Project Title: Integrating AI-Powered Oral Health Risk Assessment into OpenMRS for Burn Patient Care
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Abstract

Burn patients often experience unique oral health challenges that can be overlooked in acute care. This project proposes the development of an AI-driven oral health risk assessment tool integrated within the OpenMRS electronic medical record platform to address this gap. The system will leverage machine learning (Logistic Regression and Random Forest) to predict oral health risk levels in burn patients, based on clinical and demographic data, and provide structured monitoring through OpenMRS. A REST API will deliver risk scores to OpenMRS, where rule-based logic will combine with the AI predictions to stratify patients by risk level. Clinically, this integration aims to prompt timely oral care interventions and improve outcomes for burn patients. The proposal outlines the interdisciplinary methodology, spanning data preparation, model development, system integration, and clinical workflow adaptation, as well as ethical considerations. By uniting burn care, dental expertise, and health informatics, the project is expected to enhance oral health management for burn patients and demonstrate the broader value of AI integration in healthcare.

Introduction

Burn injuries can have severe and lasting impacts on oral health, especially for patients with burns to the face and neck. Such injuries often lead to complications like oral burn contractures (scar tightening causing microstomia), loss of oral tissue elasticity, and reduced oral function (Chaudhary et al., 2019). As a result, burn survivors frequently struggle with maintaining oral hygiene and accessing dental care. Studies have shown alarmingly poor oral health outcomes in this population – for example, one cross-sectional study found that 100% of facial burn patients had dental caries, 59% had periodontitis, and 66% had poor oral hygiene status (Chaudhary et al., 2019). These oral health issues can significantly diminish quality of life; indeed, up to 94% of burn patients in one cohort reported negative oral health-related quality of life impacts such as pain and social disability (Chaudhary et al., 2021). Despite these needs, oral care may be under-prioritized during acute burn management, and there is limited structured monitoring of oral health in burn aftercare (Chaudhary et al., 2019). This gap highlights the need for proactive, systematic approaches to assess and manage oral health risks in burn patients.

Advances in artificial intelligence (AI) offer a promising solution to this challenge. AI-driven tools have demonstrated the ability to analyze patient data and predict health outcomes with high accuracy, often surpassing traditional methods (Dey et al., 2024). In dentistry and oral health, machine learning models have been used to predict risks of conditions like dental caries and periodontal disease, enabling targeted preventive care (Dey et al., 2024) For burn patients, AI technologies have already shown potential in other domains of care – for instance, aiding in burn depth assessment and predicting patient mortality with accuracies exceeding 90% (Taib et al., 2022).This suggests that an AI model could similarly be trained to predict oral health complications risk in burn survivors, serving as an early warning system for clinicians.

Integrating such an AI risk assessment tool into the clinical workflow is crucial for its impact. OpenMRS, a leading open-source electronic medical record (EMR) platform, provides an ideal environment for this integration. OpenMRS was designed for resource-constrained healthcare settings and is built as a highly modular system with a robust API, allowing easy extension and customization (Syzdykova et al., 2017)). By embedding the AI-driven risk assessment into OpenMRS, the tool can function within clinicians' existing workflow at the point of care. This integration means that whenever a burn patient's data is entered or updated, the system can automatically generate an oral health risk score and present it in the OpenMRS interface as part of the patient's record. Such seamless incorporation of AI into an EMR aligns with the broader trend toward "intelligent" EHR systems that support clinical decision-making. Research suggests that combining AI with EHRs can improve the quality of care and reduce errors, though careful design is needed to ensure accuracy and clinician trust (Alanazi, 2023).

Literature Review:

AI in Oral Health

Artificial intelligence (AI) has revolutionized oral healthcare by enhancing diagnostic and predictive capabilities. Machine learning models such as Logistic Regression, Random Forest, and gradient boosting have been successfully applied to predict risks for dental caries, periodontal disease, and other oral health complications. Notably, AI models often surpass traditional statistical methods in accuracy, sensitivity, and specificity. A recent study found that machine learning outperformed conventional regression in predicting dental caries, enabling earlier risk identification and tailored preventive care strategies (Dey et al., 2024). For a more detailed discussion, please refer to Appendix A.

Objectives and Research Questions

Project Objectives: The primary objective of this project is to develop and integrate an AI-powered oral health risk assessment system for burn patients within the OpenMRS platform. This overarching goal can be broken down into several specific objectives: (1) to curate and preprocess a dataset of burn patients with relevant oral health and clinical features for machine learning; (2) to train and validate two predictive models (Logistic Regression and Random Forest) that estimate a patient's risk of developing significant oral health complications (such as severe dental decay, periodontal infection, or oral mucosal lesions) post-burn; (3) to implement the best-performing AI model as an external RESTful service that can interface with OpenMRS; (4) to design a rule-based decision logic that works alongside the AI model's output to stratify patients into risk categories (low, moderate, high) with clear clinical action triggers; and (5) to seamlessly incorporate the AI risk assessment into the burn patient care workflow in OpenMRS, including the user interface and notifications for care providers. Through these objectives, the project aims to bridge the gap between raw predictive analytics and actionable clinical information.

Research Questions: In pursuit of the above objectives, the project seeks to answer the following key research questions:

- *RQ1:* What are the most important patient factors (e.g., burn severity, time since injury, oral hygiene practices, etc.) that influence the risk of oral health complications in burn patients, as identified by the AI models?
- *RQ2:* How do the performance of a Logistic Regression model and a Random Forest model compare in predicting oral health risk levels in burn patients (in terms of accuracy, sensitivity, specificity, and clinical usefulness)?
- *RQ3:* What is the impact of integrating the AI-based risk assessment into OpenMRS on clinical workflow and decision-making in a burn care setting? For instance, does the system improve the timely identification of high-risk patients and prompt earlier dental interventions compared to the standard practice?
- *RQ4:* How can rule-based clinical knowledge (e.g., existing guidelines or expert rules about oral care in burns) be combined with AI predictions to enhance the reliability and acceptance of the risk assessment? Does this hybrid approach improve the stratification of patients into risk categories over using AI alone?

By answering these questions, the project will evaluate not only the technical performance of the models but also their practical value in a clinical context. The questions address both the "black box" of the AI (understanding which factors drive its predictions) and the "human factors" of implementation (impact on workflow and care outcomes). Together, the objectives and research questions ensure a comprehensive evaluation of the system from technical, clinical, and operational perspectives.

Methodology

Dataset Description: The dataset consists of 271 rows and 22 columns, containing various psychosocial and oral health-related variables.
The Key variables are:

Variable Name	Description
ORAL HEALTH VARIABLES	
DMFT	Decayed, Missing, and Filled Teeth index
CPI	Community Periodontal Index score
OHI-S	Oral Hygiene Index for dental cleanliness
OHI-14	Oral Health Impact Profile
OHS	Oral health status assessment
brushing2	Brushing Frequency
DFendscore	Facial disfigurement category – mild, medium

PYSCHOLOGICAL VARIABLES	
HADAnx	Anxiety status or condition
RSES	Self-esteem reported by the participant
MSPSS	Social support network status
HADDep	Depression
SOCIO-ECONOMICAL VARAIBLES	
Income	Income level or financial category

Data Collection and Preprocessing:

Before building the models, the provided oral health dataset undergoes preprocessing to ensure high-quality input features for training. The first step involves data cleaning, where missing or inconsistent values are handled by either filling or removing them, and outliers are corrected. Standardization of fields such as "brushing frequency" and "income range" ensures consistency. Next, feature selection is conducted to identify the most relevant predictors of oral health risk, focusing on clinical indices such as DMFT, CPI, OHI, and OHIP-14, as well as psychosocial factors like anxiety and depression. A binary risk label may be derived to categorize patients as "high risk" for poor oral health outcomes, based on severe CPI and high DMFT values. Encoding and transformation are then applied to convert categorical variables into numerical representations. For example, CPI scores such as "calculus," "4–5 mm pockets," and "6+ mm pockets" are mapped to ordinal values, while gender categories ("male," "female") are converted into binary dummy variables. Additionally, numeric features like age, income, and index scores are normalized or scaled to facilitate convergence in logistic regression models. Once the data is cleaned and transformed, it is split into training and validation sets, typically in an 80/20 ratio, to assess model performance on unseen data and prevent overfitting. If the dataset is small, cross-validation techniques are used to maximize generalizability. In cases of class imbalance, methods such as up-sampling or class weighting are applied to ensure balanced representation of "high risk" cases. The final outcome is a structured dataset, where each patient record is represented by a comprehensive feature vector that captures oral health status, behaviours, and demographics. This preprocessing pipeline is carefully documented and designed to be reproducible, allowing it to be consistently applied to new data before both training and real-world model predictions.

Machine Learning Model Development:

Two supervised machine learning models – Logistic Regression and Random Forest – will be developed to predict oral health risk in burn patients. The outcome variable will be a defined measure of oral health risk or status. This could be a binary outcome (e.g., whether a patient developed a significant oral complication during their hospital stay or within a certain follow-up period) or a categorical risk level (low/medium/high) assigned based on expert criteria. The Logistic Regression model will provide a baseline: it is a linear model that outputs the probability of the outcome and offers easy interpretability through its coefficients (odds ratios for each risk factor). The Random Forest model, an ensemble of decision trees, is chosen for its ability to capture nonlinear relationships and interactions between features, and it often yields higher predictive accuracy for complex clinical data. Model training will involve hyperparameter tuning using techniques like grid search or cross-validation (for example, tuning the regularization strength for logistic regression, and the number of trees and depth for the random forest). Performance metrics such as accuracy, area under the ROC curve (AUC), sensitivity (recall for high-risk cases), specificity, and precision will be calculated on the validation set. In line with similar studies in oral health prediction, we expect the machine learning models to potentially outperform simpler statistical methods in identifying at-risk patients (Dey et al., 2024). Throughout model development, care will be taken to avoid overfitting – strategies will include using cross-validation, limiting model complexity, and performing feature selection if necessary (e.g., removing highly collinear or low-importance features). Additionally, the feature importance output from the Random Forest and the coefficients from Logistic Regression will be examined to answer RQ1 about key risk factors, which also aids in clinical interpretability of the models.

External AI Deployment (REST API):

After selecting the best-performing model (or even both, if comparative use is desired), the chosen model will be deployed as a standalone AI service. This will likely be implemented using a Python-based framework (such as Flask or FastAPI) or a Java service, depending on compatibility with OpenMRS. The model will be serialized (for instance, using Python's pickle or joblib for a scikit-learn model) and loaded within the service. A RESTful API will be developed where an HTTP POST request to the service with a patient's data (in JSON format) returns the predicted risk score or category. The input to the API will consist of the necessary fields (age, burn characteristics, etc.) for that patient, which OpenMRS can provide through its own API. For security and privacy, this communication will occur over HTTPS and will not store patient identifiers beyond the immediate computation. By keeping the AI model as an external service, we maintain modularity – the core OpenMRS system remains unchanged, and the AI can be updated or scaled independently. OpenMRS's REST module allows the system to consume external web services, so the plan is to create a custom OpenMRS module or script that triggers a call to the AI service whenever a relevant event occurs (for example, when a burn patient's record is created or updated, or at set intervals during hospitalization) *(Refer to Appendix B for Detailed Logic and Implementation)*.

Risk Stratification Logic:

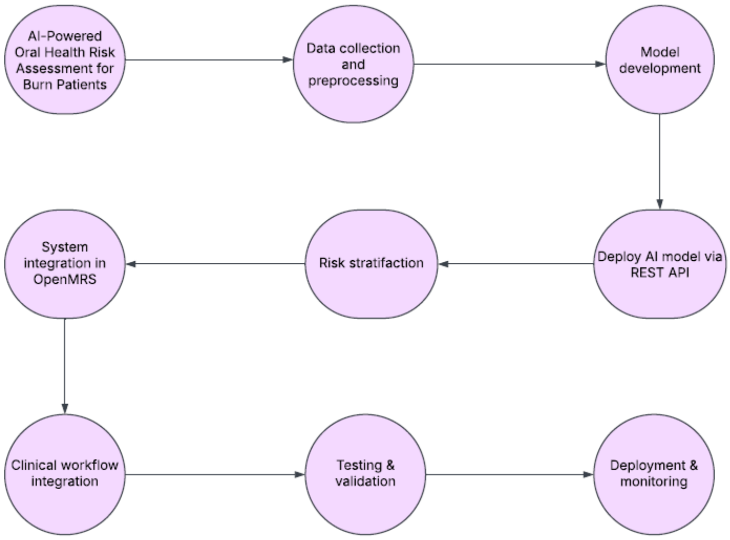
To enhance the robustness of risk assessment, a hybrid approach combining machine learning (ML) predictions with expert-driven rule-based logic is implemented. This ensures that critical risk factors, which algorithms might overlook, are captured using established oral health guidelines and clinical expertise. The rule-based system operates through a set of IF-THEN conditions that assign patients to high risk based on predefined criteria, regardless of or in addition to ML model outputs. For instance, if a patient has a poor Oral Hygiene Index along with deep periodontal pockets (CPI ≥6 mm) or has skipped dental check-ups for over a year while presenting with a high DMFT score, they are flagged as high risk. Similarly, extreme values, such as a DMFT count exceeding 15 or an OHIP-14 score indicating severely compromised quality of life, automatically trigger a high-risk classification. Conversely, while protective factors like regular brushing may mitigate risk, they do not override severe indicators. These rules are embedded within OpenMRS using Groovy scripts or SQL-based flags, ensuring seamless integration with the ML model's probability-based predictions. The

AI model assigns a risk probability from 0 to 1, which is translated into actionable categories through a rule-based layer. Thresholds are defined in collaboration with clinical experts, with a probability above 0.7 or the presence of critical conditions (such as oral burns with severe facial scarring) marking a patient as high risk. Intermediate probabilities (0.4–0.7) are categorized as moderate risk unless overridden by red flags, while low-risk cases fall below 0.4. Additional expert rules ensure that care gaps are not missed, such as automatically flagging a patient as high risk if they lack oral care within seven days of ICU admission or have a history of poor hygiene documented by nursing staff. By integrating AI-driven insights with clinician-authored rules, the system maintains high sensitivity to severe cases while fostering trust in automated assessments. This hybrid risk stratification enables proactive intervention, triggering alerts in OpenMRS for dental consultations in high-risk cases or reminders for staff to reinforce oral hygiene for moderate-risk patients. The combination of AI predictions with expert-driven logic ensures a comprehensive and transparent approach to oral health risk assessment, balancing advanced data-driven insights with clinical intuition *(Refer to Appendix B for Detailed Logic and Implementation)*.

Clinical Workflow Integration in OpenMRS:

Integrating the risk assessment into OpenMRS involves both technical embedding and user interface design to fit the clinical workflow. Technically, the custom OpenMRS module will handle communication with the AI service and store or cache the results. Each burn patient's record in OpenMRS will have new data fields (concepts in OpenMRS terminology) for oral health risk score and risk category. These can be stored as observations attached to a specific encounter (for example, a "Burn Oral Health Risk Assessment" encounter type) or as patient-level data. The module can be configured to update these fields whenever the patient's data changes significantly (triggering a recalculation) or at routine intervals (such as daily). From a user perspective, the OpenMRS dashboard for burn patients will be customized to display the current oral health risk level prominently. For instance, a colored indicator (green for low, yellow for moderate, red for high) could be shown next to the patient's name or vital signs. Clicking on this indicator might open a detailed view showing the factors contributing to the risk (e.g., "High risk due to extended time since burn and poor oral hygiene") to provide transparency. Additionally, we will integrate clinical decision support notifications: if a patient is classified as high risk, the system can generate an alert for the responsible clinician (e.g., as a pop-up or a notification in their task list) recommending an intervention such as a dental evaluation or enhanced oral care. Training will be provided to the clinical team on how to interpret and act on the risk assessment. The goal is to embed the tool in the normal care routine – for example, during morning rounds, the care team can review the risk status of each burn patient in OpenMRS and plan appropriate oral care steps for the day. This reduces reliance on memory or sporadic consults and ensures oral health is consistently considered. Because OpenMRS is already used for documenting burn patient information, this integration keeps all data in one place, which is vital for clinician adoption. By involving burn unit staff in the design of the interface (through feedback sessions or usability testing), we will ensure that the risk assessment is presented in a clear, non-intrusive way that complements their workflow rather than complicating it.

FLOWCHART: Integrating AI-Powered Oral Health Risk Assessment into OpenMRS for Burn Patient Care



Expected Outcomes and Impact

If successful, this project will yield both immediate clinical benefits and broader contributions to healthcare innovation. **For burn patients**, the integration of AI-powered oral health risk assessment is expected to lead to earlier identification of oral health problems and preventive intervention. High-risk patients could receive timely oral hygiene support, prophylactic treatments (such as antimicrobial mouthrinse or antifungal medication if indicated), or referral to dental specialists before minor issues escalate. Over time, this should translate into fewer severe oral complications, less pain, better nutrition (through improved ability to eat), and overall improved quality of life for burn survivors. The continuous monitoring may also empower patients in their rehabilitation phase – for example, patients and caregivers can be educated about the risk score and encouraged to maintain oral care routines if the risk is elevated.

For clinicians and the burn care team, the project offers a new level of decision support. Nurses and physicians will have a quantifiable risk indicator to consider during care planning, ensuring that oral health is systematically addressed alongside other aspects of burn recovery. This can increase the interdisciplinary nature of burn care, fostering collaboration between burn specialists, nursing staff, and dental professionals. Clinicians may find that the AI tool helps prioritize limited resources – for instance, if there is one dental consult slot available, it can be allocated to the highest-risk patient as identified by the system. By reducing the chance of overlooking oral issues, the tool acts as a safety net in the fast-paced, high-stress burn unit environment.

For the healthcare system, improved oral health management in burn patients can have economic and operational benefits. Preventing complications like oral infections can shorten hospital stays or reduce ICU days (e.g., avoiding ventilator-associated pneumonia that can be linked to poor oral hygiene (Shi et al., 2010)), thereby lowering costs. Additionally, the structured data collected (oral health scores, risk levels, outcomes) becomes a valuable dataset for quality improvement and research. Hospitals could analyze this data to refine care protocols or justify the inclusion of oral health professionals in burn care teams. The project also demonstrates a model for incorporating AI into existing health IT systems, which can be extended to other applications. For example, the same framework could in the future be applied to nutritional risk assessments, mental health risk screenings, or other supportive care aspects in various patient populations.

On a technological front, one expected outcome is a working prototype of an OpenMRS module for AI integration. This module (and the external AI service code) could be shared with the OpenMRS community and adapted for other use cases, amplifying the impact beyond this project. It will serve as a case study in bridging the gap between predictive analytics and EMR-based clinical workflows. By demonstrating that an AI tool can be seamlessly embedded and accepted in routine care, the project can inspire similar efforts in resource-constrained settings where OpenMRS is prevalent, thereby expanding the reach of AI benefits to under-served areas.

In summary, the project’s impact is multifaceted: **clinically**, better oral health and patient outcomes; **operationally**, enhanced workflow and resource allocation; and **strategically**, a blueprint for integrating AI into healthcare delivery in an ethical and effective manner. If the outcomes align with expectations, we anticipate publishing the results to contribute to the scientific literature on burn care and health informatics, as well as advocating for the adoption of such tools in practice. The success metrics will include improved oral health indices in the pilot population, positive feedback from clinicians (measured through usability surveys), and the sustained use of the tool without adverse events. Achieving these outcomes will indicate that the project has met its goals of improving patient care and advancing interdisciplinary innovation.

Project Milestones and Timeline

To ensure the project is completed in a systematic and timely fashion, a detailed timeline with milestones is outlined below. The project is expected to span approximately 12 months, broken into key phases:

Phase 1: Requirements Gathering and Data Acquisition (Week 1)

- **Activities**: During this initial phase, the team will consult with burn unit clinicians and oral health specialists to define data requirements and finalize the list of features for the model.
- **Milestone**: By the end of Week 1, we anticipate having assembled the retrospective dataset of burn patient records and any supplementary oral health data needed for model training.

Phase 2: Data Preprocessing and Exploratory Analysis (Week 2)

- **Activities**: In this phase, the raw data will be cleaned and pre-processed as described in the methodology. We will perform exploratory data analysis to understand variable distributions and correlations, and to finalize the outcome definition for model training.
- **Milestone**: A summary report of the dataset (including any handling of missing values and descriptive statistics), and a locked-down version of the dataset ready for modeling by the end of Week 2.

Phase 3: Model Development and Validation (Week 3)

- **Activities**: The machine learning models (Logistic Regression and Random Forest) will be developed in Week 3. This includes coding the models, running training algorithms, and tuning hyperparameters via cross-validation.
- **Milestone**: By the end of Week 3, initial models with performance metrics on validation data will be available. Week 3 will focus on model evaluation and selection – comparing the two models' performances and conducting any necessary recalibration. Additionally, feature importance analysis will be documented to inform the rules and explainability.

Phase 4: System Integration Development (Week 4)

- **Activities**: In this phase, the technical integration components will be built. Week 4 will concentrate on developing the external AI service (REST API) and testing it in a standalone mode with sample data. By mid-week, we aim to have the AI service containerized or deployed on a test server. Week 4 will involve developing the OpenMRS module to interface with this API. This includes creating fields in OpenMRS for risk scores, writing the logic to call the API with patient data, and updating the OpenMRS UI.
- **Milestone**: Completion of an end-to-end test in a staging environment – e.g., entering a test patient in OpenMRS and receiving a risk assessment from the AI service automatically. We expect to have a working prototype of the integrated system by the end of Week 4.

Phase 5: Testing and Refinement (Week 5)

- **Activities**: With the system in place, thorough testing will be carried out. Week 5 will involve unit testing and bug fixing for the software (ensuring the OpenMRS module handles various use cases correctly, the API is robust to missing data, etc.), as well as validation of the risk predictions on a set of test patients. We will run the

system in parallel with historical cases (or a small live pilot with a subset of patients) to ensure the predictions align with clinical expectations. Feedback from clinicians will be gathered to refine the user interface and alert logic in Week 5. If the model is found to be misclassifying certain cases, adjustments (either model retraining with more data or tweaking rules thresholds) will be made.
- **Milestone**: Achieving a stable system with clinician sign-off that it is ready for broader use – indicated by successful pilot tests and positive user feedback by the end of Week 5.

Phase 6: Evaluation and Monitoring (Week 6)

- **Activities**: After deployment, the last week will focus on evaluating the impact and performance of the system in actual use. We will collect data on key indicators – for example, how often high-risk alerts occur and what actions are taken, any reduction in oral health issues compared to a pre-implementation baseline, and user satisfaction surveys. Interim adjustments may be made if any issues arise (for instance, if clinicians report alert fatigue, we might adjust the frequency or thresholds). By the end of Week 6, we will analyze the outcome data to assess whether the tool met its expected benefits (addressing RQ3 regarding impact on workflow and patient outcomes). The final milestone is the completion of a project report and a presentation for the faculty review detailing the results, lessons learned, and recommendations for future work. At this stage, we will also outline plans for sustaining the system beyond the pilot (who will maintain the service, how it can be scaled up, etc.).
- **Milestone**: Completion of a project report and presentation for the faculty review and stakeholders by the end of Week 6.

Name	Roles and Responsibilities
Kevin	- Requirements Gathering and Data Acquisition (Week 1)
	- System Integration Development (Week 4)
Subina	- Data Preprocessing and Exploratory Analysis (Week 2)
	- Testing and Refinement (Week 5)
Shruti	- Model Development and Validation (Week 3)
	- Deployment and Training (Week 6)
All	- Evaluation and Monitoring (Week 7), Model Development (Week 3)

Conclusion

In conclusion, this project proposal outlines a comprehensive plan to integrate an AI-powered oral health risk assessment system into the OpenMRS platform for burn patient care. Burn patients are a uniquely vulnerable population who face significant oral health challenges, yet these issues often receive insufficient attention amidst the complexities of burn treatment. By leveraging modern AI techniques and embedding them in a widely-used clinical information system, we aim to provide an effective tool for early identification of patients at high risk of oral complications. The introduction and literature review highlighted that poor oral health can considerably affect burn patients' recovery and quality of life (Chaudhary et al., 2019) (Chaudhary et al., 2021), and that AI-driven models have proven capable of enhancing risk predictions in healthcare (Dey et al., 2024) Building on this evidence, our methodology details an interdisciplinary approach: gathering clinical data, developing machine learning models, and working closely with clinicians to integrate the tool into everyday workflows with appropriate ethical safeguards. The expected outcome is a more proactive and structured oral health management process for burn patients, leading to better patient outcomes and a demonstration of improved care delivery through technology.

This project stands at the intersection of clinical medicine, dentistry, and health informatics, and its successful execution will require ongoing collaboration between these domains. Burn care specialists, dental professionals, and software developers will need to communicate regularly to refine the risk model and its integration. The interdisciplinary nature of the work is a strength, as it ensures that the final product is clinically relevant, technically sound, and user-friendly. The impact of the project, as discussed, could be significant: not only improving the lives of burn patients but also providing a model for how AI can be responsibly implemented in electronic medical record systems to augment clinical decision-making. We also recognize that this is a pilot endeavor – lessons learned here will inform future iterations. Potential future directions include expanding the model to incorporate new data types, such as photographic images of oral tissues analyzed by computer vision, which could further enhance risk assessment accuracy. Additionally, once validated in one setting, the approach could be expanded to other hospitals using OpenMRS, or adapted to assess other risks in burn patients (for instance, nutritional deficiencies or mental health risks), making use of the same integration framework.

In closing, the integration of AI-powered oral health risk assessment in OpenMRS for burn patients represents an innovative step toward holistic burn care. It exemplifies how technological advancements can be harnessed to fill gaps in care – in this case, bridging burn therapy and oral health. The proposed project is academically rigorous, technically feasible, and clinically meaningful. Upon completion, we anticipate not only immediate benefits for the participating institution and its patients but also valuable insights for the broader medical community on improving outcomes through intelligent, integrated health systems. We look forward to the opportunity to carry out this project and contribute to advancing patient care at the confluence of technology and medicine.

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Appendices:

Appendix A

AI in Oral Health: Artificial intelligence applications in dentistry have grown rapidly, demonstrating improved diagnostic and predictive capabilities for oral diseases. Machine learning models, including logistic regression and more complex algorithms like random forests and gradient boosting, have been applied to predict dental caries risk, periodontal disease progression, and other oral health outcomes. Notably, AI models often outperform traditional statistical approaches in these tasks. For example, a recent study comparing machine learning to conventional regression for caries prediction found that the best ML model achieved higher accuracy, sensitivity, and specificity than the traditional model (Dey et al., 2024) These results indicate that AI-driven risk assessment can provide precise and meaningful evaluations of oral health risks, enabling clinicians to identify high-risk patients earlier and tailor preventive strategies accordingly.

Oral Health in Burn Patients: Burn patients, particularly those with facial burns, represent a vulnerable group with respect to oral health. The literature on this specific intersection is relatively limited (Chaudhary et al., 2019), but the studies that exist highlight serious concerns. Chaudhary et al. (2019) documented widespread dental problems in facial burn patients, as noted earlier, and attributed these to both direct and indirect effects of the burn injury (Chaudhary et al., 2019). Physical changes such as scar formation can restrict mouth opening and reduce the efficacy of oral self-care, while the trauma and prolonged hospitalization often lead to disruptions in routine dental hygiene practices (Chaudhary et al., 2019). Another study by Chaudhary et al. (2021) linked poor oral health status in burn victims to a significantly reduced oral health-related quality of life (Chaudhary et al., 2021) (Chaudhary et al., 2021). Patients reported chronic pain, difficulty eating and speaking, and social embarrassment due to oral issues, all compounded by the psychological stress of disfigurement. These findings underline the importance of systematic oral health surveillance in burn care. Currently, however, there are no widely adopted protocols for regular oral examinations or risk assessments in burn units. Dental consultations may be infrequent or only prompted by acute problems. This gap in care motivates the integration of a tool that can continuously track oral health indicators in burn patients and alert providers to emerging risks.

OpenMRS and Health IT Innovations: OpenMRS (Open Medical Record System) is a flexible, open-source EMR platform used globally, especially in low-resource settings, to capture and organize patient data (Regenstrief Institute, 2022). Technologically, OpenMRS is built on a modular architecture: new functionalities can be added via modules without altering the core system (Syzdykova et al., 2017b). It also offers RESTful web services and supports standards like HL7 FHIR, facilitating interoperability and integration with external applications (Syzdykova et al., 2017b). These features make OpenMRS an attractive foundation for implementing clinical decision support tools, including AI-driven modules. The OpenMRS community has recognized the potential of AI in enhancing care delivery; for instance, pilot projects have explored using machine learning on OpenMRS data to predict patient outcomes and guide treatment decisions () (). While specific applications for oral health within OpenMRS have not been widely reported, the platform's success in managing HIV, tuberculosis, and chronic disease data indicates it can be customized for niche needs like burn patient oral care. Recent developments in OpenMRS (such as the Reference Application and O3 interface) focus on improved user experience and easier form creation, which will be advantageous when building the oral health risk assessment forms and dashboards. In summary, OpenMRS provides a mature and adaptable infrastructure where an AI-powered risk assessment tool can be embedded to directly assist clinicians during routine documentation and care planning.

By synthesizing these three areas of literature, we see a convergence of opportunity: the oral health challenges in burn patients necessitate better monitoring; AI techniques offer advanced predictive power to identify risk; and OpenMRS furnishes a ready environment to deploy such innovations in real clinical workflows. This project stands at the intersection of these domains, aiming to contribute to each: it will extend oral health research for burn patients, apply and evaluate AI models in a new context, and enhance OpenMRS with an innovative clinical decision support capability.

Appendix B: A detailed document outlining AI risk assessment integration within OpenMRS, including implementation details, risk stratification logic, and system integration can be accessed via the following link:

https://docs.google.com/document/d/1WHmo79nK5RszUS5r5hJJV_frWm1iX6PRMFF8FioDfuQ/edit?usp=sharing

Dataset: https://opendata.usm.my/items/140e4211-8ff4-4599-b517-f8ffd84301e7