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Translating periodontal data to knowledge in a learning health system

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ABSTRACT

Background. A learning health system (LHS) is a health system in which patients and clinicians work together to choose care on the basis of best evidence and to drive discovery as a natural outgrowth of every clinical encounter to ensure the right care at the right time. An LHS for dentistry is now feasible, as an increased number of oral health care encounters are captured in electronic health records (EHRs).

Methods. The authors used EHRs data to track periodontal health outcomes at 3 large dental institutions. The 2 outcomes of interest were a new periodontitis case (for patients who had not received a diagnosis of periodontitis previously) and tooth loss due to progression of periodontal disease.

Results. The authors assessed a total of 494,272 examinations (new periodontitis outcome: n = 168,442; new tooth loss outcome: n = 325,830), representing a total of 194,984 patients. Dynamic dashboards displaying performance on both measures over time allow users to compare demographic and risk factors for patients. The incidence of new periodontitis and tooth loss was 4.3% and 1.2%, respectively.

Conclusions. Periodontal disease, diagnosis, prevention, and treatment are particularly well suited for an LHS model. The results showed the feasibility of automated extraction and interpretation of critical data elements from the EHRs. The 2 outcome measures are being implemented as part of a dental LHS. The authors are using this knowledge to target the main drivers of poorer periodontal outcomes in a specific patient population, and they continue to use clinical health data for the purpose of learning and improvement.

Practical Implications. Dental institutions of any size can conduct contemporaneous self-evaluation and immediately implement targeted strategies to improve oral health outcomes.

Key Words. Clinical outcomes; big data; decision making; dental informatics; epidemiology; population health.

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Evidence-based decision making in health care is becoming more complicated. Clinicians must make decisions that integrate evolving scientific evidence, taking into account many data points. Once these decisions are made, little information is available about their long-term impact, limiting the ability to learn from and ultimately improve health outcomes.[1] The National Academy of Medicine[2] has called for the development of a learning health system (LHS) in which patients and clinicians work together to choose care on the basis of best evidence[3] and to drive discovery as a natural outgrowth of every clinical encounter to ensure innovation, quality, and value at the point of care. An LHS is a health system in which internal data and experience are systematically integrated with external evidence and that knowledge is put into practice. As a result, patients receive higher-quality, safer, and more efficient care.[4] This vision of an LHS has remained largely aspirational, especially in dentistry.

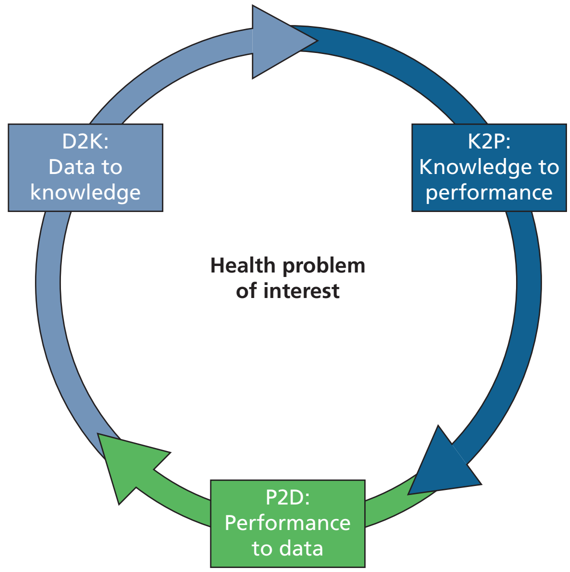

Figure 1. Overview of the learning loop as part of the learning health system framework. Adapted from University of Michigan Medical School.[5]

As shown in Figure 1, a learning loop is a key part of an LHS in which data are collected, organized, analyzed, and converted into useful knowledge and insights (data to knowledge). The knowledge is then used to spur optimal care decisions through tools such as predictive analytics,[6] clinical decision support, and other knowledge management systems (knowledge to performance).[7] The findings from these improvement strategies are used to drive the next learning loop (performance to data). As such, the LHS requires a robust data infrastructure to provide real-time access to knowledge and digital capture of the care experience.[8] This infrastructure requires comprehensive data sources, thoughtful data oversight, and appropriate data use[9] to ensure the trust of patients and providers.

Electronic health record (EHR) data, although ubiquitous, are an underused resource in dentistry.[10] This inability of the health care system to learn from EHR data can lead to suboptimal health outcomes.[9] The EHR is a key data source for an LHS for a variety of reasons. First, although they lag behind medical practices and hospitals, dental practices in the United States are increasingly adopting EHRs.[11] Second, EHR data have the potential to provide much more detail on patient-level encounters than administrative claims or other data sources.[12] Third, the immediate availability of data that is possible with EHRs allows for real-time use in clinical care. Bringing key information to the provider during the clinical encounter has the potential to improve clinical decision making. The timeliness of these data also allows for frequent assessment to identify patient-reported outcomes; to use machine learning algorithms to match suitable patients with clinical trials, observing their specific enrollment criteria; and to monitor practice trends for various patient populations.[9] The ways in which patient data are generated, stored, and used in the EHR are fundamental to the LHS.[10]

Periodontal disease management is well suited to serve as a model for an LHS pilot implementation in dentistry. First, periodontal disease and caries represent the 2 biggest threats to oral health in the United States.[13] Second, periodontal disease is associated with other inflammatory and systemic conditions, such as cardiovascular disease and diabetes.[13] As such, it touches on multiple areas of health care delivery, including prevention, diagnostics, therapeutic procedures, and chronic disease management. This characteristic of periodontal disease care is especially important because clinicians may need to coordinate efforts with other providers in prevention and chronic disease management. As the vision of an LHS aspires to achieve effective care coordination, modulating periodontal care provision can affect those efforts. Third, there is a standardized approach to the collection, curation, and classification of clinical periodontal information. In 2017, the classification of periodontal disease was updated during the World Workshop on the Classification of Periodontal and Peri-implant Diseases.[14] Due to the multifactorial nature of periodontal

ABBREVIATION KEY

EHR: Electronic health record.
LHS: Learning health system.
NA: Not applicable.
Perio: Periodontitis.
T_0: From 6 through 36 months before the reporting period.
T_1: During the reporting period.

Table 1. Summary and specifications of the periodontal outcome measures.

VARIABLE	ELECTRONIC MEASURE 1 (NEW PERIODONTITIS)	ELECTRONIC MEASURE 2 (NEW TOOTH LOSS DUE TO PERIODONTAL DISEASE)
Measure Summary	The incidence of new periodontitis, measured as the percentage of previously periodontally healthy patients or patients with gingivitis and with teeth who had received a diagnose of new periodontitis in the reporting period (year, quarter, month) and had a prior examination in the previous 3 years. This measure assesses the success in prevention of periodontitis in patients under care. Clinically, this involved periodontal risk information (for example, smoking status, diabetes diagnosis and extent of control, plaque biofilm levels, and oral hygiene self-care compliance) along with periodontal charting metrics (for example, probing depths, bleeding on probing, furcation involvement, mobility, recession, gingival margin, and clinical attachment levels).	The incidence of new tooth loss due to periodontal disease is measured as the percentage of patients who were assessed with new tooth loss related to periodontal disease in the reporting period (year, quarter, month) and had a prior examination when teeth were present. This measure assesses the success in prevention of tooth loss due to periodontal disease in patients under care.
Denominator Logic	Includes patients seen for an examination during the reporting period (T_1 visit), and seen at a prior examination from 6 through 36 months earlier (T_0 visit). Patients are only included in the denominator if they were at least 16 years old, had teeth, and had not received a diagnosis of periodontitis at their T_0 visit.	Includes patients seen for comprehensive, periodic, or periodontal examination (T_1 visit) and were dentate at their most recent prior examination (T_0 visit) from 6 through 36 months earlier. Patients younger than 16 years at their T_0 visit were excluded.
Numerator Logic	Includes patients from the denominator who had received a diagnosis of periodontitis at the T_1 visit.	Includes patients from the denominator who lost additional teeth due to periodontal disease between T_0 and T_1.

disease and the considerable variation in its diagnoses, the development of EHR-based algorithms that determine periodontal disease outcomes has proven to be an arduous task.[15] Together, these characteristics of periodontal care delivery make it an informative model in which to translate LHS concepts into action.

In this article, and as a first step with a focus on the data-to-knowledge and knowledge-to-performance parts of the learning loop, we report on the aggregation of relevant EHR clinical data elements to arrive at clinical periodontal diagnostic information, and then follow up the patients longitudinally for up to 3 years to measure their periodontal health outcomes. The outcomes of interest were new periodontitis diagnosis (for patients who had not received a diagnosis of periodontitis previously) and tooth loss due to progression of the disease in a patient who had received a diagnosis of periodontitis previously. We also introduce interactive dashboards to aid with the presentation of actionable clinical data to clinicians, patients, and administrators. In our study, we showcased the potential of EHR data and how we could start to use these available data to create a learning loop in dentistry on the basis of large data sets measuring periodontal health outcomes.

METHODS

Two electronic measures of periodontal health outcome were developed and implemented within 3 dental institutions—2 dental schools and 1 accountable care organization. Each of the participating sites has a record of established research collaboration, uses the axiUm (Exan) EHR platform, and is an adopter of a standardized dental diagnostic terminology, with use rates greater than 95%.[16] Each of the participating institutions treats a diverse population, including private practices, specialty clinics, and teaching clinics. Institutional Review Board approval from the University of Texas Health Science Center at Houston was obtained to conduct our study. Strengthening the Reporting of Observational Studies in Epidemiology guidelines were followed.[17]

After careful review of the American Academy of Periodontology 2017 periodontal disease diagnostic criteria,[14] the critical data elements for periodontal diagnoses and new tooth loss due to periodontal disease were itemized. Next, an electronic script was developed to locate and extract each element from the appropriate section of the EHR. The measure summary and respective denominator and numerator specifications are presented in Table 1. Data were extracted from 3 calendar years (2017, 2018, 2019). Data included all qualifying visits in the year and the required data from the prior examination that may have occurred up to 3 years earlier.

Table 2. Concordance between the automated algorithm and manual chart review.

VARIABLE	%
New Periodontistis Diagnosis	
Sensitivity	98.52
Specificity	96.20
Positive predictive value	97.79
Negative predictive value	97.44
New Tooth Loss Due to Periodontal Disease	
Sensitivity	97.67
Specificity	100.00
Positive predictive value	100.00
Negative predictive value	99.83

Automated query implementation and validation in the EHR framework

Structured query language scripts were used to extract data in a standard format at all sites. The query generated a list of patients eligible to be included in both the denominator and the numerator. Each site tested the query before implementation. We compared the performance of the automated query with the results of a manual electronic chart review of more than 500 charts across the sites, which was considered the reference standard. Two calibrated, independent reviewers at each site, with experience in electronic patient chart reviews, conducted these reviews. To evaluate the concordance between the automated and manual queries, we calculated sensitivity, specificity, positive predictive values, and negative predictive values.

Analytic methods

Descriptive

To synthesize and visualize the clinical information, we developed an interactive dashboard aggregating periodontal data from each site over time. Descriptive statistics were calculated for each measure score and available patient characteristic. The dashboard displays the frequency and percentage of both new periodontitis and new tooth loss as a time series chart during the study period. To determine trends and outlying measure scores, we used both statistical process control[18] and analysis of proportions[19] methods. The statistical process control methods can highlight whether the variation exhibited by means of a series of points occurred beyond random variation. The analysis of proportions methods adjust for denominator size when determining whether a particular point is a statistical outlier compared with the overall mean measure score. We used bar graphs to illustrate comparative new periodontitis and new tooth loss measures across the various patient dimensions.

Associational

To estimate multivariate associations, a multivariable logistic regression for repeated measures modeling the odds of new periodontitis and modeling the odds of new tooth loss was performed. We reported the odds of a new periodontitis diagnosis and new tooth loss as the measure of association, along with the corresponding estimates of precision and 95% CIs. Each model included the following covariates: sex, age, smoking status, plaque status, diabetes status, and time between consecutive visits. All tests were conducted at the standard significance level ($P < .05$). The interactive dashboard tool was created using the dashboard tool Tableau (Salesforce), and all analyses were performed with *R* statistical software (R Foundation for Statistical Computing).

RESULTS

Our queries retrieved a total of 494,272 examinations (new periodontitis measure: n = 168,442, new tooth loss: n = 325,830), representing a total of 194,984 patients. Mean (SD) age in our sample was 42.8 (16.4) years. When comparing the measure scores calculated from the automated query with those calculated from manual review, the sensitivity, specificity, positive predictive value, and negative predictive value for each measure were all greater than 95.0% (Table 2).

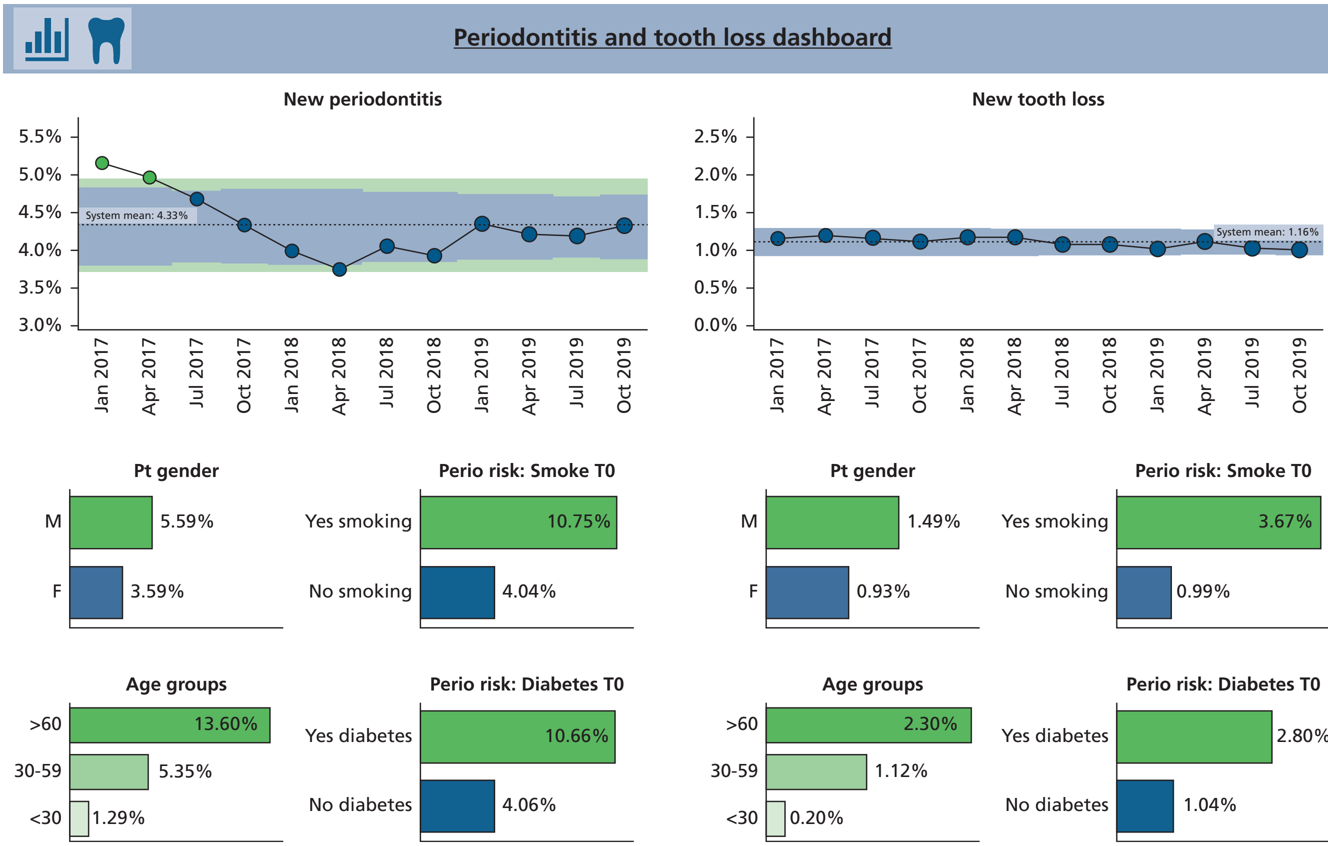

Figure 2. Dashboard displaying performance on new periodontitis and tooth loss measures over time (according to quarter) using a control chart. Dashboard also indicates whether performance during a specific quarter was statistically different from the system mean. Users can compare demographic and risk factor differences for patients in the numerator. F: Female. M: Male. Perio: Periodontitis. Pt: Patient. T_0: From 6 through 36 months before the reporting period.

Different dashboard views that show the distribution of patient characteristics (age, sex) and periodontal outcomes (new periodontitis, new tooth loss) are presented in Figure 2. The number of incident cases and mean scores for periodontitis and tooth loss for all sites according to year are shown in Table 3. The overall incidence of new periodontitis was 4.3%, and the incidence of new tooth loss was 1.2%.

New periodontitis

The new periodontitis section includes a plotted times series of new periodontitis cases according to quarter, which represent 12 time points (range, January 2017-December 2019). The chart shows that the first 2 quarters were high outliers, but that the rest of the quarters indicate a process in control, with only random variation. The 4 grouped bar charts below the line chart show the distribution of new periodontitis according to patient sex, age, smoking status, and diabetes status. The new periodontitis measure scores were higher among male patients (5.59%) than female patients (3.59%) and increased with increasing age. The measure scores for new periodontitis were higher among those who smoked (10.75%) than those who did not (4.04%). The measure scores for new tooth loss were higher among those who had received a diagnosis of diabetes (10.66%) than those who had not (4.06%).

New tooth loss

The new tooth loss section includes a plotted times series of new tooth loss cases according to quarter, which represent 12 time points (range, January 2017-December 2019). The chart shows that the quarterly measure scores were never significantly different from the system mean and were within the 95% CIs on all 12 consecutive occasions. The 4 grouped bar charts below the line chart show the distribution of new tooth loss according to patient sex, age, smoking status, and diabetes status. The new tooth loss measure scores were higher among male patients (1.5%) than female

Table 3. The number of new cases and mean scores for periodontitis and tooth loss according to year.

YEAR	NEW PERIODONTITIS DIAGNOSIS		NEW TOOTH LOSS	
	No.	%	No.	%
2017	NA*	4.7	NA	1.2
Numerator	2,300	NA	1,190	NA
Denominator	49,131	NA	100,569	NA
2018	NA	3.8	NA	1.2
Numerator	2,055	NA	1,245	NA
Denominator	53,412	NA	107,575	NA
2019	NA	4.2	NA	1.1
Numerator	2,757	NA	1,267	NA
Denominator	65,899	NA	117,686	NA
Total	NA	4.3	NA	1.2
Numerator	7,112	NA	3,702	NA
Denominator	168,442	NA	325,830	NA

* NA: Not applicable.

patients (0.9%) and rose with increasing age. The measure scores for new tooth loss were higher among those who smoked (3.67%) than those who did not (0.99%). The measure scores for new tooth loss were higher among those who had received a diagnosis of diabetes (2.80%) than those who had not (1.04%).

Adjusted analysis for periodontal disease and tooth loss with risk factors

The logistic regression confirmed the dashboard findings. Male sex was associated with increased odds of a new periodontitis diagnosis, adjusting for other covariates in the model (odds ratio [OR], 1.27; 95% CI, 1.21 to 1.34). Age categories 40 through 60 years (OR, 1.67; 95% CI, 1.58 to 1.77) and older than 60 years (OR, 1.42; 95% CI, 1.33 to 1.53) were significantly associated with increased odds of a new periodontitis diagnosis. Smoking (OR, 1.38; 95% CI, 1.27 to 1.50), high levels of plaque (OR, 1.95; 95% CI, 1.74 to 2.19), and diabetes (OR, 1.45; 95% CI, 1.16 to 1.81) were each significantly associated with increased odds of a new periodontitis diagnosis. Lastly, the increased length of time between consecutive dental visits was associated with increased odds of a periodontitis diagnosis (OR, 1.07; 95% CI, 1.02 to 1.13).

For the new tooth loss outcome, male sex was associated with increased odds of new tooth loss, adjusting for other covariates in the model (OR, 1.40; 95% CI, 1.31 to 1.50). Age categories 40 through 60 years (OR, 4.96; 95% CI, 4.40 to 5.58) and older than 60 years (OR, 9.19; 95% CI, 8.14 to 10.37) were significantly associated with increased odds of new tooth loss. Smoking (OR, 3.23; 95% CI, 2.95 to 3.54) and high levels of plaque (OR, 1.85; 95% CI, 1.58 to 2.17) were each significantly associated with increased odds of new tooth loss, and diabetes was not (OR, 1.29; 95% CI, 0.98 to 1.68). Lastly, increased length of time between consecutive dental visits was not associated with increased odds of new tooth loss due to periodontal diagnosis (OR, 1.02; 95% CI, 0.95 to 1.10).

DISCUSSION

Patient-level data from the clinical record are not only the most indicative of patient health,[20] they can facilitate the tracking of key dental outcomes.[21,22] Increased adoption of EHRs has provided the tools to efficiently extract useful data for performance measures, assess the relationships between these measures and health outcomes, and benchmark population health.[23] *Population health* is defined as "the health outcomes of a group of individuals, including the distribution of such outcomes within a group,"[24] and EHRs already provide some access to public health data to study the population for potential health improvements and act as a safety net for potential health threats.[25]

In our work involving approximately 500,000 data points and 200,000 patients from the EHRs of 3 institutions, we were able to provide insight into what has been referred to as 2 of the most meaningful clinical end points in periodontology—stability of clinical attachment level (no new periodontitis diagnosis) and tooth survival (no new tooth loss).[26] Until now, the clinical periodontology literature has mostly represented studies that use surrogate end points.[26]

Variation exists in how periodontal diagnoses are assigned, and this can be an important issue, especially at dental school clinics where multiple faculty members oversee patient care. On one end, this diverse faculty pool increases the degree of variation of assessments, but on the other end, school clinics have rigorous oversight processes that make for high-quality clinical data entry. At all of the included sites, periodontal diagnosis is customarily recorded using a standardized dental diagnosis (SNODDS[27]), with more than 95% use of structured diagnoses recorded across each site. Oral health care providers are also required to complete a standardized periodontal assessment form, in which periodontal indexes and risk factors are documented in a structured format. Previous work has assessed the quality of periodontal assessment documentation recorded within the EHR and its ability to identify patients who had received a diagnosis of periodontal disease, complete periodontal charting and periodontal risk factors.[28] We built on that and reported the development of 2 periodontal outcome measures using a large EHR data set; our approach is scalable and transferable to other important disease markers and oral health outcome measures. The 2 outcome measures we presented can be implemented to assess success in the prevention and treatment of periodontal disease, and to facilitate learning and improvement. Team members have also created checklists, notifications, and other ways to integrate these data into clinicians' workflow. The aim was to make this information accessible to improve best practices at the point of care. Our research team called this the "Rate [measuring and properly articulating the data], Communicate [presenting the data in a way that is understandable to the appropriate audience], Motivate [implementing reward systems for changed behavior and improved performance], and Iterate [to re-enter the cycle in order to foster continuous improvement]" model.

The *Oral Health in America: Advances and Challenges*[29] report affirmed that by 2035 there will be more older adults than youth in the United States. This aging US population is also more dentate. Consequently, there has never been a more important time to pay attention to periodontal health and to strategies that help us learn from clinical data to improve it. The structured data found within the EHR can help promote measure automation, which can ease the implementation process. It is easy to envision these types of practice-level quality measures aiding patients and providers alike.

The paradox of too much data creating less information has been discussed in the literature.[30] Clinical information from EHRs can be excessive and is often scattered and hard for clinicians and policy makers to access. Using an interactive dashboard tool for the processing and presentation of large amount of information allows stakeholders to explore the data on different levels. In our study, we depicted a static representation of an interactive dashboard. In actual use, filters can be used to narrow down to a particular clinic in the institution or network. Clicking on a particular quarter or month can allow for other panels to be filtered to show the characteristics for that period only. Likewise, clicking on a risk factor can filter the time series to show comparative performance across the different dimensions. Additional dashboard actions can trigger patient-level detail across time.

As elucidated earlier, although the availability of EHR data has considerable potential for improving health outcomes in an LHS, a number of existing challenges need to be addressed to realize this potential.[31] These include missing data, erroneous data, uninterpretable data, and inconsistencies in the way data are recorded among providers and over time. Another issue is that patients often receive care from multiple providers using fragmented and often poorly integrated EHR systems, making it difficult to completely track patients across practices[32] or systems. EHR information exchange, which allows health systems to access and share EHR data across organizational and geographic boundaries, needs continued enhancement and dissemination to increase the value of EHR data. In addition, critical clinical data are often recorded in unstructured, narrative text, complicating its use for learning and improvement. In our work, we relied on structured data. For dental clinics that do not use a standardized diagnosis terminology, innovations in methods such as natural language processing may be used to capture such unstructured data from the clinical narratives in the EHRs.[33,34] In addition, effective user interfaces can improve the ease and consistency of data entry, which simultaneously reduces user burden and decreases the amount of unstructured, and potentially uninterpretable, data in the EHR. Finally, there is a major need for rigorous EHR evaluation and data optimization to ensure valid and usable information.[35-37]

As illustrated in Figure 1, measurement and data generation are the first components of an LHS learning cycle. Armed with this knowledge, dental institutions can develop and implement strategies to improve performance (knowledge to performance) (Figure 1). We found that a considerable number of patients who lose teeth due to periodontal disease are smokers. Consequently, we not only ensure that tobacco screening is completed on all patients during comprehensive examinations using intelligent electronic checklists, but we have also implemented a targeted, real-time, clinical decision support tool to provide tobacco-use cessation counseling for identified patients during their hygiene visits. This tool identifies self-reported or provider-interviewed data on tobacco-use status and guides the provider through a series of questions, steps, and actions to offer comprehensive tobacco-use cessation. Appropriate referrals are also made. For the final step (performance to data), we would evaluate whether this intervention reduced tooth loss through remeasurement, thereby completing the first learning cycle of the LHS.

CONCLUSIONS

Dental institutions and practices are well positioned to learn from each other by means of sharing data, codeveloping improvement strategies, and disseminating these findings. For example, the BigMouth Dental Data Repository[38] is a consortium of 11 dental schools that share EHR data for research and quality improvement and are developing the components of an LHS. We also recognize that EHR data alone may not be inclusive enough to conduct meaningful learning. Rather, the value of EHR data might be realized when linked to other data sources, such as patient-reported behaviors, quantified self-data, and clinical trial data. As value-based care predominates, EHR data will occupy a central role in generating meaningful knowledge in support of LHS for improving oral health. ■

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