Developing and Testing Electronic Health Record-Derived Caries Indices

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Keywords

Dental informatics/bioinformatics · Electronic dental records · Outcomes research · Epidemiology · Caries detection/diagnosis/prevention

Abstract

Caries indices, the basis of epidemiologic caries measures, are not easily obtained in clinical settings. This study's objective was to design, test, and validate an automated program (Valid Electronic Health Record Dental Caries Indices Calculator Tool [VERDICT]) to calculate caries indices from an electronic health record (EHR). Synthetic use case scenarios and actual patient cases of primary, mixed, and permanent dentition, including decayed, missing, and filled teeth (DMFT/dmft) and tooth surfaces (DMFS/dmfs) were entered into the EHR. VERDICT measures were compared to a previously validated clinical electronic data capture (EDC) system and statistical program to calculate caries indices. Four university

clinician-researchers abstracted EHR caries exam data for 45 synthetic use cases into the EDC and post-processed with SAS software creating a gold standard to compare the VERDICT-derived caries indices. Then, 2 senior researchers abstracted EHR caries exam data and calculated caries indices for 24 patients, allowing further comparisons to VERDICT indices. Agreement statistics were computed among abstractors, and discrepancies were resolved by consensus. Agreement statistics between the 2 final-phase abstractors and the VERDICT measures showed extremely high concordance: Lin's concordance coefficients (LCCs) >0.99 for dmfs, dmft, DS, ds, DT, dt, ms, mt, FS, fs, FT, and ft; LCCs >0.95 for DMFS and DMFT; and LCCs of 0.92–0.93 for MS and MT. Caries indices, essential to developing primary health outcome measures for research, can be reliably derived from an EHR using VERDICT. Using these indices will enable population oral health management approaches and inform quality improvement efforts.

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Introduction

Electronic health records (EHRs) provide dental researchers the ability to extract vast amounts of patient data quickly, accurately, and economically, thus enhancing and expanding all forms of scientific discovery. Perhaps the most useful oral health measure is the patient's caries experience, expressed as a caries index [Bratthall, 2000; Ditmyer et al., 2011; Gruebbel, 1944; Klein et al., 1938; Marthaler, 2004; Monse et al., 2010; van Dommelen and Schuller, 2016]. Caries indices measure the severity of dental caries among populations and individual patients and can be used for prevalence estimates; they allow for longitudinally evaluating interventions for preventing and treating disease and can be used for incidence estimates. Traditional research methods of defining, measuring, and comparing caries indices of populations have enabled successful epidemiologic comparisons. However, these methods have known limitations including standardization of measurements, high costs associated with labor-intensive data acquisition, difficult participant enrollment, examiner and abstractor calibration, slow results production, and often limitations in research designs that result in less generalizability [Kahn et al., 2007; Song et al., 2013].

EHRs seem ideal to overcome such limitations; yet, using EHR data for research has specific challenges. These include the nonuniversal EHR implementation and utilization by practices and providers, different and incompatible EHR systems commonly used in practices, nonstandardized data input interfaces, nonsearchable data elements, missing data fields, lack of diagnostic codes, incomplete clinical information, and data governance and security issues [de Lusignan et al., 2006; Gilbert et al., 2011; Kahn et al., 2007; Kristianson et al., 2009; Liu et al., 2013; Mansson et al., 2004; Schleyer et al., 2007; Sung et al., 2003; Terry et al., 2010]. Overall, the predominant problem with current EHR systems is that they are designed and developed to focus on clinical care and administrative tasks rather than research. Thus, despite EHRs' potential digital benefits, researchers needing to employ traditional research methods can be challenged using EHR data. In past caries indices research, examiners and abstractors had to either infer if a filled or missing tooth was due to caries or simply not differentiate between them, thus reducing the validity of caries studies [National Health and Nutrition Examination Survey, 2016; World Health Organization, 2013].

Several recent developments have addressed the challenges to caries indices research. First, EHRs are increas-

ingly common in dental practices. While only 11% of dental offices used computers in 1984, 78% did in 2013 [Schleyer et al., 2013]. Standardized dental diagnostic terminology (SNOMED, SNODENT, and the interface terminology within the EHR, SNODDS) now allow clinicians to input diagnosis data associated with dental procedures, thereby recording reasons for filled and missing teeth [Kalendarian et al., 2011; White et al., 2011]. Second, standardized diagnostic terminology within the EHR allows for more accurate caries index scores by designating the reasons for conditions found and recorded. Having expanded conditions and specific diagnoses allows for analyzing decayed surfaces (permanent and primary) and lesion depth, including enamel lesions (initial caries), shallow dentin lesions (moderate caries), and deep dentin lesions (extensive caries). Third, many dental schools, dental maintenance organizations, and dental accountable care organizations use the same EHR software. Data from these sources are more standardized, accessible, and extensive as an enormous repository for analysis [Walji et al., 2014]. Lastly, clinical trials research utilizing EHR data is potentially more cost-effective than using paper-based data collection [Pavlovic et al., 2009]. Even with good, standardized decayed, missing, and filled data, carefully chosen with an eye for caries research efforts, EHR systems have generally lacked automated data abstraction algorithms that allow provider inputs in the EHR to be quickly converted into usable research formats. This is especially true of caries indices where no automated abstraction and indexing procedures to derive caries indices currently exist. This paper reports on the design, development, and validation of an algorithm (denoted as Valid Electronic Health Record Dental Caries Indices Calculator Tool [VERDICT]) that automatically abstracts EHR data on decayed, missing due to decay, and filled teeth due to decay at the tooth and tooth surface levels and then calculates traditional caries indices for primary and permanent dentition.

Materials and Methods

This study was conducted with UCSF Institutional Review Board's approval to evaluate a program in the Willamette Dental Group (WDG), which serves over 400,000 patients in over 50 offices throughout Oregon, Washington, and Idaho. WDG utilizes the same EHR as most United States and Canadian dental schools and several large practices, axiUm (Exan Corporation, Coquitlam, British Columbia, Canada). The EHR contains standardized clinical interfaces for charting conditions and findings of decay as well as required diagnostic terminology for all planned and completed procedures. The software also captures diagnosis with procedures

so reasons for treatment are recorded, for example, restorations or extractions due to decay. All WDG offices successfully implemented the EHR by 2013 and all care provider teams receive standardized training and calibration for data entry procedures to standardize patient care [Mertz et al., 2017]. All providers are required to utilize the EHR and are evaluated by their consistent and accurate adherence to the EHR through process and appropriateness of care measures. Adherence rates throughout WDG offices exceed 98% for process of care measures, including charting and treatment planning [Mertz et al., 2017].

For this study, caries was defined as any cavitated caries lesion that penetrated into dentin in accordance with WHO protocols [World Health Organization, 2013]. An algorithm was developed to translate existing WDG odontogram and treatment history data into caries indices, including indices of decayed (cavitated dentin caries, D, d), missing (M, m), and filled (F, f) designations of permanent (DMF) and deciduous (dmf) tooth surfaces (S, s) and teeth (T, t). The research team worked iteratively with programmers providing specifications and expertise to develop and configure the algorithm (VERDICT) to determine caries indices using EHR data. Online supplementary Table 1 (for all online suppl. material, see www.karger.com/doi/10.1159/000499700) lists the 36 caries indices produced from automated scripts that abstract data from each patient's digital odontogram and treatment history.

The algorithm, based on the data schema framework and EHR structure, consists of 4 essential parts:

1 *EHR data*: The actual charted findings of decay, restorations, dentition, missing teeth, and planned procedures due to decay are collected by providers during patient care. Importantly, no additional data collection was required; the system utilizes EHR data already recorded and available.

2 *Configuration*: Configuration is the mapping process that allows the provider-charted entry to be interpreted by the algorithm to accurately determine decayed, missing, and filled designations and calculate the caries indices. The mapping includes designating the procedures and materials that represent restorations and the conditions and diagnoses that indicate decay. The algorithm was developed based on the data schema, framework, and EHR structure.

3 *Automated resolution process*: When decayed surfaces are restored or teeth are extracted/exfoliated, charted decay conditions are updated (e.g., changed to be no longer decayed). For clinical care, a manual EHR process "resolves" a decay finding after restoration or extraction. When this manual process is not properly completed, an automated process each day resolves any decay conditions not manually resolved.

4 *Calculation*: Using EHR data (1 and 3) and the configuration (2), the algorithm computes caries indices starting with the patient's first EHR-recorded visit and all subsequent visits. No additional data is stored, as indices are calculated in real time for any new visits since the last calculation.

Two-Phase Testing of VERDICT

Initial testing of the VERDICT algorithm entailed creating 45 synthetic use cases that represented synthetic patients with a wide range of possible oral conditions including positive and negative controls. Data included synthetic use cases with all teeth present, all teeth missing, all teeth decayed, no teeth with decay, all tooth surfaces filled, no tooth surfaces filled, and many more scenarios (online suppl. Table 2, Figures). Cases also balanced primary, per-

manent, and mixed dentitions. Use cases were entered into a special research area of the EHR.

Four university clinician-researchers served as independent abstractors based on their extensive experience in utilizing dental EHRs and determining decayed, missing, and filled teeth (DMFT) from EHR odontograms and treatment histories. Abstractors were trained to use a validated electronic data capture program, the CAries Research INstrument (CARIN) software package [Regents of the University of California, 2009; Warren et al., 2015]. Modeled on the NHANES two-pass system [National Health and Nutrition Examination Survey, 2016], CARIN allows dental researchers to enter dental examination data in real time or by post-examination abstraction from paper or electronic odontograms via a graphical user interface and converts the data into a usable electronic form for epidemiologic and clinical research. Instructions were given about navigating the EHR, reading the odontogram and treatment history, and abstracting data to enter into CARIN. Each clinician-researcher independently abstracted EHR data (Fig. 1a) from the 45 synthetic use cases into the CARIN software (Fig. 1b). Sixteen of the most common caries indices or their components (online suppl. Table 1) were calculated for each test case using SAS software (SAS Institute, Cary, NC, USA). Disagreements among abstractor results were resolved by consensus. Each abstractor also completed 6 repeat patient scenarios randomly selected to estimate intra-rater reliability. These consensus caries indices became the gold standard for evaluating the validity of the VERDICT algorithm in this phase of testing.

VERDICT was executed on all 45 use cases for 16 indices. These were then compared to the gold standard-derived indices for each scenario using Lin's concordance correlation (LCC) for person-level indices. The first phase of algorithm testing showed generally good concordance. Discrepancies were identified and further algorithm refinement was conducted to address missing teeth and surfaces due to decay (versus any other reason), utilize diagnostic codes (to better identify restorations and extractions due to caries), resolve conditions when there was a subsequent restoration of a tooth, add counts of decayed surfaces planned for restoration or extraction due to caries, address stainless steel crowns due to decay, and (optionally) include incisal surfaces. After algorithm refinement, testing was conducted on a purposive sample of patient data.

The second phase of testing utilized 24 actual WDG patient records. This patient sample was purposive; patients were chosen to best test the VERDICT algorithm with various caries experiences, ages, dentitions, and insurance plans, as well as new and recall patients. A general goal of patient selection was to identify a sample to assess automated calculations with real data, covering many types of decay, as well as missing and filled surface patterns. To reduce the influence of possible sample patient types, 6 distinct subgroups of sample study patients were specified (Table 1).

Additional stratification for longitudinal validation included only patients with an initial visit (new patient or continuing care visit) (T0) and a regular continuing care visit (T1). An equal number of patients with 2 insurance payer types (Medicaid and private) were used for socioeconomic status generalizability. This resulted in 24 distinct subgroups of study patients with at least 10 patients each. One patient was selected from each subgroup to test the algorithm. In selecting the specific patient from each subgroup, attempts were made to identify some patients whose caries indices changed between the exam dates (except for group E as these pa-

Fig. 1. Example synthetic scenario odontogram in axiUm (a) and CARIN (b).

Table 1. Purposively sampled patient subgroups

Group	Gender	Age group	Level of decay
A	Male	13–18	Extreme (DMFS >30)
B	Female	6–12	High (DMFS 15–25)
C	Male	13–18	Moderate (DMFS 10–15)
D	Female	6–12	Moderate (DMFS 10–15)
E	Male	13–18	None (DMFS 0)
F	Female	3–5	Moderate (DMFS >10), with missing teeth due to decay

tients were selected to have no decay at each time point). Additionally, cases with more than 1 finding category (e.g., primary/permanent, decayed/missing/filled) were given preference.

As in the first phase of testing, 2 trained and calibrated abstractors, a senior university dentist-researcher, and a senior software

developer independently abstracted data from this sample of 24 patient odontograms and treatment histories at 2 different times, T0 and T1 ($n = 48$), using CARIN; indices were calculated with SAS. Disagreements between abstractor results were resolved by consensus agreement. Each abstractor was again randomly as-

Table 2. Gold standard versus VERDICT concordance for synthetic use cases ($n = 45$)

Measure	Description	LCC	Lower 95% CL	Upper 95% CL
DMFS	Number of decayed, missing, or filled permanent tooth surfaces	0.95	0.92	0.98
DMFT	Number of decayed, missing, or filled permanent teeth	0.96	0.93	0.98
DS	Number of decayed permanent tooth surfaces	1.00	1.00	1.00
DT	Number of decayed permanent teeth	1.00	1.00	1.00
FS	Number of filled permanent tooth surfaces	1.00	1.00	1.00
FT	Number of filled permanent teeth	1.00	1.00	1.00
MS	Number of missing permanent tooth surfaces	0.92	0.88	0.96
MT	Number of missing permanent teeth	0.93	0.90	0.96
dmfs	Number of decayed, missing, or filled primary tooth surfaces	1.00	1.00	1.00
dmft	Number of decayed, missing, or filled primary teeth	1.00	1.00	1.00
ds	Number of decayed primary tooth surfaces	1.00	1.00	1.00
dt	Number of decayed primary teeth	0.99	0.98	1.00
fs	Number of filled primary tooth surfaces	1.00	1.00	1.00
ft	Number of filled primary teeth	0.99	0.98	1.00
ms	Number of missing primary tooth surfaces	1.00	0.99	1.00
mt	Number of missing primary teeth	1.00	1.00	1.00

CL, confidence limit; VERDICT, Valid Electronic Health Record Dental Caries Indices Calculator Tool; LCC, Lin's concordance correlation.

signed 6 repeat patient scenarios to estimate intra-rater reliability. The consensus for the 24 sample patient charts became the gold standard for this phase of testing. The VERDICT algorithm then processed the 48 patients charts (at T0 and T1), and the results were compared to the expert abstractor gold standard.

Results

VERDICT was successfully designed, tested, and validated to produce caries indices from an EHR. For each synthetic use case scenario, the odontogram and treatment history are shown in the online supplementary Figures. The corresponding VERDICT (EHR-derived) caries indices for each use case are listed in online supplementary Table 2. For the 45 synthetic test cases, agreement between the caries indices produced by VERDICT and the gold standard method are shown in Table 2.

Disregarding the positive and negative controls (i.e., extremes of no caries and all teeth carious, all teeth present and all teeth extracted, no restorations and all surfaces with restorations), among synthetic use cases 64% had decayed or filled surfaces; their mean number of decayed, missing, or filled primary and permanent surfaces was 31 (dmfs + DMFS = 31), while their mean number of decayed primary and permanent surfaces was 5 (ds + DS = 5). Investigators agreed that the synthetic use cases represented enough variation to initially test the algorithm well. VERDICT caries indices as-

sociated with missing teeth and surfaces due to decay had the lowest correlation with the gold standard in the first pass. Intra-rater reliability ($n = 6$ use cases) was excellent for all 4 abstractors: LCC > 0.93 for DMFS, DMFT, dmfs, dmft, ds, dt; LCC > 0.85 for DT; and LCC > 0.74 for DS. By design, the iterative development continued until the algorithm matched the gold standard consensus (i.e., perfect agreement between the gold standard and VERDICT caries indices for the 45 synthetic use case scenarios).

The EHR-derived VERDICT caries indices were successfully generated and validated from the purposive sample of 24 patients charts at 2 different time points ($n = 48$). A representative odontogram and VERDICT caries indices are shown in Figure 2. Agreement between the VERDICT algorithm and the 2 abstractors was nearly perfect: LCCs > 0.99, for all indices. The first abstractor overlooked a few missing surfaces, while the agreement between VERDICT and the second abstractor (gold standard) was perfect (LCCs = 1.0; Table 3). Intra-rater reliability ($n = 6$ patient charts) was perfect for both abstractors (LCCs = 1.0).

Discussion/Conclusion

The purpose of this study was to develop and validate an algorithm that automatically determines caries indices from an EHR. The study's results show that the algorithm

Fig. 2. Example patient odontogram (a) and caries indices EHR-derived automated procedures using VERDICT (b).

developed (VERDICT) is a valid instrument. Developing this algorithm was an essential part of an ongoing evaluation of a caries management program assessing oral health disparities in children. This study has demonstrated a valid and feasible process to produce accurate caries indices for large populations with the ability to follow those populations and the individuals within them longitudinally using EHR data. Creating a primary oral health outcome measure through a valid EHR algorithm for producing automated caries indices opens new doors to dental researchers:

1 Caries outcomes research can now use caries indices obtained on a large scale from an EHR.

2 Larger sample sizes for caries research can be collected quickly and inexpensively as compared to conventional randomized prospective clinical trials and epidemiologic studies.

3 Longitudinal studies on individual patients and populations can now be conducted. This is especially important when tracking the therapeutic effects of behavioral and clinical preventive interventions.

4 Extent of disease can be assessed in both primary and recurrent carious lesions.

5 A more comprehensive variety of caries indices are now available, including tracking enamel lesions and incisal edge lesions. (However, when contrasting with national, state, and most other published data, comparable traditional caries indices should be used since the number of tooth surfaces at risk differ.)

6 Other researchers can validate their caries index calculation software with this set of 45 synthetic use cases and results (online suppl. Table 2 and Figures).

7 Real-time communication to providers on the caries experience of individual patients and the population of patients under their care is now possible, for example, through data dashboards, allowing for real-time patient care decisions regarding caries interventions.

The EHR algorithm has the optional capability of producing caries indices that include enamel lesions, third molars, and incisal surfaces, as well as extent of decay, information normally not obtained in research using traditional caries indices, giving the opportunity for more granular data on extent of decay. This is due to the inclusion of the dental diagnostic interface terminology within the EHR. However, for comparability to state, national, and other published data, the traditional caries indices should be used to keep the number of teeth and number of tooth surfaces standardized.

The method used to test the EHR algorithm, comparing caries index outputs to more labor intensive, expertly determined caries indices in 45 synthetic use case scenarios and then using a subset of patient EHR data, could be replicated to disseminate and adopt the automated techniques in other EHR systems. As EHR use continues to expand throughout dentistry and medicine, algorithms to exploit the accumulating data are increasingly being explored, developed, and validated. Validation procedures routinely and necessarily involve using expert examiners

Table 3. Abstractors versus VERDICT concordance for patient EHR-data at 2 visits ($n = 48$)

Abstractor	Measure	LCC	Lower 95% CL	Upper 95% CL
1	DMFS	1.00	1.00	1.00
1	DMFT	1.00	1.00	1.00
1	DS	1.00	1.00	1.00
1	DT	1.00	1.00	1.00
1	FS	1.00	1.00	1.00
1	FT	1.00	1.00	1.00
1	dmfs	1.00	0.99	1.00
1	dmft	1.00	1.00	1.00
1	ds	1.00	1.00	1.00
1	dt	1.00	1.00	1.00
1	fs	0.99	0.99	1.00
1	ft	1.00	1.00	1.00
1	ms	0.99	0.99	0.99
1	mt	1.00	1.00	1.00
2	DMFS	1.00	1.00	1.00
2	DMFT	1.00	1.00	1.00
2	DS	1.00	1.00	1.00
2	DT	1.00	1.00	1.00
2	FS	1.00	1.00	1.00
2	FT	1.00	1.00	1.00
2	dmfs	1.00	1.00	1.00
2	dmft	1.00	1.00	1.00
2	ds	1.00	1.00	1.00
2	dt	1.00	1.00	1.00
2	fs	1.00	1.00	1.00
2	ft	1.00	1.00	1.00
2	ms	1.00	1.00	1.00
2	mt	1.00	1.00	1.00

Note there were no patients with missing teeth (MT) and missing surfaces (MS) for permanent teeth due to decay in this purposive sampling ($n = 0$). Gold standard was abstractor 2.

CL, confidence limit; VERDICT, Valid Electronic Health Record Dental Caries Indices Calculator Tool; LCC, Lin's concordance correlation; HER, electronic health record.

to create a gold standard against which algorithms can be tested [Barnado et al., 2017; Castro et al., 2015; Gruschow et al., 2016; Lingren et al., 2016; Sharma et al., 2017].

The algorithm developed and reported here was configured for the WDG axiUm EHR software implementation. Alternative implementations of axiUm would require modifying VERDICT mappings as not all implementations of axiUm contain the same configuration of dental conditions, procedures, and diagnosis. Implementation at other institutions using axiUm with the standardized dental diagnostic terminology and standardized dental procedures would be straightforward, requiring only customization to include any unique caries findings

and conditions but not customization of the algorithm. The portability of VERDICT to other axiUm EHR implementations allows for further disseminating the automated procedures to derive caries indices. The next steps are to disseminate VERDICT to a small number of dental institutions to refine the mapping processes required for these institutions to utilize VERDICT.

Other EHR systems could adapt the structure but would require modifications of the algorithm's code for their EHR. For other dental EHR software, such as Dentrix or Epic Wisdom, which have the same dental procedures, the algorithm could be readily adapted for the caries conditions and findings. Since these software programs do not utilize the standardized dental diagnostic terminology, the caries indices would include fillings due to decay and other reasons, until they incorporate dental diagnostic terms. Most dental EHR systems have sufficient detail to record findings, conditions, planned and performed procedures, which would provide for the capability to determine caries indices. The inclusion of dental diagnostic terms provides more accurate caries indices, as teeth filled due to fracture, trauma, and other noncaries reasons would not be included in the calculation. Currently, calibrated observers do not know the reason for fillings and assume that the restorations are due to decay. The algorithm reported in this paper can be configured with and without dental diagnostic terms. We believe that the most accurate caries indices utilize diagnostic terms where fillings due to noncaries diagnoses are excluded.

Study Limitations

This study did not seek to assess reliability of provider EHR data input on oral conditions and diagnoses. An accurate caries index derived by the algorithm depends upon a valid assessment of oral conditions, properly recording findings, and using and inputting diagnostic codes, which is inherent in any caries measurement. Note that in WDG practices, oral conditions are charted using findings, conditions, and diagnostic terminology paired with the planned and completed procedures. Though inaccurate oral condition entries into the EHR can happen chair-side, such charting errors should be similar to those made in all other methods of data recording of oral conditions for clinical or research purposes. It was not the goal of this paper to evaluate the accuracy of clinician observations as compared to standard calibrated observers. Future studies could evaluate accuracy of clinician observations as compared to calibrated observers. Clinician behavior, motivation, incentives, biases, caries diagnosis training, and reimbursement are all factors that may in-

fluence a clinician. In this study, we assume appropriate, accurate charting, diagnosis, and treatment. An honest mistake would be random error. Intentional “upcoding” would lead to higher caries indices. Similarly, intentional “downcoding” would lead to lower caries indices.

We believe that the EHR-derived caries indices reported here can be disseminated and utilized in large-scale observational studies. WDG EHR data are quite similar to national data; for WDG adults patients aged 35–44, the prevalence of untreated decay (DS >0) is 27.6% at the initial visit, which is very close to a national estimate of 27.8% using NHANES data reported by Health People 2020 [US Department of Health and Human Services, 2018].

Conclusion

This study has successfully demonstrated the validity of the designed and programmed automated procedures using EHR data to determine caries indices (VERDICT). Caries indices, important primary outcome measures for research and patient care, can be reliably derived from an EHR. These validated caries indices can be used for research purposes to study caries prevention interventions and examine program evaluations of caries prevention, in health disparities research, and produce longitudinal outcomes of dental caries in patient care.

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Statement of Ethics

The study protocol has been approved by the research institute’s committee on human research (UCSF FWA IRB #00003471, protocol #15-17631), and a waiver of the requirement to obtain a signed consent form from study subjects (or their parents or guardians) was granted as (1) the research involves no more than minimal risk to the subjects; (2) the waiver or alteration will not adversely affect the rights and welfare of the subjects; (3) the research could not practicably be carried out without the waiver or alteration; and (4) whenever appropriate, the subjects will be provided with additional pertinent information after participation.

Disclosure Statement

J.M.M., J.B.E., T.G., and E.B. are employees of the WDG. R.B. is a paid consultant to WDG and UCSF and is a UCSF affiliate. J.M.W. was previously a paid consultant for Skourtes Institute (nonprofit foundation) for development and implementation of CAMBRA/PEMBRA/PDCP (clinic decision support and standardized care in the EHR, UCSF) and data analytics, and WDG for quality improvement. J.M.W. also contributed toward Intellectual Property for DDS (dental diagnostic system, Harvard) and CAMBRA/PEMBRA/PDCP (UCSF). All other authors have no conflicts of interest to declare.

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Author Contributions

J.M.W., R.B., L.J., and S.A.G. substantially contributed to conception and design; contributed to acquisition, analysis, and interpretation of data; drafted the manuscript; critically revised the manuscript; gave final approval; and agree to be accountable for all aspects of work ensuring integrity and accuracy. E.A.M., J.M.M., J.B.E., and A.M.K. substantially contributed to conception and design; contributed to acquisition, analysis, and interpretation of data; critically revised the manuscript; gave final approval; and agree to be accountable for all aspects of work ensuring integrity and accuracy. T.G. contributed to design; contributed to acquisition and interpretation of data; critically revised the manuscript; gave final approval; and agrees to be accountable for all aspects of work ensuring integrity and accuracy. E.B. contributed to conception; critically revised the manuscript; gave final approval; and agrees to be accountable for all aspects of work ensuring integrity and accuracy. S.V.K., S.B., and R.V. contributed to acquisition and analysis; critically revised the manuscript; gave final approval; and agree to be accountable for all aspects of work ensuring integrity and accuracy. W.S. contributed to design; contributed to acquisition, analysis, and interpretation of data; critically revised the manuscript; gave final approval; and agrees to be accountable for all aspects of work ensuring integrity and accuracy.

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