because it impacts patient counseling, treatment, and diagnostic coding for insurance purposes. Increased use of the one-step confirmatory testing strategy (i.e., concurrent testing of FBG and HbA_{1c} on a single blood draw) does not require patients to return for a second visit and may improve rates of confirmatory testing (20).

System-level interventions, such as EHR-based clinical decision support (CDS) to automate risk assessment using data routinely available in the EHR, are needed to support scalable approaches to decrease variation in diabetes screening across clinics. Interventions focused on increasing guideline awareness have limited effectiveness (25). Furthermore, current diabetes screening guidelines miss many individuals with undiagnosed disease and are inadequate for discriminating between those with and without prediabetes and diabetes (24,26). New approaches to diabetes risk assessment using EHR data from clinical practice, such as random glucose, to design tools for implementation into EHR-based CDS are needed (24,27). CDS provides health care professionals with actionable knowledge

Table 4—Screening yield among patients completing a gold standard screening test in 1 of the 12 clinics in a safety-net health system from 2010 to 2015

		Teaching clinics		Nonteaching clinics									
	Total	Clinic 1	Clinic 2	Clinic 3	Clinic 4	Clinic 5	Clinic 6	Clinic 7	Clinic 8	Clinic 9	Clinic 10	Clinic 11	Clinic 12
N	39,992	1,652	1,320	6,178	3,550	3,757	3,950	5,573	1,318	4,544	5,138	1,385	1,627
(%)	(100)	(4.1)	(3.3)	(15.4)	(8.9)	(9.4)	(9.9)	(13.9)	(3.3)	(11.3)	(12.9)	(3.5)	(4.1)
Diabetes yield	10.6	10.4	12.8	12.7	13.4	10.1	8.3	9.5	10.2	11.4	10.9	10.0	3.5
Prediabetes yield	43.3	46.6	52.4	46.0	36.3	46.9	43.8	42.3	39.8	43.6	45.2	44.6	27.7
Diabetes yield by USPSTF guideline ($n = 20,595$)													
Eligible	10.5	11.3	13.0	10.6	8.7	10.6	11.2	11.2	8.5	12.0	10.2	9.2	3.4
Ineligible	5.8	4.5	4.3	7.5	6.2	5.4	6.3	5.8	6.8	5.8	5.3	5.6	1.8
Prediabetes yield by USPSTF guideline													
Eligible	37.7	44.9	48.7	33.7	21.2	37.2	51.1	40.5	33.7	39.7	39.7	39.0	24.2
Ineligible	26.4	25.0	24.8	29.7	17.5	30.7	36.2	31.0	26.0	25.6	24.8	26.6	14.6
Diabetes yield by ADA guideline ($n = 39,185$)													
Eligible	9.3	9.8	10.5	9.4	8.8	8.9	9.9	9.6	9.4	10.8	9.0	8.7	3.0
Ineligible	3.4	2.1	3.3	5.2	3.7	3.4	3.6	3.4	3.6	3.4	3.7	2.7	1.5
Prediabetes yield by ADA guideline													
Eligible	35.9	39.9	42.6	33.8	22.3	38.0	49.3	39.9	34.3	37.4	36.5	37.5	21.2
Ineligible	18.6	19.4	15.4	20.2	12.3	22.7	24.5	21.3	18.3	19.3	18.6	16.3	13.1

Data are presented as the percentage of patients completing a gold standard diabetes screening test.

and patient-specific information that is intelligently filtered and presented at appropriate times to enhance care delivery (28). Well-designed CDS interventions can improve the health not only of individual patients but also of populations of patients by presenting the right information, to the right people, in the right format, through the right channel, at the right time (29). Such tools can support efficient risk assessment and targeted screening in large clinical populations and may help close diabetes screening gaps (11).

Strengths of our study include assessment of screening practices in a large, integrated, indigent health care system that uses a single, comprehensive EHR. The safety-net system provides comprehensive care and coverage to all patients regardless of insurance status, which removes insurance-related barriers to diabetes screening and maximizes receipt of health care and preventive care within the system.

Our study is not without limitations. First, because our study was conducted within an integrated safety-net system, our findings may not be generalizable to other practices and health systems. Second, we were unable to account for provider factors and clinical factors not discretely captured in the EHR. Provider experience and clinic-specific practices may account for additional, unmeasured variation in our study. Third, our analyses were limited to patients aged 18–65 to maximize receipt of health care services in the safety-net system. Thus, our findings may not reflect screening practices in those aged 65 and older, who are more likely to have multiple risk factors and be eligible for guideline-based screening. Fourth, we were unable to reliably exclude patients with hyperglycemic symptoms from the screening cohort by using EHR data. Fifth, our findings may underestimate the use of FBG for screening in clinical practice because we were unable to identify "fasting laboratory panels" within the EHR. Finally, our primary outcome definition of diabetes and prediabetes was based on a single gold standard diabetes screening test and did not include a second, confirmatory test, as recommended by guidelines (1).

Despite well-recognized national diabetes screening guidelines and national awareness campaigns to improve identification of individuals with prediabetes, diabetes screening practices varied widely across free-standing clinics in a large, safety-net health system. Diabetes screening guidelines were inconsistently used in risk assessment, resulting in similar screening rates among those who did and did not meet screening criteria. However, detection of undiagnosed diabetes and prediabetes among those not eligible for guideline-indicated screening was substantial. New, data-driven approaches to diabetes risk assessment designed for use and implementation in clinical practice are needed to close diabetes screening gaps and improve early detection of patients with prediabetes and diabetes.

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