

Predictive Models for Oral Frailty in Older Adults —An AI-driven Systematic Review

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Abstract

Background: Population aging has become a core challenge in global public health, with increasing attention paid to oral frailty (OF) among older adults. However, current studies on OF in the elderly exhibit high methodological heterogeneity and insufficient model validation, necessitating a systematic review. **Objective:** To systematically retrieve and evaluate literature on predictive models for oral frailty in older adults using artificial intelligence (AI), and to synthesize model performance metrics (AUROC, sensitivity, specificity, calibration) and predictors. **Methods:** The PRISMA statement and CHARMS checklist were followed. Systematic searches were performed in PubMed, Web of Science, Cochrane Library, CNKI, Wanfang, VIP, and Sinomed databases up to June 2026. AI-generated search keywords included "elder/old", "oral frailty", and "model." Inclusion criteria were: (1) participants aged ≥ 60 years; (2) development of a predictive model for oral frailty; (3) model performance validated internally or externally; (4) full text available. Data (first author, publication year, study type, sample size, age, geographic region, predictors, model development and validation methods, performance metrics, presentation format) were extracted using AI. Bias was assessed using the PROBAST tool. Given anticipated high heterogeneity (differences in populations, oral indicators, frailty definitions, and algorithms), a narrative synthesis was conducted. **Results:** A total of 629 articles (424 in English, 205 in Chinese) were retrieved, with 29 finally included. Most studies were cross-sectional, with two retrospective studies. A high risk of bias was common across current models, with OFI-8 ≥ 4 being the predominant criterion for oral frailty. Most studies used logistic regression to develop the model, while two studies also employed some other machine learning methods (e.g., Random Forest, Decision Tree, Support Vector Classifier, K-Nearest Neighbors) for model development. Limitations included lack of external validation, sufficient sample size and model interpretability. **Conclusion:** AI can efficiently facilitate systematic reviews of predictive models for oral frailty in older adults. Current models are transitioning from questionnaire-based tools to those incorporating orally collected biomarkers. Future research should prioritize longitudinal cohort designs, include dynamic changes in oral indicators, adopt acceptable model performance thresholds (AUROC ≥ 0.80) for screening eligibility, implement rigorous external validation, and leverage AI to extend oral frailty screening from specialized hospital settings to community-based proactive early warning.

Keywords

Artificial Intelligence, Elder, Oral Frailty, Predictive Models, Systematic Review