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**INTEGRATING MACHINE LEARNING INTO DHIS2 TO PREDICT MULTIDRUG
RESISTANT TUBERCULOSIS: A CASE OF THE DHIS2'S ELECTRONIC CASE-
BASED SURVEILLANCE SYSTEM**

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DECLARATION

I, Mark Outeke, affirm that the information provided in this dissertation is entirely original and has never been submitted to any other institution for consideration, publication, or any other purpose. I hereby submit this proposal to the Makerere University School of Public Health and Higher Degrees Research and Ethics Committee as part of the requirements for obtaining a Master of Health Informatics degree from Makerere University.

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LIST OF ABBREVIATIONS

MDR_TB	Multidrug-resistant tuberculosis
1D CNN	One-dimensional Convolutional Neural Networks
AFB	Acid-Fast Bacilli
AI	Artificial Intelligence
AIDs	Acquired Immunodeficiency Syndrome
ANN	Artificial neural networks
API	Application Programming Interface
AUC	The area under the curve
CNN	Convolution Neural Networks
CSV	Comma-Separated Values
DHIS2	District Health Information Software 2
DOT	Directly Observed Therapy
DSR	Design Science Research
DS-TB	Drug-susceptible tuberculosis
E.H.R	Electronic Health Record
eCBSS	electronic Case-Based Surveillance System
GDPR	General Data Protection Regulation
GIS	Geographical Information System
HIPAA	Health Insurance Portability and Accountability Act
HISP	Health Information Support Program
HIV	human immunodeficiency virus

iHRIS,	Integrated Human Resources Information System
IIIE	Industrial Information Integration Engineering
IRB	Internal review board
LASSO	least absolute shrinking and separation operator
LPHS	Local Partner Health Services
LMICs	Low- and middle-income countries
LMIS	Laboratory Management Information System
ML	Machine Learning
MOH	Ministry of Health, Uganda
MTB	Mycobacterium Tuberculosis
NTLP	National Tuberculosis and Leprosy Control Program
OPD	Outpatient department
PCA	Principal Component Analysis
PCs	Personal Computers
PDF	Portable Document Format
PII	Personal Identifiable Information
PPV	positive predictive value
RF	Random Forest
RIF	Rifampin
SDG	Sustainable Development Goal
SVM	Support Vector Machine
TB	Tuberculosis

TSR	Treatment Success Rate
USAID	United States Agency for International Development
WHO	World Health Organization

OPERATIONAL DEFINITIONS

Multi-drug resistant tuberculosis (MDR-TB) is defined as a disease caused by strains of *Mycobacterium tuberculosis* that are resistant to treatment with isoniazid and rifampicin(Nathanson et al.). This disease has one of the world's highest morbidity and mortality rates.

The Electronic Case-Based Surveillance system (eCBSS) is a digital, continuous, and systematic collection, analysis, and reporting of data related to TB infection and TB disease by Uganda's National Tuberculosis and Leprosy Control Program (NTLP) (World Health Organization, 2021). The National Tuberculosis and Leprosy Program of Uganda, under the National Disease Control Program of the Ministry of Health in Uganda, is mandated with functions that establish country-wide quality diagnosis and treatment services for TB and Leprosy as well as coordinate the implementation of TB and leprosy control activities.

TB case notification is the detection, identification, and registration of a TB case into the NLTP's eCBSS.

MDR-TB status of the patient is a confirmation of sensitivity to at least isoniazid and rifampin through a test. These tests can be culture-based or molecular (like the Xpert MTB/RIF test)(WHO 2018).

Notification is detecting a new or relapsed TB case in the NTLP through the DHIS2's eCBS System.

Tracking is the process of following a patient and their changing medical status from notification into the eCBS System, lab studies, imaging, and other diagnostic and therapeutic interventions up to the treatment outcome.

Dependent variable – MDR-TB status (2-level categorical variable of yes and no expressed as values 0 and 1)

Independent variables – Age, sex, being in contact, having smoked, receiving previous TB treatment, receiving improper treatment, having interruptions in first-line medication treatment, losing weight, hemoptysis, as well as experiencing adverse side effects of the different regimens of drugs.

ABSTRACT

Multidrug-resistant tuberculosis (MDR-TB) remains a critical public health challenge in Uganda, where cases continue to rise. The existing electronic Case-Based Surveillance System (eCBSS) tracks patients and treatment adherence for Drug-Susceptible TB (DS-TB) but lacks integration with machine learning (ML) for predictive analytics and data-driven decision-making. This study developed and tested an ML-powered web application integrated into DHIS2's eCBSS to predict the likelihood of MDR-TB development among DS-TB patients and identify geographic hotspots.

Objective: The study aimed to gather user requirements, develop, and validate an ML-integrated analytical dashboard within DHIS2's eCBSS to support healthcare workers in predicting MDR-TB risk and visualizing hotspots through a GIS module.

Methodology: A Design Science Research approach guided the development, using a User-Centered Design framework. In-depth interviews were conducted with healthcare workers from three high-volume TB treatment facilities in Uganda's Central Region, all using eCBSS. Requirements informed the development of a one-dimensional deep neural network (1DNN) in Python and a web interface built with JavaScript and Node.js for local DHIS2 deployment. The ML model was validated using accuracy, AUC, and confusion matrices, while usability testing assessed ease of use and satisfaction.

Results: Two major themes emerged: user requirements (functional and non-functional) and implementation needs. Functional needs included real-time alerts, risk scoring, and adherence tracking, while non-functional needs emphasized scalability, security, and usability. The 1DNN achieved 92% accuracy and an AUC of 0.96, demonstrating strong predictive performance. The GIS module effectively visualized MDR-TB hotspots, supporting targeted interventions. Usability testing showed high satisfaction (mean scores 4.65–4.87/5), though participants recommended improved search, filtering, and clearer error handling.

Conclusion: Integrating ML and GIS into DHIS2's eCBSS significantly enhanced predictive capacity, spatial analysis, and resource allocation, demonstrating the potential of AI-driven tools to strengthen MDR-TB management in Uganda.

CHAPTER ONE

INTRODUCTION AND BACKGROUND

1.0 Introduction

With high rates of morbidity and mortality, multidrug-resistant tuberculosis (MDR-TB) continues to be a serious global public health concern, especially in low- and middle-income nations like Uganda. When *Mycobacterium tuberculosis* strains develop resistance to primary anti-TB medications, MDR-TB develops, making treatment more difficult and raising the possibility of transmission and unfavorable consequences (Mujuni et al. 2024). Even with improvements in diagnostic tools, MDR-TB cases are still not promptly identified or clinically managed, which leads to treatment failures and continued disease spread (Jackson Dumo Lodiong, Izudi, and Amanee Elias Lumori 2024; White et al. 2022). To track and report TB cases and treatment outcomes, Uganda's Ministry of Health, in collaboration with the National Tuberculosis and Leprosy Control Program (NTLP), has integrated the Electronic Case-Based Surveillance System (eCBSS) into the District Health Information Software 2 (DHIS2) platform (Chikwado 2023). This system currently lacks advanced predictive analytics that could enable early detection of patients at risk for developing MDR-TB and support timely intervention.

The implementation of machine learning (ML) into health information systems has the potential to significantly improve tuberculosis (TB) surveillance through enhanced data utilization for predictive analytics and decision-making support. Machine learning algorithms analyze complex datasets, such as clinical, demographic, and geographic information, to identify patterns that indicate the risk of MDR-TB (Althomsons et al. 2022; Chikwado 2023; Gichuhi et al. 2023). Despite these opportunities, challenges including incomplete data capture, limited technical capacity, and system interoperability have impeded the implementation of ML-powered solutions within the current TB surveillance frameworks in Uganda (Mujuni et al. 2024). This study aimed to fill existing gaps by creating, integrating, and validating a machine learning-based web application within the DHIS2 eCBSS to forecast MDR-TB risk in drug-susceptible TB patients. The application incorporated a Geographic Information System (GIS) module for visualizing MDR-TB hotspots, thereby facilitating targeted patient's personalized interventions.

The research utilized a Design Science Research methodology alongside user-centered design principles to identify healthcare worker requirements, develop a machine learning model using a deep neural network, and construct a React-based dashboard integrated with DHIS2's eCBSS. Model development data were obtained from event-level patient records from the deployed eCBSS in Uganda. The evaluation of model performance was conducted rigorously, revealing high accuracy and predictive validity. Usability testing involving healthcare workers demonstrated the application's effectiveness in improving TB case management and informing resource allocation decisions. This study demonstrated the practicality and advantages of integrating machine learning technologies into national health information systems to enhance MDR-TB surveillance, guide policy decisions, and ultimately improve patient outcomes in Uganda.

1.1 Background.

Multidrug-resistant tuberculosis (MDR-TB) is a significant issue worldwide. The diagnostic ability of this problem has outpaced clinical management, creating questions about the quality of care offered by healthcare givers to TB patients. A significant 3.1% increase in these cases from 450,000 in 2020 to 437,000 in 2021 – a period of the COVID-19 pandemic – was noticed by the World Health Organization and documented in their global tuberculosis report (Global Tuberculosis Report WHO 2020). India, Russia, and Pakistan contributed the highest number, with India contributing 26% of global cases, the Russian Federation contributing 8.5%, and Pakistan contributing 7.9% MDR-TB cases, according to the same report (Global Tuberculosis Report WHO 2020). Africa's contribution to the total burden of MDR-TB cases is not clear from recent sources; however, the WHO estimated that by 2016, there were 451,551 cases with resistance to rifampicin. The WHO – in its 2022 Global Tuberculosis report – states that out of the nearly seven and half million (7,465,430) cases of TB notified, four hundred and ten thousand (410,000) cases were projected to have MDR-TB and of which only one hundred seventy five thousand (175,650) were diagnosed and began treatment (WHO Global Tuberculosis Report, 2022). A significant number was missed for several reasons, such as limited access to rapid diagnostics, weak health systems, poor integration between public and private sectors, patient-related barriers such as stigma and poverty, inadequate surveillance systems, and delays in treatment initiation (Deshmukh et al. 2015; Falzon et al. 2014; Hoang et al. 2015; Martin et al. 2021; Mpagama et al. 2019).

Healthcare providers can track these missed MDR-TB cases through electronic surveillance systems and contribute to the global and national MDR-TB prevalence surveillance (Calderwood et al. 2010). These global trends highlight the urgency of understanding Africa's contribution to the MDR-TB burden, where surveillance gaps remain pronounced.

In Africa, it was reported that Nigeria and South Africa contributed to 48% of the MDR-TB burden in Africa, and that the region with the highest burden of multidrug-resistant tuberculosis (MDR-TB) was not explicitly mentioned (Ismail et al. n.d.). This gap exists due to the absence of MDR-TB-specific surveys in Africa, as highlighted in a study by Amor et al. (Ben Amor et al. n.d.) published in 2008 that emphasized the necessity for drug resistance surveys in Africa to assess MDR-TB rates in countries without such surveys. According to Amor et al., the underreported threat of multidrug-resistant tuberculosis in Africa underscores the critical need for drug resistance surveys to assess MDR-TB rates in countries without these surveys, indicating that National TB Programs (NTPs) in Africa may not be performing better than their counterparts in other regions. The limited regional surveillance capacity and outdated reporting systems in Africa, particularly in East Africa, further illustrate the magnitude of the challenge in countries like Uganda

Publications in 2022 found that there were insufficient reports on the pooled prevalence of MDR-TB in East Africa, which could be due to poor laboratory facilities, outdated databases, and poor surveillance mechanisms and reporting procedures (Molla, Reta, and Ayene 2022a). However, for Uganda, the WHO reports that over 1400 cases of MDR-TB were notified – a 3 per 100,000 incidence (WHO Global Tuberculosis Report 2022). The same report mentions that only 761 cases were Laboratory-confirmed, and yet only 414 were started on second line treatment, leaving many cases undiagnosed. This persistent diagnostic and treatment gap underscores the importance of strengthening Uganda's surveillance and tracking systems to ensure timely detection and management of MDR-TB cases.

Failure to diagnose these missed MDR-TB cases not only leads to prolonged infectiousness and continued community transmissions but also contributes to increased morbidity and mortality, delays in treatment, amplification of drug resistance to extensive states and higher economic burden since its treatment expensive for both patients and the health systems (Dheda et al. 2017; Molla, Reta, and Ayene 2022b). In addition, undiagnosed MDR-TB cases undermine national TB control programs by skewing surveillance data, hampering resource allocation, and impeding the

achievement of global TB elimination targets (Barteka et al. 2025; Tiberi et al. 2021). These implications underscore the critical need to strengthen diagnostic capacity, ensure timely initiation of effective treatment, and integrate predictive technologies that can support early detection and patient tracking within Uganda's surveillance systems. Addressing these systemic and operational inefficiencies calls for technological innovations capable of improving patient tracking and real-time data use in Uganda's TB program

According to a report by USAID's Measure Evaluation project, there is still room for improvement in the quality of tuberculosis services in Uganda (Oyediran 2020). Alongside issues such as the cost associated to seeking care by TB patients being prohibitive in terms of transport to return to the health facility, the turnaround time for sputum test results from the laboratory, and the difficulty in tracking patients due to poor patient address records (Zawedde-Muyanja et al. 2022), contributed to gaps in the quality of healthcare for TB patients. Despite the integration of technology such as an electronic surveillance system to track TB patients' diagnosis and prognosis to curative states (Oyediran 2020), and also capable of recording patients' information, which would have bridged the gap of the inadequate patient record, gaps in the utilization of this system exist.

This electronic system, referred to as the Electronic Case-Based Surveillance System (eCBSS), is a District Health Information Software 2 (DHIS2) instance implemented in 2020 by the Ministry of Health (MOH) Uganda to track TB patients who receive treatment and care at health facilities. The eCBSS is based on DHIS2 Tracker, which is a web-based open-source software platform used for data management and analysis (Kamara 2023). The introduction of the eCBSS under DHIS2 represented a significant step toward digitalizing TB surveillance, yet gaps in its utilization limit its full potential.

DHIS2, which stands for District Health Information System 2, is a comprehensive software platform designed for health information systems (HIS) (Dehnavieh et al. 2019). Its primary objective is to support the collection, validation, analysis, and presentation of both aggregate and patient-based statistical data within the healthcare sector (DHIS2 2019). DHIS2 serves as a versatile tool for integrated health information management activities, offering a generic framework that can be tailored to various health information needs (Byrne and Sæbø 2022). It is an open-source software developed by the Health Information Systems Programme (HISP) and is

widely used in over 40 countries across Africa, Asia, and Latin America, including nations like Kenya, Tanzania, Uganda, Rwanda, Ghana, Liberia, and Bangladesh. DHIS2 is built on free and open-source Java frameworks, allowing for flexibility, scalability, and customization to meet the diverse requirements of health information systems globally. The DHIS2 Electronic Case-Based Surveillance System (eCBSS) is a comprehensive platform used for disease surveillance, early warning, and health emergencies. It is designed to prevent, detect, and respond to infectious disease threats by enabling case notification and surveillance for notifiable diseases (Kinkade et al. 2022). DHIS2 integrates various surveillance methods, including event-based surveillance and rumor monitoring, to detect unusual public health events early. This system collects data from diverse sources like media reports, rumors, and community feedback to identify potential health risks promptly. While DHIS2 provides a robust framework for health data management, integrating advanced analytics such as machine learning could transform it from a data repository into a predictive decision-support system.

The implementation of the DHIS2's eCBSS aimed to improve the quality of TB services in Uganda by providing a more efficient and effective way of tracking TB patients' diagnosis and prognosis in curative states (Kamara 2023). However, according to Oyediran et al., this hasn't improved the tracking of patients either (Oyediran 2020). The eCBSS lacks predictive capabilities, as evidenced by the absence of specific references to predictive analytics or machine learning integration within the system (Stop TB Partnership 2022), and yet it could implement artificial intelligence techniques such as Machine learning (ML). Incorporating ML techniques into electronic systems can significantly influence personalized care for patients by healthcare providers, thereby improving the quality of care. This integration of machine learning can enhance the healthcare system in several ways, including optimizing case definitions for more accurate and efficient surveillance, discovering patterns in clinical data, and providing powerful solutions for large or complex data, ultimately driving public health action (Parums 2023). This means that the patients who are still receiving suboptimal care can receive a more personalized touch guided by a decision support tool for healthcare givers, thereby improving service delivery. Building on DHIS2's infrastructure, the integration of ML presents an opportunity to bridge existing data-use gaps and enhance the quality of TB care delivery.

Machine learning can predict certain outcomes, such as the development of MDR-TB with its associated factors. Evidence suggests that the utility of machine learning in accurately predicting diseases from whole genome sequencing data highlights the potential of machine learning in predicting drug resistance in TB (Deelder et al. 2019). The integration of machine learning techniques into electronic systems can further enhance the predictive capabilities of surveillance systems, enabling more accurate and timely diagnostics, and supporting personalized care for patients by healthcare providers (Cara et al. 2022). Despite this promise, there remains limited empirical exploration of embedding ML within Uganda's eCBSS to support real-time prediction and targeted interventions.

While machine learning could provide solutions mentioned above, there is limited research to explore its integration in existing legacy systems, such as the eCBSS, to support the early identification and management of MDR-TB cases. Given the high burden of TB in Uganda and the increasing threat posed by drug-resistant strains, it is important to investigate the feasibility and impact of embedding machine learning techniques into the current surveillance infrastructure. This will positively influence the workflow process re-engineering at TB clinic settings to support decision making for policymakers at the Ministry of Health (MOH), TB program managers in the regions, and healthcare workers to design personalized care for TB patients in Uganda.

Therefore, this study proposed the development of a machine learning web application integrated into the DHIS2-based electronic Case-Based Surveillance System (eCBSS) to predict the likelihood of MDR-TB development among TB patients. User requirements were gathered to design and develop a machine learning-powered web dashboard that summarizes patient data. The application was tested and validated with healthcare workers before its integration into the DHIS2 eCBSS. Missing data, such as weight, MUAC, height, and genomic resistance results, undermines the ability to monitor patient prognosis effectively. Moreover, reliance on paper-based registers and unstructured patient records continues to disrupt the timely use of data for clinical decisions.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction.

This review assesses the literature on how the user requirements for the development of a web application for healthcare givers are collected and analyzed before the requirements engineering process that maps them to functionalities. Furthermore, it provides literature of previous works done in the development and integration of AI and ML applications in systems for healthcare workers, the impact of that integration, and how it was measured. Therefore, as a guiding process to this study's objectives in achieving the artifact, an ML web-powered application with DHIS2's eCBSS to predict the likely development of MDR-TB in DS-TB susceptible patients in Uganda.

2.2 User requirements elicitation in healthcare artifact development and its importance.

User requirements are essential to the adoption of healthcare systems because they have a direct impact on the efficacy and success of these systems. According to Ghaleb et al., user satisfaction, efficiency, and overall system usability can all rise when healthcare systems are designed to accommodate users' wants, preferences, and workflows. This is ensured by comprehending and adopting user requirements(Ghaleb and Mohamed 2018). Organizations can improve user acceptance, lessen resistance to change, and ultimately improve the adoption and utilization of these technologies within healthcare settings by matching the design and functionality of healthcare systems with user requirements(Chute et al. 2022). Healthcare workers such as Clinicians: Medical doctors, nurse practitioners, physician assistants, Physicians: Licensed medical doctors, Data Clerks: Individuals responsible for data entry, Laboratory Technicians: engaged in laboratory testing and analysis, Program managers: engaged in strategic management of the clinic – are users of these systems. Failure in correctly eliciting their requirements and involving users in the development process is a reason why pilots, prototypes, and continued utilization of the systems degenerate away from the primary objectives of decision support (Hay, Klonek, and Parker 2020).

It is therefore important to consider User requirements before designing and developing a web application for healthcare givers. According to Spatar et al., adoption of a healthcare system is based on several factors. These factors include; user satisfaction, perceived usefulness, perceived

ease of use, information quality, system flexibility, clear user interfaces, system mobility and accessibility, dose functionality, ease of learning,, alignment with workflows, and quality of care. (Spatar et al. 2019). In their study, they applied the Technology Adoption Model, a framework to deliver the elicitation of requirements that ensure users' satisfaction. Furthermore, impact on quality of care, infusion, and diffusion of the technology are constructs of that model as well. They, however, didn't explicitly identify the type of techniques that deliver robust user requirements.

Another systematic review by Pacheco et al, structured interviews were deemed successful in both conventional and global software development (GSD) contexts (Pacheco, García, and Reyes 2018). Based on the calibre of the questions developed, the same analysts discovered that structured interviews allowed them to acquire comprehensive information. It was suggested that structured interviews be used in conjunction with other methods such as surveys, questionnaires, and brainstorming to improve the calibre of needs (Pacheco et al. 2018). However, the flexibility and spontaneity that planned interviews can provide can be limited, which might make it more difficult to explore complicated or changing issues. Users could also not feel completely comfortable expressing their wants if the interview questions are poorly written or if there is a lack of connection between the interviewer and the interviewee. Therefore, unstructured interviews can exploit this deficiency and deliver quality user knowledge for specific components of features for an application in development, leaving options for change as the utilization of the application evolves. This approach can lead to a deeper understanding of user needs, preferences, and expectations, which is crucial for developing software that aligns closely with user requirements.

According to a study by Teixeira et al., the user requirements were identified through a user-centered requirement engineering process involving various techniques of requirements elicitation and validation. The study involved end-users, including physicians, nurses, laboratory staff, administrative staff, and patients, who were directly or indirectly involved in all steps of the research. The user requirements were generated for a web-based information system designed to manage clinical information in hemophilia care. The methodology used a combination of three well-known methodological approaches: object-oriented systems analysis (OOSA), task analysis (TA), and prototyping, in an iterative development process combined with grounded theory in a triangulation work (Teixeira, Ferreira, and Santos 2012).

Understanding the techniques in elicitation of user requirements is followed by a structure of known requirements in related implementations that have delivered healthcare information interventions. By leveraging established elicitation techniques and drawing insights from past implementations, developers and healthcare professionals can identify key requirements essential for designing effective healthcare information interventions. This structured approach helps ensure that the developed systems align with user needs, enhance decision-making processes, and ultimately improve healthcare outcomes.

Demands, expectations, and limitations of end users or stakeholders who will interact with a software system are referred to as user requirements. From the viewpoint of the user, these requirements specify the required features, functionalities, and attributes of the system. User requirements are essential to software development because they direct the solution's design, development, and testing to make sure it successfully satisfies user needs. User requirements encompass functional, usability, and user interface aspects essential for software development. Functional requirements include data management for input, retrieval, and processing, along with system functionalities like user authentication and integration capabilities.

A publication by Penn et al., from a study on developing a community health management system (Penn et al. 2019), usability requirements focus on user experience elements such as ease of use and efficiency in task completion. In their evaluation study, they purposively selected stakeholders according to their experience after identifying their key roles in the provision of the interventions to improve health in their communities. They provided the participants with semi-structured interviews to elicit the user requirements. One of the requirements themes was User interface requirements to emphasize visual design for aesthetic appeal and interactivity for engaging user experiences. Through their work, by categorizing user requirements into these themes and sub-themes, development teams can effectively capture and address end users' needs, ensuring that software solutions are user-friendly, efficient, and visually appealing to enhance overall user satisfaction and system effectiveness. Therefore, this approach could deliver the elicitation of user requirements from healthcare workers at TB treatment facilities in Uganda in guiding the development of a web application powered by ML to predict the development of MDR-TB, enhancing the utilization of the data within DHIS2's eCBSS, and improving outcomes for drug-susceptible TB patients. Themes such as understanding roles and cadres at TB clinics, assessing

patient loads, exploring current methods and tools for patient management, identifying challenges in monitoring MDR-TB, determining frustrations in data use, evaluating data availability, discussing essential patient information, envisioning user interface features, integrating web applications into daily workflows, emphasizing communication and collaboration among healthcare workers, considering personalized care impacts, addressing data privacy and security concerns, offering training sessions, highlighting feedback mechanisms, setting expectations for system responsiveness, scalability, reliability, and accessibility requirements, discussing sustainability factors, and inviting additional suggestions or concerns regarding the development and implementation of the patient management web application for monitoring MDR-TB in TB patients would provide a scope for the user requirements for a proposed study.

2.3 Machine learning in predicting MDR-TB.

Machine learning has gained traction in public health management by facilitating the exploration of different phenomena and predicting outcomes. Studies have shown that there are techniques that have proven to predict MDR-TB with the variables mentioned in the above section. Documented predictive models and techniques, their application, impact, and performance are discussed in this section.

In a systematic literature review by Abhinav Sharma et al., various ML techniques deployed over whole genome sequencing data demonstrated the predictive and detective transmission of DR-TB. In their paper, they declared that variations exist in the clinical and performance capabilities of the different ML techniques, especially when given a different combination of feature engineering procedures and the training dataset. However, they recommended a stacked ensemble of the different techniques that can learn from the irregular performances of one and counter it with another (Sharma et al. n.d.).

In another study by Yang, Y., et al., the researchers applied a rules-based approach to study the sensitivities from the best-performing models that signified an increase in the area under the curve for a particular drug – pyrazinamide, in the treatment of MDR-TB, meaning that machine learning can be reliable in not only early detection but also treatment (Yang et al. n.d.). The researchers argued that their models improved the sensitivities of pyrazinamide and streptomycin by 15 and 24% to 84 and 87% ($P < 0.01$), respectively.

A group of researchers went further ahead and selected three ML algorithms; Logistic regression (LR), Random forests (RF), and one-dimensional Convolution neural networks (1D CNN) on 10,575 isolates from a genome span for detecting different genetic features for drug-resistant tuberculosis in sixteen countries (Kuang et al. 2022). These researchers presented their ML model's performance for each algorithm and showed that the 1D CNN performed the highest with an average F1-score of 96.7% for predicting resistance across the different drugs in both first-line and second-line regimens. This greatly signifies a potential for higher performance of selected ML models than the rules-based approach above.

Away from the genotypic and phenotypic drug resistance studies, a study by Mian Hiader Ali et al., conducted in Pakistan had results that suggested the classification models such as the support vector machine (SVM) and random forest (RF) accurately predicted the outcome of multidrug-resistant tuberculosis in patients previously treated with TB with few non-genetic data variables. The performance scores for the two ML techniques were over 65% accuracy and were visualized in their publication. The researchers recommend that it is useful in the diagnosis and prevention of MDR-TB; however, they did not present other performance criteria such as the positive predictive value (PPV), the Area under the curve (AUC) of the ML techniques, and as well as the sensitivity. (Ali et al., 2021). This implies that the classification properties of their algorithms might not have performed as expected due to poor-quality data and the presence of an imbalanced dataset. This further explains how their results were of a biased nature. The researchers should have applied the PPV and AUC in determining what validations and calibrations were needed for their project, and later presented their findings.

According to a study by J-B Ma et al., it is possible to develop a predictive nomogram for the successful treatment outcomes of MDR-TB using ML techniques such as least absolute shrinking and separation operator (LASSO). The ensemble of LASSO with Multivariate logistic regression for that particular study demonstrated a concordance index (C-Index) of 0.75, AUC of 0.75, a sensitivity of 0.64, a specificity of 0.773, and an accuracy of 0.967. With a leave-one-out cross-validation method, this nomogram was able to correctly predict unsuccessful treatment outcomes with prognostic factors of age, sex, health education, and lung lesion distribution (Ma et al. 2023). Therefore, it is possible to predict other outcomes with ML while managing MDR-TB, especially with an available limited dataset.

Electronic systems contributed substantially to infectious disease surveillance by capturing case data and presenting it in real time. Studies such as that by Njeru, I et al., conducted in Kenya over the use of DHIS2, have signified the use of continuous training to users for these systems and how it made the impact on reporting; as completeness and timeliness, increasing from 45 to 62% and 30 to 51% respectively(Njeru et al. 2020). However, these systems face challenges including; inaccurate interpretation and prediction of the population's health status, limited competence to use the systems by health workers, and the low numbers of these trained health workers to both manage patients and the system (Jayatilleke 2020).

Machine learning has demonstrated that the prediction of population and individual health outcomes, such as diseases of public health concern, is possible(Habehh and Gohel 2021). Some studies have identified the commonly applied ML techniques such as SVM, RF, CNN, ANN, and Naïve Bayes favored in outcome prediction (Rashid et al. 2022; Uddin et al. 2019; Yu et al. 2023). Ensembles with feature engineering over different sets of data demonstrate how the data is processed and organized into training and test data before the algorithms can test the model on new inputs from variables collected as data elements from a patient or a cohort (Albahra et al. 2023). For that reason, ML techniques embedded into electronic disease surveillance systems such as the eCBSS can enhance their predictive capability for population and cohort management of cases of MDR-TB.

The Uganda Tuberculosis Implementation Research Consortium of Makerere University's College of Health Sciences developed and validated a clinical risk score that uniquely identified suspects who likely had TB from those who did not. This study by Baik et al. applied known ML methods, such as LASSO, on data from South Africa, assessed the discrimination of their methods with ROCs, and applied Cox linear logistic regression for calibration. The validation of the score was repeated within Ugandan adults living mostly in urban areas, and their model performed with similar results despite the different population distribution and characteristics (Baik et al. n.d.). The researcher's work, done in the known machine learning language R, is shared on GitHub, a project and coding repository, and can be publicly accessed. However, this study did not acquire its data from an electronic surveillance system such as that of DHIS2's eCBSS. Furthermore, its risk score is pending external validation, and studies can investigate more.

It is in the above cases that I propose the development of a web-based analytical application for clinicians in the early detection of the development of MDR-TB using machine learning algorithms. The application shall predict the outcome based on the data collected in the electronic Case-based Surveillance system (eCBSS) of the National TB and Leprosy program as used at the TB clinics.

2.4 Current DHIS2 tracker eCBSS environment.

Uganda adopted DHIS 2 as its national system for weekly TB notification reporting in 2020. As a result, the national program has been able to track the development of TB diagnoses at the facility level. Over the past two years, the platform underwent improvements to include a case-based tracker system that was trialed at 100 sites. Each of the 15 RRHs (Regional Referral Hospitals) participated in this pilot, and the eCBSS platform promptly gathered and analyzed the data (The Stop TB Partnership 2022).

The DHIS2 tracker application has the capacity for the collection of individual-level (or case-based) transactional data, such as medical records for specific patients, confirmed and suspected cases during a disease outbreak, logistical data on particular commodities, or student records, among many others (DHIS2 2023). According to DHIS2's documentation, its granular ability allows the collection of data from the lowest facility level while ensuring that it is meeting the WHO standards and alignment with national implementations of key health programs, such as HIV, TB, Malaria, and COVID-19 surveillance.

The tracker, according to guidance on creating an electronic information system to track the Prevention of Mother-to-Child Transmission of HIV by measure evaluation – a USAID project for Health information systems strengthening – can append the patient's history of care to the record of services received even after registration (Cristina de la Torre 2019). This is a functionality beyond the known DHIS2's aggregate data collection. The Tracker allows for computerized scheduling of future appointments as well as automatic detection and reporting of missed appointments through SMS, e-mail, and dashboards, among others.

At the health facilities managing MDR-TB, some of the processes remain manual. Processes such as presumptive TB screening, treatment outcome, treatment monitoring, and contact tracing remain manually recorded in the registers and later entered into the eCBSS (The Stop TB

Partnership 2022). Alongside other challenges such as the inadequate IT infrastructure at these facilities, the implication of the time factor to track the patient through those stages is interrupted, and yet the electronic system is capable of doing that –according to the *Uganda Digital TB Surveillance System Assessment report of 2022*(The Stop TB Partnership 2022). This will eventually lead to poor treatment monitoring.

The importance of understanding the ethics of deploying Machine learning applications in clinical environments is crucial. According to Sana et al, to increase adoption and satisfaction, the ML community must take concerted and purposeful action(Tonekaboni et al. 2019). This effort aims to proactively anticipate clinicians' demands by doing exploratory research to discover specific technological difficulties that can be addressed with an explainable ML system. The goal is to construct trustworthy ML systems, encourage confidence in continuing use, and improve medical workflows and procedures.

The works of Sana et al, produce the realization of integration of AI and ML in several clinical environments. One such study is that of Marcus et al., where an HIV prediction model was created and validated to identify potential Pre-exposure prophylaxis (PrEP) candidates in a major healthcare system (Marcus et al. 2019). Their study identified that prediction algorithms employing EHR data can identify people at high risk of HIV acquisition who may benefit from PrEP by 2.2% in three years. Such results would direct the facilities policy to include the provision of knowledge and scheduling the use of PrEP in identified patients by healthcare providers. The data used in the study were from the Care system of Kaiser Permanente Northern California Hospital and its consortium facilities. Therefore, the DHIS'2 eCBSS architecture of being capable of operating from multiple facilities while collecting data from the same characteristics of patients can benefit from such a study in identifying patients who require a specific intervention by their healthcare provider.

Another study applied ML to Malaria with an application; AIDMAN, an artificial intelligence-based object detection system developed for malaria diagnosis. AIDMAN utilized the YOLOv5 model to detect cells in thin blood smears, followed by an attentional aligner model (AAM) for cellular classification using multi-scale features and attention mechanisms. A convolutional neural network classifier was then employed for diagnosis, minimizing false positives. AIDMAN achieved high diagnostic accuracy of 98.62% for cells and 97% for blood smear images, with

prospective clinical validation accuracy in Sierra Leone-China Friendship Hospital reaching 98.44%. These results demonstrated AIDMAN's potential to assist in malaria diagnosis, particularly in areas lacking experienced parasitologists and equipment in a clinical setting.

Although there are a few thorough descriptions of this utilization in peer-reviewed or grey literature, data from DHIS2 systems are used. Researchers discovered that, frequently, when it comes to access to data and the reporting of data from the cascade in the system, there is a centralized versus a decentralized pattern of use. Additionally, they discovered that the many conceptualizations of data use and how it is conceptualized are not made plain (Byrne and Sæbø 2022). Therefore, an immediate call for data use studies and the impact these systems especially in managing patients, would demonstrate the true capabilities of the systems alongside any further structural and technical improvements, such as machine learning.

2.5 Integration of DHIS2 with Machine Learning Applications.

The integration of health information systems has become a critical aspect of modern healthcare management, enabling seamless data exchange, improved decision-making, and enhanced public health outcomes. DHIS2's flexibility and modular architecture have made it an attractive choice for health information management (Roland 2018). By leveraging the power of ML algorithms, predictive analytics can be applied to health data collected through DHIS2, such as the eCBSS, enabling the identification of patterns, trends, and potential outcomes, including MDR-TB (Javaid et al. 2022). Furthermore, accelerating patient risk classification for enhanced care might benefit from the design of visual aids to use graphs in explaining the risk scores and predictive models (Badgeley et al.).

Several studies on the impact of applications such as LifeFlow, EventFlow, VISITORS, EHDVIZ, and DICON show that machine learning can influence the clinical outcomes of patients (Deng and Denecke 2014; Monroe et al. 2013; Pennington et al. 2014; Plaisant et al. n.d.). Some of these applications applied data stored in updated repositories and data warehouses, much like the DHIS2's eCBSS. The applications, developed with machine learning algorithms and visualizations, are in several development languages.

Another study that demonstrates the DHIS2 integration with Machine learning is that of Kuderha (Kuderha et al. 2023), where ML algorithms were applied to identify the anomalies in

malaria data. The study aimed to develop a novel framework for Data Quality Assessment for DHIS2 by utilizing Machine Learning techniques. The framework would primarily target the identification of both random and systematic mistakes in routine surveillance data related to malaria. To guarantee that only reliable and consistent data is kept in the DHIS system, the study sought to create machine learning models for outlier detection. This would maximize the possibility of deriving actionable knowledge from the data to support more informed decision-making. The study discovered that the machine learning models included in the suggested framework were effective in identifying systematic and random mistakes (local or global outliers) in the regular monitoring data for malaria. The models showed high precision scores but did not obtain high AUC values for random errors. However, systematic errors were successfully found using good performance indicators, suggesting that the methodology could find data inconsistencies and guarantee data quality in the DHIS2 system. The implication to decision makers is that they allocate resources for malaria case prevention and management over projected trends derived from the outputs of reliable data, rather than those earlier entered in the system.

Furthermore, a study by Katweisgye et al, set out to integrate DHIS2 data for Malaria cases to improve malaria case prediction in Uganda (Katwesige et al., 2020). By Combining malaria case data from the DHIS2 electronic Health Management Information System with climatic data from the Uganda National Meteorological Authority, they were able to apply feed-forward neural network (Artificial Neural Network), employed a sigmoid activation function in the hidden layers and a linear function in the output node, implemented using the software WEKA and the results showed that integrating two weeks of historical weather data with reported malaria cases led to more accurate predictions compared to using only current case data. This suggests that climatic factors can significantly influence malaria outbreaks. Including this data in forecasting models can be beneficial to policy and decision makers from development partners and responsible ministries. It can help them prepare for outbreaks by allocating resources such as finances for drugs, healthcare workers for rapid response, and materials such as mosquito nets and diagnostic tools.

DHIS2's architecture enables the construction of repositories and data warehousing from numerous systems, and this calls for clear systems integration. However, according to Murat Pasa_Uysal, systems with machine learning capabilities may be highly prone to failure or easily fall short of intended goals, especially in Healthcare (Uysal 2022). This researcher suggests the use of an enterprise integration architecture following three key principles: principles of Action

Research, Design Science Research, and Industrial Information Integration Engineering (IIIE). He emphasizes these methods to ensure that the objectives of machine learning-based web applications in healthcare maintain their key objective and avoid overestimation that might lead to discontent decision-making. DHIS2's current predictor algorithms are applied to generate data values based on expressions such as targets, thresholds, or estimated values, especially for missing values (DHIS2 Documentation 2021). This is not sufficient, especially the linear algorithms that are used for estimation, requiring that the organization unit be maintained, giving the need for more rigorous algorithms and an ensemble for ML techniques. Researchers such as Cheng et al., in their development and validation study, applied machine-learning models with *An Ensemble Approach for Accurate Real-Time Influenza Forecasting in Taiwan*. The results signified an accurate prediction in seasonal peaks with testing data and performed the same during a four-week validation (Cheng et al. 2020), meaning that the same can happen over data in DHIS2's eCBSS.

Another study by Finnegan, A. et al set out to apply machine learning to a vast amount of data from several datasets provided by a consortium of projects under the USAID. In this study, even though a larger amount of data was missing in DHIS2 instances of the iHRIS, the researchers remained with a good number of variables to run ML models on. The results which were from an exploratory study signified how staffing, supplies, and services are highly correlated (Finnegan et al. n.d.). This means DHIS2 plays an important role in being more than just a Health Information System, and that its architecture can accommodate further systems integration or development.

DHIS2's application platform provides features to develop, build, test, encapsulate, publish, and release applications. Furthermore, provides runtime support for User interfaces, API data fetching, server, as well as authentication. The applications, however, have to go through bootstrapping to create upgradable templates. These templates contain scripts that build, test, pack, deploy, publish, manage configuration, and versioning of the application for it to remain functional across different versions of DHIS2 (DHIS2 2021). This means that embedding an application built with the architecture in mind makes the integration of a web-based ML application possible.

2.6 AI with ML in Healthcare.

The interpretation of laboratory findings and other patient information is easier through machine learning, which aids in the early detection of diseases. Through knowledge discovery in the database, the low-level data might be transformed into high-level information to learn about the

illness patterns and promote early diagnosis (Alanazi 2022). Moreover, to enhance disease prediction accuracy and reduce the model-training period, we actively preprocess the data collected for constructing a dataset to handle missing values. Only then should significant features be chosen and applied to the model (Wang et al. 2018).

To evaluate the status of diseases and predict their future dynamics, modern technologies like artificial intelligence and machine learning are frequently used in data analysis (Agrebi and Larbi 2020). By creating a variety of forecasting models to offer insights on predictions of clinical information, dissemination or response is possible. The prediction models are useful for preventing illnesses and preserving years of life with a disability (Neumann et al. 2022). Due to the high expenses and resource usage involved with conventional monitoring systems, they also save significant amounts of money. These new technologies are anticipated to develop into effective tools for easing the gathering of more precise and timely data, which will produce evidence-based data (Javaid et al. 2022). Decision-makers should be able to identify regions where the model forecasts a specific risk category with the use of these strategies.

Summary of the literature review.

Multi-drug-resistant tuberculosis remains a national threat to Ugandans and an issue of global concern given the current level and rapidity of international travel. Electronic systems to manage the ever-growing problem exist. However, we need more enhancements to make these systems efficient. Several studies have demonstrated that enhancing electronic surveillance system with AI and ML technologies through a cascade of managerial levels increases their predictive ability and can influence decision-making. However, we require more studies on the challenges of implementation and investigations. DHIS2 systems remain a pivot technology in LMICs such as Uganda and are earmarked by the Ministry of Health as central systems providing real-time data and repositories. Enhancements to these systems will increase how the country responds to endemics such as MDR-TB. Therefore, a study to embed ML into one such system as the eCBSS is highly recommended.

CHAPTER THREE

3.0 Problem Statement

Uganda's electronic Case-Based Surveillance System (eCBSS) currently functions mainly as a data-collection platform rather than an analytical decision-support tool, revealing a critical gap between the system's existing passive use and the expected predictive capability needed to identify MDR-TB risk in real time. The World Health Organization (2022) estimates that Uganda reported approximately 1,400 cases of multidrug-resistant tuberculosis (MDR-TB) annually, equivalent to an incidence of 3 per 100,000 population. Of these, only 761 cases are laboratory-confirmed and 414 initiated on treatment, leaving many cases undiagnosed and unmonitored. The continued rise of MDR-TB, coupled with underutilized surveillance data, indicates an urgent need to strengthen predictive and analytical capabilities within Uganda's TB surveillance system.

The lack of predictive analytics and poor system utilization delay the identification of high-risk patients. This results in prolonged transmission, increased morbidity and mortality, and greater economic and treatment burdens for both the health system and affected communities. Several systemic challenges contribute to this problem, including incomplete data capture, limited technical capacity, inadequate infrastructure, poor system interoperability, insufficient user training, and reliance on manual record-keeping. Furthermore, the eCBSS operates primarily as a passive data repository, with no embedded tools for predictive analysis or automated decision support.

Recognizing these limitations, previous efforts had focused primarily on improving data collection and system adoption by more facilities within the existing DHIS2 framework in the country. While crucial for surveillance, these initiatives had not adequately addressed the critical need for advanced analytical capabilities. The ability to proactively identify at-risk patients and enable timely interventions such as personalized treatment courses is important. This study sought to develop and integrate a machine learning-based web dashboard, into the DHIS2 eCBSS. The system would later be tested, validated, and demonstrate the ability to provide real-time MDR-TB risk predictions using patient data, to facilitate early intervention by healthcare providers.

3.1 Justification.

According to Chapter 5 of the Uganda National Guidelines for The Programmatic Management of Drug-Resistant Tuberculosis, the NTLP defines a category named *Failure of re-treatment regimens and chronic TB cases* as one that has a more than 80% chance of acquiring MDR-TB. The NTLP case-finding strategy for Drug Resistance Surveillance (DRS) mentions the utilization of data to design an effective case-finding strategy and treatment regimens to estimate the number of patients to be enrolled, drug needs, and the drug procurement process. However, the policy does not explicitly mention the sources of the data and the systems in use. This can be because this policy hasn't been updated from the published version of 2011. Furthermore, because the DHIS2's eCBBS was implemented much later in 2020. Therefore, this study will inform the improvement of the policy by identifying the suitable integration requirements, development, and deployment of the artifact applying machine learning for the development of MDR-TB in the DS-TB patients with the highest risk.

This study is therefore justified as a timely intervention to bridge this policy-implementation gap. It will (1) assess the integration potential of machine learning technologies within existing electronic TB surveillance infrastructure, (2) identify system and policy bottlenecks that limit predictive case-finding, and (3) contribute to the modernization of national TB control strategies. The development and deployment of an ML-based artifact tailored to predict MDR-TB risk among DS-TB patients will not only inform future updates to the guidelines but also support the NTLP's mandate to use surveillance data more effectively, as well as the TB clinics' staff in decision-making, ultimately improving DS-TB patient outcomes and resource planning.

3.2 Conceptual Framework for the development of an ML-powered web-based application.

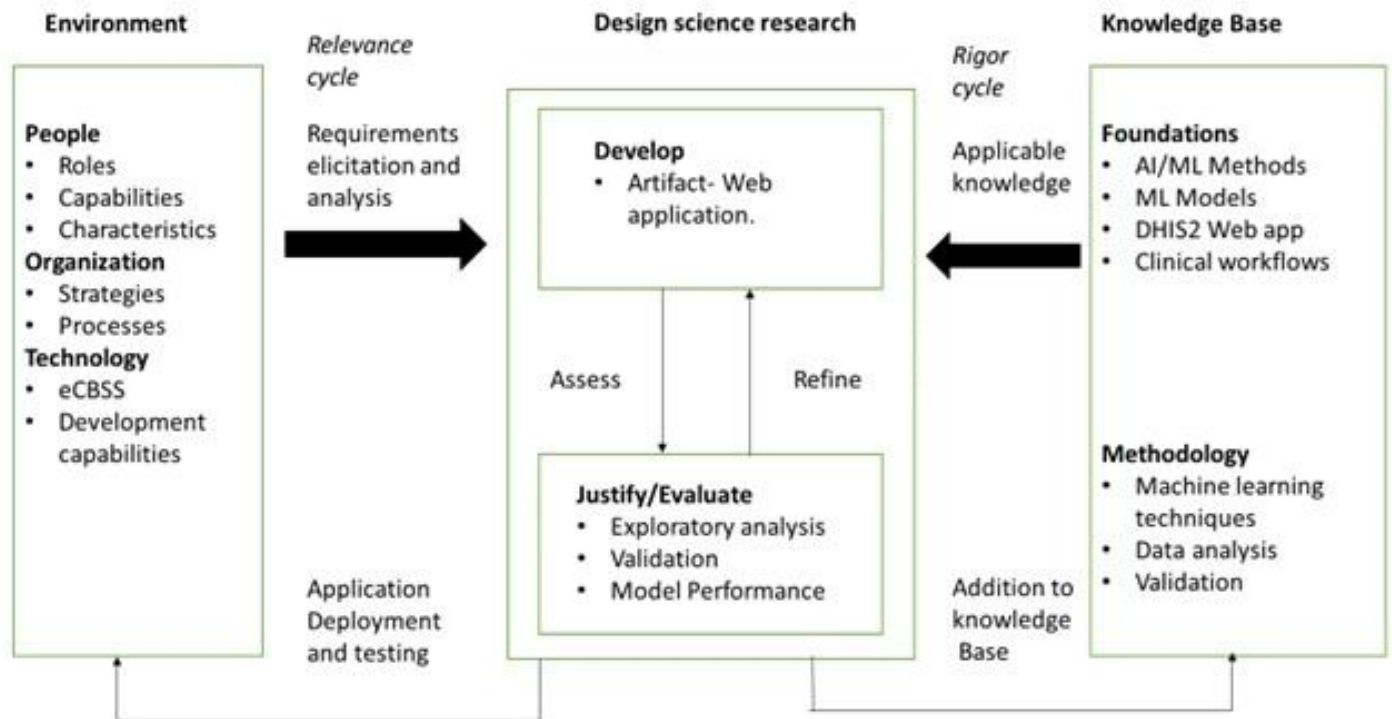


Figure 1: Conceptual Framework, adopted from Henver 2007,

3.3.1 Narrative

The study adapted the Henver 2007 conceptual framework on delivering an ML web-powered application by Samuel Nii Odoi Devine et al.(Devine, Kolog, and Atinga 3 AD). In their paper on applying a design science research approach to developing a knowledge base system for African traditional herbal medicine, they emphasized the three stages that comprise this commonly used method for developing artifacts: knowledge base, design science, and environment. These phases are connected repeatedly in cycles rather than being autonomous. Their study differed in the type of artifact delivered and the setting of the implementation from this study.

The conceptual framework illustrates a comprehensive design science research approach for developing an MDR-TB prediction application, wherein the three objectives were methodically achieved as follows: The first objective of determining user requirements was accomplished through the Relevance cycle connecting the Environment to Design Science Research, incorporating requirements elicitation and analysis from healthcare workers' roles and capabilities,

organizational strategies and processes, and existing technological infrastructure within the eCBSS platform; the second objective of developing and integrating the machine learning web-based analytical application with GIS capabilities was achieved through the Develop phase, where theoretical frameworks were established based on AI/ML methods from the Knowledge Base, the web application artifact was designed specifically for DHIS2's eCBSS platform, and the Rigor cycle ensured incorporation of advanced machine learning techniques and proper validation approaches; finally, the third objective of testing and validating the application's performance was accomplished through the Justify/Evaluate phase, which implemented exploratory data analysis, rigorous validation procedures to verify prediction accuracy, comprehensive model performance assessment, and real-world application deployment and testing, with feedback loops enabling continuous refinement based on actual performance, thereby maintaining scientific rigor while ensuring practical relevance for TB management within existing DHIS2 systems.

3.4 Main Research Question

This study explored how a web-based application, leveraging machine learning, can predict the development of MDR-TB among patients within the DHIS2 Electronic Case-Based Surveillance System (eCBSS) in Uganda. Furthermore, the study wanted to determine how to optimize data utilization, enhance decision-making support for healthcare providers to ensure high-quality healthcare delivery to TB patients in the region.

3.5 Research Questions.

The study aimed to answer these specific questions:

1. What were the specific requirements for developing and integrating a machine-learning web-based application into DHIS2's electronic case-based surveillance system to predict MDR-TB?
2. How would this web-based application, powered by machine learning, promote the effective utilization of data, enhance decision-making support, and positively influence the quality of patient care delivered by healthcare providers within the facilities where it is deployed?
3. How could integrating this application with a Geographical Information System (GIS) module influence decision support making by healthcare givers in understanding TB patients' drug adherence, contact tracing, and predicting screening strategies for new cases?

CHAPTER FOUR

4.0 Research Objective.

The main objective of this research was to develop, test, and validate the integration of a web-based analytical dashboard application within the DHIS2's eCBSS, powered by a machine-learning model that predicts the development of MDR-TB in TB patients. This integration sought to influence the utilization of data among healthcare givers at TB treatment clinics. The application was designed to improve care and treatment by supporting decision-making for personalized care among DS-TB patients and eventually improving the quality of healthcare services received by the patients.

4.1 Specific Objectives.

The specific objectives of this study were to:

- i. Determine user requirements from healthcare workers at TB clinics, for the development of a machine learning web-based application within DHIS2's eCBSS to predict TB patients who are likely to develop MDR-TB.
- ii. Develop and integrate a machine learning web-based analytical application with a Geographical Information System (GIS) module, into the DHIS2's eCBSS for healthcare workers at TB clinics in Uganda.
- iii. Test and validate the performance of the machine learning web-based application within DHIS2's eCBSS among healthcare workers at TB treatment facilities in Uganda.

CHAPTER FIVE

RESEARCH METHODOLOGY

5.0 Introduction.

In this section, I describe the study design, scope of the study, participants, and the Design science research scope that led to the development and testing of the ML web application. This section also discusses the proposed ML techniques for the integration within the DHIS2 eCBSS system, as demonstrated.

5.1 Study Design.

The Design Science Research (DSR) process model guided the implementation of the artifact. The process began by understanding the problem of data underutilization, as experienced by healthcare providers, who formed the user group described in the study's participant section of this dissertation and from whom the requirements were elicited.

A Qualitative study was conducted in May–July 2024 in Mukono General Hospital, Entebbe Regional Referral Hospital, and Mulago TB ward at the Mulago National Referral Hospital in Central Uganda. These facilities were selected because they contributed a high volume of laboratory-confirmed DS-TB cases (> 1000, according to the eCBSS) in the last five years that have been notified in the eCBSS, actively use the eCBSS, and have strategic healthcare personnel with roles in MDR-TB surveillance and treatment. This ensured the inclusion of knowledgeable personnel and relevant clinical contexts, enhancing the richness and applicability of the data collected for designing AI-enhanced prediction tools.

The study analysed the collected requirements and initiated a design and development process rooted in requirements engineering. This iterative approach actively involved users as product owners to ensure the application's functionality aligned with their needs. Through continuous engagement, user feedback shaped the design until satisfaction with the application's functionality was achieved. Following this, a prototype of the web application was developed and demonstrated within DHIS2's eCBSS to establish proof of concept. The evaluation of the prototype involved collecting feedback from participants, assessing the application's performance, and documenting the findings for further refinement and validation.

According to Nieuwland et al., to ensure proactive dissemination of the study findings and overcome the limitations of the process, it is crucial to communicate them for further research (Nieuwland, O'Mara, and Mackenbach n.d.). Therefore, this study prioritized the first four stages of the DSR framework and developed the Application first out of the eCBSS due to requirements by the implementing and deployment body, the MOH, Uganda's division of health information, and in preparation for publishing in peer-reviewed journals beyond the academic requirements of the School of Public Health. Furthermore, communication ensured that facilitation of future collaborations is possible; sharing processes for the development of other artifacts that will prevent delays and minimize mistakes in articulating the design ideas.

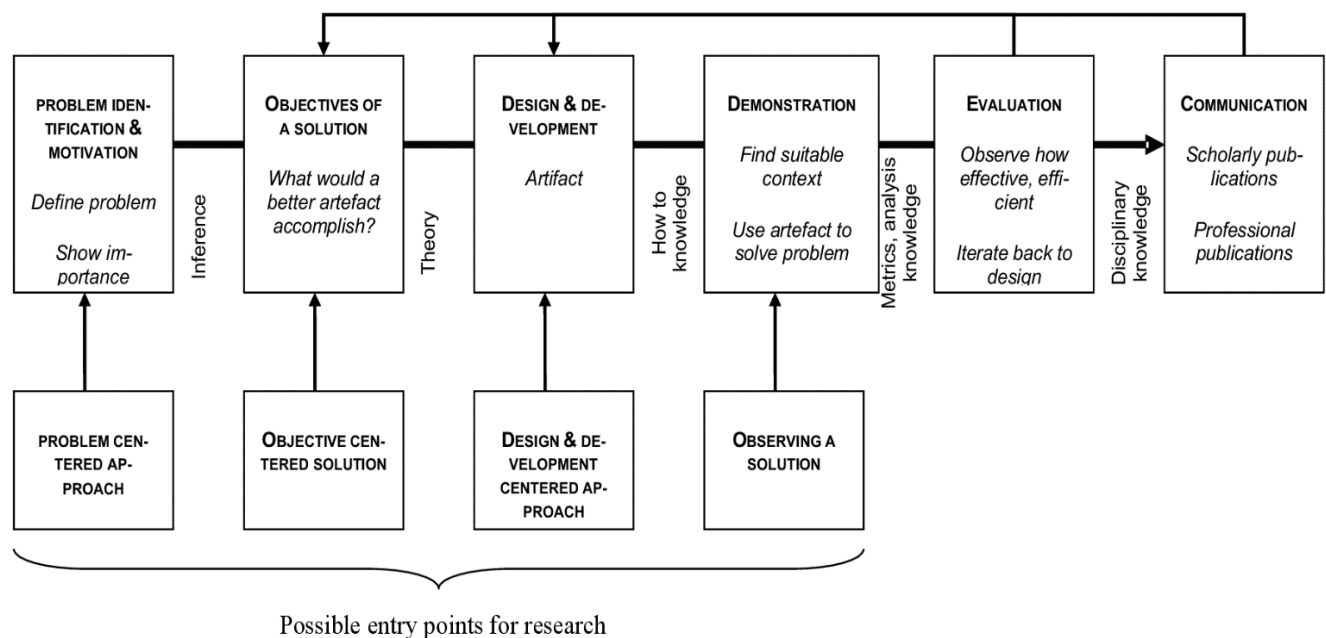


Figure 2: DSR methodology as cited from K. Peffers, T. Tuunanen et al.

5.2 Study sites.

This study followed the DSR methodology and guided the collection of user requirements for the web application solution from three high-volume health facilities: Mukono General Hospital, Mulago ward 5&6 and Entebbe Regional referral Hospital in the districts of Mukono, Kampala, and Wakiso in Uganda respectively. These sites were purposely chosen because of the high volume of DS-TB patients throughout the year.

5.3 The participants

The selected participants included clinicians, physicians, data clerks, and laboratory technicians who are stationed at those health facilities managing DS-TB. The facilities in the study are National, General, and regional referral hospitals. These were essential in the requirements gathering process since they were the main product owners in the user-centered approach of the DSR methodology. They were the target participants for the User requirements qualitative in-depth interviews. Furthermore, their insights in the testing and verification of the usability of the application was important, and thus the same group responded to the Post Study Usability Test Questionnaire (PSUTQ), which was used to assess the user acceptability of the artifact.

1. Clinicians/Physicians:

Clinicians and physicians play critical roles in the creation of a web application for predicting Multi-Drug Resistant Tuberculosis (MDR-TB). Their knowledge and insights into the clinical workflow and decision-making process around MDR-TB diagnosis and treatment were crucial in designing the application's functionality and usability. Clinicians and physicians ensured that the application aligns closely with their needs and expectations by specifying requirements such as the necessary patient data inputs, preferred prediction visualization methods, and integration capabilities with existing clinical systems, thereby increasing its effectiveness in supporting MDR-TB management.

2. Data Clerks:

Data clerks have extensive experience in the management and organization of patient data in healthcare facilities, making their contribution critical to the creation of a web application to forecast MDR-TB. Their knowledge of existing data management systems, such as data sources, formats, and accessibility, informed the integration of patient data into the application. By describing data standards, privacy needs, and potential obstacles in data collection and maintenance, data clerks helped to ensure the prediction model's correctness, security, and reliability, laying the groundwork for effective clinical decision-making.

3. Laboratory Technicians:

Laboratory technicians play an important role in the creation of a web application for predicting MDR-TB, since they provide crucial information about laboratory testing techniques and outcomes pertinent to MDR-TB diagnosis. Their diagnostic test expertise, laboratory data interpretation, and awareness of testing frequency and reliability all contribute to the incorporation of laboratory data into the prediction model. By sharing insights into the sorts of diagnostic tests done, result interpretation, and data integration needs, laboratory technicians help healthcare providers forecast MDR-TB more accurately, increasing the online application's clinical utility. The study also discovered that the laboratory technologists are the initial point of identifying MDRTB cases through the lab Xpert system, which is an LMIS that handles sample testing for TB.

4. Doctors

Doctors, as frontline healthcare practitioners in charge of clinically diagnosing and treating MDR-TB patients, had a significant impact on the development of a web application for illness prediction. Their clinical skills and firsthand experience with MDR-TB patients gave them unique insights into the disease's clinical presentation, development, and management. Doctors verified that the prediction model incorporated relevant clinical data and aligns with best practices in MDR-TB management by exchanging information on symptoms, risk factors, treatment procedures, and clinical practice expectations for the application. Their contributions improved the application's ability to assist rapid diagnosis and individualized treatment decisions, resulting in better patient outcomes in the fight against MDR-TB.

5.3.0 Inclusion and exclusion criteria.

This section outlined the key population's eligibility for the study for the use of the web-based application, with consideration of the number of years at the facility and knowledge of the use of digital technologies. It also highlighted the criteria for the variable selection for the model prediction development for a web application with data fetched from the eCBSS.

5.3.1 Inclusion criteria

Participants must have fulfilled particular inclusion requirements according to their profession, clinical background, employment status, certification/licensure, and availability in order to be eligible to take part in the study. Clinicians were healthcare professionals who actively participated in patient care, such as physicians, nurse practitioners, medical doctors, and physician assistants. The variables of interest are the predictors of the likely development of MDR-TB as captured by the eCBSS at the treatment facility.

Variables of interest.

This procedure began by consulting with domain experts, who are the participants categorized below, to identify key variables based on theoretical or empirical links with the desired outcome. Following that, exploratory data analysis helped identify potential predictors and examined their correlations with the outcome variable. I used this step-by-step methodology to efficiently determine the most influential factors for inclusion in the ML model development.

For the participants.

1. Occupation:

- Clinicians: Medical doctors, nurse practitioners, physician assistants, and other healthcare professionals actively involved in TB patient care at the TB treatment facilities.
- Physicians: Licensed medical doctors with a minimum of two (2) years of clinical experience within the TB care and treatment facilities.
- Data Clerks: Individuals responsible for data entry and management within a TB healthcare or treatment setting who have accessed the eCBSS or a DHIS2 system.
- Laboratory Technicians: Certified professionals engaged in laboratory testing and analysis accessed the eCBSS or a DHIS2 system.

2. Clinical Experience:

- Clinicians and Physicians: Minimum of 1 year of clinical practice within TB treatment.
- Data Clerks and Laboratory Technicians with 1-3 experience in handling electronic health records systems within healthcare settings, including TB treatment facilities.

3. Employment Status:

- Currently employed in a clinical, medical, data management, or laboratory role with active use of electronic health records within a TB treatment facility.

4. Certification/Licensure:

- Clinicians and Physicians: Active and valid medical license issued by the Uganda Medical Association or another accredited institution.
- Data Clerks: Certification or relevant educational background in data management with a concentration in electronic health record systems, preferably knowledge and access to a DHIS2 system.
- Laboratory Technicians: Certification or relevant educational background in laboratory technology.

5. Availability:

- Willingness to participate in the study for the entire duration through user requirements collection, development, and testing.
- Availability to attend required training sessions and meetings.

5.3.2 Exclusion Criteria:

Some circumstances resulted in exclusion from the research by participants who did not meet the above criteria. Since the unit of analysis is the participants themselves, it was important to include only relevant healthcare workers who fulfilled the first and third objectives of the study.

1. Bias in the results of the study:

To ensure the validity and objectivity of the study, participants displaying bias—such as those with predetermined opinions about the effectiveness of machine learning in TB management—were identified and excluded.

2. Unpredictable circumstances for the study participant:

Participants, for one reason or another, had participated in the requirements elicitation but fell sick, died, or became disabled during the pre- and post-period of the demonstration or testing of the

ML-powered Machine learning web application within the local DHIS2 system, which would render gaps in the evaluation of the study.

3. Withdrawal from the study:

Data and analysis of these participants who were lost to follow-up by the study were dropped. Participants who willingly dropped out of the study destabilized the expected results.

Incompatibility with Ethical Standards:

Participants whose involvement violated ethical standards or regulations governing the research, especially with access to sensitive patients' data, were excluded from the study to ensure the sensitivity of data is maintained.

5.4 Sample size.

Stratified purposive sampling was employed by the participant criteria outlined in Section 5.3.1 of this dissertation, but also on the expert knowledge in the clinical management of TB. One participant from each identified category was selected from each of the three study facilities described in Section 5.2 (Study Sites). Based on existing literature, thematic saturation is typically achieved by the twelfth interview (Sandelowski 1995; Sim et al. 2018; Vasileiou et al. 2018); thus, a total of twelve (12) participants were purposively selected for the study. However, due to time constraints, three participants were unavailable during the testing and validation phases and did not provide feedback during user testing.

5.5 Sampling procedure.

Participants for user requirements elicitation and system testing were selected using a stratified purposive sampling approach based on information power and expert knowledge in the management of TB, ensuring representation of healthcare providers from the different health facilities outlined in Section 5.2 (Study Sites) and based on the criteria detailed in the participant selection section of this methodology.

5.6 Study variables.

The recognized factors linked to the development of MDR-TB were studied and sourced from numerous publications in scientific journals of science. Several of these studies discuss the

multitude of their occurrence through different parameters, and all focus on the non-biological ones, which I explored in this segment of the chapter.

Globally, age, place of residence, education, marital status, bad habits like drinking too much alcohol and smoking, and concurrent infections like diabetes mellitus, HIV, Acid-Fast Bacilli (AFB) smear, pulmonary space, history of tuberculosis, and history of anti-tuberculosis treatment are all important risk factors for MDR TB (Salari et al. 2023). A study by Ying Xi et al. found that certain factors are independent of the clinical setting and include: Positive sputum AFB smear, lung cavity, previously diagnosed TB, and a history of anti-TB therapy (Xi et al. 2022).

In Africa, especially sub-Saharan Africa, HIV has continually been associated with the development of MDR-TB, and its management has been very difficult as it brings about interaction and toxic effects that are also difficult to manage (Lalloo and Pillay n.d.). Umesh G Lalloo et al. in their study signify that, whereas managing has the benefits of pooling resources together into one project or program, other health system problems pose a threat to this engagement. Inadequate isolation facilities, inconsistent drug supplies, inadequate contact tracing, limited laboratory resources, delayed detection of drug-resistant TB, increased workload for healthcare professionals, lack of clinical experience, and inadequate environmental and personal protection in drug-resistant patients are cited by the researchers to affect the progress of the successful treatment of MDR-TB (Lalloo and Pillay n.d.). These attributes are cited by another researcher to contribute to health system factors associated with the development of MDR-TB (de Vries et al. 2017).

In Uganda, and according to several studies (Baluku et al. n.d.; Batte et al. n.d.; Okethwangu et al. 2019) that have alluded to the same factors above, have listed the same among those from similar regions in Africa. Selecting these as variables from the eCBS system and applying ML algorithms, predicted the development of MDR-TB.

The purpose of the proposed study, however, leaned towards the selection of available variables as captured within the eCBSS. I enhanced these variables by incorporating other health system or patient variables, although in a synthetic way, such as residence and work area, a delivered a GIS module of the dashboard to predict the development of MDR-TB in TB patients attending various TB treatment centers, and also provide hotspots mapping respectively. We can overcome the challenges of capturing geometry data for each patient by utilizing the Integrated TB case tracking form that details the approximation to locate the patient's likely residence.

By mining the eCBSS, I obtained independent variables that are involved in the development of MDR-TB. These included: Age, sex, being in contact, having smoked, receiving previous TB treatment, receiving improper treatment, having interruptions in first-line medication treatment, losing weight, haemoptysis, as well as experiencing adverse side effects of the different regimens of drugs.

The dependent variable for this study is the MDR-TB status of a TB susceptible patient as registered within the eCBSS known to have resistance to both rifampicin and isoniazid and captured under the element of “**Transferred to 2nd line treatment**”.

5.7. Data collection.

In-depth interviews with the participants mentioned in section 5.3 of this dissertation were conducted at the three identified health facilities and used to gather user requirements for the Web application. The questionnaire collected information such as the requirement name, functional and nonfunctional features, description, category, and any specific notes on performance needs. After the development, another online questionnaire was issued to collect usability and performance feedback from the participants.

5.7.1 Data collection tools.

A qualitative questionnaire guide adapted from literature on the elicitation of user requirements for the development of applications for healthcare providers from studies as those of Ahmad et al. and others was designed and used for this study (Ahmad et al. 2023; Saparamadu et al. 2021; Tajudeen et al. 2022). The tools and materials used in this process included a questionnaire guide with 22 open-ended questions that was developed from the constructs of the User Centered Design Framework tested through cognitive interviews with three TB clinic personnel (a clinical officer, a nurse, and a health records assistant) to assess clarity, relevance, and interpretability. Each participant was asked to complete the questionnaire while verbalizing their thought process (think-aloud protocol), and follow-up probing questions were used to elicit deeper insights into their understanding of each item. The feedback obtained revealed ambiguities in terminology (e.g., 'workflow') and concerns about certain concepts (e.g., data privacy). As a result, several items were reworded for clarity, and additional explanatory text was added where necessary. The responses were collected through a Sony voice and sound recorder, analyzed, and mapped with a requirement engineering tool to specify the preferred features by the participating healthcare givers. Both of

these tools were provided in the appendix section of this dissertation. After development and during testing, a usability questionnaire was administered to assess usability and participant acceptance of the web application.

5.7.2 Data analysis.

An inductive analysis was conducted on the interview recordings using ATLAS.ti. V9 (version 9) to determine participant preferences for important solution components. This method followed the user-centered design framework and involved the bottom-up development of themes and a codebook grounded in the interview data.

Additionally, user testing with a Usability Test Questionnaire (UTQ) was administered to end-users, soliciting their feedback on functionality, usability, and overall satisfaction of the DHSI2 web application. Furthermore, the analysis of the usability assessed the different selected components of the User Centered Design framework for evaluation, adapted for this study to deliver a prototype. The Cronbach's Alpha index was calculated to determine if the questionnaire items were consistent and reliable in measuring usability. In addition, the Kruskal-Wallis Test, a non-parametric test, was used to compare usability scores across the different cadres, and a 95% confidence interval (CI) for the mean usability score was computed to quantify the uncertainty around the average perceived usability. Descriptive statistics were generated to summarize central tendencies and variability, and usability scores were also stratified by cadre to examine potential differences in experience. Furthermore, Principal Component Analysis (PCA) was conducted to explore underlying dimensions of the usability questionnaire and to assess whether the items loaded onto common usability constructs such as system quality, usefulness, information quality, and interface quality. All analyses were conducted using Python (Pandas, SciPy, Statsmodels, and Scikit-learn libraries).

5.8 Quality Assurance and Control.

To ensure the reliability and accuracy of the predictive model, I utilized the existing data within the eCBSS to test and validate with the same datasets. The model accuracy was represented by the area under the curve, the Receiver Operating Characteristic curve, the confusion matrix, specificity, F1 score, accuracy, and precision.

By implementing advanced Python imputation methods, the study handled missing data variables by utilizing KNN imputers since ML models require complete datasets, as evidenced in the code shared on the public repository at GitHub link provided in the later section. Interviews for the collection of user requirements exhausted all functional and non-functional operations of the web application. The survey tool for usability testing was issued online to the participants, and only they could edit it.

5.9 Data management.

A number of crucial actions were involved in the data management for this study. These processes were intended to guarantee the accuracy and reliability of the models that are being used. Data-driven visualizations, data cubes, and feature-based analytics are used in the process, which starts with data exploration and ends with insights into the dataset.

In line with this, the researcher carried out data mining from the eCBSS, cleaning, labeling, and modelling for the machine learning Deep learning model. I applied data management tools in machine learning, including preprocessing, transformation, and data cleaning with filtering, to streamline and optimize the entire data management process for the study. The code was written with Python packages such as numpy, pandas, scikit-learn – among others – that shall create a pipeline for the web application components that display the final model's performance.

5.10 Web application development, testing, publishing, and documentation.

This section will provide the methodology for the web solution development and testing, as well as an analysis plan for its intended impact.

5.10.1 Web application development.

Following the DHIS2 architecture for web applications, I developed the interactive solution in Python and React following an analysis of the user requirements gathered prior. The runtime environment from DHIS2 supported the application. Furthermore, DHIS2 provided scripts for building, testing, packing, deploying, publishing, and API data fetching.

Python 3.0, JavaScript, and TypeScript were preferred with React for its extensive use, making the application usable across different versions, and the application able to operate in other tracker-based DHIS2 systems. The application had an interactive user interface developed in React to engage with more features about a particular patient. This way, the physician, doctor, or data clerk

at the facility can interact with the patient's files and arrange personalized care. The web pages ran HTML5 standard with React scripts and CSS styles as encouraged by the DHIS2 web app development platform. Furthermore, a Geographical Information System (GIS) enhancement through GeoPandas, Leaflet, and React was deployed to offer the GIS's granular data components. The GIS capabilities were important in providing location tracking and spatial variability in disease incidence.

5.10.1.1 Application Development Life Cycle.

Choosing the Scrum Agile web app development technique was the best option in the dynamic and quick-paced environment of healthcare settings like TB clinics, where accuracy, adaptability, and effective communication are vital. Scrum's iterative process fits the changing demands of healthcare professionals perfectly, enabling continual improvement of the web-based application to satisfy shifting clinical specifications.

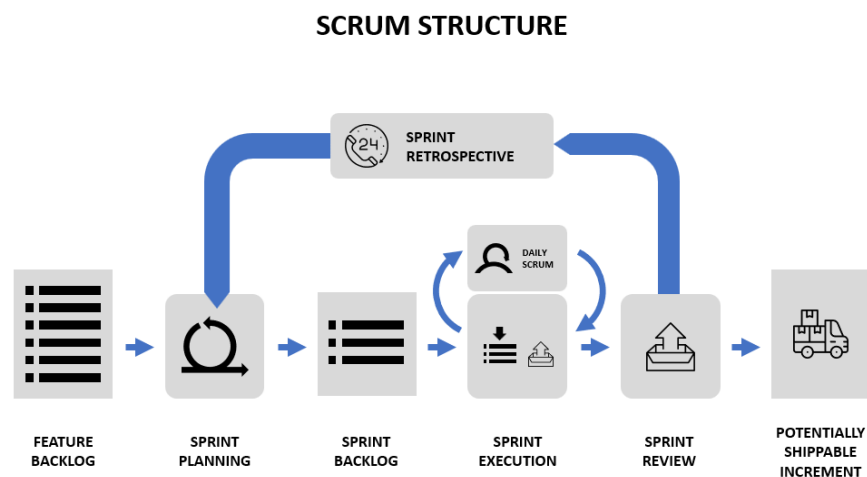


Figure 3: Scrum methodology for the development process

The methodology involved actively engaging medical professionals, software developers, and end users, emphasizing routine cooperation and feedback. This approach aimed to foster a deeper understanding of the clinical workflow and generate a customized solution. Additionally, Scrum's time-boxed sprints guaranteed consistent progress and frequent checkpoints, allowing for timely

modifications and fostering openness in the development process. I utilized this methodology to ensure delivery by assigning the target users at TB clinics as product owners.

After analyzing the gathered requirements as described in the data collection plan, I produced a product plan listing the features of the product backlog. The developers can now provide Wireframes to the end-users – the clinicians and doctors at the TB clinics – before mapping them onto the product backlog. The developers can then release a product increment after satisfying the users through the testing phase, before finally uploading it into the application framework.

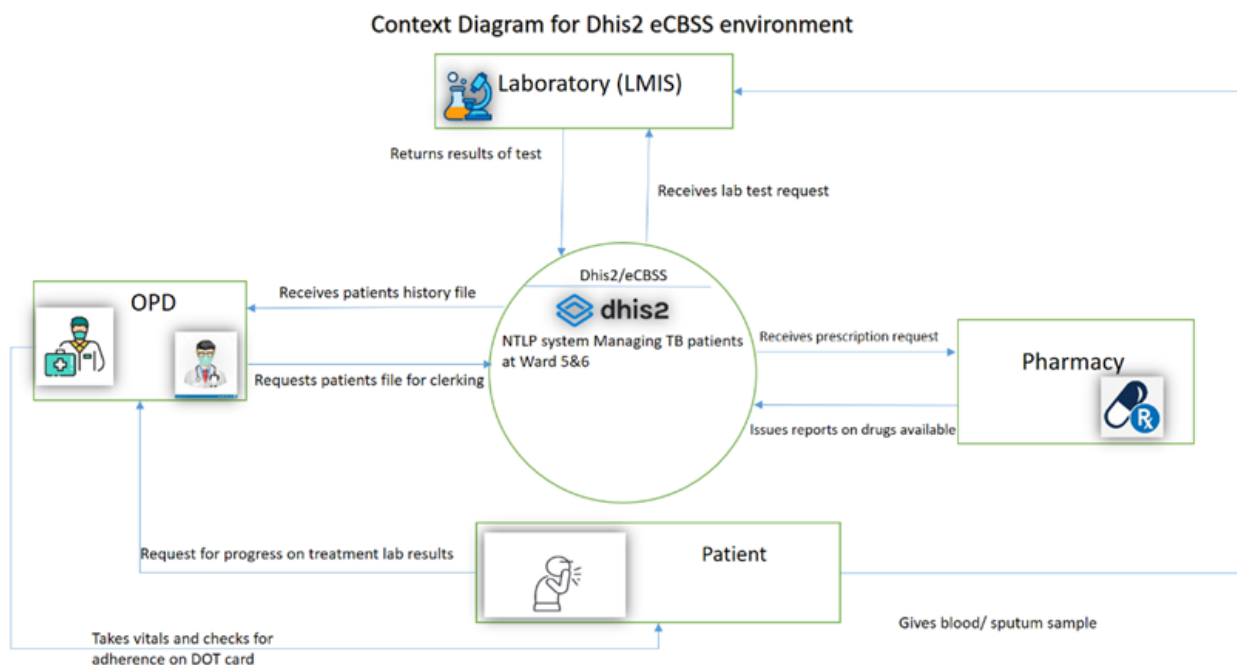


Figure 4: Context View of DHIS2's eCBSS Clinical Environment

The above representation describes the current environment within which the eCBS system operates in at the Mulago wards 5 and 6 of the Mulago National Referral Hospital in Uganda. At the OPD, the doctor examines a TB patient, and their details are collected in the individual files of the patient. The patient proceeds to the various points, such as the laboratory or pharmacy,

depending on their current scheduled visit. A data clerk then receives the files and enters the data into the manual registers before entering it into the DHIS2 tracker capture application about this new visit. This is the same approach at both the laboratory and the pharmacy.

Proposed DHIS2 eCBBS Environment.

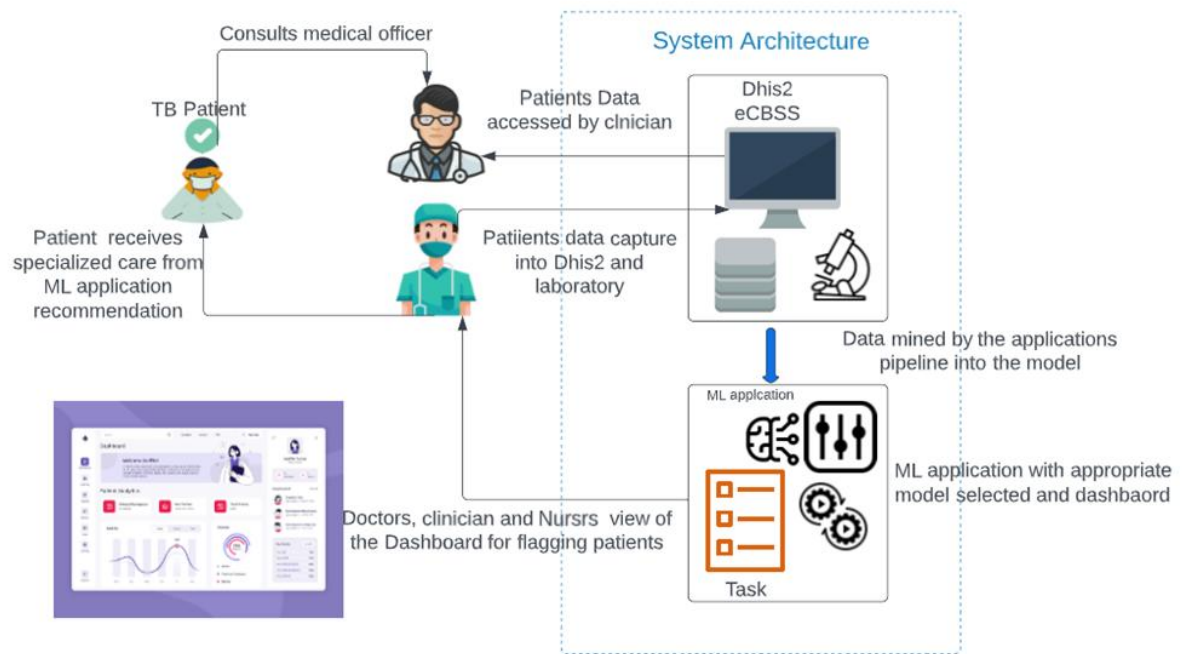


Figure 5: Proposed DHIS2 eCBSS Environment after ML Integration.

5.10.2 Machine Learning Model Development.

The researcher developed a pipeline and supervised a machine-learning model applying data preprocessing, test and training dataset combination, and validation for new patients' data. Algorithms such as Support Vector Machine (SVM), Deep learning algorithms of Deep Neural Networks (DNN), and Random Forests (RF) were written in Python 3.0 for the model ensemble. Preference for these methods is from documented studies mentioned in the literature review section of this paper, along with how their performance affected similar studies.

i. Model rationale.

The selection of a one-dimensional deep neural network (1DNN) as the predictive model was guided by both technical and contextual considerations of the study. Although several algorithms including Support Vector Machines, Random Forests, and XGBoost, were evaluated, their deployment within the DHIS2 framework proved impractical due to compatibility limitations with TensorFlow.js, the runtime environment for client-side execution in JavaScript. They therefore were not included in this study. The 1DNN, on the other hand, could be seamlessly converted from Keras into a browser-executable format, enabling real-time predictions without dependence on stable internet connectivity—an essential feature for TB clinics in Uganda’s resource-limited settings. This client-side architecture also enhanced data privacy, as patient information remained local during inference. Structurally, the model employed a funnel design (128–64–32 neurons) optimized for efficiency and stability using ReLU activations and sigmoid output for binary classification. The model achieved an accuracy of 92% and an AUC of 0.96, confirming its robustness in capturing complex, non-linear interactions in patient data. Overall, the 1DNN was selected for its balance of predictive accuracy, computational efficiency, and deployment feasibility within the DHIS2 environment.

Model development commenced after access to the API data fetching authentication for the development instance of the eCBSS on a local machine. To begin, I initiated a pipeline development process starting from the data fetched by the Web API, followed by standardization.

ii. Data Preprocessing and Feature Engineering Pipeline.

The dataset underwent a comprehensive multi-stage feature engineering workflow. Initial data curation was performed using pandas: 19 domain-irrelevant features were removed manually, and columns with missing values exceeding 10% of the dataset were eliminated using threshold-based filtering. Categorical and numerical features were identified and processed separately. Categorical variables were encoded using sklearn's LabelEncoder, mapping discrete categories to integer labels with an offset of +1 to distinguish encoded values from missing data. Both numerical and encoded categorical features underwent imputation via k-nearest neighbors (KNN) using sklearn's KNNImputer with k=10 neighbors, which preserves local data structure and relationships superior to distributional assumptions of mean/median imputation. Numerical features were then normalized using StandardScaler, centering to mean=0 and scaling to unit variance—a prerequisite for efficient gradient-based neural network optimization. To address class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) from imbalanced-learn was applied with sampling_strategy=0.4 and k_neighbors=5, generating synthetic minority-class samples to achieve

balanced class representation. The binary target variable was initially mapped from categorical labels ('Yes'/'No') to binary integers {0, 1}, then converted to one-hot encoded format using TensorFlow's `to_categorical` utility for multi-class neural network compatibility. The balanced dataset was partitioned into training (80%) and testing (20%) sets using sklearn's `train_test_split`. A deep neural network comprising three fully connected layers (128, 64, 32 neurons with tanh activation) followed by a sigmoid output neuron was trained using TensorFlow/Keras with binary cross-entropy loss and the Adam optimizer for 30 epochs with batch size 32. Model evaluation employed multiple performance metrics: test accuracy, Area Under the Receiver Operating Characteristic Curve (AUC-ROC) via `roc_auc_score`, confusion matrix, classification report (precision, recall, F1-score), and corresponding visualizations (ROC curves, confusion matrix heatmap, metrics heatmap via seaborn). Feature importance was assessed by extracting and aggregating absolute weights from the first dense layer, ranking features by their contribution to the network's initial transformations. Finally, all preprocessing artifacts (scaler parameters, label encoder mappings, KNN imputer objects, trained model weights) were serialized using joblib and JSON formats. Inference on new data was conducted via a dedicated preprocessing pipeline that applies identical transformations, imputation, categorical encoding, scaling, and one-hot conversion, to ensure consistency between training and inference stages, with batch predictions saved to CSV format for downstream analysis.

Following the initial hold-out test set evaluation, the trained model underwent a secondary consistency validation phase to verify reproducibility and robustness of predictions on the training dataset using the serialized inference pipeline. Specifically, the trained model, along with its associated preprocessing artifacts (StandardScaler parameters, KNN imputer objects, and label encoder mappings), was reloaded from disk and applied to the original dataset via an inference wrapper function that replicates the exact preprocessing transformations applied during model training. This inference-based validation served two critical purposes: (1) to confirm that preprocessing transformations (imputation, encoding, scaling) were deterministically reproducible when applied through the serialized artifacts, and (2) to ensure that model predictions remained consistent across different invocation contexts, validating that no data leakage or preprocessing inconsistencies existed between training and inference stages. The predictions generated via the inference wrapper, encompassing class labels, prediction probabilities, and classification thresholds (0.5), were output to a CSV file containing class assignments and confidence scores for all observations. This inference phase effectively functions as an external consistency check: by reapplying the model to the original data and obtaining deterministic results, we demonstrate that (a) the preprocessing pipeline is reproducible and (b) the model generalizes consistently when subjected to identical preprocessing conditions. The agreement between training-phase validation metrics (test set accuracy, AUC-ROC, precision, recall, F1-score) and the deterministic predictions generated through the serialized inference pipeline serves as empirical evidence that the model is robust and that preprocessing-to-prediction

mappings are stable and repeatable. This dual-validation approach, while combining hold-out test set evaluation with inference-pipeline consistency verification, provides comprehensive assurance that the developed deep neural network model behaves in a both discriminative capability on unseen test data and reproducible, deterministic behavior on previously-seen data, critical prerequisites for trustworthy model deployment in production environments.

iii. The model's architecture

The DNN's architecture included multiple dense layers, with the output layer using a sigmoid activation function to produce a probability value $P(y = 1 | x)$ where x represents the input feature vector for an individual. Mathematically, the prediction is expressed as:

$$P(y = 1 | x) = \sigma(w^T x + b),$$

Where:

- $\sigma(z) = \frac{1}{1 + e^{-z}}$ the sigmoid activation function,
- w is the weight vector,
- X is the input feature vector, and
- b is the bias term.

The model minimizes the binary cross-entropy loss function, defined as:

$$L = -\frac{1}{N} \sum_{i=1}^N [y_i \log P(y_i | x_i) + (1 - y_i) \log(1 - P(y_i | x_i))],$$

Where:

- N is the number of samples,
- y_i is the true label for sample i , and
- $P(y = 1 | x)$, is the predicted probability for sample i .

This probability directly represents the model's confidence in classifying an individual as MDR-TB resistant. By applying a threshold to the probability, such as $P(y = 1 | x) > 0.5$, the classification decision is made.

iv. **Model Evaluation Metrics and Implications.**

The performance of the one-dimensional deep neural network (1DNN) model was evaluated using multiple standard classification metrics to ensure robustness, interpretability, and clinical relevance. These included accuracy, precision, recall (sensitivity), F1-score, and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC). Accuracy measured the overall correctness of predictions, while precision and recall provided insights into the model's ability to correctly identify true MDR-TB cases without overestimating risk. The F1-score balanced these two measures, ensuring the model performed consistently across both positive and negative classes. The AUC-ROC was particularly emphasized because it indicates the model's discriminatory ability; that is, how well it distinguishes between DS-TB patients likely to develop MDR-TB and those who are not. An AUC of 0.96 demonstrated excellent performance, confirming the model's suitability for clinical risk prediction and decision support. The confusion matrix was used to visualize true and false classifications, aiding in the assessment of sensitivity versus specificity trade-offs.

The choice of these metrics was guided by their interpretability for healthcare applications and their relevance to public health decision-making, where minimizing false negatives (missed high-risk patients) is as critical as controlling false positives. By applying this comprehensive evaluation framework, the model's results could be meaningfully linked to clinical and operational outcomes, reinforcing the reliability of the integrated dashboard for real-world use in Uganda's TB surveillance context.

5.10.3 GIS Module Development

The Geographic Information System (GIS) module was designed to visualize the spatial distribution of predicted MDR-TB risk and identify potential hotspots to support targeted public health interventions. To ensure patient confidentiality, the spatial component was developed using **synthetically generated coordinates** that corresponded to de-identified patient records rather than actual household or facility locations.

Synthetic coordinates were generated by introducing controlled random spatial offsets within district boundaries while maintaining the proportional geographic distribution of patients across health facilities. This approach preserved the spatial integrity of the data for visualization and hotspot detection while eliminating the risk of re-identification.

The GIS module was implemented using **Leaflet.js** and integrated within the DHIS2 web application through the existing mapping API. GeoJSON layers representing district boundaries and health facility catchment areas were used as base maps. For clustering analysis, the **DBSCAN (Density-Based Spatial**

Clustering of Applications with Noise) algorithm was employed to group synthetic points based on density thresholds, allowing the identification of areas with relatively higher predicted MDR-TB risk. The module was optimized for offline use, enabling healthcare workers to visualize and interpret hotspot patterns even in settings with intermittent internet connectivity.

This GIS integration complemented the predictive model by translating patient-level risk data into actionable geographic insights if the GIS coordinates can be captured into DHIS2, thereby supporting decision-making for targeted screening and resource allocation while maintaining strict adherence to data privacy and ethical standards.

5.10.4 Testing and Training of Users.

The developed prototype was demonstrated to users as part of the testing and training process. This involved showcasing the key functionalities of the ML-powered web application, including how to navigate the interface, interpret risk scores, receive alerts, and manage patient data. The demonstration allowed users to interact with the system in a controlled environment, ask questions, and provide immediate feedback, which was essential for refining both usability and user support materials.

5.11 Ethical consideration.

Upon approval of this study by the Internal Review Board for the School of Public Health of Makerere University and the NTLP at MOH, I prepared a set of consent forms that abided by the Good Clinical Practices rules for the participants. These were presented physically to relevant facilities with an introduction letter of the solution to address MDR-TB. No Personally Identifiable Information (PII) from participants was collected beyond the agreed criteria, as this was to maintain their privacy. I ensured exclusive protection of hard copy data, containing participants' responses. Electronic data obtained from the eCBSS was confined within both the online and local versions of the DHIS2 environment and remains under electronic protection provided by security applications.

Any unauthorized access to personal data was and still will be promptly reported to the Institutional Review Board (IRB), National Tuberculosis and Leprosy Program (NTLP), Ministry of Health (MOH), and other relevant bodies affected by such incidents.

CHAPTER SIX: RESULTS.

Introduction

In this chapter, the researcher presents the results of the study that followed the elicitation of the user requirements that informed the development of the ML web application with a GIS Module. The section begins by describing the study participants and their characteristics and distribution.

Table 1: Summary of demographics for participants

Name of Facility and distribution of participants	
Mulago National Referral Hospital TB ward	4
Mukono General Hospital	4
Entebbe RRH	4
Facility Type and distribution of participants	
National Referral Hospital	4
District General Hospital	4
Regional Referral Hospital	4
Cadre distribution of participants	
Clinical Officer	3
Data Clerk	3
Lab technologist	3
Nursing Assistant	3
Gender and distribution of participants	
Male	6
Female	6
Numeric Variable Summary (Age)	
Mean (SD)	41.9 (SD = 9)
Median (IQR)	40 (IQR 32.7, 50)
Age Summary by Cadre (Mean)	
Clinical Officer	42
Data Clerk	33
Lab Technologist	38
Nursing Assistant	54

Themes that emerged from the user elicitation analysis are discussed under section 7.1, *user requirements elicitation*, in this dissertation. In addition, the chapter presents the development of the artifact and system testing and usability assessment among the selected participants at the three health facilities in Uganda.

The study effectively identified key user requirements from healthcare providers, organized into functional, non-functional, and implementation needs. Functional priorities centered on tools like risk scoring, real-time alerts, treatment adherence tracking, and outcome monitoring, while non-functional needs focused on reliability, scalability, and usability. A 1D deep neural network model achieved strong performance, with 92% predictive accuracy and an AUC of 0.96, validating its ability to forecast multidrug-resistant tuberculosis (MDR-TB) risk.

A React-based dashboard, integrated into DHIS2's electronic Case-Based Surveillance System (eCBSS), incorporated a GIS module to map MDR-TB hotspots geographically. Usability tests showed high acceptance among healthcare workers, with average ratings of 4.65–4.87/5 on factors like interface clarity and data visualization. However, participants highlighted opportunities to refine search features and error-message handling. These outcomes underscore the potential of combining machine learning and geospatial analytics within DHIS2 to strengthen TB surveillance systems and support data-driven public health decisions.

6.1 User Requirements Elicitation.

From the analysis of the user requirements, two major themes emerged from the interviews with the participants and included: the proposed web application's user requirements, categorized as functional and nonfunctional, and the Administrative requirements, as human resources, hardware, and suitability needs. The functional and nonfunctional requirements shaped the development of the machine learning-powered web application to provide decision support for personalized care towards DS-TB patients and monitor the development of MDR-TB. The themes are discussed below, starting with functional and nonfunctional requirements, whose format is a table that summarizes the intended system requirement derived from the user as well as the deduced specification and a supporting quote.

6.1.1. The web application's user requirements.

User requirements refer to the features and qualities that end-users expect from a system to perform their tasks effectively (Kalankesh et al. 2020). For the proposed web-based decision support application for DSTB care, these requirements were gathered through interviews with healthcare workers and reflect both functional needs—such as alerts, risk scoring, and patient tracking—and non-functional aspects like reliability, scalability, and usability.

i) Functional requirements.

Functional requirements describe what a system should do as the specific behaviors, features, or functions it must support to meet user needs or business goals (Parsaei et al. 2024). Healthcare workers at the study’s chosen facilities identified the following to be the functional requirements, and they are presented in tables for easier mapping.

A summary table of the Functional user requirements.

Table 2: Summary of Functional requirements

REQ. ID	USER REQUIREMENT FUNC.	SYSTEM REQUIREMENT	SYSTEM SPECIFICATION REQUIREMENT	SUPPORTING QUOTE
REQ-001	Real-time alerts and notifications for critical patient events	The system must detect and send alerts for abnormal results or new diagnoses in real-time	Implement an automated, event-driven alert mechanism that pushes notifications to designated healthcare personnel instantly	“Well, there should be a quick mechanism that alerts or sends messages to care providers. If at all, there is maybe an abnormal result, and maybe an alert that there is a new diagnosis, an alert that maybe the baseline.” [P#11]
REQ-002	Display MDR-TB risk scores for patients.	The system must compute and display individualized MDR-TB development risk scores.	Integrate a predictive model using patient metrics (e.g., treatment history, lab results) to generate and visualize dynamic risk scores.	“It should be able to prioritize alerts either based on patient or based... because normally the patients have the date they came in and the date they are coming back, so for this information it must be able to tell me that this patient is supposed to come back today...” [P#06]

REQ-003	Prioritize alerts based on patient visit schedules	The system must prioritize alerts based on appointment date or clinical urgency	Implement scheduling logic that queues alerts by urgency and proximity of appointment dates	“It must be able to tell me that this patient is supposed to come back today, that would be an alert. For one who will come tomorrow, I will need it tomorrow and not today.” [P#06]
REQ-004	Group patients based on risk levels	The system must classify patients into predefined risk groups	Use clustering or classification techniques to label and display patient risk categories in the UI	“We even put that there is a risk group. So, if you take something there, every eye is going to look at how that risk is important in our management.” [P#09]
REQ-005	Display essential patient baseline information.	The system must consolidate and display patient demographics and clinical history.	Develop a UI component that shows contact info, past TB episodes, adherence history, and treatment dates.	“On the user interface, we automatically like to see their phone contact of the patient, we need the names, the history of the patient’s treatment, and when they last had TB? How long were they on treatment? Were they adhering?” [P#06]
REQ-006	Track follow-up outcomes and treatment adherence	The system must monitor and log patient adherence and follow-up activities.	Provide features to record treatment updates, generate adherence alerts, and summarize follow-up interactions.	“Even tracking patients' progress. Like to get to know whether a patient is taking their medication or not, like that follow-up.” [P#10]

REQ-007	Automate appointment scheduling with clinical summaries	The system must generate future appointments and pre-visit summaries	Enable calendar-based scheduling with patient-specific summaries derived from clinical data	“And also scheduling appointments ahead of time with clinical summaries of patients, such that you anticipate the difficulties you are going to encounter with these particular patients.” [P#11]
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ii) Non-functional requirements.

Non-functional requirements describe how a system should operate rather than what it should do. These requirements define the quality attributes, performance criteria, and constraints that ensure the system functions effectively under various conditions (Parsaei et al., 2024). From the interviews conducted with healthcare workers at the selected facilities, several critical non-functional requirements were identified. These are presented in the table below for clarity and structured mapping to system design specifications.

A table for mapping the nonfunctional requirements.

Table 3: Summary of Nonfunctional Requirements

REQ. ID	USER REQUIREMENT FUNC.	SYSTEM REQUIREMENT	SYSTEM SPECIFICATION REQUIREMENT	SUPPORTING QUOTE
NFR-001	Scalability across multiple care levels and growing data volumes	The system must support a growing number of users and datasets without degrading performance	Employ a scalable cloud-based infrastructure and microservices architecture that can dynamically allocate resources	“It should be available to all levels of care... both even private and public facilities where TB care is provided. Not restricted to only public.” [P#11]
NFR-002	Reliability and high availability	The system must minimize downtime and ensure consistent availability	Integrate failover mechanisms, real-time system health monitoring, and implement maintenance routines	“I think it should be very high. Because we basically base on them on decision-making... especially during entry, it should be more sensitive...” [P#02]
NFR-003	Data validation and intelligent data handling	The system must validate data at entry and manage records based on patient treatment status.	Implement automated data validation checks and intelligent record lifecycle management.	“A hundred percent validation... It automatically removes patients who are okay... It keeps on putting them in

				the back to create more space...” [P#06]
NFR-004	Security and privacy of patient data	The system must restrict access to sensitive information and prevent data breaches.	Use role-based access controls, end-to-end encryption, and secure login/authentication methods.	“Restricted access to only key people, responsible people for a given kind of information.” [P#06]
NFR-005	Accessibility on various devices and role-based views	The system must be accessible on smartphones, desktops, and support user-specific access restrictions	Implement responsive design, device compatibility, and role-based user interface components	“It can be accessed on smartphones as well. It can be used on a smartphone.” [P#02] and “There are things, like a doctor does... should be closed [from others].” [P#09]
NFR-006	Usability and intuitive interface design	The system must be user-friendly and easy to navigate for healthcare staff.	Design streamlined workflows, intuitive layouts, ISO-aligned usability standards, and provide user training/support.	“There should be usability and quality elements addressed... and there should be a backup system.” [P#09]

NFR-007	Responsiveness and fast performance	The system must respond quickly to user inputs and data operations even under heavy loads.	Optimize backend performance, database queries, and utilize caching where appropriate.	“It should definitely get faster... since this is an AI-based system, they become better with more information.” [P#06]
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i) Hardware requirements.

To effectively implement and support the various features and functionalities identified in the elicitation process, the TB clinic participants require robust hardware infrastructure. Participants were not satisfied that the current internet connection at the facilities limited their use of applications such as the eCBSS. They therefore suggested the need for reliable internet and network connection to facilitate the continued use of the application. High-performance servers with ample processing power, memory, and storage capacity are essential for maintaining patient dashboards, supporting graphical representations of drug adherence trends, and ensuring data integrity with redundant storage solutions. Therefore, a recommendation to enhance these infrastructure components includes upgrading the existing internet connectivity to high-speed, stable networks, investing in modern computing devices, and deploying secure, scalable server environments. These enhancements will ensure uninterrupted access to the application, enable real-time data processing, and support the system's advanced functionalities such as analytics, alerts, and risk scoring. Such improvements are crucial to guarantee the system's responsiveness, reliability, and long-term sustainability in routine clinical workflows.

A quote from one participant states that:

“It moves into the IT point of view. Because if you're looking at those factors, we're going to need a lot of space, a lot of server space, a lot of RAM, and constant, how do I call it, IT care?” [P#11].

6.1.2. Implementation requirements.

Another theme that emerged was the administrative needs of the staff at the clinics, with sub-themes of human resource and sustainability requirements for the successful implementation of the ML web-powered application.

i) Human resources need.

Staffing needs emerged as a critical theme influencing the successful implementation and long-term sustainability of the proposed web-based decision support application for DSTB care. Participants emphasized that without adequate human resource capacity, even the most well-designed systems may fail to deliver the intended benefits. Concerns ranged from system usage and maintenance to user training and ongoing support. Several participants highlighted the existing burden on healthcare workers and the need for dedicated personnel to manage digital health systems effectively.

A participant particularly mentioned verbatim that,

" it should be a technical person to be checking the system time from time and to be servicing." [P#09].

In addition, training was another need to sustain the use of the new application lest it be abandoned upon initial implementation, as staff emphasized the importance of continuous capacity building to ensure all users are confident, competent, and comfortable navigating the system in their routine workflows. The preferred mode of training was one-on-one sessions with participants.

A participant was quoted in support as;

"Why am I claiming it's physical? Because if I sit and you start teaching, I might hear but not understand what to do. I may forget. But if I do it physically, it will stay in my head." [P#02].

Furthermore, participants emphasized the need for comprehensive training on using the patient dashboard effectively, particularly to promote its use in research and data analysis. Continuous training for current staff was seen as essential to ensure that staff turnover does not compromise the system's usability or continuity.

Another participant was quoted as alluding to it;

“Training should be there and should provide mechanisms of data analysis for usability into others like reports, analysis, and should be accessed by researchers, they will support its continued existence, such that people don’t need to get data from files.” [P#11],

ii) Sustainability requirements.

Sustained use of the online application at the TB clinic depends on ongoing training, stable internet connectivity, consistent funding, and access to suitable equipment such as computers, laptops, or tablets with data access. Additionally, securing resources for system maintenance and periodic upgrades is vital. Ensuring that the clinic is equipped with updated devices and reliable internet will be key to supporting the long-term functionality of the machine learning-powered web application.

Participants emphasized these with quotes below,

" That you can probably say to people that maybe after six months, a refresher, this is how we, if there's somebody new on board, let them look at this. You cannot sustain saying you're going to train people all the time. Maybe after a number of years, probably three, you can say let's review and see how have you been, what do you need to change and how has it been working." [P#01].

" I think one is internet, internet coverage, then also the equipment themselves. They have to be serviced if you are using the computers. At certain times they have to come and do a check to see if they are moving on, if software is fine, those things. And also, the end users themselves, at one time you have to check our understandings, what are some of the upcoming issues in the system, do we need change?"

" Of course, maintenance, the trainings, that is all around funding. If you don't have funds, you can't do maintenance, you can't train people." [P#03].

6.2 Developing and integrating the artifact.

In this study, I concentrated on the ML integration and developed the application first out of the DHIS2 system in React, which is a web application development framework with robust and flexible user-friendly components that are used to develop interfaces. React is also the same framework that is used to build core DHIS2 applications, and as such, was sufficient for building the application. JavaScript, a programming language that makes web pages more interactive, was used to build the components; however, DHIS2 prefers TypeScript, another language that restricts state management and provides efficiency in memory management. The Integrated Development Environment (IDE) was Visual Studio Code, a source code editor that's available for Windows, macOS, and Linux and supports multiple languages. A development instance of the DHIS2's eCBSS was provided by the MOH's DHI to assist the researcher in understanding its implementation and guide the application development. This was crucial in understanding the naming convention of DHIS2 to maintain the names of data points, data elements, reports and features so that the intended application doesn't divert from the original concept. However, there were challenges in applying development directly into the development instance, as its user rights are restricted to protect the stability of the instance. Upon the advice of HISP Uganda, a local instance was implemented by the researcher to demonstrate the integration of the ML application.

6.2.1 The Machine Learning project to predict MDRTB.

Python was chosen as the primary programming language due to its extensive ecosystem of machine learning packages. TensorFlow and Scikit-learn frameworks were used to create, train, and test models. These technologies allowed for quick management of big datasets and the flexibility to deploy a variety of machine learning methods. The dataset used for this machine learning project was sourced from the DHIS2 system, which captures event-level data related to DS-TB cases reported in public health facilities in Uganda. This dataset included patient-level records with relevant demographic, clinical, and treatment-related attributes.

Key Aspects of the Dataset:

Table 4: Description of data utilized for the Model

ASPECT	DETAILS
Data size and scope	98,209 unique patient event entries
Gender distribution	61,692 male, 36,517 female patients.
Outcome distribution	5,123 cases were used, 4,665 were labelled ‘No’ (not transferred to second-line treatment), and 459 were ‘Yes’, indicating MDR-TB development. This reflects an imbalanced dataset .
Feature overview	202 features were available. After removing features with insufficient data, 48 features remained, categorized as: • Demographic: Age, gender. • Clinical: Treatment history, medication adherence, comorbidities, prior TB test results. • Temporal: Treatment duration, follow-up intervals • Synthetic GIS: Simulated coordinates approximating Uganda's 2016 administrative boundaries (districts, parishes, villages).
Target variable	The target variable was binary : • 0 = Not transferred to 2nd line (no MDR-TB) • 1 = Transferred to 2nd line (MDR-TB), enabling a classification task.

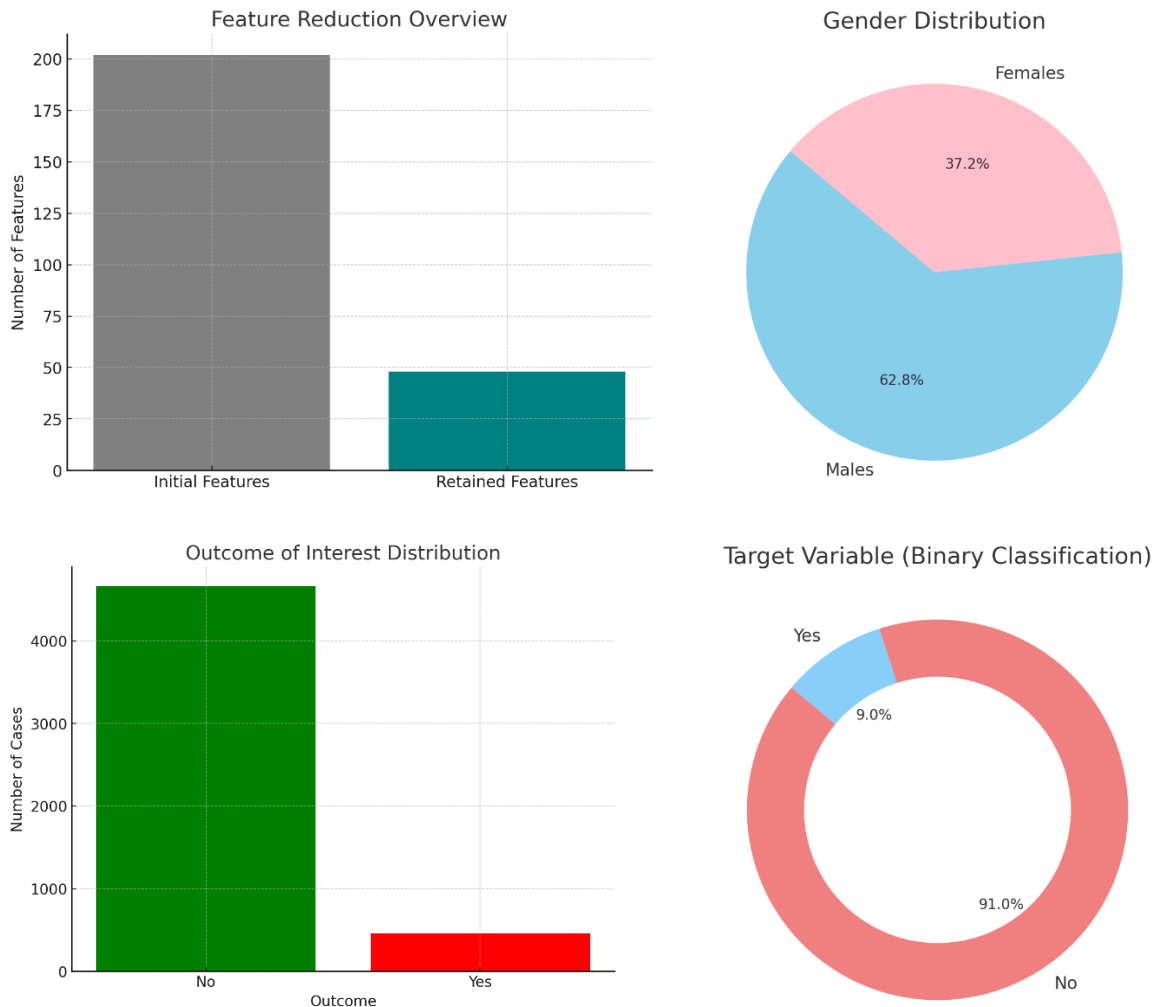


Figure 6: Summary of the Data used for model training and validation, showing from the first figure with initial features and retained features, the male-to-female ratio, the outcome of interest, and the target variable with an imbalanced dataset.

Model Training and Prediction

The DNN was trained on a preprocessed dataset with binary labels indicating the classification categories: "No" (negative class) and "Yes" (positive class). After training, the model's performance was assessed on a separate test dataset. The output layer of the DNN used a sigmoid activation function, which produced probabilities ranging from 0 to 1 for each sample. A threshold of 0.5 was applied to these probabilities to determine the final classification:

- A predicted probability $P(y=1|x) > 0.5$ classified the sample as "Yes."
- Otherwise, the sample was classified as "No."

Confusion Matrix Results

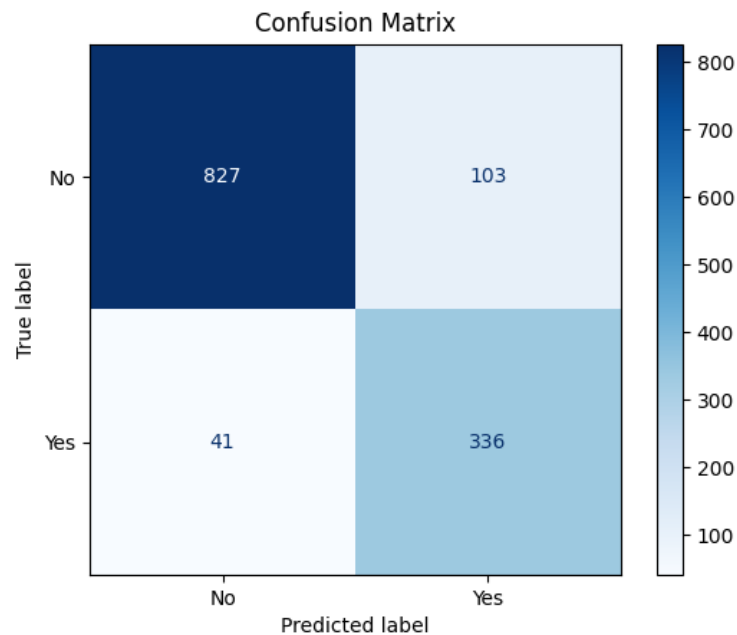


Figure 7: Confusion matrix for the DNN training dataset

The confusion matrix, presented in the above Figure, was constructed by comparing the predicted labels with the true labels in the test dataset. It contains the following elements:

- **True Negatives (827):** The number of samples correctly classified as "No."
- **False Positives (103):** The number of samples incorrectly classified as "Yes."
- **False Negatives (41):** The number of samples incorrectly classified as "No."
- **True Positives (336):** The number of samples correctly classified as "Yes."

These values were derived from the prediction outputs of the DNN on the test dataset, ensuring that the evaluation reflected real-world performance.

i) Interpretation

The confusion matrix provides valuable insights into the model's performance:

- **Sensitivity (True Positive Rate):** The model correctly identified 336 "Yes" cases, highlighting its ability to detect positive instances.

- **Specificity (True Negative Rate):** The model correctly classified 827 "No" cases, indicating its reliability in identifying negative instances.
- **Error Rates:** The matrix also revealed areas of improvement, such as reducing false positives (103) and false negatives (41), which directly impact overall accuracy and predictive power.

A classification report of the model's performance was as follows in the table below.

Table 5: Classification report for the model performance

Metric	Class "No"	Class "Yes"	Macro Average
Precision	0.89	0.76	0.82
Recall	0.95	0.89	0.92
F1 Score	0.92	0.82	0.87
Support	930	377	

ii) Explanation of the Report

1. Precision

- For **Class "No"**: A precision of **0.89** indicates that 89% of the predictions labelled as "No" were accurate.
- For **Class "Yes"**: A precision of **0.76** shows that 76% of the predicted positives were correct.

2. Recall (Sensitivity)

- For **Class "No"**: A recall of **0.95** indicates that the model identified 95% of the true negatives.
- For **Class "Yes"**: A recall of **0.89** highlights the model's capability to correctly capture positive instances.

3. F1 Score

- The **F1 Score** provides a single number that balances precision and recall, ensuring a more holistic evaluation. For **Class "No"**, the F1 is **0.92**, while for **Class "Yes"**, it is **0.82**.

4. Support

- **Support** values show the number of test samples present in each class:
 - For **Class "No"**, there were **930** test samples.
 - For **Class "Yes"**, there were **377** test samples.

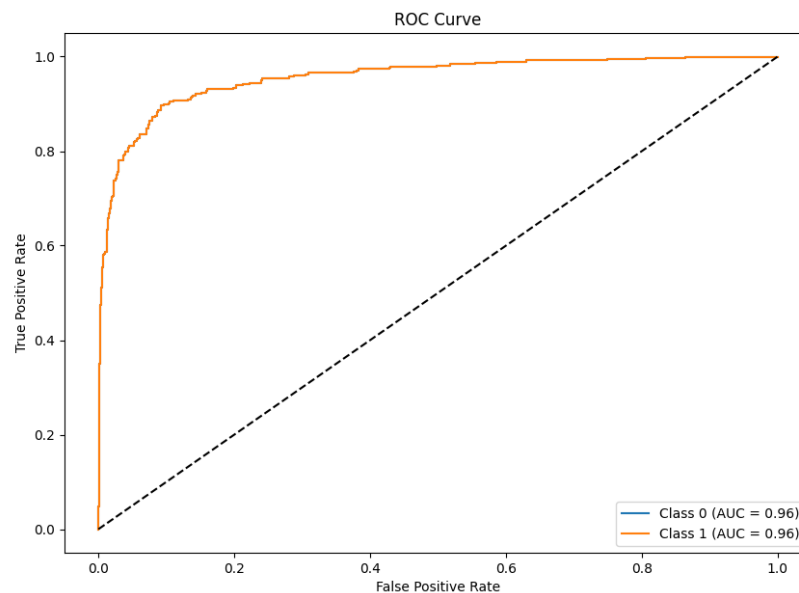


Figure 8: Receiver operation characteristics curve for AUC of 0.96 for both classes

The ROC curve shown in the figure above explains the built DNN's binary classification model in predicting two classes (Class 0, "No", and Class 1, "Yes"). The model had a remarkable Area Under the Curve (AUC) value of 0.96 in both classes, showing strong discrimination between positive and negative samples. The curves were near the top-left corner, indicating that the model maintained a high True Positive Rate (TPR) while keeping the False Positive Rate (FPR) low at various classification criteria. This result indicated that the model was highly effective at

identifying real positives while generating few false positives, making it ideal for applications needing accurate binary predictions.

Once the deep neural network (DNN) model was trained and evaluated, it was saved in the HDF5 format as a .h5 file. This format was chosen for its compatibility with TensorFlow and its ability to store both the model architecture and weights. The model was saved using the following function in Python: `model.save('model.h5')`. However, this format couldn't run in the application without flattening it into a JSON format.

The model was saved and then transformed into a TensorFlow.js-compatible format so that it could be used in a web application. The TensorFlow.js Converter, a program made to convert TensorFlow or Keras models into an approachable web format, was utilized in the conversion process. The code snippet below was used in Google Colab, a safe environment for managing large-scale AI workloads, to transform the model into a *model.json* capable of running in web applications.

```
import tensorflow as tf
import tensorflowjs as tfjs

# Define paths
model_path = '/content/sample_data/model.h5' # Path to your Keras model
output_dir = 'tfjs_model' # Desired output directory

model = tf.keras.models.load_model(model_path)

# Convert the model
tfjs.converters.save_keras_model(model, output_dir)

print(f"Model converted and saved to: output_dir")
```

The output of the conversion was a *model.json* and a *weights.bin* file that store the model's weights in a flat JSON format to be associated with the model and run in the web browser when the application is run. This was downloaded from the Collab environment and loaded into the public file of the React project for building the application.

6.2.2 Implementation in React for the web dashboard application development.

The project in React, coded with VS Code IDE, defined JavaScript components necessary to build the interfaces for the web application dashboard with ML predictions and contributing factors. They were named as follows:

1. **HotspotData.jsx** – This defined the use of patients' GIS coordinates to mark, at a granular level of parish and village, which is not yet possible in DHIS2. The coordinates from all patients would load through a mapping package and were used to create hotspots of those close to each other in a radius of two kilometers (2Kms). This data was used to create the GIS module, whose utilization can guide contact screening strategies and curate personalized care delivery to patients who are far away from the facilities or for some reason prefer to receive care from home.
2. **PredictionProcessor.jsx** – this hosted the logic of extracting the patient's event data points as captured in the Tracker Capture application of the eCBSS. It also hosted the logic for loading the TensorFlow model and its weights, the pipeline for converting the selected features necessary for tensor inputs, the calculation logic of the contributing factors using integrated gradient values since its binaries for react were the only ones available for the implementation, and finally the display of the prediction score with a doughnut chart and bar chart for the contributing factors.
3. **TrackedEntityContext.js** – the logic of maintaining the state of the patient's data across the different components to avoid mutability was controlled in this context.
4. **TrackedEntitiesTable.jsx** – This component hosted the logic for extracting the data from the eCBSS and presents it in table form for the user to select the desired patient whose details they were interested in.
5. **TrackedEntityDetails.jsx** – This hosted the actual dashboard of the selected patients with features of the summary of the patient's details, such as cards for essential information, tables for baseline data, charts for weight monitoring, and the GIS map.

In the React application, TensorFlow.js was integrated to enable real-time predictions directly in the browser on event data. The integration began with the installation of TensorFlow.js via npm:

npm install @tensorflow/tfjs.

The converted model was then loaded into the application using the TensorFlow.js `tf.loadLayersModel` method. The code snippet below illustrates this:

```
const loadModel = async () => {
  try {
    const model = await tf.loadLayersModel('/model.json', {weights: 'weights.bin'});
    model.compile({
      optimizer: 'adam', // Specify your optimizer
      loss: 'binaryCrossentropy', // Use appropriate loss based on your model
      metrics: ['accuracy'], // Metrics for tracking
    });return model;
  } catch (error) {
    console.error('Error loading the TensorFlow model:', error);
    return null;
  }
};
```

To make predictions, the patients' data was processed to match the format during the model's training phase. The process included scaling numerical features and encoding categorical variables. After preprocessing, the data was converted into a TensorFlow.js *tf.tensor* object to serve as input to the model. The prediction workflow in React involved loading the model and feeding the event data tensor for inference. The React application utilized these predictions to classify each event associated with tracked entity data dynamically. Whenever a user selected a tracked entity, the corresponding event data was preprocessed and passed to the model for prediction. The results were displayed in real time, providing insights into the likelihood of developing MDR-TB for each case represented by the doughnut chart displaying the risk score in probability format. This approach ensured seamless integration between machine learning capabilities and user interaction, leveraging the full potential of TensorFlow.js in a web-based environment.

6.2.3 The integration of the React application into a DHIS2 instance of the eCBSS.

After the successful components have been tested as user interfaces displaying the different dashboard views, the project is bootstrapped with DHIS2-specific configuration from the *d2 app*

scripts initialization that creates the structure of a DHIS2 application. After development, the app was built using the *yarn build* or *npm run build* command, which compiles the source code into optimized static files. The build output was then packaged into a ZIP file, containing all necessary files such as *index.html* and the *manifest.webapp* configuration, which describes the app's metadata and dependencies. Finally, the ZIP file was installed in a DHIS2 instance via the App Management interface, where it is uploaded and made available for use. This project's file can be accessed at the researcher's GitHub page through this link: <https://github.com/Mark-Outeke/predict-mdrtb>.

A user journey to the web application dashboard.

This section presents how the healthcare workers access and interact with the dashboard, with their precondition being that they were authenticated and logged into the DHIS2's eCBSS. The sections further present the basic flow to the single-page dashboard after accessing the patients list page. The first figure below is a high-level use case diagram for the actors at the health facilities and their interaction with the DHIS2 ML web application.

A high-level use case diagram

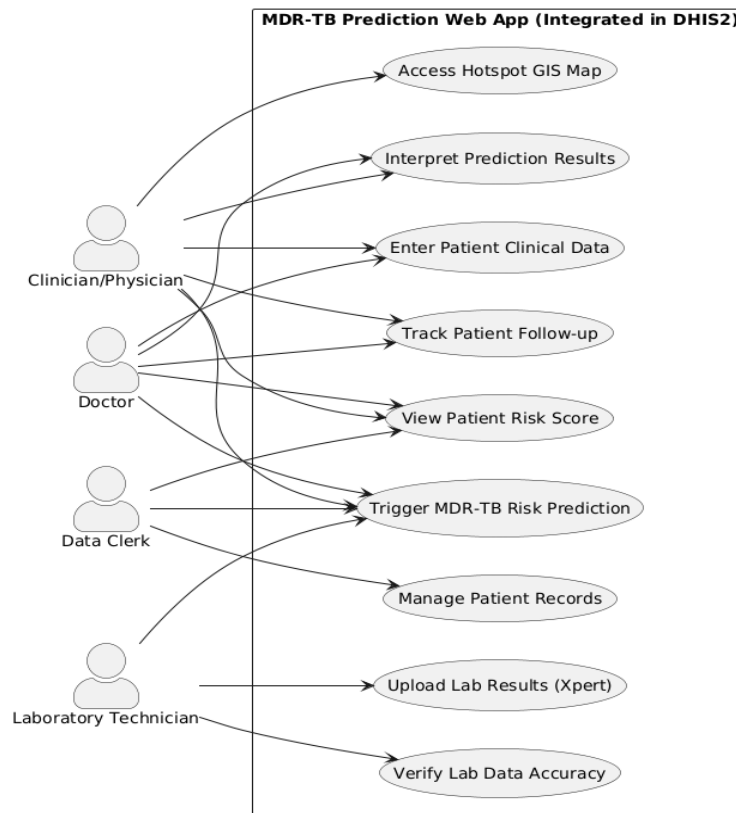


Figure 9: High-level use case diagram for the actor's interaction and the application

The next section presents the landing page and subsequent sections of the single-page dashboard and its features, such as the essential patient information, prediction overview with contributing factors, nutritional monitoring chart, follow-up tests and results, as well as the GIS map to show hotspot approximation and patient location.

Predict MDR-TB									
Menu Predictions Model Model Explanations									
Search by name									
Family Name	Given Name	Patient Name	Sex	Org Unit	TB No	Age in Years	National ID	GIS Coordinates	
Toggle SortBy	jam			Mulago NRH - Ward 5&6(TB Ward)			789lokm2345678cm		
Mugala	Namuddu	Cade	Male	Mulago NRH - Ward 5&6(TB Ward)	1407/10	48	627781863n	[32.56690933194293, 0.338811383360935]	
Musimenta	Ocan	Fabre	Male	Mulago NRH - Ward 5&6(TB Ward)	4993/17	56	288000996d	[32.64227445537724, 0.317928013425043]	
Nantongo	Apiyo	Nantale	Male	Mulago NRH - Ward 5&6(TB Ward)	2004/82	39	429469607w	[32.572857017633496, 0.321391382060915]	
Atimango	Kansiime	Namazzi	Female	Mulago NRH - Ward 5&6(TB Ward)	2228/68	55	222819468n	[32.56552688714656, 0.338441401704591]	
Lakot	Nagawa	Bacia	Male	Mulago NRH - Ward 5&6(TB Ward)	8250/92	62	461081363q	[32.6293972488841, 0.311714256094087]	
Kiconco	Kabagambe	Faatih	Female	Mulago NRH - Ward 5&6(TB Ward)	5228/11	40	354191796s	[32.62731186935935, 0.308327667866767]	
Kobusinge	Ocan	Caci	Female	Mulago NRH - Ward 5&6(TB Ward)	2418/52	41	695456368b	[32.5721435492406, 0.3291139520014]	
Katongole	Naigaga	Cadis	Male	Mulago NRH - Ward 5&6(TB Ward)	7939/13	56	340098054s	[32.64258239471856, 0.318701114616651]	
Mudondo	Lukwago	Eadburt	Female	Mulago NRH - Ward 5&6(TB Ward)	7854/21	24	475360763u	[32.53833314810884, 0.333176247220074]	
Kirabo	Kiconco	Zaahid	Female	Mulago NRH - Ward 5&6(TB Ward)	7262/86	55	822520522o	[32.639836236980834, 0.268383628537972]	
Namukasa	Kagoya	Saagar	Male	Mulago NRH - Ward 5&6(TB Ward)	3625/10	57	900475091w	[32.60935979403784, 0.337248274032181]	
Nantale	Namata	Saailima	Female	Mulago NRH - Ward 5&6(TB Ward)	5247/79	36	323232625e	[32.63018682910709, 0.361156781349802]	
Turyasingura	Nabwire	Yadnysena	Male	Mulago NRH - Ward 5&6(TB Ward)	5354/15	32	545846880a	[32.64172481480369, 0.325754400786427]	
Nanfuka	Kibirungi	Caddarik	Female	Mulago NRH - Ward 5&6(TB Ward)	7218/31	60	906709666l	[32.640184774738344, 0.318632034029353]	
Nabukeera	Nanyonjo	Kizza	Female	Mulago NRH - Ward 5&6(TB Ward)	6627/14	40	110487692b	[32.57004650510481, 0.331411535381934]	
Awino	Lakot	Zachary	Female	Mulago NRH - Ward 5&6(TB Ward)	6791/53	20	827759682y	[32.573197930307224, 0.397831924212261]	
Kemigisha	Aqaba	Dacey	Female	Mulago NRH - Ward 5&6(TB Ward)	9350/29	43	521719570f	[32.63319122434104, 0.319062196556291]	

Figure 10: The entry point of the patient's table

The figure above represents the entry to the de-identified and pseudo coded patient's data table, similar to the tracker capture's application table, displaying the patient's attributes as demographic information, the facility they are attached to, and identification information. The pseudo name use was to avoid the use of real patient data and prevent privacy and confidentiality concerns for the study, however the data that built the model was from real patient data in the eCBSS . Once a patient has been identified through either a search or their recent appearance in the table, their dashboard can then be displayed after the user has clicked on that specific patient. Upon scrolling through the user can view features of the patient's essential information summarized on cards rather than in a data entry from the tracker capture application. Furthermore, they can view the patient's prediction overview with the calculated risk score for developing MDRTB, as according to the data captured so far within the eCBSS. The user can also view the contributing factors that are utilized for investigating what the prediction model leaned on for the particular score. Beyond that, as a feature requested by the study participants, a summary of baseline data from when the patient began treatment and the possible fluctuation of their weight to monitor their nutrition status indicators, including weight, BMI, and MUAC, provided they were captured consistently. In

addition to that, a dashboard view of follow-up results and tests done at any stage of the treatment was included to assist in making decisions on interventional treatment required if the positive results persisted or any other indication.

The dashboard view for the patient's summary with the prediction as a doughnut chart and the contributing factors.

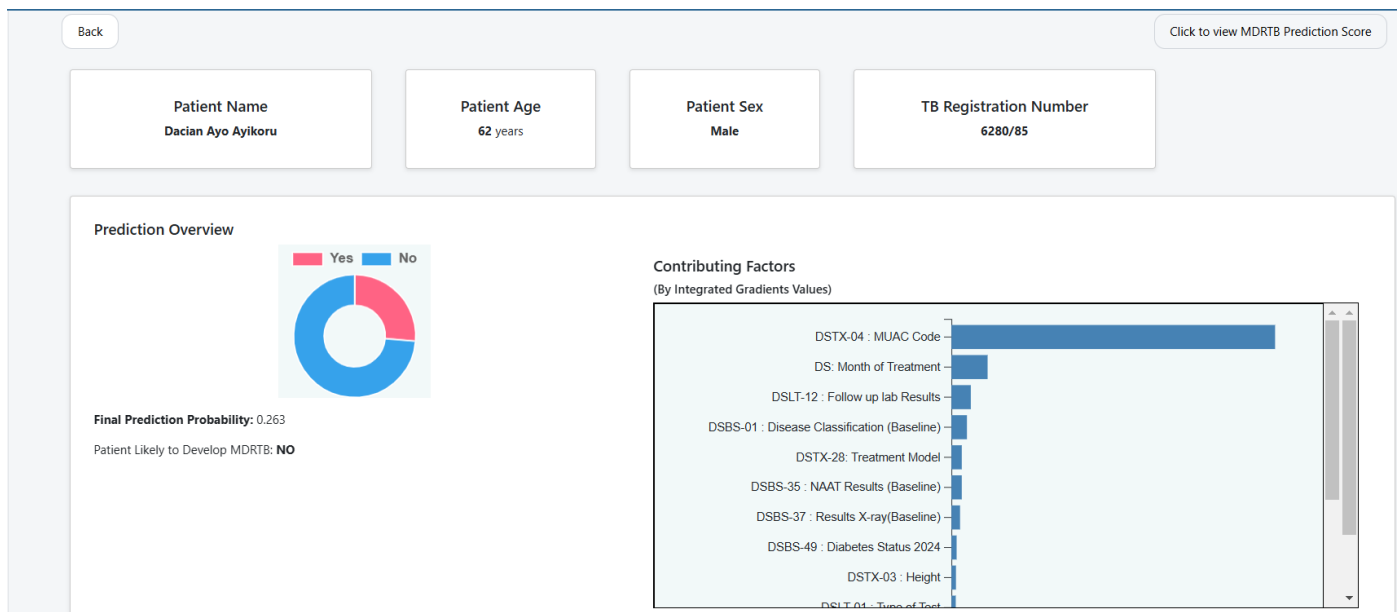


Figure 10: The predictions overview with the contributing factors displayed

The view displays the contributing factors to the selected patient and their values in ascending order.

Sorted Contributing Factors and their Values	
These explain why the patient is likely to develop MDRTB.They should be used to guide clinical decision making and to inform treatment decisions.	
Feature	Contributing Factor Value
DSTX-04 : MUAC Code	25
DS: Month of Treatment	1-2 Weeks
DSLT-12 : Follow up lab Results	MTB detected, rifampicin resistance detected
DSBS-01 : Disease Classification (Baseline)	Pulmonary Clinically Diagnosed (P-CD) TB
DSTX-28: Treatment Model	Non-Digital Community DOT
DSBS-35 : NAAT Results (Baseline)	MTB detected, rifampicin resistance not detected
DSBS-37 : Results X-ray(Baseline)	Normal
DSBS-49 : Diabetes Status 2024	Normal
DSTX-03 : Height	181
DSLT-01 : Type of Test	GeneXpert
DSBS-16 : HIV status (Baseline)	Newly tested Positive
DSBS-08 : Started on 1st Line Treatment	Yes
DSBS-09 : DS-TB regimen	2RHZE/ 4RH
DSTX-29: RHZE(150/75/400/275 mg) given	Yes
DSTX-30: RH (150/75mg) given	Yes
DSBS-02 : Type of patient	New
DSBS-17 : ART Status	Initiated on ART
DSTX-02 : Weight (kg)	56
DSBS-11 : Diagnosed With DR TB	No
DSBS-19 : CPT/Dapson (Baseline)	Already on CPT

Figure 11: Display of the values of the contributing factors in ascending order.

A view of the Baseline data and weight monitoring chart for nutritional assessment over time

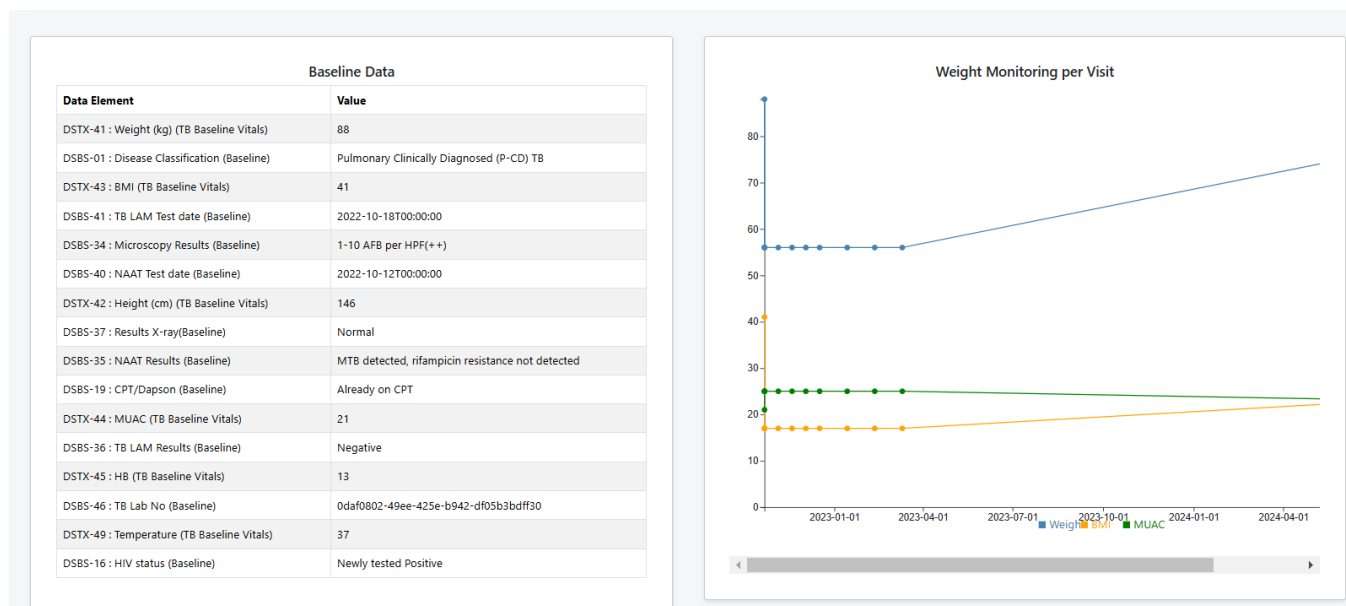


Figure 12: The Baseline data table and weight monitoring chart

A view of the follow-up test and results over the patient's treatment period.

Follow-Up Test Results				
Clinic Visit	Clinic Visit 1 (17/12/2022)	Clinic Visit 2 (17/12/2022)	Clinic Visit 3 (11/03/2023)	Clinic Visit 4 (08/04/2023)
Test Result	MTB detected, rifampicin resistance detected	MTB not detected	Positive	Positive
Type of Test	GeneXpert	GeneXpert	LAM	LAM

Figure 13: Follow-up tests and results summary for a patient visit.

A view of the map depicting the location of the patient, their proximity to a hotspot, and distance from the health facility with synthetically generated GIS patient coordinates.

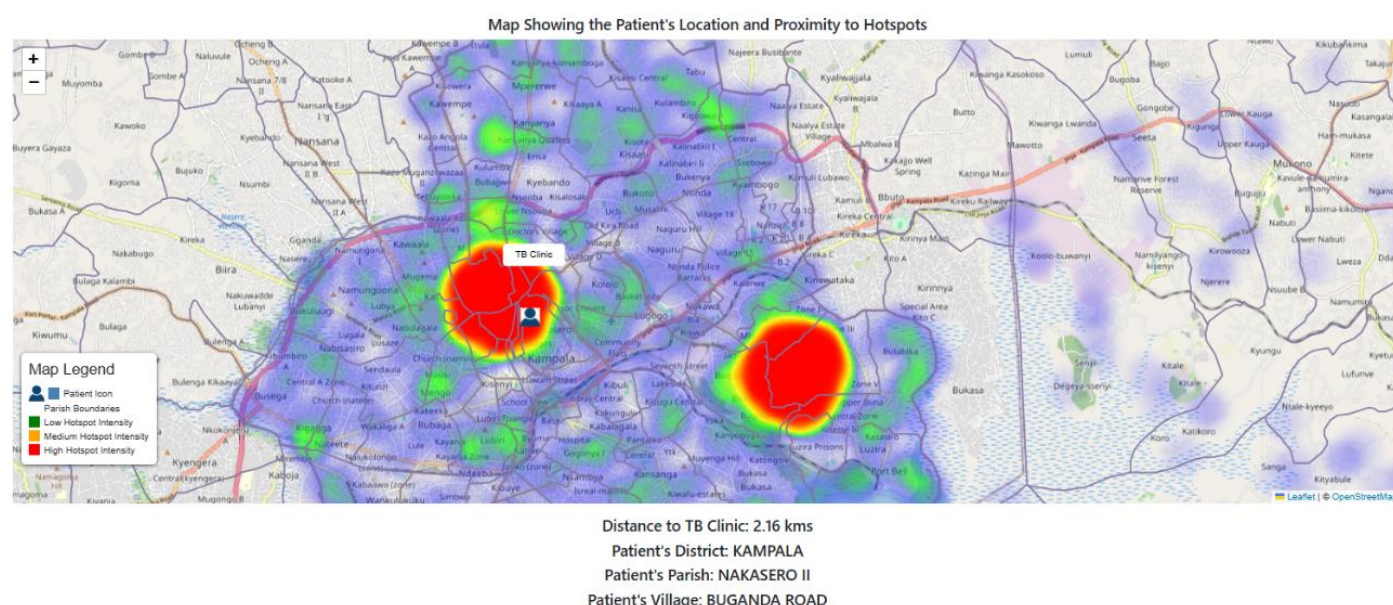


Figure 14: GIS demonstration of the Map and hotspots with the patient's proximity

The above figures depict a use case journey of how to access the application within the DHIS2 eCBSS once the integration has been successful. This use case demonstrates the core functionality of the web application, enabling healthcare professionals to efficiently access and interpret patient risk data combined with spatial information. The integration of GIS mapping with the synthetically generated coordinates enhances situational awareness and supports informed screening and interventional decisions to expand the TB program's case identification if the patients come from known hotspots.

6.3 Testing and validating the performance of the machine learning web-based application.

6.3.1 Unit testing.

i. Machine Learning Model Integration and Validation.

In order to confirm that incoming data was structured appropriately, input validation was first carried out. Missing values, wrong dimensions, and invalid inputs were checked. To ensure correct processing, edge cases such as empty or extreme values were also evaluated. The model was then tested on the original unfiltered dataset to confirm forecast consistency. To ensure accurate and repeatable predictions, performance metrics, including accuracy and the Area Under the ROC Curve (AUC), were used to assess the outputs against the expected outcomes and are represented as follows:

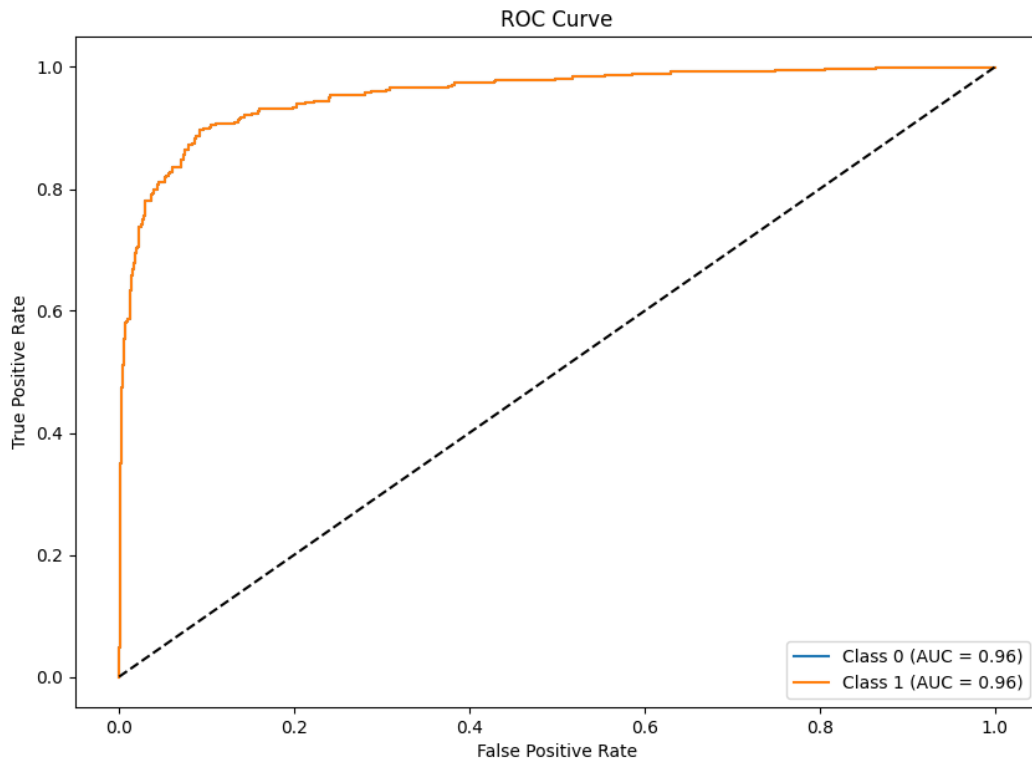


Figure 15: ROC curve from the validation process

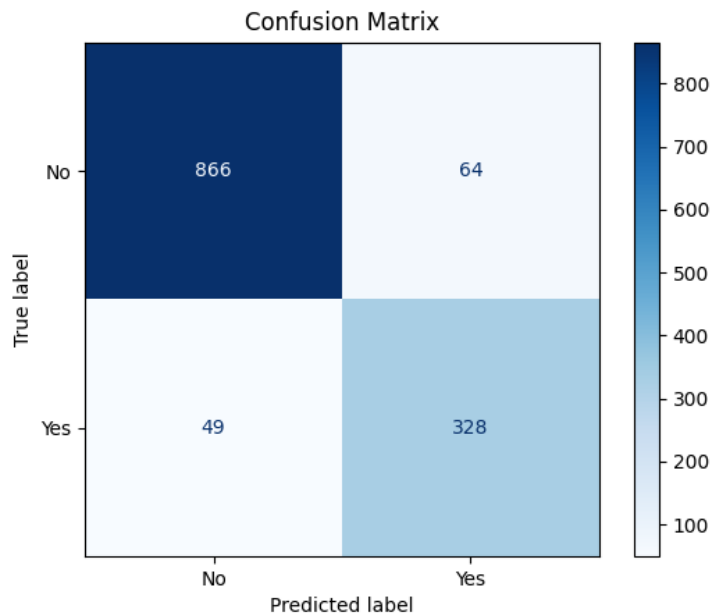


Figure 15: A confusion matrix from the validation

	precision	recall	f1-score	support
No	0.95	0.93	0.94	930
Yes	0.84	0.87	0.85	377
accuracy			0.92	1307
macro avg	0.89	0.90	0.90	1307
weighted avg	0.92	0.92	0.92	1307

Figure 16: A Classification report from the Validation

Based on the confusion matrix and classification report, the model demonstrates decent performance with an overall accuracy of 92%. The precision and recall for both classes are relatively high, indicating that the model is effective in both identifying positive and negative cases on the unfiltered original data from the development instance of the eCBSS. It is important to understand the differences in performance between the testing data and the data in the validation. The performance of the training data in the one discussed in the *Model Training and Prediction*

sections of this report. There is indeed a consistency between the two models on training data and the original after the preprocessing pipeline was maintained. This pipeline's consistency was carried on to the model's integration into the React project, with binary packages converting it into a version able to run in a browser. This means that the predictions on the synthetic data will reflect, with consistency, the predictions made over the original data during this stage.

ii. GIS visualization and Map rendering.

To guarantee accurate and user-friendly geospatial data display, the GIS visualization module was put through testing. Due to the lack of real GIS coordinates in the system, hotspot data was computed using the clustering method of DBSCAN, and synthetic data was created to mimic coordinates. Predicted MDR-TB hotspots could be visualized thanks to these artificial clusters based on a 2 km radius, which represented regions of interest based on the processed data. In accordance with the 2016 administrative data, the map featured several layers that represented Uganda's administrative borders. To maintain conformity with Uganda's official geographic structure throughout the study period, these layers possessed the names of districts, parishes, and villages, which is still a missing feature in DHI2 maps. The interactive visualization of geospatial data and hotspots was confirmed by the validation of dynamic updates. To improve usability and offer insights into the distribution of projected patients throughout the different hotspot areas, features including clustering, heatmaps, and the legend were tested. The responsiveness of user gestures like zooming was also confirmed, although still based on synthetic GIS coordinates.

6.3.2 User interface testing of the dashboard.

The application's user interface was made simple to ensure that decision-makers and healthcare professionals could easily use it. Distracting colours and excessively complicated features were avoided in favour of straightforward and user-friendly table and dashboard layouts. The prototype placed a strong emphasis on usability and clarity, making it simple for users to switch between various elements. To show an overview of the projections, contributing factors, and pertinent indicators like weight and nutritional monitoring, the dashboard featured charts. In keeping with the application's functional objectives, these visualizations were made to be both aesthetically pleasing and simple to understand. Every interface component complied with DHIS2 design guidelines, guaranteeing uniformity with the system's overall usability and aesthetic criteria.

6.3.3 Performance and Load Testing

The application was tested under different data loads to evaluate system response times, scalability, and robustness, ensuring it could handle the large datasets typical in DHIS2 systems without significant performance degradation. Light house, a DevTools component in the Chrome web browser, scored the application to have 42 in performance, 90 in accessibility, 96 in Best practices, and 100 in SEO. While the performance score appears low, this is not uncommon for Single Page Applications (SPAs) or dashboard-style web apps, which often rely on heavy JavaScript bundles and client-side rendering to deliver dynamic, interactive content(Kothapalli 2022).

6.3.4 Usability Testing (UAT)

The application was tested by end users, including health workers at the three health facilities, to verify usability, functionality, and alignment with user requirements. Feedback was collected and implemented for refinements. The analysis of this user acceptance testing was through an online tool, and the survey responses highlighted strong overall satisfaction among respondents, with particularly high scores for critical system functionalities. Although only ten (10) out of the expected twelve (12) participants at the three health facilities responded to the post usability questionnaire, this response rate is significant.

Overall Usability Score Summary

The table below presents the overall usability mean score by category and feedback item.

Table 6: Overall usability score

	Feedback Item	Mean Score
System Performance & Insights	The system improved MDR-TB risk assessment	4.78
	The data was comprehensive and useful	4.67
Usability & Navigation	System responsiveness was quick	4.56
	Interactive elements were intuitive	4.56
Areas for Improvement	Dashboard layout & filtering/search features	~3.88
	Error messages and design clarity	~4.11

Overall Perception	Willingness to recommend the system	4.56
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Per-Cadre Usability Score Summaries

An analysis was further conducted to identify variations with the different user groups and the Kruskal-Wallis test statistic to explain the difference in the mean score per cadre category, with an explanation of the resulting significance test within the 95% confidence interval.

Table 7: Per cadre usability score summary

Cadre	Mean Score	Std Dev	CI (95%)
Data Clerk/Records	86.67	15.37	(48.48 – 124.86)
Medical Lab Technologist	90.00	7.07	(26.47 – 153.53)
Nurse	85.00	14.14	(-42.06 – 212.06)
Physician/Clinician	90.33	10.02	(65.45 – 115.22)

Kruskal-Wallis Test

Kruskal-Wallis H statistic: 0.23

p-value: 0.97

p > 0.05: No statistically significant difference in usability scores between the professional groups.

PCA analysis.

Analysis was conducted to provide valuable insights into the structure of the usability questionnaire data. By reducing the dimensionality to four key constructs: System Quality, Information Quality, Interaction Quality, and User Satisfaction, the results facilitate more focused and efficient analysis of usability factors. Furthermore, the alignment of these constructs with established theoretical frameworks strengthens the validity and applicability of the findings. A scree plot below illustrates the cumulative explained variance as a function of the number of principal components. As shown, the curve exhibits a clear "elbow" after the fifth component. The first five components account for approximately 90% of the total variance, suggesting that a five-

factor solution effectively captures the underlying structure of the data. The biplot in Figure 18 below visualizes the loadings of each questionnaire item (Q1 to Q20) on the first two principal components. Interpretation of these components was guided by an analysis of item loadings, combined with theoretical considerations related to usability assessment.

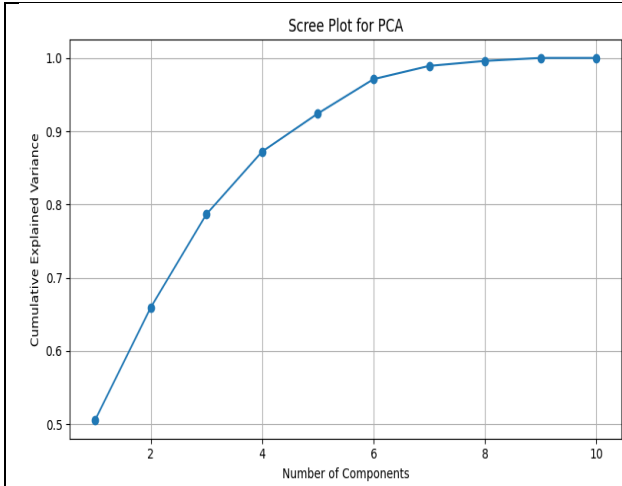


Figure 16: A PCA scree plot.

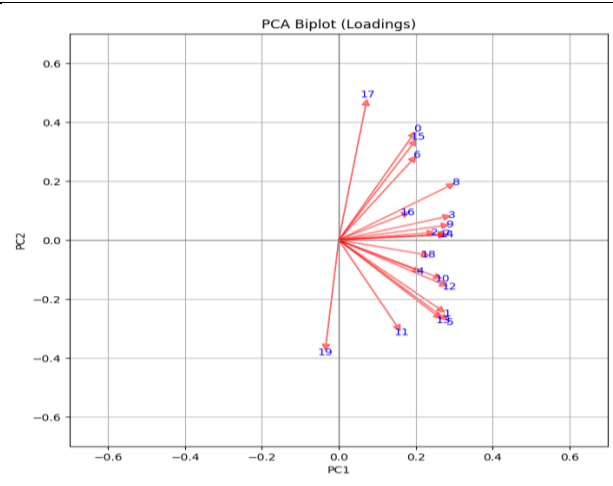


Figure 17: A PCA biplot for the Questionnaire items

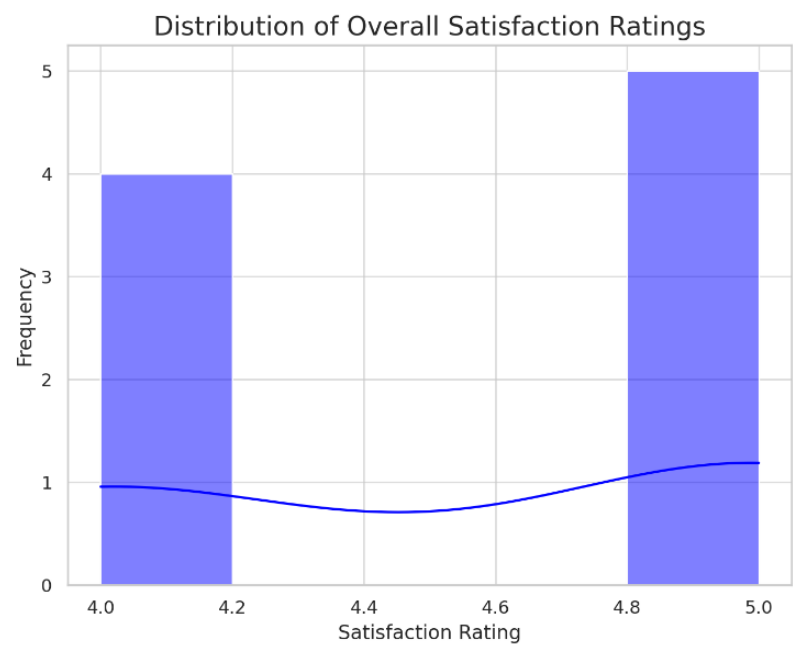


Figure 18: Satisfaction distribution across features

CHAPTER SEVEN

DISCUSSION

7.0 Discussion

This study explored integrating a machine learning (ML) application and a Geographical Information System (GIS) module into DHIS2's electronic Case-Based Surveillance System (eCBSS) to predict MDR-TB risk, followed by user acceptability testing. Guided by a user-centered design framework, the study first determined system requirements through qualitative in-depth interviews with healthcare workers. Analysis of these interviews revealed critical themes that defined the system's functional requirements, such as risk scoring, real-time alerts, and adherence tracking, and its non-functional attributes, including reliability, security, and usability. The findings also highlighted implementation needs essential for sustainable deployment, such as adequate staffing, infrastructure, and training, which informed the development of a web application dashboard designed to meet these needs. Furthermore, they directly informed the development of a web application dashboard powered by a one-dimensional deep neural network (1DNN) model, which achieved a 92% accuracy in risk prediction. Subsequent user acceptability testing confirmed that healthcare workers found the dashboard intuitive and valuable for clinical decision-making, while also providing crucial feedback for future iterative improvements to the system.

Before integrating AI into platforms such as DHIS2 to improve disease surveillance, such as for MDR-TB prediction, design gaps have to be addressed (Munthali 2023). This aligns with findings from Munthali (2023), who identified workflow integration as a primary challenge for ML in the DHIS2 ecosystem and advocated for a co-design process involving end-users to analyze their specific needs. This human-centric approach is supported by broader research in AI-driven clinical decision support systems and begins by analyzing the particular requirements (Munthali 2023). A study by Zielinska (2024) highlights that focusing on user-centered design principles, including user research, iterative design, and user feedback incorporation, enhances usability and adoption of CDSS (Elhaddad and Hamam 2024). The study also emphasizes the importance of transparency, interpretability, and trust in AI systems, aligning with our findings. The qualitative method used in this study proved advantageous, as it allowed participants to articulate their experiences and concerns, leading to a richer understanding of user needs than structured quantitative techniques

might have allowed. Exploring these requirements is crucial for the sustainable utilization of the data and the developed ML web application.

Risk cores, as an emerging requirement from our analysis, are important because they translate complex predictive analytics into a simple, actionable metric for healthcare workers. They state the need for tools that aid rapid decision making and prioritization in a busy environment (Edoh et al. 2024). This is consistent with research showing that risk stratification, which combines multiple indicators into a single, easily interpretable index, effectively aids clinical decisions and improves patient management (Chapman et al. 2019). These risk scores can be used as a means to identify patients at risk of complications early, allowing healthcare workers to intervene promptly and prioritize care effectively in fast-paced environments.

Beyond the risk scores are the real-time alerts, which are critical and should be generated dynamically from the events captured in eCBSS, including unusual lab results, reported complications, severe and adverse drug reactions, or indications of malnutrition. These event-based alerts are supported by evidence from research that healthcare workers respond with appropriate interventions such as counselling, drug combination reconsideration, and counter intervention regimens (Chen et al. 2023). According to Chen et al, alerts provide potential for medical interactions monitoring, and reminders can help prevent errors and ensure medical patient safety (Chen et al. 2023).

An intuitive ML-powered web application to track the development of MDRTB should also provide the ability to track patient drug adherence and appointment follow-up (Octaviani et al. 2024a). It has been demonstrated that automated appointment and adherence tracking greatly increases treatment effectiveness and adherence rates by enabling healthcare professionals to act early, offer psychosocial support, and customize interventions to each patient's needs (Alipanah et al. 2018; Grigoryan et al. 2022; Octaviani et al. 2024b). It is therefore important to have a feature that incorporates these requirements within the eCBSS as requested by the healthcare workers.

In addition to functional requirements, non-functional requirements such as availability, reliability, usability, security, and sustainability are critical for ensuring the effectiveness and longevity of an integrated ML-powered application (Habibullah, Gay, and Horkoff 2023). Availability, especially in settings with intermittent internet like Uganda, can be addressed with scalable cloud architectures, although caution is needed to mitigate potential

performance issues like data retrieval interruptions. This is in agreement with evidence, as such architecture has limitations as discussed by Al-Issa et al, which is prone to slowing down (Al-Issa, Ottom, and Tamrawi 2019).

Reliability guarantees consistent performance under varying loads, achieved through automated monitoring, fault tolerance, and adherence to Site Reliability Engineering (SRE) principles (Kopach-Konrad et al. 2007). According to Konrad et al, reliable healthcare systems are crucial for patient safety and trust, as fault tolerance mechanisms ensure continuous operation and minimize the risk of errors or system failures that could compromise the quality of care to patients (Kopach-Konrad et al. 2007). This makes reliability an important requirement, especially in ensuring usability.

Designing user-friendly interfaces that lessen cognitive strain on medical staff members is the main goal of usability, which promotes greater acceptance and efficient application of machine learning techniques in clinical processes (Asgari et al. 2024). Asagri et al., in their paper on the impact of EHRs on the cognitive load of health workers, suggest that reducing cognitive burden by minimizing the need for extensive paper review allows clinicians to focus more on patient care without compromising decision quality or efficiency (Asgari et al. 2024). They emphasize that well-designed electronic systems that streamline information access and present data intuitively can significantly enhance clinical workflow and reduce mental fatigue. Our findings, therefore, call for a co-design process, which was implemented alongside healthcare workers at the TB treatment facilities with developers of the proposed ML web applications.

Furthermore, while ensuring scalability due to the potential of growing data utilization and access to the eCBSS, security must be considered. Robust techniques already exist for DHIS2 systems as managed by the MOH in Uganda (DHIS2 Documentation 2024), however, studies have highlighted the importance of adhering to healthcare regulations and standards to protecting sensitive patient data via encryption, access controls, and compliance with healthcare regulations prevents breaches and misuse (Shojaei, Vlahu-Gjorgievska, and Chow 2024). For a machine learning-powered application to remain functional and impactful over time, it must be designed with sustainability in mind. This includes maintainable code, updatable models, energy-efficient infrastructure, and processes that adapt to evolving clinical workflows and surveillance policies. If sustainability is neglected, system degradation (e.g., model decay, unpatched vulnerabilities, or outdated

interfaces) becomes likely, undermining the reliability of predictions and potentially compromising patient care (Davis, Embí, and Matheny 2024). Davis et al. (2024) address the concept of technical debt in ML systems, emphasizing the need for maintainable models and efficient resource use to ensure long-term sustainability(Davis et al., 2024).

To ensure the long and sustainable use of the integrated ML web application within DHIS2's eCBSS at TB clinics, several critical non-technical factors must be addressed. Sustained use depends heavily on ongoing training programs that equip healthcare workers with both technical and soft skills necessary to effectively utilize ML tools, as highlighted in recent systematic reviews of ML implementation in clinical settings (Preti et al. 2024). Stable internet connectivity and access to suitable hardware such as computers, laptops, or tablets with reliable data access are fundamental infrastructural requirements that enable uninterrupted use and real-time data entry, which are essential for timely decision-making and patient management (Yan et al. 2025). From the analysis of our findings, consistent funding is vital to secure resources for system maintenance, periodic software upgrades, and replacement of outdated devices to prevent system degradation and ensure the application remains aligned with evolving clinical workflows and surveillance policies. Preti et al., also agree with this study's findings in the same paper by stating that without these supports, the functionality and impact of the ML-powered application risk being compromised, limiting its potential to improve MDR-TB patient outcomes (Preti et al. 2024). The findings of this study are consistent with broader evidence mentioned by the previous authors (Preti and Yan), emphasizing that successful ML adoption in healthcare requires addressing organizational culture, IT infrastructure, and continuous stakeholder engagement.

To address these identified requirements and fulfill the second objective of this study, the machine learning web-based analytical application was developed and integrated into the eCBSS. The development of the web-based analytical application represents a direct translation of the user requirements identified in the initial phase into a functional clinical decision support tool. The choice of a one-dimensional deep neural network (DNN) as the predictive engine was deliberate. DNNs are particularly adept at modeling complex, non-linear relationships inherent in-patient data, which simpler models might miss. This approach is supported by a growing body of literature demonstrating the superiority of deep learning models for disease risk stratification using electronic health data (Shickel et al. 2018). The resulting model's performance, achieving 92%

accuracy and a strong AUC score, is highly encouraging and aligns with performance benchmarks reported in other ML-based MDR-TB prediction studies, confirming the viability of this methodology for creating a reliable risk classification tool (Babirye et al. 2024).

Above the predictive performance, the adoption of this study's artifact hinges on its user's acceptability. The high satisfaction scores from healthcare workers (means between 4.65 and 4.87) are a direct testament to the efficacy of the user-centered design (UCD) framework employed throughout the study. By involving clinicians from the initial requirements-gathering stage to the final testing, the UCD framework ensures that the resulting tool is aligned with their real-world workflows and clinical needs. This approach, which prioritizes the end-user's perspective, is consistently highlighted in recent literature as essential for developing effective digital health interventions that fit seamlessly into complex clinical environments (Salimiparsa, Lizotte, and Sedig 2021). Importantly, rather than being seen as a design failure, the mixed usability feedback, which pointed out the need for better search, filtering, and error handling, should be seen as a good result of the iterative design cycle. Studies emphasize that significant ongoing user involvement in improving system usability and lowering cognitive load by such an application is key (Asgari et al. 2024).

Integrating machine learning (ML) predictions directly within a browser-based application is especially valuable in low-resource environments, such as those using DHIS2. By running predictions client-side, and as evidence with other studies from Gambia and others (Mohammed et al. 2022; Watt, Chrysoulas, and Barclay 2024), the system reduces dependence on continuous, high-bandwidth server connections which important advantage with unreliable internet connectivity such as that at TB clinics in Uganda (Pereira, de Oliveira, and de Souza 2024). This was a guiding principle for the study's artifact during the development stage. Despite the operational benefits of in-browser ML, healthcare professionals' trust and effective use of the application will depend on their interpretation of predictions. This study attempted to provide such explanations within the dashboard with the utilization of integrated gradient values of the features selected from the saved and loaded model within the development framework, and those run in-browser. However, this is insufficient as an assessment, as that done in other studies suggested the application of impact scores. Impact scores quantify a variable's influence on predictions at both individual and population levels (Shao et al., 2021). In Shao et al.'s study on Explaining Deep

Neural Network Prediction of Clinical Outcomes, they acknowledged that ground truth relationships are often unknown in real patient data, and as a workaround, simulated datasets are being used to further validate the impact, just as in this study. This also signifies the impact of the quality of data on the ML models used, where the patient's data is not captured consistently, as observed with the current utilization of the eCBSS.

Therefore, the challenge of explaining the DNN's predictions, despite the initial attempt using integrated gradients, remains a significant limitation and a primary area for future work. The findings from this study suggest that subsequent research should focus on implementing and validating more robust explainability methods, such as the impact scores proposed by Shao et al., to enhance clinician trust and ensure the tool is used as an effective and transparent decision support aid rather than an opaque 'black box'.

Rather than dictating the decision-making process of a healthcare worker by an electronic decision support tool, having a risk score model is desirable (Heider & Mang, 2022). Artificial intelligence should not replace human intelligence, developed over time through experience in handling differentiated cases of diseases (Asan, Bayrak, & Choudhury, 2020). As Asan et al suggest, the relationship between AI and human trust continues to evolve, with AI offering a distinct advantage over humans in its ability to rapidly acquire, store, and process new knowledge or learning. Therefore, caution should be exercised when using the artifacts from this study, as they do not aim to make clinical decisions but rather to present risk scores. These scores are intended to support healthcare professionals in making informed decisions independently, based on their clinical judgment and expertise.

The integration of a GIS module by this study supports enhanced TB screening strategies by enabling spatial targeting of areas with persistent TB prevalence, addressing risks of continued reinfection that hinder patient recovery. Bonnewell et al. (2020) highlighted significant spatial targeting flaws in latent TB infection screening, revealing that screening efforts were not well-aligned with high-risk foreign-born populations and that subspecialist-driven IGRA testing reduced broad detection efficacy(Bonnewell et al. 2020). This underscores the potential of GIS-based approaches to improve screening effectiveness and resource allocation. Similarly, Cudahy et al. (2019) emphasized the role of spatially targeted screening within geographic hotspots to reduce TB transmission, despite challenges in implementation(Cudahy et al. 2019). Moonan et al.

(2006) demonstrated that combining genotyping with GIS analysis can identify high-risk locations for targeted screening, resulting in higher detection rates compared to non-targeted methods. Collectively, these studies advocate for integrating geographic information systems into public health TB control to optimize risk assessment and intervention strategies.

This study was subject to several limitations. Missing or erroneous clinical observations can jeopardize the accuracy of model predictions in real-world healthcare settings. These discrepancies draw attention to the difficulties in gathering and documenting data in healthcare systems, which may eventually affect how well machine learning models work. The interpretability of deep learning models is another challenge. Deep neural networks (DNNs) are still intrinsically difficult to explain, even though integrated gradient values were used in the event data predictions for the DNN predictions at runtime within the web application. Healthcare practitioners frequently view DNNs as "black boxes," in contrast to more straightforward models like logistic regression. To foster trust and guarantee that physicians can make well-informed judgments using the dashboard results, it is essential to provide concise and understandable explanations of how these models produce predictions.

Another key limitation was the restricted compatibility of the DHIS2 platform with diverse machine learning algorithms. The system's client-side deployment requirement, based on the TensorFlow.js runtime, only supports deep learning models converted from Keras. This constraint limited the ability to implement and compare alternative algorithms such as Random Forest, XGBoost, or Support Vector Machines, which may have provided additional insights into model interpretability or performance on the identified features. Consequently, while the one-dimensional deep neural network (1DNN) demonstrated strong predictive capability, the lack of comparative evaluation within the DHIS2 environment constrains the generalizability of findings regarding the most optimal algorithm for MDR-TB risk prediction.

The validation of ground truth presented additional difficulties for the project. Since real-world clinical results frequently lack thorough validation, it might be challenging to get reliable ground truth outcomes in clinical practice. Although they were used as a workaround, simulated datasets fall short in capturing the intricacy and variety of real patient data. The effect scores and

dependability of machine learning models built on these datasets cannot be thoroughly validated due to this constraint.

Integration and scalability provide additional difficulties. Even though the dashboard was created with healthcare workers' needs in mind, it is still challenging to integrate it into current workflows in various geographical locations. The smooth operation of the system may be hampered by regional variations in internet access, technology infrastructure, and the technical literacy of healthcare personnel. Maximizing the tool's efficacy in actual healthcare settings requires compatibility and simplicity of integration across these parameters.

Furthermore, a possible drawback of the models is their generalizability across geographical areas and illnesses. Although the primary goal of this work was to predict MDR-TB outcomes, the models' performance and applicability may vary when employed for other diseases or in various geographical areas. The accuracy and efficacy of the model may be impacted by regional differences in illness prevalence, healthcare infrastructure, and demographics.

Lastly, search, filtering, and error message handling were identified as opportunities for improvement based on user feedback on dashboard design. The effectiveness and confidence of healthcare personnel in utilizing the system may be impacted by these usability problems. It will be essential to address these design constraints through feedback loops and iterative development in order to produce a more user-friendly and useful tool for healthcare decision-making. In order to ensure that AI-enhanced public health tools are used more effectively across a range of healthcare contexts and eventually improve patient outcomes and resource allocation, future research should address these constraints in order to increase the tools' robustness, interpretability, and scalability.

CHAPTER EIGHT

CONCLUSIONS AND RECOMMENDATIONS.

8.1 Conclusions

To successfully integrate an ML-powered web application, this study first elicited user requirements from key participants in healthcare facilities managing TB in Uganda. Important functional and non-functional requirements were analyzed for the development of the web application. This study also demonstrated and successfully integrated the developed machine learning web application and a GIS module into DHIS2 to predict MDR-TB risk and support health decision-making to healthcare workers at TB clinics in Uganda. Furthermore, the application's acceptability and usability were assessed to validate the applications ability to predict the development of MDR-TB and associated or contributing factors among the healthcare workers at the three health facilities and were found intuitive, acceptable, and responsive. Even though suggestions of missing attributes, such as alerts and an improved user interface, were highlighted, the application performance was within the expected range for dashboards and single-page applications. While the developed dashboard did not demonstrate high predictive accuracy, the complexity of the 1DNN interpretability requires clearer explanations for healthcare professionals. The use of risk scores offers a step toward more understandable predictions that aid the monitoring of the development of MDR-TB in DSTB patients managed at the health facilities in Uganda.

The findings also highlight that AI should complement human expertise rather than replace it. The GIS module enables targeted TB screening, ensuring effective resource allocation in high-prevalence areas. Future work should address data inconsistencies and refine interpretability methods to scale these solutions across various health domains such as HIV, diabetes, and cancer clinics, ultimately enhancing community health outcomes and resource efficiency.

8.2 Recommendations

To address the limitations identified in this study and build upon its findings, several recommendations are proposed to enhance the integration and usability of machine learning models in the DHIS2 platform.

First and foremost, the Ministry of Health in Uganda (MOH) is encouraged to provide clear and updated guidelines and procedures that are required for thorough data collection across all overlooked data points in healthcare workflows, especially at the TB clinics by the healthcare cadres, such as clinicians and nurses, and the contact tracing teams. This includes gathering information throughout crucial phases like contact tracing, triage, and community follow-up with GIS coordinates. Important patient data, including HIV history, treatment history, and other pertinent clinical information, can be systematically collected. It's also important to regularly record information on anthropometric measurements such as height, weight, and MUAC (Mid-Upper Arm Circumference). Additionally, the implementers of the DHIS2 systems and the MOH's Division of health information (DHI) in conjunction with the NTLP are encouraged to discuss the improvement of the clinical work flow to include genetic data from lab expert systems into the eCBSS, as this would improve predictive accuracy by facilitating a more thorough comprehension of patient outcomes and illness trends.

Second, all TB healthcare facilities can be encouraged to use the DHIS2 eCBSS to increase scalability and integration and lessen dependency on manual registers and paper-based operations. By doing this, the errors and data loss that come with using conventional documentation techniques would be reduced. The implementation of organized digital technologies inside the eCBSS can be given priority by policies, which can discourage the use of unstructured paper files for patient records. Furthermore, a localized offline version of the eCBSS can be put into place, with data automatically synchronizing to a central server as soon as connectivity is restored. This guarantees that data collection will continue even in isolated locations with spotty internet service. Enough computing power must be available at user terminals and healthcare institutions to meet the demands of computational infrastructure. Real-time model predictions and effective decision-making without latency or outage would be supported by reliable local and server-based computation. Healthcare professionals would be able to swiftly and precisely access, analyse, and act upon machine learning-generated insights thanks to this infrastructure.

In order for healthcare practitioners to accept and utilize the dashboard's predictions effectively, model interpretability must be improved. More transparent insights into model predictions would be provided by incorporating sophisticated Explainable AI (XAI) techniques like SHAP (Shapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations). Furthermore, the dashboard can provide feature importance, effect scores, and correlations in an understandable manner that healthcare professionals can quickly act upon by using user-friendly visual elements.

Collaborative validation with clinical professionals can be given priority due to the difficulties associated with ground truth validation. Ground truth accuracy would be increased by putting in place systems where medical professionals could examine and confirm model projections against real patient outcomes. Furthermore, using longitudinal patient data—which involves following patients over lengthy periods—can provide a reliable ground truth reference. Simulated datasets can be improved to more accurately replicate clinical complexities and evaluate machine learning models in controlled experiments, albeit they are not a perfect replacement for real-world data.

The creation of modular tools and APIs will make it simpler to integrate with the current DHIS2 infrastructure, improving scalability and integration. The dashboard interface's design and usability problems, like search, filtering, and error message handling, will be fixed by tailoring it in response to ongoing user feedback. Additionally, putting offline features into place would guarantee that medical practitioners can access the dashboard even in areas with spotty internet service.

These models' potential can be expanded to handle application scenarios other than MDR-TB. It may be possible to modify machine learning models to forecast the course of chronic illnesses like diabetes, HIV, and others. Additionally, increasing the integration of GIS modules would enhance screening and resource allocation, particularly in regions with high TB prevalence. Better-targeted treatments would be ensured by addressing urban and rural variations.

Feedback loops and ongoing user interaction are also essential. Frequent testing sessions with medical professionals from various geographical areas will reveal real-world difficulties and potential areas for development. Healthcare professionals' confidence in utilizing AI-driven dashboards would be increased through interactive training sessions and educational workshops that emphasize risk score interpretation and clinical decision-making.

Lastly, encouraging multi-institutional cooperation will improve the scalability and validation of the model. By collaborating with public health departments, research institutes, and other healthcare facilities, a variety of datasets and experiences may be shared, guaranteeing that models are verified in a range of clinical settings. More robust datasets would come from promoting open data sharing between organizations and geographical areas, which would ultimately improve model accuracy and dependability.

To enhance the effectiveness of MDR-TB prediction and tracking, the study recommends integrating Geographic Information System (**GIS**) capabilities into the DHIS2 system. This can be achieved through the DHIS2 Android app, which supports the capturing of GIS coordinates directly during data entry. The use of mobile devices equipped with GPS functionalities provides an effective means of capturing precise location data during community follow-up programs, such as those supported by the **LPHS** (Local Partner Health Services) program.

Additionally, to fully realize the benefits of a centralized surveillance system, the Ministry of Health's division of health information (DHI), can consider prioritizing the interoperability between the DHIS2 electronic Case-Based Surveillance System (eCBSS) and all other national health information systems. Having standards that ensure data exchange can address the missingness of data and improve the predictive capability of the ML application developed by this study. This can be achieved through the implementation of the Open Health Information Exchange (OpenHIE) strategy. Adopting the OpenHIE framework ensures that all essential health information systems adhere to common standards and interface specifications, allowing for seamless, real-time data flow to and from DHIS2. This consistency in data elements mapping is crucial for providing an overall patient data view and prevents data silos, thereby maximizing the utility of predictive tools and improving clinical decision-making.

These approaches would not only improve data accuracy but also enable real-time spatial tracking of patients and their contacts. This could support better decision-making for targeted interventions, enhance the monitoring of disease hotspots, and strengthen the overall surveillance and management of TB and MDR-TB cases.

In conclusion, by emphasizing data reliability, model transparency, scalability, and usability, these suggestions seek to solve the study's weaknesses. Re-engineering the clinical workflows in healthcare processes can be the main focus of future research and development. This would

guarantee that machine learning models efficiently assist medical practitioners in their endeavours to increase patient care and community health, in addition to improving clinical decision-making and public health outcomes among TB patients receiving care and treatment at TB clinics.

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APPENDICE

Appendix

i. Data collection tools.

KII	Requirements collections from health care givers at health facilities
interview guide	Study Title: Using Machine Learning to Predict Multi-Drug Resistance Tuberculosis within the eCBSS. <i>Description of Subject Population:</i> Healthcare workers at TB clinics in Referral Hospitals managing MDR-TB (Clinicians, Physicians, laboratory Technician and Data clerks) Investigators: Prof Noah Kiwanuka Mrs. Irene Wanyana Mark Outeke – MHI Graduate Student, School of Public Health, Makerere University Funding Agency: the D43 Training Program
Name of facility	
Facility type <i>(check one)</i>	☐ Referral hospital ☐ District Hospital ☐ Health center (hospital-affiliated and other health centers) ☐ Health post/dispensary ☐ Other (specify):
Gender /Sex	☐ Male ☐ Female

Age	☐	
Ownership <i>(check one)</i>	☐ Public ☐ Private ☐ Mix	
Date of interview		
Time Start/End	Start:	End:
Name of interviewer		
Introduction		
In health information systems development, the ultimate purpose of collecting and analyzing data is to improve quality and usability by enabling more informed decisions based on facts. However, information is not always available to make decisions—or if it is available, it is not always used. This study is designed to find out how users would like the DHIS2’s eCBS system to look, behave, and perform while predicting and managing MDR- and how to improve it. Your participation is requested to provide insights about functional and non-functional requirements for the anticipated Web Application. Your participation is very important to this research, but it is entirely voluntary. Your responses will be treated as confidential, and we will ensure that any statements or comments you make cannot be linked either to you as an individual or to your organization. We will be producing a report that is intended mainly to help the study, and development of the web application, the NTLP, and MOH in improving the quality of TB care while using digital tools. The interview will last about 40 minutes. I will be using a questionnaire Guide that includes questions about the type of decisions you make, what information you use for this purpose, and how you would like the system to behave. Are you willing to participate? ☐ Yes ☐ No (stop interview)		

I would like to tape-record this session so that I will be able to make an accurate and complete transcription of my notes. Again, this information will not be shared with anyone outside of the research team—that is the researcher, the School of Public Health, and the College of Health Science at Makerere University.

Guide on requirements elicitation

1. Please specify your role and cadre at the TB clinic
2. On average, how many TB patients does the clinic handle per week?
3. What methods or tools do you currently use to manage TB patients and track their progress?
4. What are the main challenges you face in managing TB patients, particularly in monitoring the development of MDR-TB?
5. Which stage of care do you think frustrates the use of data at the Clinic?
6. How readily available is patient data necessary for managing TB patients and monitoring MDR-TB development in your current practice?
7. What specific patient information do you consider essential for effective management and monitoring of MDR-TB development?
8. What features would you like to see in the user interface of the web application to facilitate patient management and MDR-TB monitoring?
9. What type of patient data do you believe would be most useful for tracking MDR-TB development and managing TB patients effectively?
10. How do you envision integrating a web application for patient management into your daily workflow at the clinic?
11. How important is it for the web application to facilitate communication and collaboration among healthcare workers involved in TB patient management?

12. In what ways do you think improved communication and care coordination among healthcare workers could positively affect TB patient outcomes, including the management of MDR-TB?
13. In what ways do you think personalizing care based on patient data could positively impact TB patient outcomes, including the management of MDR-TB?
14. How concerned are you about patient data privacy and security in the context of using a web application for patient management?
15. Would you be interested in training sessions to learn how to use and navigate the patient management web application effectively?
16. How important is it for you to have a mechanism to provide feedback on the usability and functionality of the patient management web application?
17. What level of system responsiveness do you expect from the web application in terms of loading times and data retrieval?
18. How important is it for the web application to be scalable to handle an increasing number of patients and users over time?
19. What level of reliability do you expect from the web application in terms of uptime and data accuracy?
20. Are there any specific accessibility requirements that the web application should meet to ensure usability for all users?
21. What factors do you think are crucial for ensuring the long-term sustainability and effectiveness of using a web application for patient management in our clinic?
22. Do you have any additional suggestions or concerns regarding the development and implementation of the patient management web application for monitoring MDR-TB in TB patients?

Post Study Usability Test Questionnaire (PSUTQ)

Post-Study System Usability Questionnaire (PSSUQ)

Study Title: Using Machine Learning to Predict Multi-Drug Resistance Tuberculosis within the eCBSS.

Description of Subject Population: Healthcare workers at TB clinics in Referral Hospitals managing MDR-TB (Clinicians, Physicians, laboratory Technician and Data clerks)

Investigators: **Prof Noah Kiwanuka**

Mrs. Irene Wanyana

Mark Outeke – MHI Graduate Student,

School of Public Health, Makerere University

Funding Agency: the D43 Training Program.

Introduction

Hello, my name is **Mark Outeke**, a Masters in Health Informatics Graduate student at the School of Public Health, College of Health Sciences at Makerere University. The School and I are researching the use of machine learning in predicting the development of Multi-drug resistant tuberculosis (MDR-TB). The study has selected facilities that manage and treat patients with DTSB such as this one and would like you to participate. The participation is voluntary and has no direct harm to you. We have demonstrated the Machine Learning Dashboard web application that will support you in identifying cases that are likely to develop MDRTB at your facility. The application was designed with a Machine learning model that has the capability to detect the development of MDRTB among patients' who get treatment for TB at your clinic. The Risk Score on the prediction overview card, you have seen on the dashboard provides a probability of developing MDRTB and supported by the class of Yes or No. it is important to understand that the score can increase or decrease as the patient continues to get treatment. Therefore, caution is advised in understanding that the prediction doesn't mean the person will develop or

not develop MDRTB, but rather focus on the models contributing factors that guide the treatment process to avert the development of MDRTB.

Thank you for using the Machine Learning Dashboard web application. This questionnaire is designed to gather your feedback about your experience. Your responses will help us improve the system.

Please rate each statement on a scale from 1 to 5, where:

1. Strongly Disagree
2. Disagree
3. Neutral
4. Agree
5. Strongly Agree

If a question does not apply, select N/A.

The questionnaire includes questions about:

- **System Quality:** How easy the system was to learn and navigate.
- **Information Quality:** The accuracy, relevance, and clarity of the data presented.
- **Interaction Quality:** The responsiveness and usability of interactive features.
- **User Satisfaction:** Your overall confidence, time savings, and satisfaction with the system.

At the end, there are open-ended questions for additional feedback. Please share any suggestions or improvements you'd like to see. Thank you for your time!

* Indicates required question

Identification

Please provide us with the recent information to enable us stay in touch with you as well as ensure quality feedback.

1. Name *

2. Health care Cadre

Mark only one oval.

☐ Data Clerk/Records

☐ Lab Technician

☐ Physician/Clinician

☐ Nurse

☐ Other:

3. Years of Service at the TB clinic

4. Email Address *

5. Phone No.

System Quality

6. The system was easy to learn.

Mark only one oval.

1 2 3 4 5

Strongly Disagree

☐ ☐ ☐ ☐ ☐

Strongly Agree

7. The layout of the dashboard was intuitive and well-organized.

Mark only one oval.

1 2 3 4 5

Strongly Disagree

☐ ☐ ☐ ☐ ☐

Strongly Agree

8. I was able to find the information I needed without difficulty.

Mark only one oval.

1 2 3 4 5

Strongly Disagree

☐ ☐ ☐ ☐ ☐

Strongly Agree

9. Navigating between the table of tracked entities and patient dashboards was straightforward.

Mark only one oval.

1 2 3 4 5

Strongly Disagree

☐ ☐ ☐ ☐ ☐

Strongly Agree

10. The design and layout of the table of tracked entity instances were clear and visually appealing.

Mark only one oval.

1	2	3	4	5
Stro	☐	☐	☐	☐
Strongly Agree				

Information Quality

11. The patient summary dashboard provided relevant and useful information.

Mark only one oval.

1	2	3	4	5
Stro	☐	☐	☐	☐
Strongly Agree				

12. Data displayed on the patient dashboard was accurate and reliable.

Mark only one oval.

1	2	3	4	5
Stro	☐	☐	☐	☐
Strongly Agree				

13. The system clearly highlighted the most critical information for decision-making.

Mark only one oval.

1	2	3	4	5
Stro	☐	☐	☐	☐
Strongly Agree				

14. The predictions and insights provided by the machine learning model were easy to interpret.

Mark only one oval.

1 2 3 4 5

Stro ☐ ☐ ☐ ☐ ☐ Strongly Agree

15. Additional patient details (e.g. demographics, treatment history) were easily accessible.

Mark only one oval.

1 2 3 4 5

Stro ☐ ☐ ☐ ☐ ☐ Strongly Agree

16. The system responded quickly when I selected a tracked entity instance.

Mark only one oval.

1 2 3 4 5

Stro ☐ ☐ ☐ ☐ ☐ Strongly Agree

17. Loading the patient summary dashboard after selecting an instance was fast.

Mark only one oval.

1 2 3 4 5

Stro ☐ ☐ ☐ ☐ ☐ Strongly Agree

18. Buttons links and other interactive elements were easy to use.

Mark only one oval.

2 3 4 5

Stro ☐ ☐ ☐ ☐ ☐ Strongly Agree

19. Error messages (if any) were clear and helpful in guiding me to resolve the issue.

Mark only one oval.

1 2 3 4 5

Stro ☐ ☐ ☐ ☐ ☐ Strongly Agree

20. The search and filtering features for tracked entity instances were effective and efficient.

Mark only one oval.

1 2 3 4 5

Stro ☐ ☐ ☐ ☐ ☐ Strongly Agree

User Satisfaction

21. I felt confident using the system for reviewing patient data and predictions.

Mark only one oval.

1 2 3 4 5

Stro ☐ ☐ ☐ ☐ ☐ Strongly Agree

22. The web application reduced the time it took to access patient insights compared to traditional methods.

Mark only one oval.

1 2 3 4 5

Stro ☐ ☐ ☐ ☐ ☐ Strongly Agree

23. The system improved my ability to assess MDR-TB risk.

Mark only one oval.

1 2 3 4 5

Stro ☐ ☐ ☐ ☐ ☐ Strongly Agree

24. Overall, I am satisfied with the system.

Mark only one oval.

1 2 3 4 5

Stro ☐ ☐ ☐ ☐ ☐ Strongly Agree

25. I would recommend this system to my colleagues.

Mark only one oval.

1 2 3 4 5

Stro ☐ ☐ ☐ ☐ ☐ Strongly Agree

Open-Ended

26. What features of the web application did you find most helpful?

27. Were there any aspects of the system that you found confusing or difficult to use?

28. Were there any aspects of the system that you found confusing or difficult to use?

29. Are there additional features or data points you would like to see on the patient summary dashboard?

30. Any other comments or feedback?

ii. Consent forms

INFORMED CONSENT FORM:

Study Title: Using Machine Learning to Predict Multi-Drug Resistance Tuberculosis within the eCBSS.
Description of Subject Population: Healthcare workers at TB clinics in Referral Hospitals managing MDR-TB (Clinicians, Physicians, laboratory Technician and Data clerks)
Investigators: Prof Noah Kiwanuka Mrs. Irene Wanyana Mark Outeke – MHI, School of Public Health, Makerere University

Funding Agency: D43 Training Program
Date:

Introduction

Hello, my name is Mark Outeke, a Master in Health Informatics Graduate student at the School of Public Health, College of Health Sciences at Makerere University. The School and I are researching the use of machine learning in predicting the development of Multi-drug resistant tuberculosis (MDR-TB). The study has selected facilities that manage and treat patients with MDR-TB such as this one and would like you to participate. The participation is voluntary and has no direct harm to you.

This component of the study includes observing how you interact with the current DHIS2 (eCBSS) that is used to notify cases of TB in Uganda and ask you for inputs towards its performance improvements, especially with the use of Artificial intelligence.

About this consent form

Please listen to the reading of this form carefully. This form provides important information about agreeing to participate in the research. You have the right to take your time in making decisions about participating in this research. You may discuss your decision with others. If you have any questions about the research or any portion of this form, please ask us. If you decide to participate in this research, you will be asked to sign this form. A copy of the signed form will be provided to you for your record.

What can I expect if I take part in this research?

From the time of your acceptance to the study, the researcher will engage you in understanding the usability of the current system and its functionality to answer some questions independently and in a group. A Questionnaire either electronic or hard copy will be provided to you in two phases of the study; at the beginning, to collect user requirements; the end, when testing the enhancements with machine learning. All this is non-evasive and only requires about 45 minutes of your time.

After the observation, you will receive a small gift as a token of our appreciation for your participation.

Do I have to take part?

Participation in this study is completely voluntary. If you choose to participate, you may change your mind and leave the study at any time. You will not be treated any differently at this facility if you choose not to participate.

How many people will take part in this research?

Over 20 women will take part in this research across 3 high-volume health facilities.

How long will I take part in this research?

You will take part in this research for the duration of collecting user requirements to testing the developed web application. During the development stage, you might be engaged electronically via mail or web meeting for the progress of the application build and physically to give feedback on the interaction with the new web application.

What are the risks and possible discomforts?

We expect there to be very little risk in participating in this study. The presence of the researcher at your workplace will not cause any functional discomfort. We will ensure that data collection does not interfere with the load of work at the facility. You can choose to end your participation at any time and the researcher will leave. As with any research study, there is a possibility that

someone else may see the information we record, but all efforts will be made to protect your privacy.

Are there any benefits from being in this research study?

There are no direct benefits from being in this study, but we hope that the results of our work can benefit your community by generating important information on the role of artificial intelligence in the care of TB patients.

What will I have to pay for if I participate in this research?

It will not cost you anything to participate in this research part from the time you offer to study.

Can my taking part in the research end early?

You may decide not to continue in the research at any time without it being held against you. The person in charge of the research can remove you from the research at any time without your approval for any reason.

Confidentiality

Your name will not be reported or connected to any of the findings that result from this study. Until data collection is finished the data will be kept in a password-protected file and all paper surveys will be kept in locked cabinets that only researchers have access to. Data collected from this study may be seen by the Makerere University's School of Public Health, the National Tuberculosis and Leprosy Program of the Ministry of Health Uganda, and the Internal Review Board of the Makerere University's Directorate of Graduate Research and Training Department.

Ethical aspects of the study

This research has been reviewed and approved by the ethics committee of Makerere University's Directorate of Graduate Research and Training, the IRB of MAKSPH, and the MOH NTLP. They will also approve any changes made to the study procedures.

What will happen to the results of the research study?

The results of this study will be written up in a report which will be shared with NTLP, MOH, MAKSPH, and other policymakers. We will also publish findings from our research in academic journals. You will not be identified in any report or publication. Any new information gained during the study that would be helpful to research participants, or that may affect your willingness to continue taking part in the study, will be shared.

Questions

If you have questions in the future regarding your participation in the research, please contact one of the Investigating members listed above. If you have questions about your rights as a research subject or regarding any damage attributable to the research and wish to discuss this with someone not involved in the study, you may contact the Makerere University's Directorate of Graduate Research and Training at Level 4, Senate Building Makerere University Kampala. You can also reach the IRB at MAKSPH level 3 School of Public Health Block. Mulago.

Investigators

School of Public Health

Makerere University

Study Title: Using Machine Learning to Predict Multi-Drug Resistance Tuberculosis within the eCBSS
Description of Subject Population: Healthcare workers at TB clinics in Referral Hospitals managing MDR-TB
Investigators: Prof Noah Kiwanuka Mrs. Irene Wanyana Mark Outeke – MHI, School of Public Health, Makerere University

Funding Agency:
Date:

Statement of Consent

- i. I have read the content of this consent form, and agree to participate in this study.
- ii. I have had the opportunity to ask questions and all have been answered to my satisfaction.
- iii. I have been given enough time to consider the above information and to seek advice if I so choose.
- iv. I understand that my participation is voluntary and that I am free to withdraw at any time without giving any reason, and without my medical care or legal rights being affected.
- v. I understand that relevant authorized individuals from Makerere University's School of Public Health record sections of my responses during the study, and I permit these individuals to have access to these records.
- vi. I will be given a copy of this signed consent form. By signing the consent form, I have not given up any of my legal rights.

PARTICIPANT

I consent to participate: Yes

☐

NO

☐

_____		_____	_____
Signature or thumbprint of participant		participant name	Date
			[]/[]/[]
_____		_____	_____
Signature of the witness if thumbprint was given		Witness Name	
Date			
		[]/[]/[]	

ENUMERATOR

I confirm having met with the participant at the time of the interview to answer questions about this study.

[____]/[____]/[____]

Signature of enumerator administering consent form

Name of Enumerator

Date