Artificial Intelligence (AI): Analysis of Outcomes of Oral Healthcare at a US Dental School: Part I: Descriptive Analysis

Background: Temple University dental school (TUDS) assesses 15 health outcomes including quality of life, overall health status, oral hygiene and caries risk status, cavitated lesions, gingivitis, and periodontal pockets. These measures are automatically generated after each full clinical and interview examination. The data are summarized in a Patient Wellness Report (PWR), representing good, fair, and poor status. TUDS requires students to complete care for 30 patients plus other requirements,

Aims and Objectives: To evaluate PWRs' performance and a final dataset for investigating the correlates of outcomes of dental caries and periodontal disease.

Materials and methods: PWR records were extracted from 44,265 patients seen since January 1, 2015. Because of the variation in implementation of the PWRs, the analysis focuses on records of 21,146 patients seen between 2021 and 2023.

Results: Of the 21,146 PWR patient records,17,822 patients were assessed twice. Of those, 3,127 received two PWRs in less than 90 days and were excluded. The second PWRs were collected after 3-6 months (16%), 6-12 months (32%), or one year (53%). The analytical dataset included those patients with full treatment provided during the 2-year period (N=10,640). The AI and linear statistical analyses presented in this symposium will focus on caries risk (42% high), caries lesions (48% high), gingivitis (8% high), and periodontal pockets (20% high). An integrated outcome score was obtained by mapping the change in outcomes using a 3 by 3 matrix for the two time periods resulting in a combined outcome measure ranging from -2, -1, and 1, representing regression, or 2 and 3 scores representing improvement.

Discussion and conclusion: TUDS' model of value-based healthcare faces implementation challenges. We will present scenarios where decisions were made to assist the graduation requirements rather than assessing outcomes. A new model that only values comprehensive patient care should be implemented.

Artificial Intelligence (AI): Analysis of Outcomes of Oral Healthcare at a US Dental School: Part II: AI methods and their potential application in dental education and patient care

Background: The landscape of dental care is rapidly evolving with the integration of Artificial Intelligence (AI) and data science. AI is a state-of-the-art method to teach a computer/machine to think and learn like humans from its experiences. One of the best "teachings"/providing experience to computers/machines is through feeding large amounts of good quality datasets.

Objective: To describe the methods used in machine learning (ML) and deep learning (DL) and how they apply to the assessment of outcomes of care.

Methods & Results: None

Discussion and Conclusions: ML methods improve learning from the data and identify patterns or predicted outcomes without explicit programming. DL utilizes neural networks with multiple layers that attempt to mimic the human brain's thinking. ML is widely used to build prediction models through large datasets, while DL models are popular for computer vision and image processing. AI learning can be obtained through supervised, unsupervised, or semi-supervised learning. In supervised learning, algorithms learn through labeled datasets where there is a known outcome. In unsupervised AI learning, the outcome is unknown, and the model tries to find common patterns and clusters. Finally, semi-supervised learning learns from a dataset that is partially labeled. Various methods exist for ML debiasing, such as cross-validations, sampling, algorithmic fairness algorithms, and model transparency.

The AI models are typically (including our analysis) trained, tested, and validated using either the same validated dataset or a different dataset through transfer learning methods. It is critical to utilize multiple datasets to improve both sensitivity and specificity of the model. Some popular assumptions in AI analysis include independent and identically distributed data (each data point is assumed to be independent), feature relevance, and class balance. The AI models can include various tree-based models (XGBoost), Bayesian methods (Bayesian Network for ML and DL), linear models (liner-logistic regression), and neural networks.

Artificial Intelligence (AI): Analysis of Outcomes of Oral Healthcare at a US Dental School: Part III: Utilizing AI to develop a prediction model

Background: Temple University School of Dentistry has introduced a Patient Wellness Report (PWR) to evaluate multiple health outcomes, including oral and dental health, quality of life, literacy, and general wellness, as part of holistic dental care. This tool assesses 15 wellness dimensions on a good-fair-poor scale to track patient progress. It is critical to determine its effectiveness, especially factors responsible for disease improvement versus disease progression (DIVP).

Objectives: This analysis evaluates the effectiveness of oral and dental care on four measures of dental caries and periodontal diseases using AI.

Materials and methods: PWR datasets of 10,640 patients with cases completed between Jan-2021 – Dec-2023 were obtained. Three outcome categories and a rank-based system were created (*see Abstract 1*) for binary classification to determine DIVP. AI Random Forest, Naïve Bayes, XGBoost) and bias-reduction (cross-validations, sampling) methods were utilized for prediction. The performance of the models was evaluated using evaluation metrics (precision, recall, f-1 measures).

Results: The XGBoost model performed best with a 75% f-1, 83% precision, and 72% recall. For caries measures, age, fluoride, recall exams, dietary advice, number of bitewing radiographs exposed, and number of periodontal treatments were strong predictors of disease improvement. For disease progression, the number of restorations and a higher number of treatment codes were major predictors. For periodontal disease, the number of periodontal treatment codes, dietary counseling, prostheses, and recall exams were associated with disease improvement, and older age, poor oral hygiene, and higher number of restorations with disease progression.

Discussion and conclusion: This study demonstrated the successful application of AI to build a prediction model using PWRs in a dental school setting. We found fluoride, recall exams, periodontal treatments, and dietary advice were helpful in improving disease outcomes. It provides recommendations for other schools to utilize such tools to improve the outcomes of dental diseases.

Artificial Intelligence (AI): Analysis of Outcomes of Oral Healthcare at a US Dental School: Part IV: Comparative analysis of outcomes using the generalized linear models

Background: Temple University school of dentistry has promoted patient-centered clinical training through the Patient Wellness Report (PWR) with 15 wellness dimensions, which allows students to follow comprehensive care treatment plans and assess outcomes. It is critical to determine the effectiveness of this innovative approach for improving patient outcomes.

Aims and Objectives: The objective of this study was to identify predictors of disease improvement and progression of dental caries and periodontal outcomes.

Materials and methods: PWR data were extracted from axiUm® (electronic dental records) for 10,640 patients who completed dental procedures during 2021-23 (see the cohort generation process in Abstract#1). Four binary outcomes (two caries and two periodontal health-related) were created to measure disease progression and disease improvement. Predictors included demographics, clinical characteristics, and procedure variables. Quasi-Poisson regression with sandwich estimation was used to identify the predictors after accounting for the other predictors and baseline characteristics.

Results: The percentage of patients with disease improvement varied across four outcomes. 60% and 69% of patients experienced improvement in caries risk and caries lesions, respectively. More than 85% of patients had their periodontal outcomes improved. Multivariable regression models for caries outcomes identified predictors of disease improvement, including recall examination, fluoride procedure, number of periodontal treatments, indirect restorations, and crown/bridges. The complexity of the case, class II restorations, number of restorations, and tobacco counseling were predictors of increased caries progression. Multivariable regression models found dietary counseling and indirect restorations/crown/bridges and implants as predictors of periodontal health improvement. Higher complexity of the case and tobacco counseling were predictors for periodontal disease progression.

Discussion and conclusion: This study found several factors associated with disease improvement (recall examination, fluoride) and for disease progression (treatment complexity, tobacco counsel). It provided evidence for the effectiveness of clinical training through PWR.

Artificial Intelligence (AI): Analysis of Outcomes of Oral Healthcare at a US Dental School: Part V: Discussion of results from AI and GLM analyses

Background: In the previous presentations in this symposium (Part III and IV), we presented results from the AL and GLM, respectively.

Objective: This paper focuses on comparing the two methods and their utility in dentistry.

Methods: Please refer to Part I-IV.

Results: Both models identified factors such as fluoride applications, recall frequencies, dietary advice, oral hygiene, and number of restoration or periodontal treatments as predictors of caries or periodontal disease improvement. These findings support the hypothesis that appropriate preventive and therapeutic care have a positive impact on caries and periodontal diseases. However, there were unexpected negative findings such as the impact of the complexity of patient care and tobacco counseling in GLM. The code of tobacco counseling does not indicate that counseling was appropriately provided. AI analysis found no significant impact of tobacco counseling (either positive/negative).

Conclusions/Discussion: GLM assumes a linear association between continuous risk factors and transformed expected outcomes, provided the risk factors are not highly intercorrelated. The AI models are less constrained. For example, age, and number of completed treatments displayed a complex relationship. AI models, which require a large dataset compared with GLM, answer the question of what the best-correlated factors with the outcomes are, whereas GLM tests a linear relationship between continuous risk factors and transformed outcomes. Hence, while both approaches have value, the AI analysis can be more robust and may present a better fit with personalized care models. There are analyses that GLM cannot perform, such as analyzing automated information extracted from textual data, image segmentations through computer visions, and pattern recognition. Selection of the use of each method depends on the research question, size, and complexity of the dataset. Both AI and GLM are valuable and powerful tools used for data analytics and prediction; however, each method has strengths and limitations.