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Development and External Validation of a Multivariable Prediction Model to Identify Nondiabetic Hyperglycemia and Undiagnosed Type 2 Diabetes: Diabetes Risk Assessment in Dentistry Score (DDS)

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Abstract

The aim of this study was to develop and externally validate a score for use in dental settings to identify those at risk of undiagnosed nondiabetic hyperglycemia (NDH) or type 2 diabetes (T2D). The Studies of Health in Pomerania (SHIP) project comprises 2 representative population-based cohort studies conducted in northeast Germany. SHIP-TREND-0, 2008 to 2012 (the development data set) had 3,339 eligible participants, with 329 having undiagnosed NDH or T2D. Missing data were replaced using multiple imputation. Potential covariates were selected for inclusion in the model using backward elimination. Heuristic shrinkage was used to reduce overfitting, and the final model was adjusted for optimism. We report the full model and a simplified paper-based point-score system. External validation of the model and score employed an independent data set comprising 2,359 participants with 357 events. Predictive performance, discrimination, calibration, and clinical utility were assessed. The final model included age, sex, body mass index, smoking status, first-degree relative with diabetes, presence of a dental prosthesis, presence of mobile teeth, history of periodontal treatment, and probing pocket depths ≥5 mm as well as prespecified interaction terms. In SHIP-TREND-0, the model area under the curve (AUC) was 0.72 (95% confidence interval [CI] 0.69, 0.75), calibration in the large was −0.025. The point score AUC was 0.69 (95% CI 0.65, 0.72), with sensitivity of 77.0 (95% CI 76.8, 77.2), specificity of 51.5 (95% CI 51.4, 51.7), negative predictive value of 94.5 (95% CI 94.5, 94.6), and positive predictive value of 17.0 (95% CI 17.0, 17.1). External validation of the point score gave an AUC of 0.69 (95% CI 0.66, 0.71), sensitivity of 79.2 (95% CI 79.0, 79.4), specificity of 49.9 (95% CI 49.8, 50.00), negative predictive value 91.5 (95% CI 91.5, 91.6), and positive predictive value of 25.9 (95% CI 25.8, 26.0). A validated prediction model involving dental variables can identify NDH or undiagnosed T2DM. Further studies are required to validate the model for different European populations.

Keywords: dysglycemia, periodontitis, prediction modeling, external validation, dental, prediabetes

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Introduction

Type 2 diabetes (T2D) affects 60 million Europeans; 10% of those older than 25 y. Worldwide, 422 million adults are living with the condition (World Health Organization [WHO] 2016), with an estimated 325 million at high risk of developing T2D (WHO 2016). Diabetes-associated morbidity is significant, as is the associated economic burden, estimated as 1.32 trillion US dollars (2015), and expected to rise to 2.1 trillion US dollars by 2030 (Bommer et al. 2018). Prevention of T2D is an international health priority (WHO 2017). People with nondiabetic hyperglycemia (NDH) can delay the onset of, or even prevent, T2D via lifestyle measures or metformin (Barry et al. 2017).

Dental care professionals (DCPs) are aware of the association between tooth loss and T2D and the established bidirectional relationship between periodontitis and T2D (Sanz et al. 2018). Importantly, many people attend dental services regularly, irrespective of their general health. The reported proportion of dental patients identified as high risk for hyperglycemia approximates 32% to 40%, with the proportion with undiagnosed diabetes 11% to 47% (Chinnasamy and Moodie 2020).

DCPs are trained in risk assessment and delivering preventative advice, such as smoking cessation and dietary advice, both shared risk factors for periodontitis and T2D. There is growing support from multiple stakeholders for engaging DCPs in this manner (Greenberg et al. 2015; Yonel, Batt, et al. 2020; Yonel, Yahyouche, et al. 2020). Furthermore, studies in Europe, Africa, America, Asia, and the Middle East demonstrate support, feasibility, and cost-effectiveness of using DCPs to undertake targeted risk assessments of patients at high risk of T2D (AlGhamdi et al. 2013; Neidell et al. 2017; Yonel, Cerullo, et al. 2020).

Several risk-assessment models for T2D exist. However, many of these models have been developed for use outside dental settings and involve collecting data that would not routinely be available to dental teams, such as waist circumference, cholesterol, and blood pressure (Gray et al. 2010; Collins et al. 2011; Talakey et al. 2022). FINDRISC is a widely used model across Europe to identify people at risk of developing T2D and has been validated for use in several European populations (Jølle et al. 2019; Kraege et al. 2020). Only 2 models containing dental variables have been validated specifically for use in dental settings (Talakey et al.2022). Given the association between T2D and periodontitis, the addition of dental parameters within prediction models may aid the detection of NDH/T2D; however, further validation studies are required to demonstrate this.

Here we assessed whether measures routinely available to DCPs, such as periodontal parameters and the number of missing teeth, could be incorporated into a prediction model to allow DCPs to identify individuals who have undiagnosed NDH or T2D. Importantly, external validation was undertaken using an independent data set from the same geographic region.

Current literature supports a 2-staged targeted risk-detection process in dental settings, with a score identifying potentially at-risk patients, with anyone above the threshold being offered a point-of-care HbA1c test to confirm risk status (Yonel, Batt, et al. 2020; Yonel, Cerullo, et al. 2020). This validated risk assessment tool may assist in identifying those patients who would most benefit from blood sample collection and onward referral to an appropriate health care professional for formal diagnosis and management.

Methods

Study Design, Setting, and Source of Data

This was a 2-phased study using data sets derived from the Studies of Health in Pomerania (SHIP) project. The SHIP project comprised representative population-based cohort studies conducted in northeast Germany. SHIP-TREND-0 recruited 4,420 participants aged 20 to 84 y (50.2% response), of whom 4,322 received an oral examination (Schutzhold et al. 2015; Table 1). Phase 1 of our study involved the development of a model and point score for dental settings using SHIP-TREND-0.

Phase 2 involved external validation of the model and point score, using an independent data set, SHIP-START-0. This cohort included 4,308 individuals aged 20 to 81 at the time of baseline examination (Hensel et al. 2003). The cohort recruited 4,308 individuals, of whom 4,288 underwent oral examination (Schutzhold et al. 2015). Both SHIP-TREND-0 and SHIP-START-0 contained relevant medical and dental clinical data for model development and validation (Völzke et al. 2011).

Eligibility Criteria

Participants aged ≥40 y were eligible for inclusion. Those with existing physician-diagnosed diabetes or taking medications for diabetes were excluded.

Outcome and Candidate Predictors

The outcome variable was either NDH or undiagnosed T2D. A participant was deemed to have NDH if their HbA1c was ≥6.0% (≥42 mmol/mol) and <6.5% (<48 mmol/mol). A participant was considered to have undiagnosed T2D if they recorded an HbA1c of ≥6.5% (≥48 mmol/mol; National Institute for Health and Care Excellence 2017).

Thirteen candidate predictors were identified a priori using existing literature (Gray et al. 2010). Candidate predictors consisted of those recognized risk factors used in the previously developed T2D prediction models (Gray et al. 2010; Acharya et al. 2018), which are routinely available in a dental setting, for example, age, sex, and smoking status (Talakey et al.2022). The oral and dental risk factors were selected based on mechanistic plausibility and literature review (Gray et al. 2010; Strauss et al. 2010; AlGhamdi et al. 2013; Engstrom et al. 2013; Lalla et al. 2013; Neidell et al. 2017; Jølle et al. 2019; Kraege et al. 2020). Prespecified interaction terms were identified a priori, including age × body mass index (BMI), age × smoking status, BMI × smoking status, and first-degree relative (parent or sibling) with T2D × smoking status (Appendix 1).

Table 1. Baseline Characteristics of Eligible Participants in Both Development and Validation Data Sets for Complete Case Data.

	SHIP-Trend-0	SHIP-START-0
	Development Data	Validation Data
Variable	*n* = 3,339	*n* = 2,381
Age, y	58.6 ± 11.3	56.3 ± 9.9
Male sex	1,646 (49.3)	1,182 (49.6)
BMI, kg/m^2 (derived from self-reported height and weight)	28.9 ± 5.2	28.0 ± 4.5
Waist circumference, cm	94 ± 14.2	91.9 (SD 12.8)
Smoking status		
Never smoker	1,266 (37.9)	896 (37.6)
Former smoker	1,342 (40.2)	872 (36.6)
Current smoker	731 (21.9)	613 (25.7)
First-degree relative (parent or sibling) with T2DM, yes	1,014 (30.4)	714 (30.0)
Known hypertension or prescribed antihypertensive medication, yes (self-reported)	1,797 (53.8)	1,729 (72.6)
Glycated hemoglobin, %	5.5 ± 0.87	5.4 ± 0.68
Edentulism, yes (complete)	269 (8.1)	301 (12.6)
Self-reported bleeding on brushing, yes	1,194 (35.8)	772 (32.4)
Self-reported mobility of teeth, yes	368 (11.0)	329 (13.8)
Dental prosthesis—removable (partial or complete), yes	1,155 (34.6)	555 (23.3)
Number of missing teeth	10.1 ± 8.9	12.3 ± 9.2
Visited the dentist in the last 12 mo, yes (self-reported)	2,634 (78.9)	2,047 (86.0)
CDC/AAP classification of periodontitis		
No/mild periodontitis	1,341 (40.2)	923 (38.8)
Moderate periodontitis	1,229 (36.8)	879 (36.9)
Severe periodontitis	769 (23.0)	579 (24.3)
Undiagnosed NDH/T2DM, yes	329 (9.9)	403 (16.9)
Undiagnosed T2DM, yes	74 (2.2)	99 (4.2)

Data are presented as mean ± standard deviation or number (percentage). AAP, American Association of Periodontology; BMI, body mass index; CCA, complete case analysis; CDC, Centers for Disease Control and Prevention; NDH, nondiabetic hyperglycemia; SD, standard deviation; T2DM, type 2 diabetes mellitus.

Sample Size Determination Phase 1 (Model Development)

We assessed whether the available data were of sufficient size for model development using criteria proposed by Riley et al (Riley et al. 2018; Riley et al. 2020). The minimum sample size required was 4,616 individuals with 462 events (Riley et al. 2020). SHIP-TREND-0 (development data set) has an eligible sample of 3,339 with 329 events (an outcome fraction of 9.9%).

Sample Size Determination Phase 2 (Model Validation)

The sample size of the validation cohort (SHIP-START-0) was 2,381 with 403 events (an outcome fraction of 16.9%).

Missing Data

Data were imputed for participants who did not receive an oral exam (Appendix 2). To account for potential biases associated with missing data, multiple imputation using chained equations was used (Appendix 3). All candidate predictors plus the outcome variable were imputed (Moons et al. 2006). Twenty imputations were used (Von Hippel 2020).

Phase 1: Model Development

Initially, descriptive analyses of the original data were undertaken for candidate predictors to determine potential complexity and degree of nonlinearity within the model. Departures from linearity were tested and continuous predictors modeled with restricted cubic splines using 3 knots and assessed graphically. The Wald's test statistic was used to assess if nonlinear terms offered improvement in fit over a linear model (Vittinghoff et al. 2012). Loess smoother plots, Bayesian information criterion, and likelihood ratio tests were assessed at each stage.

Variables included in the model were selected using backward selection with a threshold of 0.2 for inclusion (Moons et al. 2012; Harrell 2015). The 0.2 threshold is the *P* value at which variables are retained in the model. A higher significance level for variable selection was used so that important variables relevant to the outcome were not missed and to avoid deleting less significant variables that may satisfy practical and clinical reasoning. Model selection was conducted separately in each of 20 imputations (Wood et al. 2008; Harrell 2015). Where a variable was retained in at least 50% of imputed data sets, it was included into the final model (Wood et al. 2008; Harrell 2015). Regression coefficients in each imputed data set were combined using Rubin's rules to provide the final model. Having fitted the main effects model, additivity assumptions

were checked through testing the prespecified interaction terms. Where the global test for additivity was significant or equivocal, prespecified interactions were retained in the model (Harrell 2015).

Heuristic shrinkage (Van Houwelingen–Le Cessie method) was applied to account for potential overfitting. The shrinkage factor was calculated and applied to the model and the intercept reestimated. The shrinkage-adjusted model is reported as the final model (Moons et al. 2012; Harrell 2015; Steyerberg 2019).

Discrimination was assessed via the area under the receiver operator characteristic curve. Calibration was assessed visually using calibration plots (Appendix 4–7) and quantified by the calibration in the large (CITL; an ideal calibration slope is 1, whereas CITL should be 0, representing the number of observed outcome events matching the number of predicted outcome events).

Score Development

The Diabetes risk assessment in Dentistry Score (DDS) was developed for simple and efficient use in dental settings. It is designed as a paper-based point-score system limiting the need for computers and additional chairside software, allowing greater accessibility. The same model development process reported in phase 1 was repeated with the omission of the prespecified interaction terms, allowing regression coefficients and intercepts to be reestimated for development of the simplified score. The method outlined by Bonnet et al. (2019) was used to create the point score system (Appendix 8a).

Engstrom et al. (2013) proposed a basic model for diabetes detection for use in dental settings that involved using only age and BMI. This model was used as a comparator for the DDS.

Phase 2: External Validation

The external performance of both our model and DDS was assessed using data from SHIP-START-0. This was assessed in each of the imputed data sets, and the intercept was reestimated to ensure the mean predicted risk equaled the observed risk. Calibration, discrimination (c-statistic), sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) were calculated. Decision curve analysis (DCA) was undertaken as a measure of clinical utility. DCA allows the net benefit of the DDS point score to be compared with alternative strategies (i.e., current practice, which involves no testing in dental settings or alternatively a population-based screening approach of testing everyone). The net benefit is assessed over a range of threshold probabilities.

All analyses and modeling were completed in Stata/SE 16.0 (StataCorp, College Station, TX, USA).

Results

SHIP-TREND-0 included 3,339 eligible participants and 329 (10%) outcome events, of whom 74 (2%) had undiagnosed T2D and 255 (8%) had NDH. SHIP-START-0 included 2,381 eligible participants including 403 (17%) outcome events, of whom 99 (4%) had undiagnosed T2D and 304 (13%) had NDH.

Model Development

Most missing data involved the dental variables, as immobile study participants were examined at home and did not undergo oral examinations. The percentage missing data related to the outcome variable was 0.5% and <1% for all nondental predictors. Missing data for dental predictors ranged from 0.0 to 18.1% (Appendix 3).

Predictors included in the final model are presented in Table 2 with their respective β coefficients, the model intercept, and shrinkage factor used to adjust the model. Nonlinear terms were not required. The shrinkage factor was 0.90 and applied to account for model optimism. The c-statistic for the shrinkage-adjusted model was 0.72 (95% confidence interval [CI] 0.69–0.75), and the CITL was acceptable at −0.025. The calibration plots of the unadjusted and adjusted models for each imputation set are in Appendix Tables 4 and 5, respectively, and showed unadjusted model slopes of 0.98 to 1.01. The expected/observed (E/O) ranged from 0.98 to 1.02. Shrinkage-adjusted models in each imputation showed slopes of 1.07 to 1.10, and E/O ranged between 1.00 and 1.04.

The DDS (Table 3A and B, Appendix Table 8a) had an area under the curve (AUC) of 0.68 (95% CI 0.65, 0.72), and calibration plots are shown in Appendix Figure 9. The mean score was 7.81 (95% CI 7.66, 7.95), with a range of 0 to 20. At the optimal threshold, the sensitivity and specificity were 77.0 (95% CI 76.8, 77.2) and 51.5 (95% CI 51.4, 51.7) respectively. The PPV was 17.0 (95% CI 17.0, 17.1), and the NPV was 94.6 (95% CI, 94.5, 94.6).

External Validation

The AUC for the final model was 0.69 (95% CI 0.67, 0.72). Calibration plots for each imputation are presented in Appendices 6 and 7 and show unadjusted model slopes of 0.90 to 0.94 and E/O of 0.68 to 0.69. The shrinkage-adjusted models show slopes of 0.92 to 0.96. DCA was used to assess clinical utility over a range of thresholds; the graphs for each imputation are given in the supplemental material (Appendix 9a). These demonstrate the net benefit of the final model in the validation data at thresholds of 0.1 to 0.35.

The DDS had an AUC of 0.69 (95% CI 0.66, 0 71; Table 3), and calibration plots can be seen in Appendix 10. The mean score was 8.1 (95% CI 8.0, 8.3). At the optimal threshold defined in SHIP-TREND-0, the sensitivity and specificity were 79.2 (95% CI 79.0, 79.4) and 49.9 (95% CI 49.8, 50.0), respectively, with a PPV of 25.9 (95% CI. 25.8, 26.0) and NPV of 91.5 (95% CI 91.5, 91.6).

The model proposed by Engstrom et al. (2013) for use in the dental setting had an AUC in SHIP-START-0 of 0.65 (95% CI 0.63, 0.68).

Table 2. Model Parameters for the Final Model Based on SHIP-TREND-0 (Development Data).

Variable	β (95% CI)	OR (95% CI)
Male sex	0.226 (−0.030, 0.483)	1.25 (0.97, 1.62)
Age, y	0.150 (0.080, 0.220)	1.16 (1.08, 1.25)
BMI, kg/m^2	0.236 (0.083, 0.390)	1.27 (1.09, 1.48)
Smoking status (ref. never smoker)		
Former smoker	−1.667 (−3.340, 0.008)	0.19 (0.04, 1.01)
Current smoker	−1.495 (−3.399, 0.409)	0.22 (0.03, 1.51)
First-degree relative (parent or sibling) with type 2 diabetes, yes	0.167 (−0.251, 0.585)	1.18 (0.78, 1.80)
Self-reported mobility of teeth, yes	0.305 (−0.049, 0.659)	1.36 (0.95, 1.93)
Edentulism, yes	0.455 (0.035, 0.875)	1.58 (1.04, 2.40)
Have you been treated for gum disease in the last 5 y (periodontitis treatment)?, yes	−0.261 (−0.619, 0.097)	0.77 (0.54, 1.10)
Number of sites with ≥5 mm pockets (ref. 0 sites)		
Up to 2 sites	−0.183 (−0.536, 0.171)	0.83 (0.59, 1.19)
3 or more sites	0.100 (−0.266, 0.466)	1.11 (0.77, 1.59)
Interaction term for Age × BMI	−0.003 (−0.006, −0.001)	1.00 (0.99, 1.00)
Interaction term for BMI × Smoking status		
BMI × Former smoker	0.043 (−0.012, 0.098)	1.04 (0.99, 1.10)
BMI × Current smoker	0.069 (0.005, 0.134)	1.07 (1.01, 1.14)
Interaction term for first-degree relative (parent or sibling) with type 2 diabetes × Smoking status		
First-degree relative (parent or sibling) with type 2 diabetes × Former smoker	0.662 (0.081, 1.242)	
First-degree relative (parent or sibling) with type 2 diabetes × Current smoker	−0.376 (−1.092, 0.340)	
Intercept	−12.257 (16.835, −7.678)	

The shrinkage factor applied was 0.912. β, linear regression coefficient; BMI, body mass index; CI, confidence interval.

Discussion

This model, which used data routinely available to DCPs, exhibited acceptable performance for the detection of NDH/undiagnosed T2D. Many diabetes prediction models exist for use in medical settings, but most include data unavailable to DCPs (cholesterol/waist circumference). Our model demonstrates that the omission of data inaccessible to DCPs offered a broadly comparable performance with those validated for use in medical settings.

A recent series of papers by Riley et al. (2018, 2020) highlights the importance of adequate sample sizes when developing models and outlines a novel method to calculate the required sample size and number of events per sample. Of the models developed for use in the dental setting (Appendix 12), most did not undertake external validation (Talakey et al. 2022) nor report their full model, limiting the ability of external validation by others.

Our study used representative population-based cohort studies for development and external validation. Although potentially marginally underpowered, it has been validated on an independent external data set, unlike most published studies in this field. A further strength is publication of the full model enabling independent validation. Our study includes parameters routinely available to DCPs to facilitate uptake within dental settings. (supplemental table, Appendix 12).

Guidance on sample size (and number of events) required to validate multivariable prediction models is less clear (Collins et al. 2016; Riley et al. 2016). Consensus was that >250 events were required to validate multivariable prediction models (Steyerberg 2019). After completion of our study, new guidance on sample size requirements for validation studies were published (Riley et al. 2021). To account for optimism within the data, a shrinkage factor was derived and applied to the model. Importantly, the model was also externally validated using a second independent data set from the same region.

The model described was designed for use in high-street dental settings. The threshold was therefore designed to optimize sensitivity, accepting a reduction in specificity; accepting a higher proportion of false positives to minimize the false negatives. Limiting false positives is important at a population level, as it may result in unwarranted referrals for diagnostic tests with associated cost. This has been addressed in the literature previously, whereby a 2-stage risk-assessment process was advocated (Yonel, Batt, et al. 2020; Yonel, Cerullo, et al. 2020). The ease of use and improved practical application of a risk model that identifies true cases can be used as a first-stage assessment. Subsequent point-of-care tests within dental settings then improve the precision of the overall risk assessment by filtering the false positives (Yonel, Yahyouche, et al. 2020).

The proportion of missing data associated with a subsection of the population sample is a study limitation. Where data were collected within the clinical setting, there was a low level of missing data (Appendix 3). A subset of the population (SHIP-Mobile) was unable to access the research site. Those participants were visited at home; thus, this negatively affected data capture and disproportionately affected the dental variables. The low levels of missing data in the clinical setting, however, reflect the proposed real-world application for our model.

Models developed in 1 population are applicable only to that population, and models rarely transfer geographically or temporally; thus, validation studies for other populations are required (Steyerberg and Harrell 2016). Although this model

Table 3. (A) DDS A Points-Score System for Probability of NDH/T2DM for Use in Dental Settings.

Variable Definition	Score
Sex	
Female	0
Male	1
Age, y	
40–49	0
50–59	2
60–69	4
70+	7
Body mass index, kg/m^2	
<25	0
25 and <30	2
30 and <35	3
≥35	6
Smoking status	
Never smoker	0
Former smoker	1
Current smoker	2
First-degree relative (parent/sibling) with type 2 diabetes?	
No	0
Yes	1
Do you have mobile teeth?	
No	0
Yes	1
Are you edentulous?	
No	0
Yes	2
Have you been treated for gum disease in the last 5 y (periodontitis treatment)?	
No	0
Yes	1
Number of sites with ≥5-mm probing pocket depths	
0–2	0
≥3	1

(B) Probabilities of the Outcome That Corresponds to the Points Total.

Points Total	Estimation of Risk
0	0.016
1	0.0205
2	0.0261
3	0.0333
4	0.0423
5	0.0536
6	0.0677
7	0.0852
8*	0.1067
9	0.1329
10	0.1643
11	0.2014
12	0.2444
13	0.2932
14	0.3473
15	0.4057
16	0.4668
17	0.529
18	0.5902
19	0.6488
20	0.7033
21	0.7525
22	0.7959
23	0.8334

Accompanying table of probabilities (absolute risk predictions) to allow the point score to be translated to predicted risk.
*In our data, the optimal point at which to refer patients is a score ≥8; at this cut point, the performance of the score is an area under the curve of 0.69 (95% confidence interval [CI] 0.66, 0.71), sensitivity of 79.2 (95% CI 79.0, 79.4), specificity of 49.9 (95% CI 49.8, 50.00), positive predictive value of 91.5 (95% CI 91.5, 91.6), and negative predictive value of 25.9 (95% CI 25.8, 26.0)

performs well in a German population, further validation studies by independent research groups are needed to determine its performance in other diverse populations. Further work is also needed to determine how well the model performs within different health care systems across Europe.

To date, 14 studies have been published in the peer-reviewed literature describing the development of models that use dental data to identify those at risk of NDH/T2D. Of those 14 studies, half were developed in a US population, only 2 were externally validated, and only 3 reported their full model allowing others to externally validate their work (supplemental table, Appendix 12).

Strauss et al. (2010) used data from the National Health and Nutrition Examination Survey (NHANES) 2003–2004 and found that 63% of those without periodontitis and 93% of those with periodontitis met American Diabetes Association guidelines for diabetes screening. Of those at risk with periodontitis, 34% had seen a dentist in the past 6 mo, 50% in the past 12 mo, and 60% in the past 24 mo. The study highlights that patients with periodontitis are both at higher risk for developing T2D and likely to be seen by a DCP, placing dental teams in an ideal position to undertake targeted risk-based detection for NDH/T2D.

There is broad stakeholder support for DCPs identifying cases of NDH/T2D (Yonel, Batt, et al. 2020). The literature supports a 2-stage process with initial targeted risk-based detection via screening questionnaire followed by point-of-care testing for those above the threshold (Yonel, Cerullo, et al. 2020). A 2-stage process is likely to reduce the number of unnecessary onward referrals to medical professionals for formal diagnosis and management.

Our model is reported in full and thus provides a foundation for further research to validate both the model and the DDS in different populations and to test the clinical and cost-effectiveness of DCPs undertaking such a process. If future research proves the model performs well with different populations, there may be scope for inclusion of such a model in digital health records, opening the door to the development of new integrated care pathways that bridge medical and dental primary care.

Care pathways need to be developed with caution and in conjunction with all stakeholders. It should be ensured that DCPs can refer appropriately to primary care physicians for formal diagnosis, management, and appropriate prevention services. Clear referral protocols must be developed and will likely differ between countries and health systems. Importantly, all relevant stakeholders must remain informed about the patients' journey after risk assessment.

Although our results are promising, further work is required to externally validate the model in different populations, especially given that a limitation of the SHIP data set is a lack of racial/ethnic diversity and the local population characteristics are unique to the region in East Germany. Unlike many other reported studies, we have been transparent in our reporting, publishing our full model as we recognize this limitation and wish to facilitate and support robust external validation of the model in further populations to account for regional differences in population composition.

In addition, further work of interest could include the comparison of our model with other models reported in the literature. A recent study comparing 4 validated and frequently used T2D risk tools in medical settings found considerable variation between the tools in the proportion of patients identified as high risk (Gray et al. 2015). This highlights the importance of ensuring that model performance is assessed in the specific population on which it will be used. Additional research on viability, feasibility, implementation, and cost-effectiveness within different health care systems is also required.

To conclude, we report a validated prediction model for NDH/T2D in dental settings. Validation in additional populations is required.

Author Contributions

Z. Yonel, contributed to conception and design, data analysis and interpretation, drafted and critically revised the manuscript; T. Kocher, contributed to data acquisition, critically revised the manuscript; I.L.C. Chapple, contributed to conception, critically revised the manuscript; T. Dietrich, contributed to conception, data interpretation, critically revised the manuscript; H. Völzke, M. Nauck, contributed to data acquisition and analysis, critically revised the manuscript; G. Collins, contributed to data analysis, critically revised the manuscript; L.J. Gray, contributed to data analysis, conception and design, critically revised the manuscript; B. Holtfreter, contributed to conception and design, data acquisition, analysis, and interpretation, critically revised the manuscript. All authors gave their final approval and agreed to be accountable for all aspects of the work.

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Supplemental Resources

Data from SHIP are available after data application and signature of a data transfer agreement. The data dictionary and the online application form are available at fvcm.med.uni-greifswald.de/dd_service/data_use_intro.php. Involving a local collaborative partner to facilitate the application process is recommended.

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