Bilaga 6. Inkluderade översikter

Tabell 1. Prediktionsmodeller för karies

Article 1/3 Prediktionsmodeller för karies

Author	Havsed et al.
Title	Multivariable prediction models of caries increment: a systematic review and critical appraisal.
Year	2023
Country	Sweden
Reference	[1]
Study design	Systematic review
Litterature search	From 1966 up to April 23, 2021
Population	Individuals of all ages, sex, and ethnicity. Caries should be defined at baseline and follow up regarding prevalence and severity on an individual basis. Alternatively, caries progression should be possible to calculate from data presented in the included study or in studies referred to
Intervention	A prediction model that expresses caries increment as a function of at least 3 variables as predictors. Predictors described in sufficient detail to allow calculation of model performance. When predictors were not described in detail but referred to, the referenced study was retrieved to recover key data.
Comparator	Additional prediction model(s) included in the study.
Outcome	Development either (i) from sound tooth/tooth surface to detectable lesion in enamel or dentin: i.e., from health to disease onset, or (ii) from initial to more extensive lesion: i.e., individual caries progression, described with thresholds to allow calculation of model performance. When not described but referred to, the referenced study was retrieved to recover key data. The outcome may be phrased as caries, caries experience, caries increment, or caries progression. In the following text, the term caries increment is defined as the number of new lesions, teeth or surfaces occurring in an individual within a stated period of time.
Setting	Oral health care without restriction to geographical location.

Other inclusion/exclusion criteria	Model performance: calibration, discrimination (e.g., AUC, area under receiver operating curve, equivalent to c-statistics) and classification measures (e.g., sensitivity, specificity, positive and negative predictive values, positive (LR+) and negative (LR−) likelihood ratios). Measure values should be correctly calculated and presented based on data described in the study and with data allowing recalculation of model performance with confidence interval.
Results	21 studies providing 66 prediction models fulfilled the inclusion criteria of which 11 were model developments and 10 were validation studies. Almost all studies were crown caries models and only three dealt with root caries. Over 150 candidate predictors were considered, and 31 predictors remained in studies of final developmental models: caries experience, mutans streptococci in saliva, fluoride supplements, and visible dental plaque being the most common predictors. Predictive performances varied, providing LR+ and LR−ranges of 0.78–10.3 and 0.0–1.1, respectively. Only four models of coronal caries and one root caries model scored LR+ values of at least 5. The risk of bias was evaluated with PROBAST and all studies were assessed as having high risk of bias, generally due to insufficient number of outcomes in relation to candidate predictors and considerable uncertainty regarding predictor thresholds and measurements. Concern regarding applicability was low overall
Authors' Conclusion	The review calls attention to several methodological deficiencies and the significant heterogeneity observed across the studies ruled out meta-analyses. Flawed or distorted study estimates lead to uncertainty about the prediction, which limits the models' usefulness in clinical decision-making.
Comments	The modest performance of most models question the inclusion of a wide range of predictors and indicate the need to select a few predictors based on their applicability, availability and costs.
Risk of bias	Low risk of bias

Article 2/3 Prediktionsmodeller för karies

Author	Reyes et al.
Title	Machine learning in the Diagnosis and Prognostic Prediction of Dental Caries: A Systematic Review
Year	2022
Country	Brazil
Reference	[2]
Study design	Systematic review
Litterature search	Up to December 28, 2020

Population	Data set obtained from human subjects (radiographic, photographic, or near-infrared light transillumination images, and medical records).
Intervention	Diagnostic or prognostic prediction of dental caries assisted by non-logistic regression (non-LR) ML algorithms.
Comparator	Expert's judgment, clinical/histological examination, classifiers reference as logistic regression (LR)
Outcome	Analysis of machine learning (ML) performance in detection, diagnosis, or prognostic prediction of dental caries (outcomes such as accuracy/precision, sensitivity/recall, specificity, receiver operating characteristic curve, area under the curve, or positive/negative predictive values).
Setting	Real clinical setting
Other inclusion/exclusion criteria	The exclusion criteria were review articles, case series, case reports, editorials, letters, comments, educational methodologies, assessments of robotic devices, and articles with fewer than 10 participants/specimen
Results	Five studies were included that evaluated prognostic prediction of dental caries. Of these, only 2 studies had prospective study design with minimum of 1 year follow-up. These studies interpreted dental caries as binary values in permanent teeth. The data set was collected from medical and dental records and a logistic regression machine learning models were tested. Both studies had high risk of bias.
Authors' Conclusion	The use of AI/ML technologies for the diagnosis and prognostic prediction of dental caries is promising and the studies focused on predicting prognosis contributed with the best evidence. However, the general applicability of the evidence was limited given that most models were developed outside of the real clinical setting with the prevalence of unclear/high risk of bias. It is essential to expand the research on the subject, carrying out validation in independent samples and contributing to developing cost-effectiveness analysis, which supports the introduction of these technologies into clinical practice
Comments	The systematic reviews included also studies that evaluated models for caries diagnostics. The included studies that evaluated prediction models had both cross sectional and prospective design. The results extracted apply to the two prospective studies on prediction models that were included in the review.
Risk of bias	Moderate risk of bias

Article 3/3 Prediktionsmodeller för karies

Author	Rokhshad et al.
Title	Current Applications of Artificial Intelligence for Pediatric Dentistry: A Systematic Review and Meta-Analysis
Year	2024
Country	Germany
Reference	[3]
Study design	Systematic review and meta-analysis
Litterature search	Up to July 2023
Population	Data from pediatric patients, including radiographs (panoramic radiographs, bitewings, periapical radiographs), intraoral photographs, saliva and biofilm samples, and questionnaires about the oral health of children, aged 13 years or younger (i.e. when all primary teeth are likely to have exfoliated)
Intervention	AI to classify (classification–assigning predefined labels), detect (object detection–identifying and locating specific object), segment (segmentation–partitioning an image into distinct regions), or predict (regression–predicting continuous numerical values) oral and dental conditions
Comparator	A reference test or standard of care regression (predicting continuous numerical values)
Outcome	Accuracy, sensitivity (recall), specificity, the area under the curve (AUC, which measures the overall discriminatory ability of a binary classification model), precision (also known as positive predictive value), F1-score (combines precision and recall), root mean square error (RMSE, which measures average prediction error), intersection over union (IoU, which measures mask similarity between ground truth and predicted masks), and incidence rate ratio (IRR, which is used to compare rates of events) are commonly used evaluation metrics in AI tasks
Setting	Clinical settings
Other inclusion/exclusion criteria	Studies that did not evaluate data from children, mention details of the dataset used (including data modality), explain the AI model clearly, nor evaluate any of the outlined outcomes were excluded. Conference abstracts that did not allow sufficient data extraction were also excluded.
Results	Twelve studies were included that used AI models to predict early childhood caries of which four were included in meta-analysis. The predictors obtained data from questionnaires, biofilm/saliva samples, intra-oral radiographs and clinical examinations. The most common AI task was regression and the most common AI model was ANN (deep

	learning that uses multilayer mathematical operations to analyze complex data based on artificial neural networks). Results from meta-analysis showed that accuracy ranged from 60 percent to 98 percent, sensitivity ranged from 20 percent to 97 percent, and specificity ranged from 54 percent to 99 percent. Mean sensitivity was 86 percent, specificity 82 percent, and AUC 89 percent. Early childhood caries predication had an overall of low certainty of evidence based on GRADE.
Authors' Conclusion	The overall body of evidence regarding artificial intelligence applications in pediatric dentistry does not allow for firm conclusions. Current applications of AI have accuracy levels exceeding 60% in the prediction of early childhood caries. Future studies should focus on a comparison of AI against the standard of care and employ a set of standardized outcomes and metrics to allow comparison across studies
Comments	The systematic reviews included also studies that evaluated AI models for caries diagnostics. These results are not included in this table
Risk of bias	Moderate risk of bias

Referenser

1. Havsed K, Hansel Petersson G, Isberg PE, Pigg M, Svensater G, Foresight Research C, et al. Multivariable prediction models of caries increment: a systematic review and critical appraisal. Syst Rev. 2023;12(1):202. Available from: https://doi.org/10.1186/s13643-023-02298-y
2. Reyes LT, Knorst JK, Ortiz FR, Ardenghi TM. Machine Learning in the Diagnosis and Prognostic Prediction of Dental Caries: A Systematic Review. Caries Res. 2022;56(3):161-70. Available from: https://doi.org/10.1159/000524167
3. Rokhshad R, Zhang P, Mohammad-Rahimi H, Shobeiri P, Schwendicke F. Current Applications of Artificial Intelligence for Pediatric Dentistry: A Systematic Review and Meta-Analysis. Pediatr Dent. 2024;46(1):27-35.

Tabell 2. Prediktionsmodeller för parodontit och tandförlust

Article 1/2 Prediktionsmodeller för parodontit och tandförlust

Author	Chow et al.
Title	Systematic Review of Prognosis Models in Predicting Tooth Loss in Periodontitis.
Year	2024
Country	Singapore
Reference	[1]
Study design	Systematic review
Litterature search up to	Up to December 2, 2022
Population	Patients with periodontitis
Intervention	Prediction model development or external evaluation
Comparator	Not specified
Outcome	Tooth loss The primary outcome measure was model performance,
Setting	Not specified
Other inclusion/exclusion criteria	Studies were excluded if they targeted specific populations like special needs patients, did not have a cohort on which model performance could be evaluated, focused on prognostic factors without formal development of a prediction model, predicted outcomes other than tooth loss, and were not original data (such as reviews or editorials)
Results	Out of 45 studies included, 22 were external validation studies. Remaining studies were model development studies. Study design was both retrospective and prospective. Prediction was made either on patient or tooth level. Included studies assessed according to 11 different models/systems. All studies reported a complete list of candidate predictors. Only 25 of the included studies reported performance measures, the median C-statistics was 0.671 with a range of 0.57–0.97. Based on the PROBAST instrument, all included studies were appraised with high risk of bias.
Authors' conclusion	Many models are currently available, and many report moderate to excellent discrimination. However, all studies evaluating these models are at a high risk of bias, primarily because of inappropriate handling of missing data and inappropriate model evaluation (in particular, not assessing calibration). While this review is unable to recommend any model for clinical practice, it has collated the existing models and their model performance at external validation

	and their associated sample sizes, which would be helpful to identify promising models for future external validation studies.
Comments	
Risk of bias	Moderate risk of bias

Article 2/2 Prediktionsmodeller för parodontit och tandförlust

Author	Du et al.
Title	Prediction models for the incidence and progression of periodontitis: A systematic review
Year	2018
Country	Australia
Reference	[2]
Study design	Systematic review
Litterature search	Up to April 26 2018
Population	Adults aged 18 years or older
Intervention	Model containing at least two risk factors. Describing the development, validation or assessment of a model that was constructed to predict the incidence or progression of periodontitis used in the general population
Comparator	Not included
Outcome	Periodontitis incidence or progression
Setting	Not specified
Other inclusion/exclusion criteria	The predictors include but are not limited to tooth-related factors (initial periodontal status), oral health-related factors (tooth brushing, interdental cleaning, pattern of dental visits), subject-related factors (smoking, diabetes, alcohol consumption and overweight/obesity), inherited factors (family history of periodontitis), psychological factors and socioeconomic/demographic factors.
Results	Five studies with 12 prediction models were included. The prediction models showed great heterogeneity precluding meta-analysis. Four models from one study examined the incidence, while others assessed progression. Age, smoking and diabetes status were common predictors used in modelling. Other common predictors included oral examination parameters such as bleeding on probing (BOP), clinical attachment loss (CAL), and degree of tooth loss. The number of predictors in the studies varied between

	4 and 11. Only two studies reported external validation. Predictive performance of the models (discrimination and calibration) was unable to be fully assessed or compared quantitatively
Authors' conclusion	Existing predictive modelling approaches were identified. However, no studies followed the recommended methodology, and almost all models were characterized by a generally poor level of reporting
Comments	
Risk of bias	Moderate risk of bias

Referenser

1. Chow DY, Tay JRH, Nascimento GG. Systematic Review of Prognosis Models in Predicting Tooth Loss in Periodontitis. J Dent Res. 2024;103(6):596-604. Available from: https://doi.org/10.1177/00220345241237448
2. Du M, Bo T, Kapellas K, Peres MA. Prediction models for the incidence and progression of periodontitis: A systematic review. J Clin Periodontol. 2018;45(12):1408-20. Available from: https://doi.org/10.1111/jcpe.13037

Tabell 3. Prediktionsmodeller för bettavvikelser

Article 1/1 Prediktionsmodeller för bettavvikelser

Author	Jiménez-Silva et al.
Title	Craniofacial growth predictors for class II and III malocclusions: A systematic review
Year	2020
Country	Chile
Reference	[1]
Study design	Systematic review
Litterature search	Search April 2019- updated 23 August 2020
Population	Patients of both genders and all ethnicities were included. The selection criteria were as follows: • Growing subjects with Class I, Class II, or Class III malocclusion. • No history of surgical procedures in the facial or cranial regions. • No previous orthopedic or orthodontic treatment. • Absence of syndromes or abnormalities affecting facial or cranial growth.
Intervention	Methods to predict growth in patients with skeletal class II and III malocclusion.
Comparator	Skeletal class I craniofacial growth
Outcome	**Primary Outcomes:** The study aims to identify predictors of vertical and/or sagittal growth in growing subjects with Class II and III malocclusions by employing: • Clinical Examination: Includes occlusal, intraoral, and extraoral evaluations. • Laboratory Analysis: Examination of biological samples. • Imaging Methods: Utilization of cephalometric analyses such as Steiner, Ricketts, Delaire, among others. Models were constructed using computational modeling, mathematical equations, and other statistical analysis methods. **Secondary Outcome:** Evaluate the risk of bias in these studies to determine their methodological quality.
Setting	The study focuses on growth patterns irrespective of geographical location.
Other inclusion/exclusion criteria	**Other inclusion criteria:** **Databases and language** Eight databases were searched for relevant studies. There were no language restrictions; however, the analysis included studies in Spanish, English, and Portuguese, as these were the primary languages used by the researchers.

	Study design Only cohort studies were identified, focusing on designing or proposing methods to predict growth in patients with skeletal Class II and III malocclusions.
Results	A total of 10 articles were included, and their methodological quality was assessed using the QUADAS-2 tool. The studies were categorized based on the growth predictors for malocclusion as follows: (1) class II (n=4); (2) class III (n=5) and (3) class II and III (n=1). The predictors were predominantly derived from cephalometric data and constructed by using mathematical equations, structural analyses, computational techniques, and software programs, among other methods. The analyzed studies exhibited methodological heterogeneity and were generally of low to moderate quality. For Class II malocclusion, the predictors with the best methodological quality were based on mathematical models and the Fishman system for maturation assessment. For Class III malocclusion, the Fishman system demonstrated the potential to provide reliable growth predictions for both short- and long-term periods.
Authors' conclusion	The limited available evidence indicates that there are few reliable predictors for estimating craniofacial growth in Class II and III malocclusions. In general, all predictors were designed based on cephalometric and clinical data using mathematical equation, computerized structural superimposition, network and computational modeling, cluster analysis, software methods and Fishman method.
Comments	• The literature search proved challenging to replicate, even though the initial information appeared relevant. • Ten studies were included, but none utilized the same variables for their prediction models. • These prediction models have not been tested on different populations, limiting the evaluation of their external validity.
Risk of bias	Low risk of bias according to ROBIS (low risk of bias in all domains).

Referenser

1. Jimenez-Silva A, Carnevali-Arellano R, Vivanco-Coke S, Tobar-Reyes J, Araya-Diaz P, Palomino-Montenegro H. Craniofacial growth predictors for class II and III malocclusions: A systematic review. Clin Exp Dent Res. 2021;7(2):242-62. Available from: https://doi.org/10.1002/cre2.357

Tabell 4. Riskbedömningsmodeller för bettfysiologiska tillstånd

Article1/2 Riskbedömningsmodeller för bettfysiologiska tillstånd

Author	Burr et al.
Title	The role of sleep dysfunction in temporomandibular onset and progression: A systematic review and meta-analyses
Year	2020
Country	USA
Reference	[1]
Study design	Systematic review
Litterature search	Up to April 29 2019
Population	• Adult populations, 18 years of age and older • Patients with orofacial or TMD disorders, pain and included sleep quality self-reported outcome measures. (SROMs) were identified.
Intervention	• Identify Self-Report Outcome Measures (SROM) of sleep quality, and determine diagnostic and prognostic value of SROMs related to sleep quality and Temporomandibular disorders (TMD)
Comparator	Prediction of developing TMD
Outcome	**Primary Outcome:** Diagnosis of TMD was defined by Axis I and II components of both RDC/TMD and DC/TMD.
Setting	Dental practices and universities from four settings in the US.
Other inclusion/exclusion criteria	Other inclusion criteria: • Fulltext articles • Clinimetric properties of sleep quality SROMs, and diagnostic or prognostic studies related to sleep quality and TM disorders/oro-facial pain. • This review focused on four multidimensional SROMs: The Pittsburg Sleep Quality Index (PSQI), Epworth Sleepiness Scale (ESS), Symptom Checklist 90-Revised (SCL-90R) and Sleep Assessment Questionnaire. Other exclusion criteria: • Studies were excluded if the studies were non-English • Patients with confounding diagnoses (e.g. cancer, headaches, bruxism and/or trigeminal neuralgia). • Book chapters, stand-alone abstracts, theses, opinions and correspondences were excluded.
Results	18 studies were included in this systematic review, and their methodological quality was assessed using the COSMIN in the clinimetric study (n=1). For diagnostic studies (n=11), the Quality Assessment tool for Diagnostic Accuracy Studies (QUADAS) was used. In Prognosis Studies (n=6) the QUIPS tool was used. Four of the prognostic studies were cohort studies (same population described in four different

	publications with different time periods and their methodological quality were moderate to high risk of bias. Nine different assessment tools were used; only the Pittsburg Sleep Quality Index (PSQI) has been validated in patients with painful TM disorders. Overall, sleep dysfunction was diagnostic for painful TM disorders. The pooled relative risk of sleep dysfunction was 1.71 (95% CI, 1.30 to 2.26). When PSQI scores were greater than 5/21, the unadjusted hazard ratio for development of painful TM disorders was reported to be 2.1.
Authors' conclusion	At present, the only SROM that has diagnostic and prognostic value in evaluating and managing patients with painful TM disorders is the PSQI.
Comments	Prediction of developing TMD was based upon one large cohort study with data from four publications (Bair 2013, Bair 2016, Sanders 2016 and Sanders 2017). Comments about the results: Sleep dysfunction is diagnostically important in patients with painful TMD. Further, sleep dysfunction is a predictive factor to the onset of painful TMD. The PSQI is the only SROM that has been validated in populations with painful TMD
Risk of bias	Low risk of bias. ROBIS was used as the evaluation tool. Risk of bias assessment showed low risk of bias in all ROBIS domains.

Article 2/2 Riskbedömningsmodeller för bettfysiologiska tillstånd

Author	Da-Cas et al.
Title	Risk factors for temporomandibular disorders: a systematic review of cohort studies
Year	2024
Country	Brazil
Reference	[2]
Study design	Systematic review
Litterature search	Up to April 23 2021
Population	• 18 years age and older • Without TMD at baseline
Intervention	• Non-Modifiable factors: Gender, age, race, genetic factors, • Modifiable factors: General health, comorbidities and other pain conditions, physical trauma, occlusal-related factors, sleep, stress psychosocial and disability.

Comparator	Prediction of developing TMD
Outcome	**Primary outcome:** TMD outcome assessed by clinical examination based on RDC/TMD, DC/TMD or following the guidelines of the AAOP.
Setting	Dental practices and universities
Other inclusion/exclusion criteria	**Other exclusion criteria:** • 1.Studies not evaluating TMD • Studies using a diagnostic tool other than RDC/TMD, DC/TMD or AAOP guidelines • Presence of interventions in the study sample • Studies that did not report association rates or P-values • Randomized controlled trials, case-control, cross-sectional, before-after, abstracts, reviews, case-reports and series, protocols, short communications, personal opinions, letters, posters, conference abstracts, and laboratory research (*in vivo* and *in vitro* studies) • Full-text not available • Articles not written in latin-roman alphabet
Results	21 cohort studies were included in this systematic review and their methodological quality was assessed using Joanna Briggs Institute Critical Appraisal Checklist for Cohort Studies. 13 studies presented a low risk of bias, 7 studies were judged with a moderate risk of bias and one presented a high risk of bias. Statistically significant factors were female gender, symptoms of depression and anxiety, perceived stress, sleep quality, symptoms of obstructive sleep apnea and presence of any comorbidity, such as Irritable Bowel Syndrome, lower backpain, headache frequency, tension-type headache, migraine and mixed headache. Moreover, high estrogen and low testosterone levels in utero, greater pain perception, jaw mobility pain, pain during palpation, orofacial anomalies, as well as extrinsic and intrinsic injuries were also significant.
Authors' conclusion	Several factors seems to be involved in TMD onset, however, more studies with standardized methodology are necessary to confirm these findings.
Comments	Each risk factor was evaluated according to GRADE into high, moderate, low and very low level of evidence.
Risk of bias	Low risk of bias. ROBIS was used as the evaluation tool and showed low risk of bias in all domains.

Referenser

1. Burr MR, Naze GS, Shaffer SM, Emerson AJ. The role of sleep dysfunction in temporomandibular onset and progression: A systematic review and meta-analyses. J Oral Rehabil. 2021;48(2):183-94. Available from: https://doi.org/10.1111/joor.13127
2. Da-Cas CD, Valesan LF, Nascimento LPD, Denardin ACS, Januzzi E, Fernandes G, et al. Risk factors for temporomandibular disorders: a systematic review of cohort studies. Oral Surg Oral Med Oral Pathol Oral Radiol. 2024;138(4):502-15. Available from: https://doi.org/10.1016/j.oooo.2024.06.007

Tabell 5. Prediktionsmodeller för munslemhinneförändringar

Article 1/2 Prediktionsmodeller för munslemhinneförändringar

Author	Espressivo et al.
Title	Risk Prediction Models for Oral Cancer: A Systematic Review
Year	2024
Country	UK
Reference	[1]
Study design	Systematic review
Litterature search	Up to November 2022
Population	Adults in the general population
Intervention/Exposure	Risk model method using two or more risk factors to estimate the risk of developing oral cancer and are suitable for use in the general population
Comparator/reference	No requirement
Outcome	Discrimination, calibration and accuracy, of the model
Setting	No requirement
Other inclusion/ exclusion criteria	Inclusion: Primary research paper in peer-reviewed journal without language restriction. Exclusion: Non-specified head and neck cancer. Studies investigating specific population groups or models to predict disease progression.
Results	14 studies, 13 case control studies and one cohort study, describing 23 models were included. The study setting was in the general population in one study and hospital based with hospital based or mixed controls in the rest of the studies. All model studies were assessed using PROBAST, as having a high overall risk of bias with the most common issues in the population and analysis domains. The authors report and describe the included studies individually without synthesis. Most models included two or more demographic or lifestyle risk factors. Six models incorporated clinical or genetic factors and three incorporated biomarkers. Most of the identified models (n = 13) showed good or excellent discrimination (AUROC > 0.7). However, only fourteen models had been validated and only two of these validations were carried out in populations distinct from the model development population (external validation). Model accuracy was reported for three models not incorporating genetic variant factors and for three models incorporating genetic variants.
Authors' conclusion	"Several risk prediction models have been identified that could be used to identify individuals at the highest risk of oral cancer within the context of screening programs. However, external validation of these models in the target

	population is required, and, subsequently, an assessment of the feasibility of implementation with a risk-stratified screening program for oral cancer.”
Comments	
Risk of bias	Moderate risk of bias Inadequate search strategy

Article 2/2 Prediktionsmodeller för munslemhinneförändringar

Author	Uppal et al.
Title	Machine learning methods in predicting the risk of malignant transformation of oral potentially malignant disorders: A systematic review
Year	2024
Country	India
Reference	[2]
Study design	Systematic review
Litterature search	Up to August 2023
Population	Patients with confirmed clinical diagnosis of oral potential malignant disorder (OPMD), histopathological diagnosis of oral epithelial dysplasia, or oral cancer that was preceded by an OPMD
Intervention/Exposure	Machine learning methods to predict the risk of malignant transformation
Comparator/reference	No requirement
Outcome	Prediction accuracy of the machine learning methods: sensitivity, specificity, accuracy, true positive (TP), false positive (FP), false negative (FN), true negative (TN), positive predictive value (PPV), negative predictive value (NPV), F1 score, or other metrics that enable an estimation of accuracy of the model.
Setting	No requirement
Other inclusion/ exclusion criteria	Inclusion: Retrospective or prospective cohort studies reported in English. Confirmed clinical or histopathological diagnosis. Exclusion: Survival prediction or inappropriate reporting of outcomes.
Results	15 studies are included in the review. The study quality and risk of bias was assessed using the LIMEDI check-list where 3 studies were categorized with low quality, 9 with medium quality and 3 with high quality. Oral cancer cases were retrospectively followed to determine prognostic course of OPMDs and OEDs. The included studies had follow-up periods ranging from 23 to 103 months.

	The factors used in the models were spectroscopy data, DNA-content and patient risk behaviors. External validation of the methods was performed in only two of the studies. Amongst all studies, highest sensitivity (100%) was recorded for U-net architecture, Peaks Random forest model, and Partial least squares discriminant analysis (PLSDA). Highest specificity (100%) was noted for PLSDA. Range of overall accuracy in risk prediction was between 95.4% and 74%.
Authors' conclusion	"Machine learning proved to be a viable tool in risk prediction, demonstrating heightened sensitivity, automation, and improved accuracy for predicting transformation of OPMDs. It presents an effective approach for incorporating multiple variables to monitor the progression of OPMDs and predict their malignant potential. However, its sensitivity to dataset characteristics necessitates the optimization of input parameters to maximize the efficiency of the classifiers." "Furthermore, few studies with concerns in data understanding and preparation, indicated potential biases that could impact the validity of their findings."
Comments	Limited information regarding the research question and inclusion criteria.
Risk of bias	Moderate risk of bias.

Referenser

1. Espressivo A, Pan ZS, Usher-Smith JA, Harrison H. Risk Prediction Models for Oral Cancer: A Systematic Review. Cancers (Basel). 2024;16(3). Available from: https://doi.org/10.3390/cancers16030617
2. Uppal S, Kumar Shrivastava P, Khan A, Sharma A, Kumar Shrivastav A. Machine learning methods in predicting the risk of malignant transformation of oral potentially malignant disorders: A systematic review. Int J Med Inform. 2024;186:105421. Available from: https://doi.org/10.1016/j.ijmedinf.2024.105421