ORIGINAL REPORT: EPIDEMIOLOGIC RESEARCH

Screening for Diabetes Risk Using Integrated Dental and Medical Electronic Health Record Data

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Abstract: Undiagnosed diabetes and prediabetes present a serious public health challenge. We previously reported that data available in the dental setting can serve as a tool for early dysglycemia identification in a primarily Hispanic, urban population. In the present study, we sought to determine how the identification approach can be recalibrated to detect diabetes or prediabetes in a White, rural cohort and whether an integrated dental-medical electronic health record (iEHR) offers further value to the process. We analyzed iEHR data from the Marshfield Clinic, a health system providing care in rural Wisconsin, for dental patients who were ≥ 21 y of age, reported that they had never been told they had diabetes, had an initial periodontal examination of at least 2 quadrants, and had a glycemic assessment within 3 mo of that examination. We then assessed the performance of multiple predictive models for prediabetes/diabetes. The study outcome, glycemic status, was gleaned from the medical module of the iEHR based on American Diabetes Association blood test cutoffs.

The sample size was 4,560 individuals. Multivariate logistic regression revealed that the best performance was achieved by a model that took advantage of the iEHR. Predictors included age, sex, race, ethnicity, number of missing teeth, percentage of teeth with at least 1 pocket ≥ 5 mm from the dental EHR, and overweight/obesity, hypertension, hyperlipidemia, and smoking status from the medical EHR. The model achieved an area under the receiver operating characteristic curve of 0.71 (95% confidence interval, 0.69–0.72), yielding a sensitivity of 0.70 and a specificity of 0.62. Across a range of populations, informed by certain patient characteristics, dental care team members can play a role in helping to identify dental patients with undiagnosed diabetes or prediabetes. The accuracy of the prediction increases when dental findings are combined with information from the medical EHR.

Knowledge Transfer Statement: Prediabetes and diabetes often go undiagnosed for many years. Early identification and care

can lead to improved glycemic outcomes and prevent wide-ranging morbidity, including adverse oral health consequences, in affected individuals. Information available in the dental office can be used by clinicians to identify those who remain undiagnosed or are at risk; the accuracy of this prediction increases when combined with information from the medical electronic health record.

Keywords: dentists, hyperglycemia, periodontitis, prediabetic state, prevention & control, risk

Introduction

It is estimated that almost a quarter of those with diabetes in the United States, a staggering 7.2 million individuals, are not aware of their condition (Centers for Disease Control and Prevention [CDC] 2017), and almost half of those with diagnosed diabetes do not achieve optimal glycemic control (Ali et al. 2013; Stark Casagrande et al. 2013). Prediabetes is much more prevalent than frank diabetes, affecting 84 million people in the United States, and has been described as a silent precursor; it puts

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people at high risk for type 2 diabetes and for vascular disease and, according to current CDC estimates, 88% of those with prediabetes remain undiagnosed (CDC 2017).

Individuals with undiagnosed or poorly controlled diabetes are at increased risk for many health complications, including periodontitis. Indeed, multiple studies have conclusively demonstrated that diabetes adversely affects periodontal status (Taylor and Borgnakke 2008; Lalla and Papapanou 2011; Lamster et al. 2014). Young adults with diabetes have about twice the risk of having periodontal disease, and people 45 y or older with poorly controlled diabetes are almost 3 times more likely to have severe periodontitis than those without diabetes. Furthermore, periodontitis and type 2 diabetes share several risk factors (Borgnakke 2016a, 2016b), which makes the value of a team-based, interprofessional approach to prevention and treatment of patients at risk for, or affected by, either or both conditions apparent.

Within its Parameters of Care, the American Academy of Periodontology has long indicated that dentists have a role in the “identification of signs and symptoms of undiagnosed or poorly controlled diabetes mellitus” (American Academy of Periodontology 1999). Currently, patients with unknown diabetes are seen in dental clinics, leaving clues to their status, while the disease goes unrecognized and untreated with devastating consequences. Dental care settings have untapped potential for identifying undiagnosed dysglycemia, as well as contributing to the care of patients with known diabetes (Greenberg et al. 2010; Lalla and Lamster 2012; Lamster et al. 2012; Genco et al. 2014), and efforts to address this unrealized health care opportunity have shown significant promise (Borrell et al. 2007; Lalla et al. 2011; Li et al. 2011; Lalla et al. 2013; Genco et al. 2014; Herman et al. 2015; Lalla et al. 2015; Holm et al. 2016; Myers-Wright et al. 2018). Evidence further suggests that dental professionals and their patients support such efforts as

important and worthwhile (Greenberg et al. 2010; Barasch et al. 2012; Greenberg et al. 2012; Creanor et al. 2014). In this environment, the wide deployment of electronic health records (EHRs) creates an opportunity to aggregate health care data to potentially contribute toward improved health of individuals and the population as a whole.

Indeed, exploration of routinely collected clinical data from EHRs has been recognized by leaders in health information technology as a fundamental opportunity to gain insight into disease processes, understand disease associations, and improve health outcomes (Safran et al. 2007; Kalenderian et al. 2016).

The present study uses the longitudinal dental and medical data contained within the Marshfield Clinic’s (Marshfield, WI) data warehouse to further investigate dentists’ ability to contribute to the long-term goal to positively affect the care of dental patients with dysglycemia. The Marshfield Clinic has long had an integrated dental-medical electronic health record (iEHR) to support its clinics and thus provided ideal material for this work. We first examined the performance of an identification approach we previously reported in a predominantly Hispanic northern Manhattan population (Lalla et al. 2011; Lalla et al. 2013). In a distinctly different cohort, the predominantly Caucasian central, northern, and western Wisconsin rural population treated at the Marshfield Clinic, we then assessed how the model can be recalibrated to better detect diabetes or prediabetes by optimizing cutoffs for included predictors and/or by using additional information available in the iEHR.

Methods

The study population comprised patients who were seen at the Marshfield Clinic’s dental and medical practices. Marshfield Clinic, incorporated in 1916, is an independent nonprofit health care delivery organization with 10 dental and 57 medical practices serving an

expansive, largely rural population in Wisconsin and is one of the largest comprehensive dental-medical health systems in the United States (Acharya 2016). Dental services are provided through Family Health Center, a Federally Qualified Health Center for patients regardless of ability to pay or insurance status. The Marshfield Clinic’s dental centers provide care to more than 50,000 unique patients annually, and about 90% of these patients are also seen in the Marshfield Clinic’s medical centers.

We mined the patient data from the Marshfield Clinic iEHR. To promote coordination of care, the iEHR supports shared access to patient health information among dental and medical providers. It offers centralized access to demographics, medical/dental diagnoses, medications/prescription information, observation/vitals/findings lists, allergies/special conditions/problems lists, dental and periodontal charts, treatment planning, hospital information, imaging, and dental and medical appointing. The iEHR is supported by an integrated Enterprise Data Warehouse (EDW), in existence for more than 15 y, which houses the patients’ dental and medical information. The intent of this sophisticated data warehouse is to be the sole reporting source for high-quality integrated information related to patient care, research, and operations.

The present study data spanned 10 y, from January 2005 through May 2015. The study protocol was approved by the Marshfield Clinic Research Institute and the Columbia University Institutional Review Boards, and it conforms to STROBE guidelines. Our study population included individuals age 21 y and older who had undergone a baseline periodontal examination in at least 2 quadrants. Of note, most subjects (93%) had a 4-quadrant periodontal examination and only 6.5% had 2 quadrants examined. To be included, patients also needed to 1) indicate that they did not have diabetes or “high blood sugar” at the time of the first dental visit and 2) have had a fasting plasma glucose (FPG) or hemoglobin

Table 1.
Variables Included in the Predictive Models.

Variable	Source	Description
Missing teeth	Dental EHR	Number of missing teeth, out of 28 (i.e., excluding third molars)
Deep pockets (DP)	Dental EHR	% of teeth with ≥ 1 site with probing depth ≥ 5 mm
Age	Dental EHR	Age at first periodontal examination (which included 2 or more quadrants)
Sex	Dental EHR	Patient reported, male or female
Race	Dental EHR	Patient reported, dichotomized to White or non-White
Ethnicity	Dental EHR	Patient reported, dichotomized to Hispanic/Latino or non-Hispanic/Latino
Hypertension	Medical EHR	Any combination of 2 of the following (documented twice or more): diagnosis based on <i>ICD-9</i> codes (401.0–401.9); prescription of antihypertensive medications; diastolic blood pressure ≥ 90 mm Hg or systolic ≥ 140 mm Hg
Overweight Obesity	Medical EHR	Body mass index 25 to 29.9 kg/m ² Body mass index ≥ 30 kg/m ²
Hyperlipidemia	Medical EHR	Diagnosis based on <i>ICD-9</i> codes (272.0, 272.2, and 272.4)
Smoking status	Medical EHR	Patient reported, current/never/former

EHR, electronic health record; *ICD-9*, *International Classification of Diseases, Ninth Revision*.

A1c (HbA1c) test in their medical EHR within 3 mo of the first periodontal examination.

Our outcome variable was glycemic status, based on the blood test result according to current American Diabetes Association (ADA) criteria: prediabetes, HbA1c 5.7% to 6.4% or FPG 100 to 125 mg/dL; diabetes, HbA1c $\geq 6.5\%$ or FPG ≥ 126 mg/dL. The predictors we considered were age, sex, race, ethnicity, number of missing teeth, percentage of teeth with at least 1 pocket ≥ 5 mm (deep pockets [DP]), overweight/obesity, hypertension, hyperlipidemia, and smoking status. For those subjects who did not have a full-mouth periodontal examination, calculation of the percentage of teeth with deep pockets was based on the number of teeth examined, not on the total number of teeth present. All of these variables are defined in Table 1. Because the study population was overwhelmingly non-Hispanic White, we dichotomized both race and ethnicity in our analysis.

We started with a simple predictive model (“base model”) that included only 2 dental variables, missing teeth and

percentage of teeth with at least 1 deep pocket (≥ 5 mm), as these proved useful in predicting undiagnosed dysglycemia in our earlier work and since we are interested in the model’s use in dental care settings. We then considered an “integrated” model that included age, sex, race, ethnicity, overweight/obesity, hypertension, hyperlipidemia, and smoking status, in addition to the 2 variables in the base model. The area under the receiver operating characteristic (ROC) curve was calculated for these 2 logistic regression models, and the difference between the 2 curves was assessed using the de Long-de Long-Clarke test. Furthermore, a “propensity score” estimating the probability of a subject having prediabetes or diabetes was created (as described below) based on the integrated model. The sensitivity, specificity, positive predictive value, and negative predictive value of the base model and the propensity score (using different optimal cutoffs), together with their 95% confidence intervals (CIs), were then calculated. Since there was only a small portion of missing data, completers analysis was performed. All

statistical analyses were conducted in SAS version 9.4 (SAS Institute). The ROC plot was generated using R version 3.0.1 (R Foundation for Statistical Computing).

Results

The characteristics of the study population are shown in Table 2. As noted above, all participants denied having diabetes or “high blood sugar” at the time of the initial dental examination, so glycemic status (normoglycemia vs. prediabetes vs. diabetes) is based on a blood test result (HbA1c or FPG) from the medical EHR, within 3 mo of the periodontal examination. When multiple glycemic measures were available within the 3-mo period, we selected the test result that was closest to the periodontal examination.

The Figure shows the ROC curves of the 2 predictive models considered: base and integrated. The ROC analysis revealed that the base model had an area under the curve (AUC) of 0.59 (95% CI, 0.57–0.60). The integrated model had an AUC of 0.71 (95% CI, 0.69–0.72), a significant improvement over the base model ($P < 0.0001$).

Table 2.
Study Population Characteristics (*N* = 4,560).

	Normoglycemia ^a	Prediabetes ^a	Diabetes ^a	<i>P</i> Value ^b
Number of subjects	2,165 (47.5)	1,709 (37.5)	686 (15)	
Age	44.7 ± 15.6	52.6 ± 15.6	55.0 ± 15.2	<0.001
Sex, female	1,403 (65)	877 (51)	366 (53)	<0.001
Race, White	2,003 (93)	1,595 (93)	637 (93)	0.621
Ethnicity, non-Hispanic/Latino	2,011 (93)	1,599 (94)	643 (94)	0.615
Number of missing teeth	3.0 ± 5.1	3.7 ± 5.6	4.7 ± 6.5	<0.001
Percentage of teeth with ≥1 site with probing depth ≥5 mm	14 ± 24	18 ± 26	19 ± 27	<0.001
Hypertension ^c	794 (37)	1,014 (59)	542 (79)	<0.001
Body mass index category				<0.001
Overweight ^c	620 (31)	412 (26)	124 (20)	
Obesity ^c	941 (47)	986 (63)	462 (73)	
Hyperlipidemia ^c	1,078 (50)	1,190 (70)	532 (78)	<0.001
Smoking status ^c				<0.001
Current smoker	668 (31)	494 (29)	165 (24)	
Former smoker	722 (33)	658 (39)	283 (42)	
Never smoker	766 (36)	548 (32)	233 (34)	

Data shown as count (%) or mean ± standard deviation.

^aBased on medical record blood test result and American Diabetes Association guidelines: normoglycemia, HbA1c <5.7% or fasting plasma glucose (FPG) <100 mg/dL; prediabetes, HbA1c 5.7% to 6.4% or FPG 100 to 125 mg/dL; diabetes, HbA1c ≥6.5% or FPG ≥126 mg/dL.

^bTwo-sample *t* test for continuous variables and chi-squared test for categorical variables.

^cAs defined in Table 1.

Based on the fitted integrated model (and using the variables described in Table 1), we generated the following algorithm for a propensity score that estimates the probability that an individual may have prediabetes or diabetes:

$$1 / [1 + \exp (1.903 + 0.004 \times \text{missing teeth} - 0.383 \times \text{DP} - 0.022 \times \text{age} + 0.195 \times \text{female} + 0.010 \times \text{White} + 0.344 \times \text{non-Hispanic/Latino} - 0.682 \times \text{hypertension} - 0.727 \times \text{overweight/obesity} - 0.375 \times \text{hyperlipidemia} - 0.138 \times \text{current smoker})].$$

Performance characteristics of the base model and the integrated model's propensity score are summarized in Table 3. We first considered previously

identified cutoffs (Lalla et al. 2013) for the 2 variables in the base model (first row) and then calculated new optimal cutoffs, based on the current ROC curve/population (second row). Correct identification of dysglycemia ranged from 52% to 65% with the base model. A propensity score above 0.49 correctly identified 70% of the dental patients with undiagnosed prediabetes or diabetes.

Discussion

Few studies in the past have focused on noninvasive measures to screen for undiagnosed dysglycemia in dental care settings and/or statistical algorithms applying risk-based modeling by using demographic data, self-reported health status data, and/or clinical data (Borrell et al. 2007; Strauss et al. 2010; Li et al.

2011). We previously used NHANES III (National Health and Nutrition Examination Survey III) data to explore the potential to predict undiagnosed diabetes in dental settings (Borrell et al. 2007) and then conducted the largest prospective study to date in a mostly Hispanic, northern Manhattan cohort in which the presence of ≥26% teeth with at least 1 deep pocket or ≥4 missing teeth correctly identified 75% of dental patients with undiagnosed prediabetes or diabetes (Lalla et al. 2013). Of note, even in medical settings, there is not a single diabetes prediction model that is universally accepted. It is well recognized, however, that certain racial/ethnic groups are at significantly increased risk for diabetes, and it has been suggested that recalibration of algorithms may be necessary when

Table 3.

Sensitivity, Specificity, Positive Predictive Value (PPV), and Negative Predictive Value (NPV).

	Sensitivity	Specificity	PPV	NPV
≥4 missing teeth or ≥26% teeth with at least 1 pocket ≥5 mm	0.52 (0.50–0.54)	0.60 (0.58–0.63)	0.59 (0.57–0.61)	0.47 (0.51–0.55)
≥2 missing teeth or ≥20% teeth with at least 1 pocket ≥5 mm	0.65 (0.63–0.67)	0.49 (0.46–0.51)	0.58 (0.56–0.60)	0.55 (0.52–0.58)
Propensity score ≥0.49	0.70 (0.68–0.72)	0.62 (0.60–0.64)	0.67 (0.65–0.69)	0.65 (0.63–0.68)

The 95% confidence intervals are shown in parentheses.

Figure. Receiver operating characteristic curves of candidate predictive models. Base model (dashed line curve): number of missing teeth + % of teeth with at least 1 deep pocket. Integrated model (solid line curve): number of missing teeth + % of teeth with at least 1 deep pocket + age + sex + race + ethnicity + hypertension + overweight/obesity + hyperlipidemia + smoking status.

models are applied to different populations (Tabak et al. 2012). With this in mind, the current study, in a primarily White rural population, sought to identify whether information available in dental records can be used to screen for patients with unknown prediabetes or diabetes and whether an integrated dental-medical EHR offers further value to the identification process.

Designing and conducting prospective studies can be expensive and time-consuming. An approach that focuses on “secondary use” of health data collected within EHRs is an alternative (Acharya et al. 2013; Liu et al. 2013; Schleyer et al. 2013). Indeed, the American Medical Informatics Association has stated that “secondary use of health data

can enhance healthcare experiences for individuals, expand knowledge about disease and appropriate treatments, strengthen understanding about the effectiveness and efficiency of our healthcare systems, support public health and security goals, and aid businesses in meeting the needs of their customers” (Safran et al. 2007).

Marshfield Clinic has made a significant commitment to the development of its clinical information systems over the past 40 y, and as part of this effort, it has developed a robust integrated dental-medical EHR environment. The work that we report here leverages the rich dental and medical longitudinal data within Marshfield Clinic’s data warehouse. The approach is novel and makes most sense since type 2 diabetes has several

well-described risk factors and early signs that can be readily available in dental and/or medical records.

Our findings suggest that missing teeth and deep probing depths alone, information that is readily available in any dental setting, can help identify people with previously unrecognized dysglycemia. As previously discussed (Lalla et al. 2013), increased sensitivity is most important when evaluating the performance of diabetes screening approaches in nontraditional health care settings. Individuals identified with potential dysglycemia by a member of the dental team can be referred to a physician/medical team for further evaluation, advice on/management of modifiable risk factors, a formal diagnosis, and appropriate care. In the present study, the best performance was achieved by a model that took advantage of the integrated dental-medical EHR, adding age, sex, race, ethnicity, overweight/obesity, hypertension, hyperlipidemia, and smoking status to the base (2 dental variables only) model. The algorithm for the propensity score can easily be embedded as a trigger within the EHR of an integrated health care system or even a standalone dental practice to flag those who may have/are at risk for diabetes and remain unrecognized and thus provide valuable just-in-time clinical decision support.

Although the ability to generalize from our specific study population is limited and the identified predictive models and variable cutoffs will need to be further tested in future large prospective studies in diverse populations, the present findings are in concert with our previous

findings in a mostly Hispanic urban population and similar to results reported by other investigators in the United States and abroad (Lalla et al. 2011; Lalla et al. 2013; Genco et al. 2014; Herman et al. 2015; Holm et al. 2016). We acknowledge that some of the major risk factors for type 2 diabetes were considerably more prevalent in the present study cohort compared to current national figures. For example, overweight/obesity in our study population was 84.5% vs. 70.7% nationally and hypertension was 51.5% vs. 33.5% nationally (National Center for Health Statistics 2017). This again may limit generalizability of our results and, at least partially, explain the higher prevalence of dysglycemia noted in our study population. We also recognize that data used in our analyses, including periodontal measurements, were recorded by multiple providers in several dental and/or medical clinics. Our objective, however, was to explore screening approaches on the basis of real-world clinical data rather than controlled, tightly calibrated data (as in a traditional prospective research study), which may not always translate to real clinical practice.

Taken together and considered in the context of previous work, the present results corroborate the ability of information available in the dental office to help identify people at risk for prediabetes or diabetes. Furthermore, they clearly demonstrate that the accuracy of the prediction increases when dental findings are combined with information from the medical EHR. This work makes use of a large integrated dental-medical EHR database to establish diabetes risk algorithms that can be effective in the real world. Early diabetes identification and treatment can reduce the development of complications and improve quality of life. In addition, results from this study have the potential to affect periodontal treatment decision making in affected individuals, change clinical practice by providing a much-needed evidence base, and inform large intervention trials.

Author Contributions

A. Acharya, C. Kunzel, contributed to conception, design, and data interpretation, critically revised the manuscript; B. Cheng, contributed to conception, design, data analysis, and interpretation, critically revised the manuscript; R. Koralkar, B. Olson, contributed to data acquisition and analysis, critically revised the manuscript; I.B. Lamster, contributed to conception and design, critically revised the manuscript; E. Lalla, contributed to conception, design, and data interpretation, drafted and critically revised the manuscript. All authors gave final approval and agree to be accountable for all aspects of the work.

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References

- Acharya A. 2016. Marshfield clinic health system: integrated care case study. *J Calif Dent Assoc.* 44(3):177–181.
- Acharya A, VanWormer JJ, Waring SC, Miller AW, Fuehrer JT, Nycz GR. 2013. Regional epidemiologic assessment of prevalent periodontitis using an electronic health record system. *Am J Epidemiol.* 177(7):700–707.
- Ali MK, Bullard KM, Saaddine JB, Cowie CC, Imperatore G, Gregg EW. 2013. Achievement of goals in U.S. diabetes care, 1999–2010. *N Engl J Med.* 368(17):1613–1624.
- American Academy of Periodontology. 1999. Parameter on periodontitis associated with systemic conditions. *J Periodontol.* 71(5 Suppl):876–879.
- Barasch A, Safford MM, Qvist V, Palmore R, Gesko D, Gilbert GH; Dental Practice-Based Research Network Collaborative Group. 2012. Random blood glucose testing in dental practice: a community-based feasibility study from the dental practice-based research network. *J Am Dent Assoc.* 143(3):262–269.
- Borgnakke WS. 2016a. Modifiable risk factors for periodontitis and diabetes. *Curr Oral Health Rep.* 3(3):254–269.
- Borgnakke WS. 2016b. “Non-modifiable” risk factors for periodontitis and diabetes. *Curr Oral Health Rep.* 3(3):270–281.
- Borrell LN, Kunzel C, Lamster I, Lalla E. 2007. Diabetes in the dental office: using NHANES III to estimate the probability of undiagnosed disease. *J Periodontol Res.* 42(6):559–565.
- Centers for Disease Control and Prevention. 2017. National diabetes statistics report, 2017. Atlanta (GA): U.S. Department of Health and Human Services.
- Creanor S, Millward BA, Demaine A, Price L, Smith W, Brown N, Creanor SL. 2014. Patients’ attitudes towards screening for diabetes and other medical conditions in the dental setting. *Br Dent J.* 216(1):E2.
- Genco RJ, Schifferle RE, Dunford RG, Falkner KL, Hsu WC, Balukjian J. 2014. Screening for diabetes mellitus in dental practices: a field trial. *J Am Dent Assoc.* 145(1):57–64.
- Greenberg BL, Glick M, Frantsve-Hawley J, Kantor ML. 2010. Dentists’ attitudes toward chairside screening for medical conditions. *J Am Dent Assoc.* 141(1):52–62.
- Greenberg BL, Kantor ML, Jiang SS, Glick M. 2012. Patients’ attitudes toward screening for medical conditions in a dental setting. *J Public Health Dent.* 72(1):28–35.
- Herman WH, Taylor GW, Jacobson JJ, Burke R, Brown MB. 2015. Screening for prediabetes and type 2 diabetes in dental offices. *J Public Health Dent.* 75(3):175–182.
- Holm NC, Belstrom D, Ostergaard JA, Schou S, Holmstrup P, Grauballe MB. 2016. Identification of individuals with undiagnosed diabetes and pre-diabetes in a Danish cohort attending dental treatment. *J Periodontol.* 87(4):395–402.
- Kalenderian E, Halamka JD, Spallek H. 2016. An EHR with teeth. *Appl Clin Inform.* 7(2):425–429.
- Lalla E, Cheng B, Kunzel C, Burkett S, Ferraro A, Lamster IB. 2015. Six-month outcomes in dental patients identified with

- hyperglycaemia: a randomized clinical trial. *J Clin Periodontol*. 42(3):228–235.
- Lalla E, Cheng B, Kunzel C, Burkett S, Lamster IB. 2013. Dental findings and identification of undiagnosed hyperglycemia. *J Dent Res*. 92(10):888–892.
- Lalla E, Kunzel C, Burkett S, Cheng B, Lamster IB. 2011. Identification of unrecognized diabetes and pre-diabetes in a dental setting. *J Dent Res*. 90(7):855–860.
- Lalla E, Lamster IB. 2012. Assessment and management of patients with diabetes mellitus in the dental office. *Dent Clin North Am*. 56(4):819–829.
- Lalla E, Papapanou PN. 2011. Diabetes mellitus and periodontitis: a tale of two common interrelated diseases. *Nat Rev Endocrinol*. 7(12):738–748.
- Lamster IB, Cheng B, Burkett S, Lalla E. 2014. Periodontal findings in individuals with newly identified pre-diabetes or diabetes mellitus. *J Clin Periodontol*. 41(11):1055–1060.
- Lamster IB, Kunzel C, Lalla E. 2012. Diabetes mellitus and oral health care: time for the next step. *J Am Dent Assoc*. 143(3):208–210.
- Li S, Williams PL, Douglass CW. 2011. Development of a clinical guideline to predict undiagnosed diabetes in dental patients. *J Am Dent Assoc*. 142(1):28–37.
- Liu K, Acharya A, Alai S, Schleyer TK. 2013. Using electronic dental record data for research: a data-mapping study. *J Dent Res*. 92(7 Suppl):90S–96S.
- Myers-Wright N, Lamster IB, Jasek JP, Chamany S. 2018. Evaluation of medical and dental visits in New York City: opportunities to identify persons with and at risk for diabetes mellitus in dental settings. *Community Dent Oral Epidemiol*. 46(1):102–108.
- National Center for Health Statistics. 2017. Health, United States, 2016. With chartbook on long-term trends in health. Hyattsville (MD): Centers for Disease Control and Prevention, U.S. Department of Health and Human Services.
- Safran C, Bloomrosen M, Hammond WE, Labkoff S, Markel-Fox S, Tang PC, Detmer DE; Expert Panel. 2007. Toward a national framework for the secondary use of health data: an American Medical Informatics Association white paper. *J Am Med Inform Assoc*. 14(1):1–9.
- Schleyer TK, Ruttenberg A, Duncan W, Haendel M, Torniai C, Acharya A, Song M, Thyvalikakath TP, Liu K, Hernandez P. 2013. An ontology-based method for secondary use of electronic dental record data. *AMIA Jt Summits Transl Sci Proc*. 2013:234–238.
- Stark Casagrande S, Fradkin JE, Saydah SH, Rust KF, Cowie CC. 2013. The prevalence of meeting A1c, blood pressure, and LDL goals among people with diabetes, 1988–2010. *Diabetes Care*. 36(8):2271–2279.
- Strauss SM, Russell S, Wheeler A, Norman R, Borrell LN, Rindskopf D. 2010. The dental office visit as a potential opportunity for diabetes screening: an analysis using NHANES 2003–2004 data. *J Public Health Dent*. 70(2):156–162.
- Tabak AG, Herder C, Rathmann W, Brunner EJ, Kivimaki M. 2012. Prediabetes: a high-risk state for diabetes development. *Lancet*. 379(9833):2279–2290.
- Taylor GW, Borgnakke WS. 2008. Periodontal disease: associations with diabetes, glycemic control and complications. *Oral Dis*. 14(3):191–203.