PERSONALIZED PROGNOSIS FOR CHRONIC WOUND HEALING:

PREDICTING HEALING TIME USING A MULTIVARIATE APPROACH

Puja Darshana Mishra

Submitted to the faculty of the School of
Informatics in partial fulfillment of the
requirements
for the degree of
Master of Science in Health Informatics,
Indiana University

May 2025

Accepted by the Faculty of Indiana University,
in partial fulfillment of the requirements for the degree of
Master of Science in Health Informatics

Master's Project Committee

Dr. Saptarshi Purkayastha
Program Director, Health Informatics
Associate Professor, Data Science, Health Informatics

____

© 2025

Puja Darshana Mishra

ALL RIGHTS RESERVED

Table of Contents

LIST OF FIGURES AND TABLES

ABSTRACT

PUJA DARSHANA MISHRA

PERSONALIZED PROGNOSIS FOR CHRONIC WOUND HEALING: PREDICTING HEALING TIME USING A MULTIVARIATE APPROACH

Chronic wounds pose a significant healthcare burden, often leading to prolonged hospital stays, recurrent infections, and increased risk of amputation. Despite technological advancements, current treatment strategies frequently lack individualized insight, relying instead on population-based guidelines that fail to address patient-specific healing trajectories. This project explores the development of a personalized machine learning-based tool to predict wound healing time using structured multivariate patient data. A Streamlit-based application was developed to automate the extraction of structured patient data from Continuity of Care Documents (CCDs) using Blue Button.js which could be integrated with the model. Temporal Fusion Transformer (TFT) was implemented to model patient-specific wound healing trajectories. Both epistemic and aleatoric uncertainty were quantified using Monte Carlo dropout and predictive variance, respectively. Model evaluation used metrics such as MAE, RMSE and Quantile loss.

CHAPTER ONE: INTRODUCTION & SIGNIFICANCE OF PROJECT

Chronic wounds, defined as wounds that fail to progress through a normal and timely reparative process, represent a significant clinical and public health challenge. These include diabetic foot ulcers, venous leg ulcers, and pressure injuries—conditions that contribute to increased patient morbidity, extended hospitalizations, and significant healthcare costs. In the United States alone, chronic wounds affect approximately 4.5 million individuals and generate more than $25 billion in annual healthcare expenditures (Nguyen et al., 2020). The complexity and heterogeneity of these wounds, compounded by comorbidities such as diabetes, cardiovascular disease, and aging-related factors, demand more personalized approaches to care (Velickovic et al., 2023).

Despite advancements in electronic health records (EHRs), current wound care practices continue to rely heavily on generalized protocols. These systems often overlook patient-specific factors such as wound characteristics, comorbidities, and demographics. Moreover, EHRs tend to underutilize real-time and multimodal data, limiting clinicians' ability to predict healing outcomes dynamically (Dabas et al., 2021). The absence of tools that provide individualized recovery forecasts represents a critical gap in current wound care models (Velickovic et al., 2023). This project addresses that gap by developing a machine learning-based prediction tool for estimating wound healing time, tailored to individual patient profiles. The objective is to enhance precision medicine efforts and optimize wound management strategies in both inpatient and outpatient settings.

Emerging predictive models powered by Artificial Intelligence (AI) and Machine Learning (ML) provide a framework for more responsive, personalized care. ML models such as Transformers, GRUs, and LSTMs have demonstrated high accuracy in wound healing prediction, particularly when trained on multimodal time-series data (Zhang et al., 2024; Zeng et al., 2023). These models help identify patients at risk for delayed healing, inform treatment strategies, and minimize preventable outcomes like infection or amputation (Fang et al., 2022; Kim et al., 2023). The Temporal Fusion Transformer (TFT) model, in particular, excels at capturing complex temporal dependencies, making it well-suited for predicting healing timelines.

The integration of these models into interactive, user-friendly platforms such as Streamlit can bridge the gap between technical capability and clinical usability. Streamlit allows for the rapid deployment of predictive tools that are interpretable and accessible to clinicians and patients alike, thus supporting shared decision-making. This project aims to create a transparent, personalized wound healing forecast model integrated into a Streamlit-based interface which would not only advance wound care precision but also enhance communication, engagement, and timely intervention, thereby improving outcomes and reducing healthcare costs.

CHAPER TWO: LITERATURE REVIEW

Chronic wounds fail to progress through a normal reparative process and pose a major clinical and economic burden. These include diabetic foot ulcers, venous leg ulcers, and pressure injuries, which are associated with high rates of morbidity, frequent hospitalizations, and substantial healthcare costs. These wounds are often complicated by comorbidities such as diabetes, cardiovascular disease, and the physiological consequences of aging, necessitating a move toward more patient-specific management strategies (Velickovic et al., 2023).

2.1 Limitations of Traditional Wound Care Systems

Chronic wound management traditionally relies on EHR systems and clinician-driven assessments. However, these tools often fail to capture dynamic, patient-specific variables such as real-time wound progression, socioeconomic factors, and adherence behaviours (Dabas et al., 2023; Velickovic et al., 2022). Manual tools such as the Bates-Jensen and Leg Ulcer Measurement systems are subjective and resource-intensive (Wang et al., 2015). These limitations lead to delayed diagnoses and interventions, particularly for conditions like diabetic foot ulcers that require individualized approaches. The inability of EHRs to integrate multimodal data types or provide real-time analytics hinders proactive care delivery (Wu et al., 2020).

2.2 Advances in Personalized Models for Wound Prediction

Personalized care is a cornerstone of chronic wound management, where healing is rarely linear and varies across individuals. Technologies that support dynamic, individualized intervention planning are essential for improving outcomes and reducing avoidable complications. Recent developments in ML and AI have led to the emergence of personalized predictive models capable of processing diverse data sources including wound imaging, comorbidities, and patient demographics. Algorithms like CNNs, GRUs, and Transformer-based models have achieved over 80% prediction accuracy for chronic wounds and pressure injuries (Fang et al., 2022; Zhang et al., 2024). These tools can dynamically adjust treatment plans based on individual trajectories, thereby supporting clinical decision-making and improving adherence (Andrelean et al., 2024).

Smart technologies, such as wearable sensors and intelligent bandages, have also been integrated with ML systems to provide continuous wound monitoring and early warning alerts (Weigelt et al., 2022). This aligns with the 4P model of modern healthcare—predictive, preventive, personalized, and participatory (Andrelean et al., 2024).

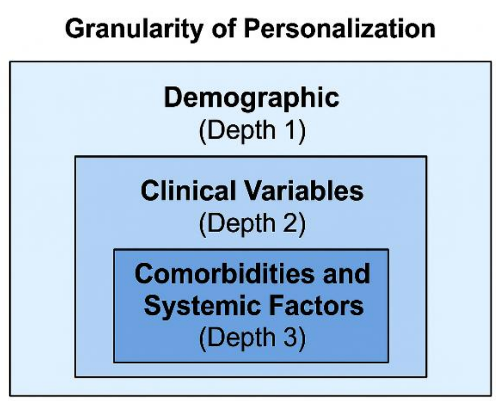

Figure 2.1. Personalization deepens from basic demographics (Depth 1), to clinical wound variables (Depth 2), and finally to complex comorbidities and systemic factors (Depth 3).

2.3 Streamlit for Data Driven Applications in Healthcare

Streamlit, an open-source Python framework, has emerged as a powerful tool to translate complex machine learning models into intuitive, interactive applications that support precisely this kind of personalization. Unlike traditional web frameworks that require extensive front-end development expertise, Streamlit allows for rapid prototyping and deployment of data-driven applications with minimal code. Its simplicity makes it well-suited for healthcare, where clinicians and patients alike benefit from user-friendly interfaces that give meaningful, real-time insights (Kadam et al., 2023, p. 1712).

In wound care, Streamlit provides a vehicle for integrating predictive models with patient engagement. Chronic wounds demand continuous assessment—monitoring healing trajectories, infection risk, and treatment effectiveness. Streamlit interfaces can dynamically display wound progression trends, model outputs, and personalized recommendations, enabling clinicians to intervene early and modify care as needed. Ekambaram and Ponnusamy (2024) demonstrated a similar approach in low back pain rehabilitation, where Streamlit-powered dashboards facilitated real-time pose analysis and treatment tracking—offering a blueprint for applying such models to wound healing applications.

Several studies have showcased how Streamlit enables machine learning-driven personalization across diverse clinical use cases ranging from diabetes self-management app to deliver personalized diet, exercise, and medication recommendations which could be adapted in real-time to patient behavior and health status (Pourbehzadi, 2024, pp. 1–2) to incorporating highly dynamic data like using streamlit alongside ML models to predict calories burned during physical activity, incorporating individualized physiological inputs like heart rate, weight, and age (Kadam et al., 2023, p.1713). A wound care equivalent might use parameters like tissue granulation, infection status, and comorbidities to forecast healing time.

Mittal et al. (2025) developed a Streamlit app that translated complex cardiological prescriptions into personalized treatment plans using large language models which shows the compatibility range of Streamlit with various models and in clinical settings (pp. 87–88). Similarly, wound care plans could benefit from automated interpretation of CCD documents and integration of NLP-extracted variables into care pathways. Moreover, Streamlit supports multimodal integration.

Streamlit's simplicity and compatibility also make it a pragmatic choice for healthcare innovation. It handles state, inputs, and data caching internally, integrates easily with ML libraries like scikit-learn and PyTorch, and supports rapid deployment. In their evaluation of web frameworks, Ekambaram and Ponnusamy (2024) found Streamlit superior to Flask, Dash, and Viola in developer-friendliness and suitability for small but data-intensive healthcare applications. In sum, Streamlit does more than simplify model deployment—it enables clinicians to harness the full potential of AI in a transparent, patient-specific, and operationally feasible way. For chronic wound care, where outcomes hinge on early detection and responsive treatment, Streamlit provides the connective tissue between algorithmic intelligence and bedside decision-making. Our ultimate goal is to achieve a deeper granularity of personalization as described below:

Problem Statement

Chronic wounds present a persistent and growing clinical challenge due to their prolonged healing trajectories, high recurrence rates, and association with complex comorbid conditions. Despite the widespread adoption of Electronic Health Records (EHRs) and structured documentation like Continuity of Care Documents (CCDs), healthcare providers often lack the tools to translate this wealth of data into actionable, patient-specific predictions. Current clinical workflows rely heavily on manual wound assessments and generalized treatment protocols, which fail to account for the individualized nature of wound healing and are limited in their ability to support dynamic clinical decision-making.

While machine learning techniques have shown promise in medical prognosis, their adoption in wound care remains limited by challenges in data integration, model interpretability, and clinical usability. Thus, there is a critical need for a robust, interpretable, and accessible solution that leverages multivariate clinical data to forecast healing timelines and support early intervention.

This project addresses that gap by developing a Temporal Fusion Transformer (TFT)-based wound healing prediction model, trained on structured and time-series clinical data. The goal is to provide clinicians with real-time, personalized forecasts of wound healing outcomes, enabling timely adjustments to treatment strategies, reducing preventable complications, and advancing the delivery of precision wound care.

CHAPTER THREE: APPROACH TO SOLUTION

3.1 Suggested Approaches to Solve Problem

Initial efforts in wound prediction utilized traditional regression models, such as linear regression and decision trees, trained on structured clinical data. Nguyen et al. (2020) applied tree-based algorithms to lower extremity wound data, achieving moderate accuracy but struggling to capture non-linear temporal dynamics. Similarly, Andrelean et al. (2024) used logistic regression and random forest classifiers to assess diabetic foot ulcer risk, demonstrating promise in early classification but limited capacity for longitudinal forecasting.

While these models are interpretable and relatively easy to deploy, they fall short in handling multivariate time series and sequential dependencies critical to wound progression modeling. Several studies have utilized convolutional neural networks (CNNs) to analyze wound images. For instance, Kim et al. (2023) developed a deep-learning model for pressure injury staging using wound photographs, achieving high classification accuracy. However, most of these approaches often ignore clinical variables such as comorbidities, lab values, and medication adherence — factors that are essential for accurate prediction of healing time. Fang et al. (2022) used an LSTM model for pressure injury prediction, leveraging sensor and clinical variables, and reported accuracy above 80%. While LSTMs can capture sequence information, they often lack interpretability and struggle with long-term dependencies.

More recently, transformer architectures have gained attention in healthcare for their ability to model long-range dependencies. Zeng et al. (2023) benchmarked transformers for time-series forecasting, finding them highly effective in capturing complex temporal interactions across multiple features. Zhang et al. (2024) introduced an Extreme Adaptive

GRU-Transformer hybrid model for biomedical data, demonstrating improved generalization and uncertainty handling.

These findings suggest that attention-based models like the Temporal Fusion Transformer (TFT) are well-suited for healthcare applications that require both forecasting precision and transparency. Deploying ML models through user-friendly interfaces has become a recent trend. Streamlit-based applications, like those by Fabrizzio et al. (2023) and Pourbehzadi (2024), show that interactive AI tools can bridge the gap between data science and clinical practice. These apps allow real-time prediction, visualization, and patient-specific recommendations — key for wound care personalization. To address the challenge of predicting wound healing time with clinical relevance and personalization, we adopted a multifaceted approach that integrates advanced deep learning, robust data preprocessing, uncertainty estimation, and an interactive application. Our choices were guided by a review of existing literature, real-world healthcare needs, and the limitations of prior models.

3.2 Rationale

We selected the Temporal Fusion Transformer (TFT) as our primary predictive model due to its unique ability to handle multivariate time-series data while providing interpretability and robust performance in the presence of missing values. Unlike LSTMs or standard attention-based models, the Temporal Fusion Transformer (TFT) stands out for its ability to integrate diverse data types—including static covariates (e.g., gender, race, ethnicity), time-varying clinical inputs (such as wound moisture levels, margins, dressing changes), and even known future inputs—within a unified forecasting framework. This fusion of heterogeneous information is the foundation of its architecture and the reason behind its name.

Wound care data is inherently multifaceted, with both longitudinal variables and stable patient characteristics playing crucial roles in recovery outcomes. TFT's architecture allows it to learn complex temporal dependencies while simultaneously accounting for patient-specific factors, enabling the model to generate personalized and clinically contextualized healing predictions. By incorporating all relevant aspects of patient care, the model is better positioned to provide accurate, interpretable forecasts that can enhance decision-making and guide individualized treatment strategies.

3.3 Procedures to Solve Problem

3.3.1 Data Acquisition and Approval

This project was conducted using de-identified patient data obtained from **Emory University School of Medicine**, following approval from their Institutional Review Board (IRB). The dataset was provided for research use under data sharing agreements and ethical guidelines for human subjects research.

3.3.2 Variable Selection and Dataset Compilation

To ensure clinical relevance, we began by identifying a set of predictor variables referenced in previous wound healing forecasting literature (Table 3.1). These variables were then mapped to fields available within Emory's Electronic Health Record (EHR) system. The result was the creation of four primary datasets, each capturing a unique aspect of patient care:

Dataset 1: Laboratory Tests - Contained time-series records of diagnostic test components and corresponding values.

Dataset 2: Demographics & Care Encounters - Included patient demographics, number of outpatient visits, home health visits, and other encounter types.

Dataset 3: Comorbidities - Comprised ICD-coded diagnoses for each patient, capturing chronic and acute conditions relevant to wound healing (e.g., diabetes, cardiovascular diseases).

Dataset 4: Wound Assessments & Treatment- Included detailed wound-related observations such as wound type (e.g., pressure injury), Braden Scale scores (with subcomponents like moisture, mobility, activity, and sensory perception), wound staging, margins, dressing applied, and treatment details. All records were timestamped, enabling temporal modeling.

Table 3.3.1

Relevant variables identified from the literature

Article	**Relevant Variables Used**
Nguyen et al., 2020	Visual wound features including based on photographic wound assesment tool (PWAT) – size, depth, Type of necrotic tissue type, total amount of necrotic tissue, granulation tissue type, total amount of granulation tissue type, Edges, textual comments from wound experts
Bender et al., 2021	Patient information – Gender, age; wound characteristics – size, epithelialization, callosity, atrophie blanche, pigmentation, edema, dry skin, eczema, rubor, maceration, smell, exudate, visible tendon, visible bone, hypergranulation, fibrin, granulation, necrosis
Paddo et al. 2024	Patient details – race, gender, ethnicity, age, smoking status, BMI, wound measurements, number of wounds.
Weigelt et al., 2022	Biomarkers (proteases, reactants)
Wang et al. 2015	Wound images, colour evaluation models for healing assessment
Xu et al., 2022	Age, history of diabetes, history of stroke, Peripheral vascular disease, mechanical ventilation, Surgical history, Bilirubin.
Alderden et al., 2018	BMI, haemoglobin, creatinine, surgical time, age, glucose, lactate, albumin, Spo2<90%, Hypotension, prealbumin, Riker score, CAM, ASA score, Dopamine, Norepinephrine, epinephrine, fever.
Squiers et al.,	Gender, age, race, BMI, History of diabetes, tobacco use, prior

2022	amputation, history of MI, prior CVS incident, anticoagulant medication.
Hsu et al., 2019	Swelling, granulation tissue presence, tissue necrosis and infection
Guan et al., 2024	To identify delayed wound healing, suggested the use of baseline demographics like gender and age; wound characteristics like – size, depth, infection status; clinical indicators – like pH value, surface temperature.

3.3.3 Variable Selection and Dataset Compilation

Each dataset underwent preliminary cleaning to remove rows with very sparse data, analyze non-null counts and data types for each column. Columns with very high null percentage were then dropped. For all datasets, we grouped and sorted records by the patient identifier and their respective timestamps to ensure chronological consistency in time series modeling. Hence, only the patients whose records were present and mostly complete in all the 4 datasets were chosen (n = 2,072). The primary target for prediction was DAYS_TO_HEAL, defined as the number of days between the first assessment and last wound assessment dates. When duplicate target variables (e.g., DAYS_TO_HEAL_OUTPAT) were found, we selected the version with greater completeness.

3.3.4 Imputation of Missing Values

In this study, we dealt with a multivariate time-series dataset derived from electronic health records (EHR), where missing data is common due to asynchronous measurements, irregular documentation, or omitted entries during clinical workflows. Addressing these missing values is critical because high-quality imputations directly influence the performance and generalizability of downstream models like the Temporal Fusion Transformer (TFT).

We explored several imputation techniques, ultimately selecting a hybrid approach that balances statistical pre-processing and machine learning-based inference. To begin with, we chose imputation method based on the variable and data type. Static covariates were filled using simple methods like forward and backward filling because they do not tend to change overtime in most cases. While forward and backward fills are computationally inexpensive and maintain temporal continuity, they tend to propagate static values and fail to capture evolving patient trajectories—especially problematic when clinical features exhibit variation over time (Kazijevs & Samad, 2023). Hence, for imputing clinical time varying features we opted for more context-aware methods.

For numerical time-varying variables, we implemented the SMILES (Supervised Machine Learning for Imputing Missing Values in Time Series) approach (Zhang et al., 2020). This technique combines unsupervised pre-filling (forward and backward fill) with supervised learning using XGBoost to capture both longitudinal (temporal) and cross-sectional (inter-variable) patterns. SMILES has demonstrated superior performance in healthcare datasets, especially in scenarios where missingness is neither completely random nor uniformly distributed across variables (Kazijevs & Samad, 2023). In our setup, we applied SMILES patient-wise for time-dependent variables such as Braden Scale Score and Mobility measures, ensuring each prediction was sensitive to both prior and subsequent observations.

For categorical variables, we evaluated MICE (Multivariate Imputation by Chained Equations) with Decision Trees and Random Forests. However, due to the irregularity and volume of missingness, especially at the start of some sequences, we transitioned to a categorical variant of SMILES. We adapted the SMILES framework to work with lag and lead encodings for categorical columns, training XGBoost classifiers using contextual windows around the missing observations. This approach proved effective, particularly for variables like “Closure” and “Drainage Amount,” where the context of preceding and succeeding values provided meaningful clues for accurate prediction.

Although deep learning-based imputation methods like BRITS (Bidirectional RNN Imputation for Time Series) are known for their capacity to model bidirectional temporal dependencies (Kazijevs & Samad, 2023), It was not to used due to its high computational cost and difficulty in handling categorical variables in our setting. The use of MICE-DA was investigated, but it often introduced artifacts like "MISSING" labels in sequences where contextual inference was possible and needed.

3.3.4 Model Setup and Training:

One of the key advantages of the Temporal Fusion Transformer (TFT) is its ability to process data at the level of individual time series groups, in our case, per patient. This allows the model to learn personalized temporal patterns, adapting its attention and gating mechanisms to the unique trajectory of each individual. Unlike traditional sequence models that may aggregate across populations, TFT inherently supports personalized predictions by conditioning on patient-specific sequences and static characteristics. TFT integrates a rich architecture combining gated residual networks (GRNs), recurrent layers (LSTMs), and interpretable attention mechanisms to learn both short- and long-term dependencies, while enabling feature selection and time-aware learning (Lim et al., 2021). We implemented a Temporal Fusion Transformer (TFT) using PyTorch Lightning and the PyTorch Forecasting library. Our pipeline incorporated both manual configuration and automated hyperparameter tuning using Optuna.

In our initial experiments, we included patients with highly variable sequence lengths, ranging from short to long trajectories. Some of the shorter sequences were padded using forward-fill methods to match the expected input length. However, this padding introduced substantial noise and static redundancy into the model, which negatively impacted its ability to generalize. To mitigate this issue, we filtered the dataset to retain only patients with exactly or nearly 49 time steps, resulting in a more uniform temporal structure across samples. This improved the consistency of temporal dependencies and eliminated the need for extensive padding. As a result, the model learned more reliable patterns and showed significant improvements in prediction accuracy and training stability. With this refined dataset, we split the patients into training (80%), validation (10%), and test (10%) sets based on the patient identifier, ensuring that each patient's sequence appeared in only one partition. We then constructed TimeSeriesDataSet objects using the PyTorch Forecasting framework. We defined a custom LightningModule class (TFTLightningModule) that wraps the TFT model with configurable hyperparameters such as learning_rate, hidden_size, attention_head_size, and dropout. The model was trained to minimize Quantile Loss, suitable for robust regression under uncertainty.

For hyperparameter optimization, we used Optuna, running 10 trials to search over a defined hyperparameter space. Once the best trial was identified, we retrained the model using the optimal parameters. Final training was conducted using a structured pipeline with Early stopping (patience = 7), ModelCheckpoint was utilized to save the best model based on evaluation loss – this model could then be transferred to the Streamlit web application with ease, learning rate monitor and CSVlogger were used for reproducibility and tracking. Training ran for 30 epochs (minimum 5) on CPU, with batch-wise logging and validation monitoring.

3.3.5 Building the Streamlit web application:

The development of our application centered on creating an intuitive interface for uploading and parsing Continuity of Care Documents (CCDs), leveraging the capabilities of BlueButton.js (Amida Technology Solutions, 2014) and Streamlit (Streamlit Inc., 2023). BlueButton.js is an open-source JavaScript library designed to simplify the parsing of complex health data formats like C-CDA into JSON, facilitating easier access and manipulation of patient health records . We implemented a Node.js backend using Express.js to handle file uploads and utilize BlueButton.js for parsing the CCDs. This backend exposes a RESTful API that the frontend can interact with. For the frontend, we chose Streamlit, a Python-based framework that allows for rapid development of interactive web applications without requiring extensive frontend development experience. Streamlit has been effectively used in healthcare applications for tasks such as building analytics platforms for clinics and developing pathology detection tools . In our application, once a user uploads a CCD file through the Streamlit interface, the file is sent to the backend API, where BlueButton.js parses it, and the resulting structured data is returned and displayed in the frontend. This architecture not only streamlines the process of accessing and interpreting patient data but also lays the groundwork for integrating predictive models in the future.

CHAPTER FOUR: FINAL PROJECT DEVELOPED

Developed Project (Outcomes)

The final project culminated in the successful development of a deep learning-based clinical prediction system using the Temporal Fusion Transformer (TFT) model. The goal was to forecast wound healing time for patients using multi-modal time series data, incorporating both structured EHR records and behavioral indicators. Our model utilized past 40 timesteps of hourly data to predict the future 8 timesteps which gave adequate information for the model to learn the patterns in the data. This modelling was patient specific and generated days to heal expected per patient based on the past hourly data.

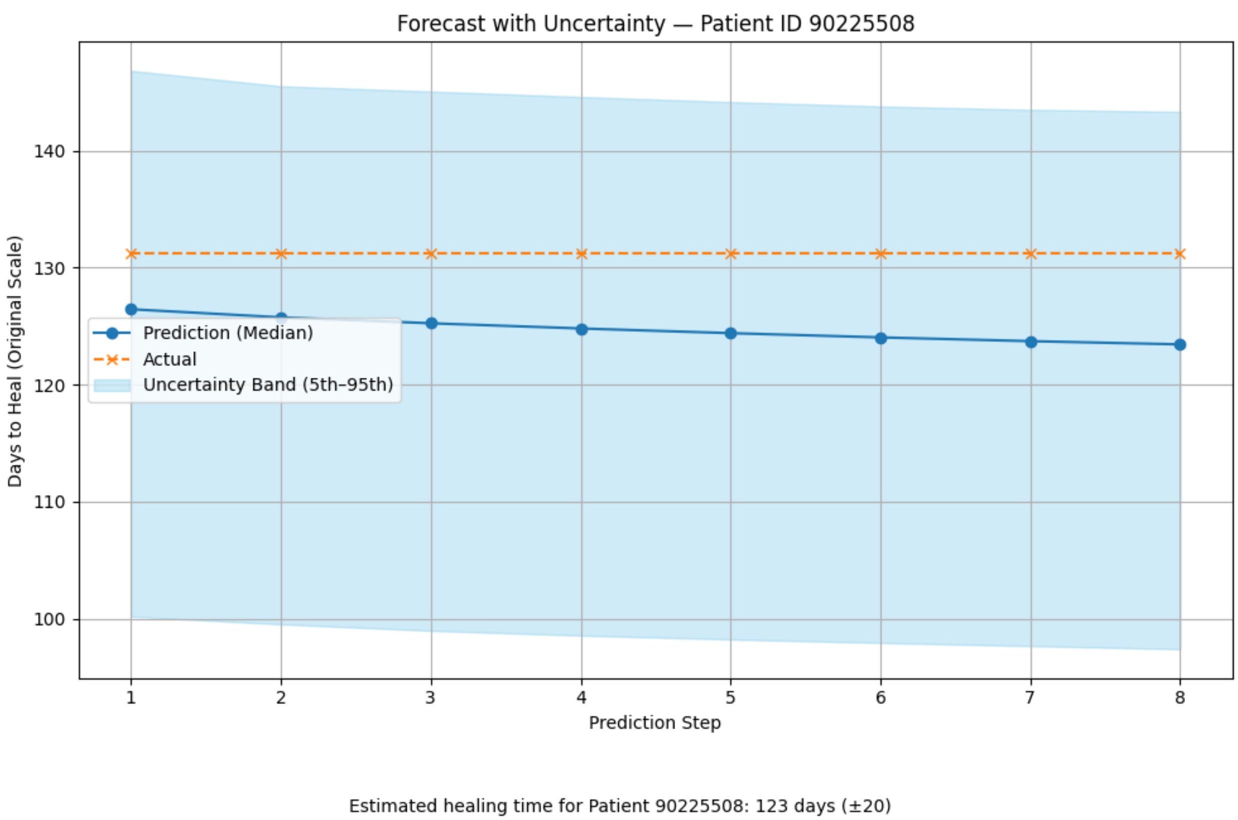

*Figure 4.1.*Estimated healing time for a patient predicted by the model along with uncertainity.

Visualizing and Interpreting Results

Fan charts and band plots (e.g., for Patient ID 90225508) were used to illustrate both the median predicted trajectory and the surrounding confidence intervals over 8 future time steps. These plots visually conveyed how confident the model was in its forecast, how uncertainty changed over time, and how well predictions matched actual recorded outcomes.

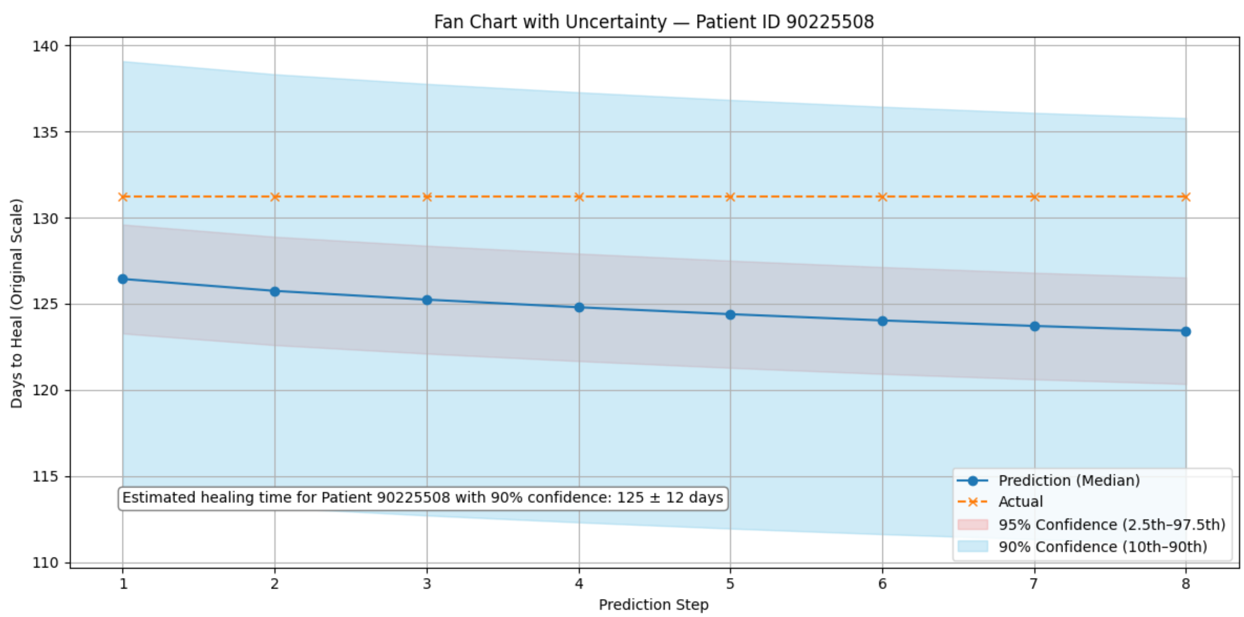

Figure 4.2. Estimated healing time for a patient predicted by the model with 90% and 95% confidence intervals.

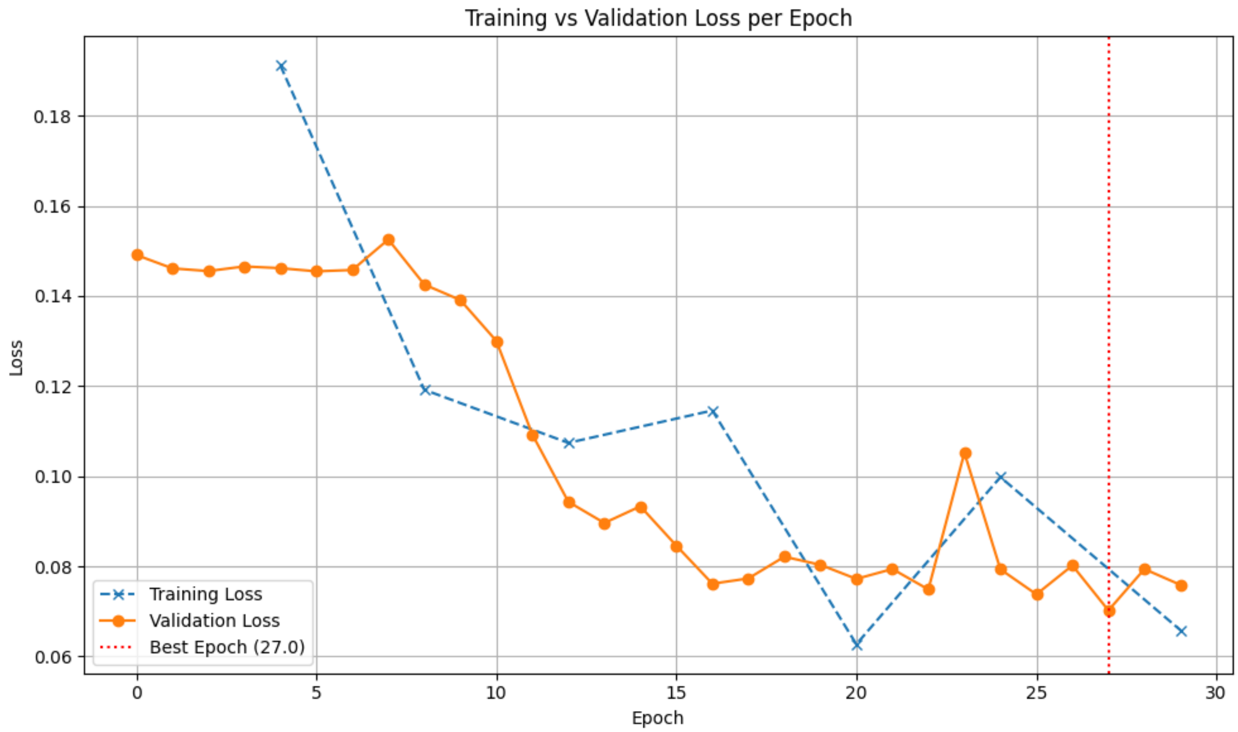

Figure 4.3 Training loss and validation loss of the Temporal Fusion Transformer (TFT) model across 30 epochs, showing best one to be the 27^{th} .

Both losses show a general downward trend, indicating that the model effectively learned patterns in the data. The gap between training and validation loss remains moderate, suggesting the model did not overfit significantly. The model was trained with early stopping enabled, and the best performance was achieved before the maximum epoch limit, saving computational resources while preventing overfitting.

Streamlit Application

To Parse a CCD/C-CDA document using the streamlit app the following steps illustrated below could be followed.

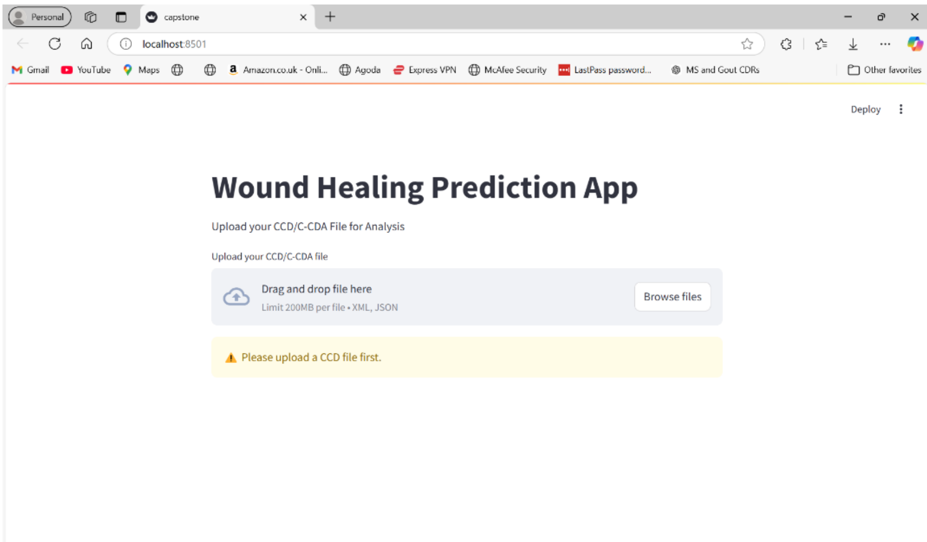

Figure 4.4 Streamlit Frontend - Upload Interface, the user interface developed using Streamlit allows users to upload CCD or C-CDA files via drag-and-drop or file browser. A prompt notifies users if no file has been uploaded.

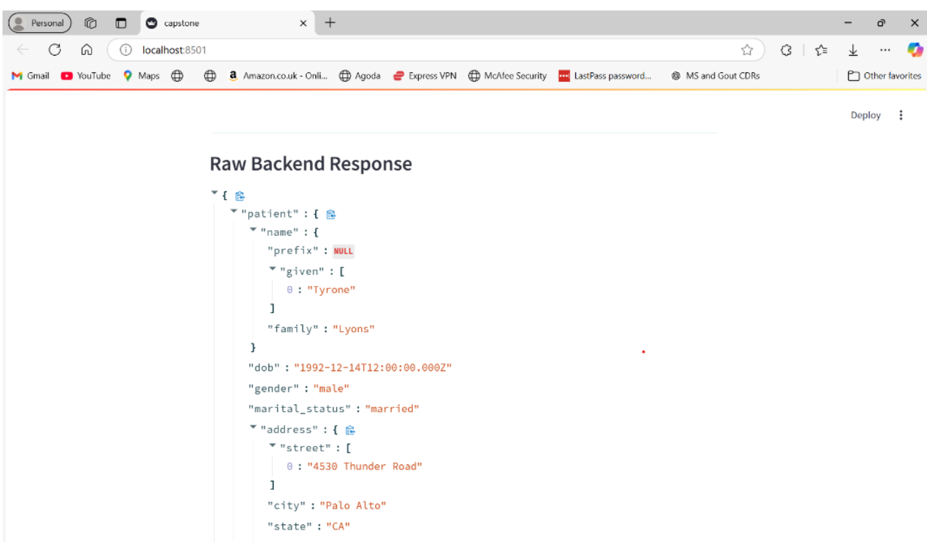

Figure 4.5 Once a file is uploaded, the Streamlit app sends it to a Node.js backend running BlueButton.js, which parses the file and returns structured JSON data. This figure shows the raw response including nested patient demographics.

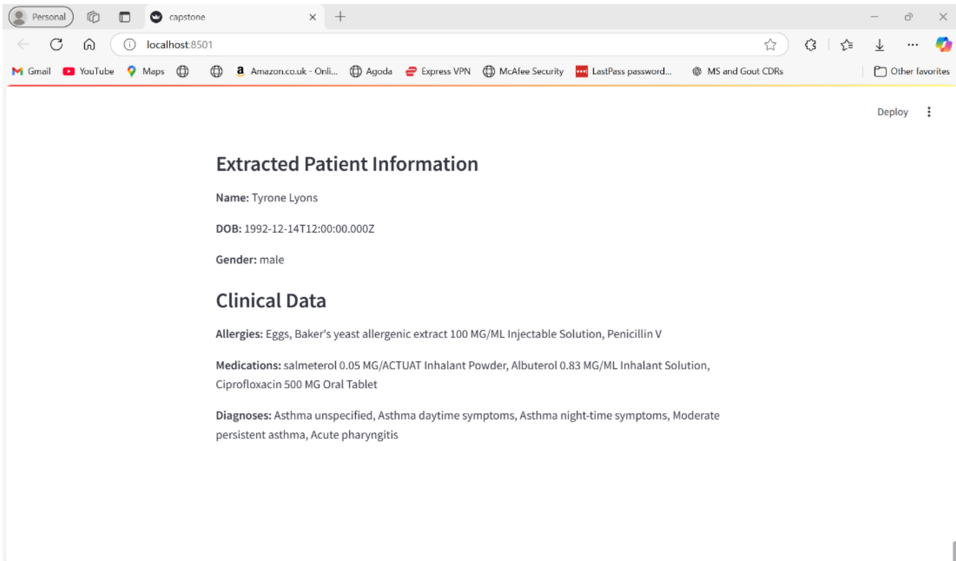

Figure 4.6 Final Clinical Data Display - Extracted View displays in human-readable format under "Extracted Patient Information" and "Clinical Data" sections which is customizable to need.

Suggested Evaluation Method

To responsibly evaluate the performance of our Temporal Fusion Transformer (TFT) model in predicting Days to heal, we employed a comprehensive strategy that assessed both point prediction accuracy and uncertainty estimation. This dual-focus evaluation is especially critical in clinical settings, where understanding confidence in model outputs can significantly impact decision-making.

We used the following metrics to quantify how closely the model's forecasts matched actual patient outcomes:

- **Mean Absolute Error (MAE)**: Measures the average magnitude of errors. For our model, the MAE was approximately 12.91 days.

- **Root Mean Squared Error (RMSE)**: Provides higher penalty for large deviations. Our model yielded an RMSE of 33.53 days.
- **Quantile Loss (q=0.5)**: Suitable for probabilistic forecasts and robust to outliers, the median-based quantile loss was 6.45.

These metrics were computed using the validation dataset with known ground truth and were averaged across multiple patients and prediction steps**.**

Quantifying Uncertainty in Predictions

Epistemic Uncertainty via Monte Carlo (MC) Dropout: To estimate epistemic uncertainty (model uncertainty), we employed MC Dropout, wherein dropout is enabled during inference and predictions are sampled multiple times (n = 30). This yields a distribution of forecasts for each patient at each prediction step. The spread of this distribution (e.g., between the 5th and 95th percentiles) represents the model's confidence, or lack thereof, in its prediction. This uncertainty results from limited training data or unfamiliar patterns. It can be reduced by improving model exposure to diverse cases thus, repeating predictions in this way helps quantify how much model weights vary in response to small input fluctuations, highlighting uncertainty from under-represented scenarios.

Aleatoric Uncertainty arises from intrinsic variability in clinical data, such as measurement noise or undocumented patient behaviour. It cannot be reduced by simply adding more data. The prediction bands generated from MC Dropout also incorporate data variability.

We computed aleatoric uncertainty as the width between the upper and lower percentiles (e.g., 90% or 95% intervals). A wider band suggests greater uncertainty about the healing trajectory for that patient, for each patient, we calculated the mean aleatoric uncertainty across all predicted days. On average, the model had a mean aleatoric uncertainty of ~67.6 days, which provides an important window of expected clinical variability in healing estimates.

To identify high-risk or ambiguous predictions, we generated a bar chart of the top 30 patients by aleatoric uncertainty. This helped surface potential edge cases, inconsistencies, or data gaps—providing both model interpretability and clinical insight.

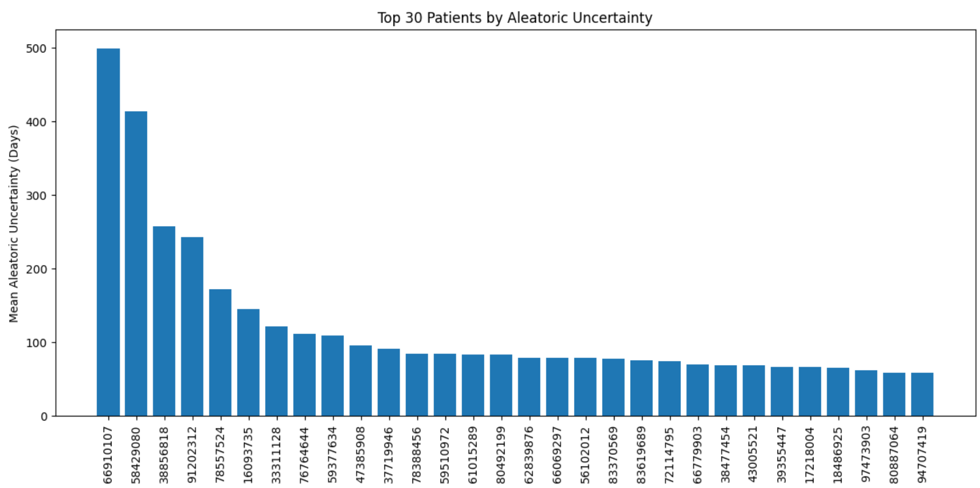

*Figure 4.7.*Histogram showing top 30 patients by Aleatoric Uncertainty

CHAPTER FIVE: DISCUSSION

5.1 Explanation of Outcomes

The outcomes of this project demonstrate the feasibility and effectiveness of using the TFT to forecast wound healing times based on multivariate, patient-specific EHR data. The model's performance—evidenced by a mean absolute error (MAE) of 12.91 days and a root mean squared error (RMSE) of 33.53 days suggests a good predictive capability within clinically acceptable margins. The quantile loss (q=0.5) of 6.45 further supports the model's robustness in producing reliable median forecasts.

Visualization techniques such as fan charts and uncertainty bands provided interpretable outputs for clinicians, highlighting not only predicted healing trajectories but also the confidence intervals around those predictions, this integration of epistemic and aleatoric uncertainty provides a valuable layer of transparency.

The development of the Streamlit application further underscores the project's emphasis on usability and real-time clinical decision support. By parsing CCD documents using BlueButton.js, this project can be further developed to integrate the model with the application where the clinical data can be extracted, passed on to the model and then present model outputs in an interactive dashboard this patient-centric platform can be readily adopted in clinical workflows due to its compatibility with CCD.

5.2 Implications of Results

The model's ability to generate individualized wound healing forecasts with a mean absolute error of ~12.9 days highlights its practical relevance in real-world wound care. Similar to findings from Fang et al. (2022) and Zhang et al. (2024), our system effectively models temporal health data for personalized outcome prediction. These insights could support clinicians in anticipating delayed healing and planning timely interventions, ultimately improving patient outcomes. The integration of multivariate patient data makes the model more reliable for the clinician and also reflects the shift toward precision wound care, as emphasized by Velickovic et al. (2023) and Andrelean et al. (2024). This tailored approach enables dynamic care planning based on patient-specific variables rather than static clinical guidelines.

The uncertainty quantification framework—using Monte Carlo dropout and prediction intervals—can be valuable in clinical research, where understanding confidence in forecasts is crucial for patient selection and intervention planning. Hence, this model could also be used to better research outcomes. By incorporating patient-specific uncertainty bands and using a minimal user friendly interface like Streamlit, the system adheres to principles of explainable AI which emphasize the importance of interpretability and clinician trust in the adoption of AI in healthcare (Kim et al., 2023; Weigelt et al., 2022).

5.3 Summary of Discussion

This project successfully designed, implemented, and evaluated a personalized wound healing prediction system using the Temporal Fusion Transformer (TFT). Through a comprehensive pipeline that included multivariate EHR data processing, imputation, deep learning, uncertainty quantification. The project demonstrated how advanced analytics can support personalized, interpretable, and actionable insights in wound care. The integration of clinical data science and user-centered design resulted in a system that not only forecasts healing time but also empowers both clinicians and patients with data-driven tools for more informed decision-making. While further validation and system integration remain future goals, this work lays a strong foundation for the use of explainable AI in personalized wound management.

CHAPTER SIX: CONCLUSION

Limitations

While the project successfully demonstrated the feasibility of predicting wound healing time using the Temporal Fusion Transformer (TFT) and deploying the model through a Streamlit application, several limitations were encountered. A significant portion of the original dataset had to be excluded due to incomplete or irregular time series. Although the initial dataset was large, only a relatively small and cleaner subset of patient data with sufficient and consistent observation was used for model training. This limits the generalizability of the results. Moreover, The model was trained and evaluated using internal cross-validation on a single-institution dataset. No external or multi-site validation was conducted. This restriction limits the ability to assess the model's stability and reproducibility in different clinical settings or geographic regions.

Despite using forward/backward fill and iterative imputation for missing values, the data remained sparse. More sophisticated imputation techniques—such as generative models, temporal attention-based filling, or graph neural network imputers—could further enhance performance. Since sparse data is a known characteristic of biomedical datasets, addressing this challenge robustly is essential for the model's long-term utility(Kazijevs & Samad, 2023).

Although a prototype Streamlit app was successfully developed and can parse CCD files for model input, full pipeline integration—where real-time predictions are produced from uploaded CCDs—could not be completed due to the unavailability of production-grade CCDs and time constraints. This limited the project's demonstration of real-time clinical usability. While BlueButton.js and CCD-based structuring were adopted for future compatibility, full integration with EHR systems (e.g., via SMART on FHIR) was outside the project scope. Achieving this would be crucial for scalable deployment in real-world clinical environments.

Summary

This project laid the groundwork for a patient-specific wound healing forecasting system by combining clinical time series data, a deep learning model (TFT), uncertainty estimation, and a clinician-friendly web interface. The system demonstrated the potential to personalize care trajectories, provide actionable insights, and ultimately support precision wound management. Looking ahead, several avenues remain open for development like incorporating more complete and multi-institutional datasets will help improve model generalizability and robustness. In conclusion, while the system is not yet production-ready, this project has proven the viability and promise of personalized, explainable AI in wound care. With further refinement, the model and accompanying application could become valuable tools in both acute and chronic wound management settings.

REFERENCES

Amida Technology Solutions. (2014). *BlueButton.js* [Software]. GitHub. https://github.com/amida-tech/blue-button

Andrelean, A., Balta, D., Neamtu, C., et al. (2024). Personalized and predictive strategies for diabetic foot ulcer prevention and therapeutic management. *Medicine and Pharmacy Reports, 97*(4), 419–428. https://doi.org/10.15386/mpr-2818

Bender, C., Cichosz, S. L., Pape-Haugaard, L., Hartun Jensen, M., Bermark, S., Laursen, A. C., & Hejlesen, O. (2021). Assessment of simple bedside wound characteristics for a prediction model for diabetic foot ulcer outcomes. *Journal of diabetes science and technology*, *15*(5), 1161-1167.

Boukovalas, S., Aliano, K. A., Phillips, L. G., & Norbury, W. B. (2023). Wound healing. In C. Townsend, R. Beauchamp, B. Evers, & K. Mattox (Eds.), *Sabiston Textbook of Surgery* (21st ed., pp. 119–149). Elsevier.

Dabas M, Schwartz D, Beeckman D, Gefen A. Application of Artificial Intelligence Methodologies to Chronic Wound Care and Management: A Scoping Review. Adv Wound Care (New Rochelle). 2023 Apr;12(4):205-240. doi: 10.1089/wound.2021.0144. Epub 2022 Jun 23. PMID: 35438547

Fabrizzio, G. C., Erdmann, A. L., & Oliveira, L. M. D. (2023). Web App for prediction of hospitalisation in Intensive Care Unit by covid-19. *Revista Brasileira de Enfermagem*, *76*(6), e20220740.

Fang, X., Wang, Y., Maeda, R., et al. (2022). Early prediction of pressure injury with Long Short-Term Memory networks. *Sensors and Materials, 34*(7), 2759-2769. https://doi.org/10.18494/SAM3868

Ganesan, O., Morris, M. X., Guo, L., & Orgill, D. (2024). A review of artificial intelligence in wound care. *Artificial Intelligence Surgery, 4*, 364–375. https://doi.org/10.20517/ais.2024.68

Guan, H., Wang, Y., Niu, P., et al. (2024). The role of machine learning in advancing diabetic foot: A review. *Frontiers in Endocrinology, 15*, Article 1325434. https://doi.org/10.3389/fendo.2024.1325434

Kadam, A., Shrivastava, A., Pawar, S. K., Patil, V. H., Michaelson, J., & Singh, A. (2023, September). Calories Burned Prediction Using Machine Learning. In *2023 6th International Conference on Contemporary Computing and Informatics (IC3I)* (Vol. 6, pp. 1712-1717). IEEE.

Kazijevs, M., & Samad, M.D. (2023). *Deep imputation of missing values in time series health data: A review with benchmarking*. Journal of Biomedical Informatics, 144, 104440. https://doi.org/10.1016/j.jbi.2023.104440

Kim J, Lee C, Choi S, Sung DI, Seo J, Na Lee Y, Hee Lee J, Jin Han E, Young Kim A, Suk Park H, Jeong Jung H, Hoon Kim J, Hee Lee J. Augmented Decision-Making in wound Care: Evaluating the clinical utility of a Deep-Learning model for pressure injury staging. Int J Med Inform. 2023 Dec;180:105266. doi: 10.1016/j.ijmedinf.2023.105266. Epub 2023 Oct 17. PMID: 37866277.

Lim, B., Arık, S. Ö., Loeff, N., & Pfister, T. (2021). Temporal fusion transformers for interpretable multi-horizon time series forecasting. *International Journal of Forecasting*, *37*(4), 1748-1764.

Mittal, C., Debnath, S., & Prabakeran, S. (2025). Customized treatment plan using GenAI for cardiological diseases. In *Challenges in Information, Communication and Computing Technology* (pp. 87-91). CRC Press.

Nguyen, H., Agua, E., Tulu, B., et al. (2020). Machine learning models for synthesizing actionable care decisions on lower extremity wounds. *Smart Health, 18*(4), 100139. https://doi.org/10.1016/j.smhl.2020.100139

Pourbehzadi, M. (2024). Enhancing Diabetes Self-Management Using Agentic AI A Streamlit Application Approach.

Retrieved from: https://www-clinicalkey-com.proxy.ulib.uits.iu.edu/#!/content/book/3-s2.0-

B9780323640626000062?scrollTo=%23hl0001546

Streamlit Inc. (2023). *Streamlit: The fastest way to build and share data apps*. https://streamlit.io

Veličković, V. M., Spelman, T., Clark, M., Probst, S., Armstrong, D. G., & Steyerberg, E. (2023). Individualized risk prediction for improved chronic wound management. *Advances in wound care*, *12*(7), 387-398.

Wang, L., Pedersen, P. C., Strong, D. M., Tulu, B., Agu, E., & Ignotz, R. (2015). Smartphone-based wound assessment system for patients with diabetes. *IEEE Transactions on Biomedical Engineering, 62*(2), 477–488. https://doi.org/10.1109/TBME.2014.2358632

Weigelt, M. A., Lev-Tov, H. A., Tomic-Canic, M., et al. (2022). Advanced wound diagnostics: Toward transforming wound care into precision medicine. *Advances in Wound Care, 11*(6), 330–359. https://doi.org/10.1089/wound.2020.1319.

Wu, N., Green, B., Ben, X., et al. (2020). Deep Transformer models for time series forecasting: The influenza prevalence case. *ArXiv preprint*. https://doi.org/10.48550/arXiv.2001.08317

Xu J, Chen D, Deng X, Pan X, Chen Y, Zhuang X, Sun C. Development and validation of a machine learning algorithm-based risk prediction model of pressure injury in the intensive care unit. Int Wound J. 2022 Nov;19(7):1637-1649. doi: 10.1111/iwj.13764.

Epub 2022 Jan 25. PMID: 35077000; PMCID: PMC9615270.

Zeng, A., Chen, M., Zhang, L., & Xu, Q. (2023). Are transformers effective for time series forecasting? *Proceedings of the Thirty-Seventh AAAI Conference on Artificial Intelligence*, 11121–11130. https://doi.org/10.1609/aaai.v37.11121

Zhang, X., Yan, C., Gao, C., Malin, B.A., & Chen, Y. (2020). *Predicting Missing Values in Medical Data Via XGBoost Regression*. Journal of Healthcare Informatics Research, 4, 383–394. https://doi.org/10.1007/s41666-020-00077-1

Zhang, Y., Wu, R., Dascalu, S.M. *et al.* A novel extreme adaptive GRU for multivariate time series forecasting. *Sci Rep* **14**, 2991 (2024).