A Machine Learning-Powered Mobile Application for Linking Blood Donors to Patients. A Case of Mombasa, Kenya

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Declaration and Approval

Declaration

This research is my original work and has not been presented for a degree in any other university. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

Signature ... . Date: **May 29, 2025**

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Abstract

Access to blood for transfusions has always been a critical healthcare challenge, with statistic indicating that an estimated seven Kenyans require blood every ten minutes. However, less than half of these individuals receive transfusions when need, leading to a high number of deaths and complications that are preventable. This crisis is driven largely by inefficiencies in traditional methods of blood donor mobilization and recruitment. These conventional systems almost always result in delays, inadequate matching of donors to patients, and insufficient blood reserves during emergencies. As the demand for blood continues to rise, the need for a more efficient and responsive system has become essential. This research aimed to address the inefficiencies by developing a machine learning-powered mobile app that is tailored to specific healthcare needs of Mombasa County. The study employed an experiential design methodology, integrating descriptive and exploratory approaches to capture both qualitative and quantitative data, which ensured a thorough understanding of existing challenges and allowed for iterative development and testing. The application facilitates the linking of patients who require blood for transfusion to nearest potential blood donors, streamlining the donor-patient matching process and improving emergency response times. The findings demonstrate that the proposed system significantly reduces the time required to find compatible donors. Tests showed an average matching time of 15 seconds from request to donor identification, indicating a substantial improvement over traditional methods. The prediction accuracy of the model at 89.9% was satisfactory, indicating its potential for practical deployment. The system's effectiveness was evaluated through testing, which confirmed its ability to accurately predict potential suitable donors and facilitate timely communication between patients and blood donors. This research contributes to the ongoing efforts to enhance blood donation systems by providing a novel approach that combines machine learning, geolocation, and geofencing technologies for improved donor-patient linkage.

Keywords: Blood transfusion, machine learning, mobile application, experiential design, geolocation, geofencing, blood group.

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Abbreviations/ Acronyms

AI	-	Artificial Intelligence
API	-	Application Programming Interface
BPSCN	-	Blood Platelet Supply Chain Network
EHR	-	Electronic Health Record
GDPR	-	General Data Protection Regulation
GPS	-	Global Positioning System
ICT	-	Information and Communications Technology
KTTA	-	Kenya Tissue and Transplant Authority
ML	-	Machine Learning
MLaaS	-	Machine Learning as a Service
MOH	-	Ministry of Health
NGO	-	Non-Governmental Organization
NHS	-	National Health Service
PWA	-	Progressive Web Application
RFID	-	Radio Frequency Identification
SDG	-	Sustainable Development Goals
SMS	-	Short Message Service
UI	-	User Interface
UX	-	User Experience
WHO	-	World Health Organization

Definition of Terms

Blood Bank A facility where blood is collected, stored, and processed for future use in transfusions, (American Red Cross, 2019).

Blood Donor An individual who voluntarily gives blood for transfusion to another person in need, (NHS Blood and Transplant, 2021).

Blood Transfusion The process of transferring blood or blood products from one person (the donor) into another person's bloodstream to replace lost components of the blood, (WHO, 2020).

Blockchain A decentralized and distributed digital ledger that records transactions across multiple computers so that the registered transactions cannot be altered retroactively without altering all subsequent blocks, (Nakamoto, 2008)

Geofencing A technology that uses GPS or RFID to create a virtual geographic boundary, enabling software to trigger a response when a mobile device enters or leaves a particular area, (Blanchard, 2018).

Geolocation The identification or estimation of the real-world geographic location of an object, such as a mobile phone, computer, or other device, using data like GPS, IP address, Wi-Fi, or RFID, (Hightower, 2018)

Machine Learning A branch of artificial intelligence that enables a system to learn from data rather than through explicit programming, improving its ability to make predictions or decisions, (Mitchell, 1997).

Mobile Application Software designed to run on mobile devices, providing users with a specific service or functionality, (Chang, 2015).

Predictive Analytics The use of statistical algorithms and machine learning techniques to identify the likelihood of future outcomes based on historical data, (Shmueli & Lichtendahl, 2017).

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Chapter 1: Introduction

1.1 Background

Blood transfusion is a very important medical procedure that significantly impacts patient care, especially in situations that are life-threatening. It is crucial for treating various conditions for example severe anemia, traumatic injuries, and during complex surgeries. However, the challenge of ensuring an adequate and timely supply of blood remains substantial, particularly in regions with high demand and limited resources (Sheu, 2019).

In Kenya, the demand for blood is really pressing. According to the World Health Organization (2020), 7 Kenyans need a blood transfusion every 10 minutes. This statistic alone highlights the continuous and urgent need for a reliable blood supply system. Women and children constitute 60% of those needing blood, which underscores the critical need for maternal and pediatric care (Sheu, 2019). Despite these alarming numbers, less than half of those in need receive the transfusions they require. This discrepancy between demand and supply often leads to preventable health crises and fatalities.

A study by The Economist (2023) reveals that nearly 52% of children admitted with severe anemia across three East African countries, including Kenya, are at high risk of death if they do not receive a blood transfusion within eight hours. This illustrates the severe consequences of delays in blood transfusion and the need for more efficient and responsive blood donation systems.

The current methods for mobilizing blood donors involve different strategies such as community blood drives, social media campaigns, and direct appeals through registered hospitals and clinics. However, all these traditional approaches often fall short in meeting the dynamic and urgent needs of healthcare facilities (Topol, 2019). For example, community drives do not always align with immediate blood needs due to their periodic nature and long intervals, while social media campaigns have the likelihood of struggling to generate the required response on time. Direct appeals, although somehow effective, often lack the necessary real-time responsiveness and coordination (Sheu, 2019).

The inefficiencies in traditional blood donor recruitment methods are worsened by logistical challenges in our blood banks. According to data from the Kenya National Blood Transfusion Service (KNBTS), blood collection and distribution are often hindered by inadequate infrastructure, limited resources, and lack of coordination among different stakeholders. This results in uneven distribution of blood supplies, with some areas experiencing shortages while others have excess stock.

There is the Bullwhip effect, a phenomenon that is observed in supply chains, which can also impact blood donation systems. This effect refers to the increasing variability in inventory levels as one moves up the supply chain in response to changes in demand. In blood donation, this can lead to larger fluctuations in blood stock levels, making it difficult to maintain a consistent and adequate supply (Cannella & Ciancimino, 2010).

To address these challenges, improvements in technology and data science offer optimistic solutions. Machine learning has that potential to optimize donor-patient matching and predict blood demand more accurately. By analyzing historical data and identifying patterns, ML algorithms can provide insights into future blood needs and boost the efficiency of donor recruitment and blood distribution processes (Ali et al., 2021).

According to Stuart & Norvig (2003), the integration of cloud computing and intelligent agents in supply chain management has also shown potential in enhancing the efficiency of blood donation systems. Cloud computing allows for the scalable and flexible management of data and resources, while intelligent agents automate and optimize various aspects of blood donation process (Russell et al., 2003).

1.2 Problem Statement

The existing methods of mobilizing and recruiting blood donors are inefficient and fail to meet the dynamic needs of healthcare facilities. Although various proposals have been made to use technology, these approaches have not fully addressed the real-time demands of hospitals and blood banks. In Mombasa, an example of this inefficiency was seen at Coast General Teaching and Referral Hospital during 2021 dengue fever outbreak, where a sudden increase in the number of patients requiring transfusions overwhelmed the hospital's blood storage. Despite social media campaigns and community drives, the hospital struggled to match donors with patients in real time, leading to delays in life-saving transfusions. Traditional methods, such as community blood drives, social media appeals, and direct outreach, lack the ability to match donor availability with urgent patient needs.

Allain et al. (2019) points out that these traditional methods often result in delayed or insufficient blood supplies, which intensifies the problem of inadequate availability of blood for transfusion. This gap demonstrates a critical need for a more responsive system which is also advanced technologically, just like the developed machine learning-powered mobile app, to streamline and optimize the patient-donor linkage process in real-time, which ultimately reduces health complications and deaths.

1.3 Research Objectives

1.3.1 General Objective

The general objective of this research is to develop a machine learning-powered mobile application to improve the accuracy and timeliness of patient-donor linkage. This app addresses existing gaps in current systems, streamline the process of connecting patients in need of blood with potential donors, and improve access to life-saving transfusions in Mombasa, Kenya.

1.3.2 Specific Objectives

i. To evaluate challenges faced in linking patients to blood donors.
ii. To analyze existing technologies used in systems for linking patients to potential blood donors.
iii. To develop a machine learning powered mobile application that instantly links patients to potential blood donors.
iv. To test the developed mobile application.

1.4 Research Questions

i. What challenges are currently faced in linking patients to blood donors?
ii. What is the effectiveness of existing technologies used in systems that link patients to potential blood donors?
iii. What features should a mobile application have to facilitate instant linking of patients to blood donors?
iv. How effective is the developed mobile application in linking patients to blood donors?

1.5 Justification

The developed mobile application represents a significant improvement over traditional blood donors recruitment methods. By making use of machine learning, the app provides real-time and accurate matching of patients to donors, which is very crucial in emergency situations. This immediate connectivity streamlines the process of finding available donors which increases the chances of timely blood transfusions and saving lives.

In addition to improving linking of patients and donors, this mobile app addresses the challenges posed by the current inefficiencies in blood donation processes. Traditional methods depend on outdated databases and manual outreach efforts, which lead to delays. By integrating predictive analytics, the application is able to anticipate donor needs and optimize recruitment strategies, which eventually leads to higher donation rates and improved patient outcomes. This innovative approach not only fulfills a very pressing need in the healthcare system but also depicts a proactive step in modernizing blood transfusion services in Mombasa.

The focus of this study on Mombasa is driven by the special healthcare challenges the county faces regarding blood transfusion services. Mombasa, which is located on Kenya's coast, is an urban center with a high population density and diverse demographics, this contributes to increased blood demand, especially in emergencies. It faces challenges in blood donation due to outdated methods, infrastructure limitations, and frequent sudden blood demand surges. The geographical location and the high use of mobile technology among Mombasa's people made it an ideal place for implementing a mobile application solution.

1.6 Scope

The scope of this study was to develop and test a mobile application specifically for the Mombasa region in Kenya. It involved analyzing existing blood donor recruitment methods, designing the application, and evaluating its performance in real-world scenarios.

1.7 Limitations

This study had several limitations that may have influenced its findings and generalizability. Firstly, the research was geographically confined to Mombasa County, thereby excluding broader national or regional variations in blood donation patterns, healthcare infrastructure, and cultural attitudes towards blood donation. As such, the findings may not be fully representative of other counties or the entire country.

Secondly, the effectiveness of the Smart Donor App was evaluated based on a limited, short-term testing phase. This preliminary assessment did not fully capture the wide range of real-world usage scenarios, long-term user engagement, or challenges such as data privacy concerns, app fatigue, and system scalability.

Finally, methodological limitations included reliance on self-reported data from users, which may be subject to response bias or inaccuracies. The study also faced constraints in controlling for confounding variables such as socioeconomic status, health literacy, and access to healthcare services—all of which could influence a user's likelihood to donate blood or use the application.

To mitigate these limitations, efforts were made to design a feedback feature to act as data collection tool, pretest the app among a small group, and triangulate user feedback. However, further studies with larger and more diverse populations are necessary to enhance the reliability and validity of the findings.

Chapter 2: Literature Review

2.1 Introduction

The demand for blood transfusions remains a critical aspect of healthcare, especially in emergencies where timely access to compatible blood can be the difference between life and death. Traditional methods of linking blood donors to patients have often been plagued by inefficiencies, including delays in donor mobilization, inadequate matching, and limited availability during urgent situations (World Health Organization, 2022). These challenges highlight the need for more innovative approaches to streamline the blood donation process and enhance the efficiency of donor-patient linkage systems.

Patel & Mehta (2024) suggest that recent advancements in technology have opened new possibilities for improving healthcare delivery, with machine learning emerging as a powerful tool in predictive analytics and decision-making. Machine learning's ability to analyze large datasets, identify patterns, and make real-time predictions has been successfully applied across various sectors, including medical diagnostics, personalized medicine, and healthcare logistics. Its application in the field of blood donor management is gaining traction as researchers explore its potential to enhance the accuracy and speed of availing blood to patients requiring transfusion, in addition to reducing wastage and optimizing the use of available resources.

Studies by Zhao & Tan (2023) in technologies like blockchain and machine learning have demonstrated promising results in automating and optimizing processes that were once manual and time-consuming, particularly in health systems that require rapid responses. By leveraging techniques such as predictive modeling and data-driven analysis, machine learning has shown potential in improving donor selection and availability forecasting, ultimately leading to more effective management of blood supply chains. These advancements underscore the importance of integrating machine learning into blood donation systems to address current limitations and improve healthcare outcomes.

2.2 Empirical Literature

The empirical literature focuses on studies that have previously explored challenges and technology-driven solutions to blood donation. The aim is to assess the approaches that have been used to optimize the blood supply chain and identify their strengths and weaknesses.

2.2.1 Challenges Faced when Requiring Blood for Transfusion

A study by Bilgin et al. (2020) focusing on the challenges faced in obtaining blood for transfusion highlights several key barriers that impact blood availability worldwide, especially in low-resource settings. These challenges include inadequate infrastructure, limited donor awareness, and logistical constraints in blood collection, storage, and distribution. Below are reasons why it is so challenging getting blood required for transfusions.

i. Inadequate Blood Donor Recruitment and Retention - One of the primary challenges is the difficulty in recruiting and retaining regular blood donors. According to a study by Bilgin et al. (2020), a significant proportion of blood donation centers in low- and middle-income countries (LMICs) face difficulties in ensuring a steady supply of blood due to low donor participation. The authors emphasize that blood donation is often perceived as inconvenient or even risky by potential donors, which deters consistent participation. Furthermore, factors like seasonal variations in donor turnout, such as during holidays, exacerbate this issue (World Health Organization [WHO], 2021). Public awareness campaigns and incentives for donors have been suggested to improve retention rates, but these measures require consistent funding and public trust in the safety of the donation process.

ii. Supply Chain and Storage Challenges - Once blood is collected, it must be safely stored and transported to hospitals in a timely manner. However, inadequate storage facilities and poor logistical systems often result in blood wastage, especially in regions with unreliable power supplies (Cameron et al., 2019). A study by Osman et al. (2018) found that in Sub-Saharan Africa, up to 20% of collected blood is discarded due to poor refrigeration and transportation systems. This is especially problematic during emergencies when the need for blood transfusions spikes unexpectedly. The lack of proper cold-chain management systems further exacerbates these challenges, limiting the shelf-life of blood and reducing the overall availability of blood supplies.

iii. Socio-Cultural Barriers and Stigma - Cultural beliefs and misconceptions about blood donation also present significant challenges. Studies show that in some communities, there is a stigma associated with blood donation, and misconceptions about the health risks involved discourage potential donors from participating (Njiru et al., 2020). In Kenya, for instance, a study by Mutuma et al. (2020) found that a lack of education on the benefits and safety of blood donation was a major barrier to increasing donor numbers. The research emphasized that educating the public about the importance of blood donation, as well as demystifying myths, could significantly improve donor rates.

iv. Financial and Policy Constraints **-** Blood transfusion services in many countries suffer from insufficient funding and poor policy frameworks. According to Kanyike et al. (2020), government policies often fail to prioritize blood collection and storage infrastructure. This is particularly true in developing countries where health budgets are constrained. The financial strain also affects the capacity of hospitals to provide adequate transfusion services, with many relying heavily on donated blood, which is subject to availability. The WHO (2021) also highlights that blood transfusion services often lack the necessary equipment for testing, blood typing, and screening for transmissible infections, further increasing the risks associated with transfusions.

v. Technological and Data Limitations **-** Despite advances in health technology, many blood banks and transfusion centers in LMICs are still using manual systems for blood collection, testing, and distribution. A study by Tsegaye et al. (2020) demonstrated that inefficient data management and lack of automation in blood banks often lead to errors, such as mismatches between blood donors and recipients, increasing the risk of transfusion reactions. Moreover, the absence of robust data analytics capabilities means that blood demand cannot always be predicted accurately, leading to either shortages or overstocking.

Therefore, to address these challenges, there is a need for multi-dimensional strategies, including improved public education and better supply chain management. Most importantly, technological advancements, such as mobile applications and ML-based systems, can play a crucial role in improving donor engagement, predicting blood needs, and optimizing transfusion practices.

2.2.2 Improving Blood Supply Chain Management Using Blockchain Technology

Pandey et al. (2022) explored the integration of blockchain technology into blood supply chain management to enhance the efficiency, transparency, and security of blood donation processes. The authors highlight that managing the blood supply chain is complex due to factors such as inventory management, donor-patient matching, blood transportation, and the high perishability of blood products. Traditionally, these processes have been prone to inefficiencies and mismanagement, resulting in wastage and critical shortages at healthcare facilities.

The study emphasized the importance of a reliable and traceable system that ensures real-time tracking of blood units from donation to transfusion. Blockchain technology, which is a decentralized and immutable ledger, was proposed as a solution to the prevalent challenges in the blood supply chain. According to the authors, blockchain offers several benefits, including increased transparency, accountability, and trust among all stakeholders in the blood donation process. By allowing donors, hospitals, and blood banks to access real-time data, blockchain improves coordination and reduces the risk of errors, such as mislabeling or improper storage.

Pandey et al. (2022) designed a conceptual framework for a blockchain-based blood supply chain management system that includes key components such as:

i. Donor Registration and Verification - Blockchain technology can be used to securely store and verify donor information, including eligibility, blood type, and medical history. This ensures that only eligible donors are accepted, reducing the risk of transmitting diseases through contaminated blood.

ii. Smart Contracts - The use of smart contracts automates the process of verifying blood donations and matching them with patient needs. These self-executing contracts can streamline processes such as donor recognition, blood type matching, and the allocation of blood units to hospitals.

iii. Real-time Tracking and Traceability - Blockchain provides a transparent mechanism for tracking blood units in real-time. Every transaction and movement of blood—from donation to processing, storage, and distribution—is recorded on the blockchain, creating a tamper-proof audit trail. This feature helps mitigate issues related to blood theft, fraud, and counterfeiting, which have been reported in some countries.

iv. Improved Collaboration among Stakeholders - By connecting all parties involved in the blood supply chain—donors, blood banks, hospitals, and regulatory authorities—on a common platform, blockchain technology fosters better communication and coordination. This minimizes delays and enhances the speed at which blood units can be delivered to those in need.

The study concluded that integrating blockchain technology into the blood supply chain could significantly reduce the inefficiencies that currently plague blood donation systems. It also highlighted that blockchain's immutability, combined with real-time data sharing, provides a high level of trust and security that is critical in life-saving operations such as blood transfusions. However, the authors acknowledged potential challenges such as the cost of implementation, technological literacy among healthcare workers, and the need for regulatory frameworks to support blockchain adoption in healthcare.

This study serves as an important reference point in demonstrating how cutting-edge technologies can be employed to improve critical healthcare services like blood supply chains. While this study focuses on blockchain, its findings can inform the development of other technological interventions, such as the developed machine learning-powered mobile application, by showing the potential for technology to address similar challenges in blood donation management.

2.2.3 Machine Learning in Blood Donation Management

2.2.3.1 Machine Learning

According to Topal (2019), Machine learning (ML) is a subset of artificial intelligence (AI) that focuses on developing algorithms enabling computers to learn from and make predictions based on data. Unlike traditional programming, where explicit instructions are provided for every action, machine learning algorithms identify patterns in data and improve their performance over time as they are exposed to more information. This capability makes machine learning particularly useful in scenarios where human expertise is limited, and large datasets are involved.

2.2.3.2 Types of Machine Learning

Machine learning can be broadly categorized into three main types:

i. Supervised Learning - In this approach, algorithms are trained on labeled datasets, which means the input data is paired with the correct output. The model learns to map inputs to outputs, making it ideal for classification and regression tasks. Common algorithms include linear regression, decision trees, and support vector machines (Bishop, 2006).

ii. Unsupervised Learning - Here, algorithms work with unlabeled data and must identify patterns or groupings within the data independently. This type of learning is useful for clustering and association problems. Common techniques include k-means clustering and hierarchical clustering (Hastie et al., 2009).

iii. Reinforcement Learning - This method involves training algorithms through a system of rewards and penalties. The model learns to make decisions by exploring its environment and receiving feedback based on its actions. Reinforcement learning is often used in robotics and game playing (Sutton & Barto, 2018).

2.2.3.3 Applications of Machine Learning

Machine learning has numerous applications across various domains. In healthcare, it is used for predictive analytics, patient diagnosis, personalized treatment plans, and optimizing resource allocation. For example, ML algorithms can analyze patient data to predict disease outbreaks, assist in medical imaging analysis, and enhance drug discovery processes (Shai et al., 2019). In the context of blood donation, machine learning can be applied to predict donor availability, assess compatibility between donors and recipients, and optimize donor recruitment strategies. According to a study by Topal (2019), ML models can effectively predict blood donor behavior and improve the efficiency of recruitment campaigns.

2.2.3.4 Technique Adopted in the Developed Solution

For the developed solution, supervised learning approach was adopted, specifically using regression algorithms, with a focus on XGBoost (Extreme Gradient Boosting). According to Russell & Norvig (2003), XGBoost is a powerful machine learning algorithm based on decision tree ensembles. It is particularly well-suited for regression tasks due to its efficiency and high performance in handling large datasets with complex relationships among features.

In implementing the XGBoost regressor, preprocessing of the input features happened first, including blood group, donation frequency, preferred time and place to donate and demographic information. The model was trained on historical data that linked patients with compatible blood donors, allowing it to learn patterns and relationships within the data. After training, the regressor was used to predict potential donor matches in real-time, improving the efficiency and effectiveness of the blood donation process.

By leveraging XGBoost, the developed solution aimed to create a responsive and accurate system that facilitates timely connections between patients in need of blood transfusions and willing blood donors, ultimately contributing to better healthcare outcomes in Mombasa, Kenya.

2.2.4 Machine Learning for Patient-Blood Matching

Another relevant study by Sharma et al. (2021) focused on using machine learning models to enhance patient-blood matching efficiency. The authors utilized predictive analytics to forecast the availability of blood units based on historical data, donation behavior, and patient demand trends. The machine learning model could accurately predict donation frequency, the likelihood of specific blood types being available, and how quickly donated blood should be allocated to different hospitals based on geographical proximity.

This study reinforced the need for a technology-driven solution to handle the complexities of blood matching, helping reduce delays and improve response times in critical cases. The proposed use of machine learning in donor-patient linkage serves as a steppingstone toward the current research's objective.

However, the study lacked considerations for mobile integration, a crucial aspect for developing nations where mobile phones is prevalent. Adding this feature could allow better geolocation tracking of blood donors, ensuring quicker response times.

2.2.5 Use of Mobile Technology to Improve Blood Donation

Mobile technology has increasingly become a crucial component in enhancing blood donation campaigns, making the process more efficient and accessible. Hesse et al. (2020) reported that mobile applications have the potential to significantly improve donor engagement, automate communication processes, and provide real-time updates on blood inventory levels. These features help to address logistical challenges and streamline the coordination between blood donors and collection centers.

Kasparian et al. (2022) emphasized the effectiveness of mobile technology in facilitating rapid donor mobilization during emergencies. Their study showed that the use of push notifications and SMS alerts can quickly inform potential donors about urgent blood needs, leading to faster response times. This approach is particularly valuable in densely populated areas where the demand for blood can be unpredictable and the need for efficient donor communication is critical.

Moreover, Afzal et al. (2023) highlighted that mobile technology, when integrated with data analytics, enables personalized communication strategies that can enhance donor retention. Mobile apps utilizing predictive analytics can send tailored reminders and incentives, thereby encouraging more regular donations from individuals. The study found that such personalized approaches lead to higher engagement rates and a more consistent supply of blood, which is vital in managing the blood supply chain effectively.

2.3 Theoretical literature

This section explores the theoretical foundations that support the integration of technology in blood donation and supply chain management. By evaluating existing frameworks and models, this section provides insights into how technology can be leveraged to improve blood donation processes and addresses the potential benefits and challenges associated with these innovations.

2.3.1 The Use of Technology in Blood Donation

Curl (2019) provides a comprehensive review of how technology has been integrated into the blood donation process over the past decade. His research highlights various technologies, including mobile applications, geolocation services, and predictive analytics, that have transformed how donors are recruited, retained, and linked to patients in need of blood. The author discusses how mobile apps have enhanced the convenience and accessibility of donation drives by notifying donors of nearby donation centers and offering reminders. Geolocation services are seen as useful in real-time tracking of donation events within a geographical radius. Predictive analytics, on the other hand, are increasingly used to analyze blood donation patterns and predict shortages, which helps in better supply chain management and planning. However, Curl (2019) points out several challenges in using these technologies. The lack of proper digital infrastructure in low-resource settings limits the scalability of these solutions. Furthermore, privacy concerns about donor data and the cybersecurity risks associated with the online management of sensitive health information are raised as major downsides. The authors also emphasize that reliance on technology could alienate potential donors who are less technologically adept.

What needs to be considered is that while the use of technology in blood donation presents significant benefits in terms of efficiency, outreach, and data-driven decision-making, challenges related to infrastructure, data security, and inclusivity need to be addressed for widespread adoption.

2.3.2 Digital Health Innovations for Blood Donation

Joélia et al. (2018) presents a conceptual framework that explores digital health innovations designed to modernize, promote, and optimize blood donation systems. The framework primarily focuses on integrating mobile health (mHealth) applications, wearable health technology, and cloud-based platforms into the blood donation ecosystem. According to their research, these technologies not only simplify the donor-patient linkage process but also provide new data sources for real-time monitoring and decision-making. The authors identify mHealth applications as a game-changer in donor engagement, allowing donors to manage their donation schedules, receive notifications, and track their health metrics. Wearable health technology, like fitness trackers, offers valuable data on donor health, which could be used to ensure donor eligibility and monitor recovery post-donation. Cloud-based platforms ensure that blood banks and hospitals can access up-to-date donor information, thereby optimizing inventory management.

Despite these advantages, the authors pointed out that the integration of these technologies into the healthcare system requires substantial investment in both infrastructure and training. Additionally, privacy and data protection concerns arise due to the use of personal health data in mHealth and wearable devices. There are also questions about the long-term sustainability of these digital innovations, especially in developing regions where healthcare infrastructure is still evolving.

2.3.3 Machine Learning in Blood Donation Systems

In recent years, machine learning (ML) has emerged as a powerful tool to improve the efficiency of blood donation systems. Kumar et al. (2020) discusses how ML algorithms can predict blood shortages and optimize donor-patient matching based on historical donation patterns and demographic data. These technologies are particularly effective in predicting the optimal times for blood drives, ensuring that blood banks are adequately stocked when demand peaks. By analyzing vast amounts of donor and patient data, ML models can accurately forecast donation behaviors, donor availability, and blood type requirements, ensuring more efficient blood distribution. Despite the potential of ML in transforming blood donation systems, Kumar et al. (2020) note that challenges remain in data quality, as inconsistent or incomplete data can affect model accuracy. Also, ethical concerns regarding the use of personal data for training these models need to be addressed to ensure donor privacy and trust. However, if implemented correctly, machine learning has the capacity to revolutionize how blood banks operate, enhancing the timeliness and effectiveness of blood donation processes.

2.3.4 Geolocation and Geofencing for Blood Donation Matching

Geolocation and geofencing technologies are increasingly being utilized to improve the precision and efficiency of blood donation matching systems. According to Patel et al. (2021), these technologies enable blood donation platforms to match donors with patients in need based on proximity and availability. Geofencing helps create virtual boundaries around donation centers, allowing the system to notify nearby potential donors of urgent blood requests, thus reducing response times. Geolocation-based notifications also ensure that only available donors within a specified radius are contacted, ensuring the practicality and immediacy of the blood donation process. Patel et al. (2021) also discusses the impact of these technologies on donor engagement, noting that real-time notifications and location-based reminders significantly increase the likelihood of donor participation in urgent cases. However, the authors emphasize that geolocation-based systems must address challenges such as donor consent, data privacy, and ensuring system accuracy, particularly in rural or underserved areas where geolocation tracking might be less reliable. Despite these challenges, geofencing and geolocation hold great promise in ensuring that blood donations are timely, targeted, and efficient.

2.4 Framework/Models for Optimizing Blood Donation Systems Using Technology

Frameworks and models play a crucial role in understanding, analyzing, and improving systems related to blood donation and supply chain management (Shokouhifar, 2020). These structures provide a conceptual framework to examine the complexities involved in the management and delivery of blood and its components, ensuring that key elements such as sustainability, resilience, and optimization are achieved.

2.4.1 A Supply Chain Network of Blood Platelets Using Grey Wolf Optimizer

Shokouhifar (2020) introduces a model for optimizing blood supply chain networks, particularly focusing on the distribution of blood platelets. The proposed framework employs a dual transshipment mechanism—vertical transshipment within hierarchical levels and horizontal transshipment between entities at the same level of the supply chain. Given the short lifespan of platelets, this model ensures that they are efficiently distributed to minimize wastage and meet demand in emergencies.

The key innovation in this model is the application of the Grey Wolf Optimizer (GWO) algorithm, an artificial intelligence technique modeled after the social hierarchy and hunting behavior of grey wolves. The GWO algorithm enables the system to optimize the routing and distribution process dynamically. This reduces costs, improves delivery speed, and maximizes the availability of platelets, thereby contributing to both the resilience and sustainability of the supply chain.

Through various simulations, the framework demonstrates the ability to achieve a balanced distribution of resources, ensuring timely platelet delivery while reducing carbon emissions associated with transportation. This resilient design allows the supply chain to adapt to disruptions, ensuring consistent availability of platelets even in the face of demand fluctuations or logistical challenges. It also enhances sustainability by optimizing routes and minimizing environmental impacts. The figure 2.1 shows the Three-echelon BPSCN model with vertical-horizontal transshipment from blood donors to blood banks and then to hospitals.

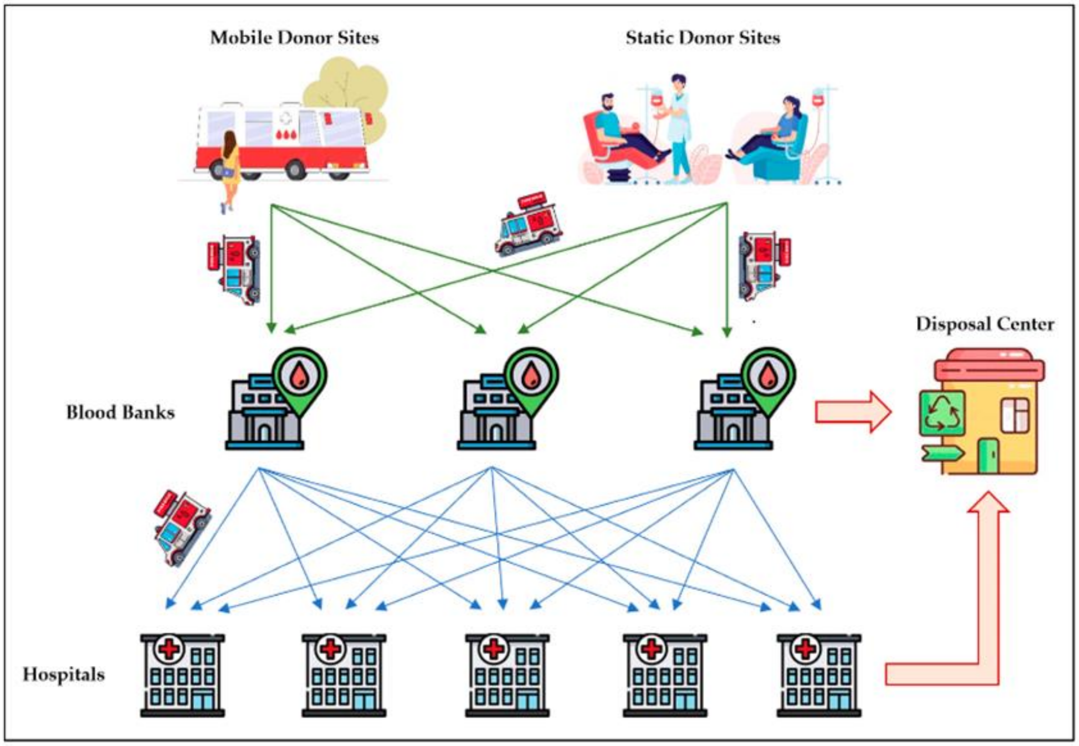

Figure 2.1: Three-echelon BPSCN Model with Vertical-horizontal Transshipment (Shokouhifar, 2020)

2.4.2 Blockchain-Based Blood Supply Chain Models

Blockchain technology has emerged as a potential solution to several supply chain challenges, including transparency, traceability, and security. According to Pandey et al. (2022), Blockchain provides a decentralized, immutable ledger that can record all transactions in the blood donation supply chain, from donor registration to the delivery of blood to patients. propose a blockchain-based framework to improve transparency in the blood supply chain, ensuring that data on blood donation, storage, and distribution is secure and accessible in real-time.

The framework leverages smart contracts to automate various aspects of blood supply chain management, such as tracking blood donation status, verifying blood quality, and monitoring storage conditions. By using blockchain, the system enhances trust between donors, healthcare providers, and patients, reducing the risk of data manipulation or fraud. The decentralized nature of the blockchain ensures that no single entity has control over the entire system, promoting fairness and accountability.

One of the key advantages of this model is its ability to improve the traceability of blood products, allowing healthcare providers to quickly track blood units, verify their origin, and monitor their shelf life. This reduces the risk of administering expired or contaminated blood to patients, ultimately improving patient safety. Additionally, the use of blockchain can help reduce administrative costs and delays by automating many of the manual processes currently involved in blood supply chain management.

However, the implementation of blockchain technology in the blood supply chain comes with challenges. These include the need for robust digital infrastructure, data privacy concerns, and the complexity of integrating blockchain with existing systems in healthcare. Despite these hurdles, the benefits of improved transparency and traceability make blockchain a promising tool for future blood donation systems.

2.4.3 Demand Forecasting and Blood Inventory Management Models

Another important model in the blood supply chain focuses on demand forecasting and inventory management. Accurate demand forecasting is critical to preventing both shortages and overstocking of blood products, which can lead to wastage (Kaur et al., 2020) presents a predictive analytics model that uses historical data and machine learning algorithms to forecast blood demand based on factors such as population demographics, seasonal trends, and disease outbreaks.

The model incorporates predictive analytics to provide real-time insights into blood demand across different regions and hospitals, allowing supply chain managers to make informed decisions about inventory levels. This minimizes the risk of stockouts during critical periods and reduces the need for emergency blood drives, which can be costly and inefficient. The model also optimizes inventory management by identifying the most efficient storage locations for blood products, considering factors such as transportation time and shelf life.

While demand forecasting models can significantly improve the efficiency of the blood supply chain, they also require access to large amounts of high-quality data. The accuracy of the predictions depends on the quality of the data used to train the models, and any errors or inconsistencies in the data can lead to incorrect forecasts. Additionally, the model's success relies on the ability of healthcare providers to quickly adapt their supply chain strategies based on the predictions, which may require additional training and resources.

2.5 Architectures of Blood Donation and Management Systems

This section entails the structured framework governing the interaction and functionality of components within blood supply chain management systems. A well designed architecture is crucial for ensuring the efficiency, reliability, and scalability of these systems, particularly in healthcare environments where demands can be unpredictable (Reem & Rashad, 2022).

Key elements of effective architecture include data collection and integration, where the deployment of IoT devices allows for real-time data on blood inventory and donor information, all integrated into a centralized system for seamless data flow. Communication protocols are also essential, as they facilitate data exchange among hospitals, blood banks, and donors, enabling timely responses to blood shortages (Reem & Rashad, 2022).

2.5.1 The Use of Web Technology and IoT to the Management of Blood Banks

Reem & Rashad (2022) explored how web technologies and the Internet of Things (IoT) can enhance the management of blood banks in developing countries. Their research indicates that integrating IoT devices into blood bank operations can streamline processes, improve inventory management, and enhance communication among stakeholders. The architecture proposed by the authors facilitates real-time monitoring of blood supplies, which is crucial for timely decision-making and emergency response. The system also includes a web-based platform that enables stakeholders to access information on blood availability and donor locations easily.

One of the primary advantages of this architecture is its ability to significantly reduce wastage by ensuring that blood supplies are monitored and utilized efficiently. Furthermore, it fosters greater collaboration among health facilities, which can lead to improved resource sharing and enhanced patient care. However, the study also identifies challenges, such as the need for substantial investment in technology infrastructure and training for personnel. Additionally, privacy and security concerns regarding patient data remain critical issues that must be addressed to ensure the successful implementation of such systems. The figure 2.2 shows the use of Web Technology and IoT to track blood from the source to destination for accountability purposes.

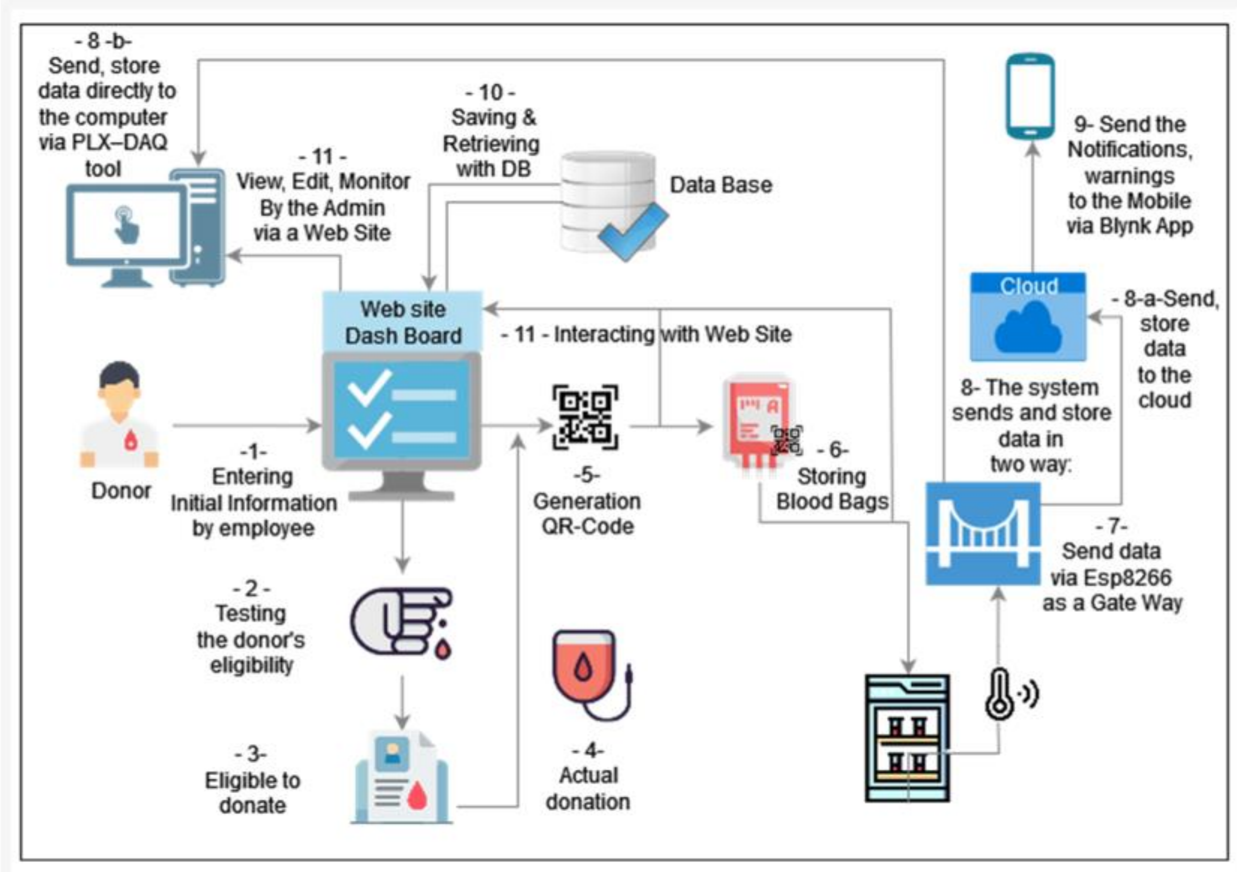

Figure 2.2: Use of Web Technology and IoT (Reem & Rashad, 2022)

2.5.2 Architecture for Blood Donation Management Systems

In their review, Yaling & Gehao (2021) examined various architectural frameworks designed for blood donation management systems. The authors highlight different approaches, including centralized and decentralized architectures, and their impact on the efficiency of blood donation processes. They analyze several case studies where these architectures have been implemented, discussing their scalability, adaptability, and the technology stack used in each instance.

According to the duo, the main benefit of adopting a well-defined architecture is the optimization of blood collection and distribution processes. Centralized architectures, for example, allow for more straightforward data management and coordination among blood banks, which can improve overall efficiency. On the other hand, decentralized architectures offer increased resilience and flexibility, allowing local blood banks to operate more independently. Despite these advantages, the authors note that decentralized systems may introduce complexities in data synchronization and inter-organizational communication. Balancing these architectural trade-offs is essential for developing effective blood donation management systems. Figure 2.3 shows a centralized architecture of Blood Donor Management System that uses internet connectivity.

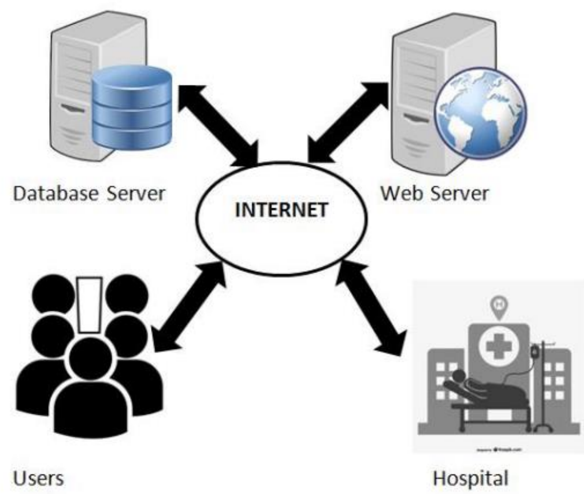

Figure 2.3: Centralized Architecture of Blood Donor Management System (Yaling & Gehao, 2021)

2.5.3 A Smart Blood Bank Management System

Thirunavukkarasu, (2020) proposed a smart blood bank management system leveraging cloud technology to address the challenges of blood supply chain management. His architecture allows for the collection of data from various blood donor devices and hospitals, including blood storage units equipped with sensors to monitor temperature and expiration dates. This data is transmitted to a cloud-based platform where it can be analyzed and accessed by authorized users in real time.

One of the notable advantages of this system is its ability to provide stakeholders with real-time insights into blood inventory levels, facilitating better decision-making regarding collection and distribution. Additionally, the use of cloud technology enhances the scalability of the system, allowing for seamless integration with other healthcare management systems. The downside to this is the reliance on cloud computing raises concerns about data security and privacy. The authors emphasize the need for robust encryption methods and secure data handling practices to protect sensitive information in this architecture.

2.6 Designs of Blood Donation Applications and Systems

This section presents a literature review on user interface designs in blood supply chain management systems. The interface design plays a pivotal role in ensuring that stakeholders, including donors, healthcare providers, and blood bank administrators, can effectively interact with the system. Effective designs enhance usability, facilitate communication, and ensure efficient operations within the blood supply chain (Custer et al., 2021).

Recent studies underscore the significance of intuitive user interfaces that allow for seamless navigation and quick access to critical information. For instance, a study by Ismail et al. (2022) emphasizes the necessity for user-friendly dashboards that provide real-time data on blood inventory levels and donor statistics. This information is crucial for managing supply levels and planning donation drives. The authors argue that clear visualizations, such as graphs and charts, can help users quickly grasp complex data, leading to more informed decision-making.

Custer et al. (2021) discuss the use of mobile technology to improve blood donation, suggesting that an interactive map showcasing nearby donation centers can significantly increase donor turnout. This technology not only aids in accessibility but also enhances the overall donor experience by simplifying the process of finding a donation location.

2.6.1 User Interface

The literature by Kaur et al., (2020) indicates that mobile-friendly interfaces can increase user engagement, especially among younger demographics who prefer accessing services through smartphones. Consequently, an adaptable layout that maintains functionality across devices is essential for modern blood supply management systems. Figure 2.4 shows the interface of BloodConnect Website.

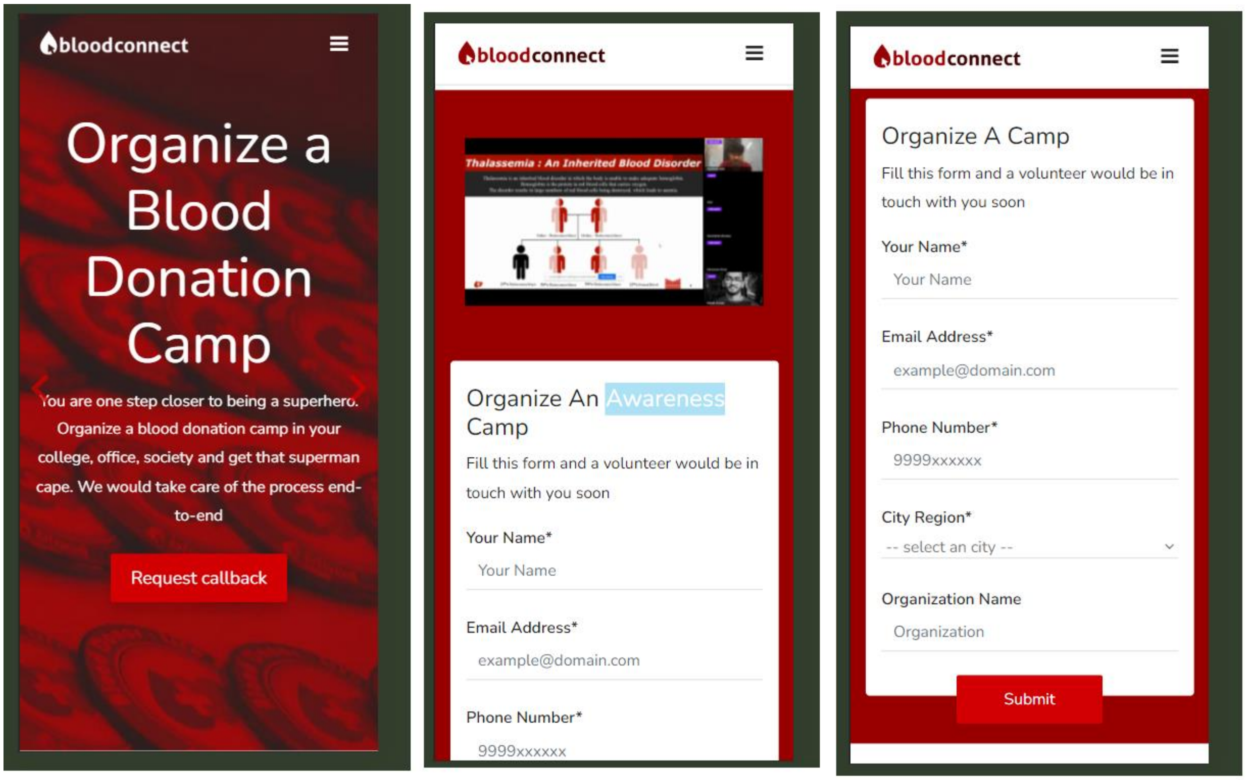

Figure 2.4: BloodConnect Website (BloodConnect, 2024)

2.6.2 Interactive design

Interactive design including email notifications and emails are important for enhancing user engagement and overall experience in applications such as LifeBank, a blood and oxygen bank based in Nigeria. LifeBank's interface employs interactive design principles that prioritize user-friendliness, allowing donors, hospitals, and the public to navigate the system with ease. The platform features intuitive menus and interactive elements that streamline processes like donor registration, blood request submissions, and tracking of blood availability in real-time.

By focusing on an engaging and responsive user interface, LifeBank not only facilitates efficient blood donation but also encourages more users to participate actively in saving lives. This approach highlights the importance of interactive design in healthcare applications, demonstrating how a well-crafted user experience can lead to improved participation rates and better health outcomes in communities. Figure 2.5 shows mobile application interface of Lifebank Blood Donation App.

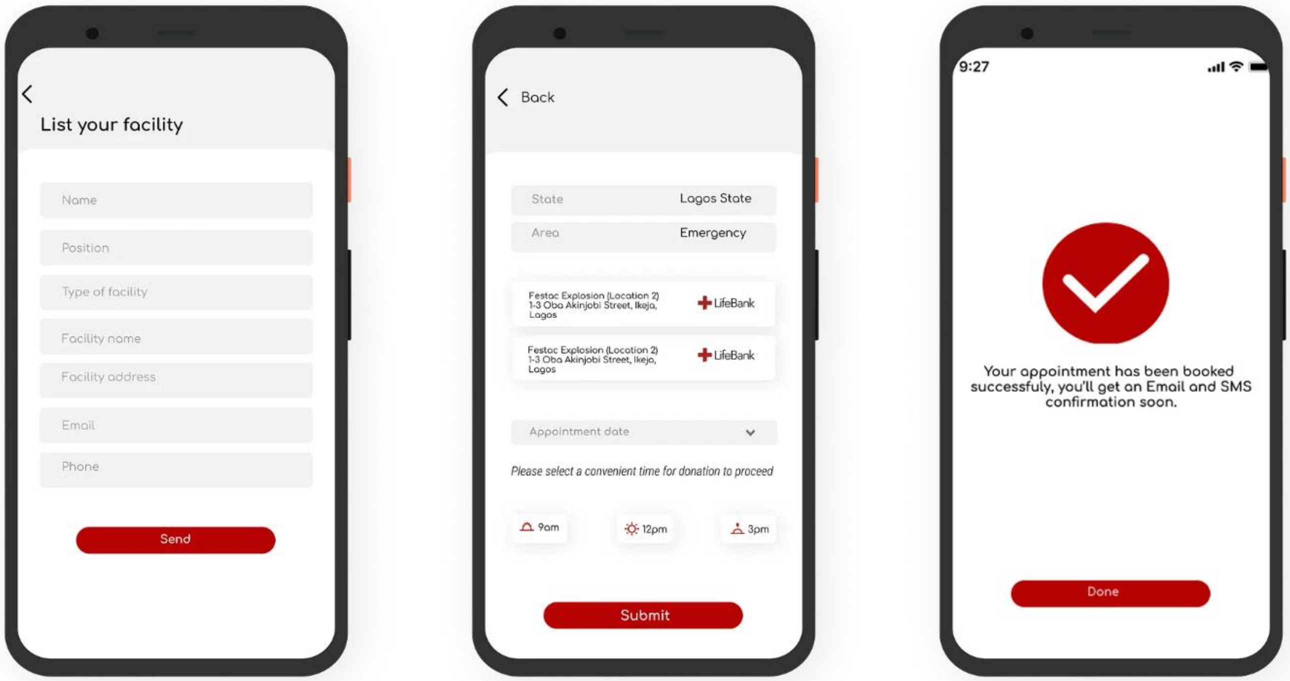

Figure 2.5: Lifebank Blood Donation App (LifeBank, 2024)

2.7 Algorithms for Blood Donor-Patient Matching

According to Cormen et al., (2009), Algorithms are step-by-step procedures or formulas for solving problems or performing tasks. They are structured sets of instructions or rules designed to solve problems, perform computations, or carry out tasks in a systematic way. They form the backbone of computer science and data processing, enabling machines to make decisions, execute tasks, and analyze data more efficiently. An algorithm's effectiveness lies in its ability to handle complex operations by breaking them down into smaller, manageable steps, guiding a machine to achieve a specific goal with precision and speed. Whether they are simple mathematical operations or complex machine learning processes, algorithms are essential for automating tasks and enhancing decision-making in various domains.

In the context of healthcare, Kourou et al., (2015) emphasizes that algorithms play a critical role in transforming raw medical data into actionable insights. They have become indispensable in medical diagnostics, treatment planning, patient monitoring, and predictive analytics. Machine

Learning (ML) algorithms like Support Vector Machines (SVM), Neural Networks, and Random Forests analyze large datasets to predict patient outcomes, detect anomalies in medical imaging, and personalize treatment plans. These algorithms help clinicians make more informed decisions, reduce diagnostic errors, and deliver more accurate and timely interventions. For instance, the application of ML algorithms in early disease detection has significantly improved the management of conditions such as diabetes, heart disease, and cancer, leading to better patient prognosis and reduced healthcare costs (Esteva et al., 2017).

Within blood supply chain management, algorithms have been specifically tailored to optimize the logistics involved in the collection, storage, and distribution of blood products. Mansoor et al., (2020) point out that Genetic Algorithms (GA), inspired by the process of natural selection, are widely used to solve optimization problems in healthcare logistics. They help in determining the most efficient way to allocate resources, schedule blood donations, and manage blood inventories to minimize shortages and wastage. Genetic Algorithms adjust their strategies dynamically, adapting to changes in demand or supply conditions, making them highly effective in maintaining a balanced blood supply chain.

Another significant algorithm in the field is the Particle Swarm Optimization (PSO) algorithm, modeled after the social behavior of birds and fish (Kennedy & Eberhart, 1995). PSO has been applied to optimize the distribution routes for blood products, reducing transportation costs while ensuring timely delivery to hospitals and clinics (Ahmed et al., 2022). The adaptability of PSO allows it to respond to fluctuations in demand, such as during emergency situations or mass casualty events, making it a valuable tool in healthcare logistics.

The integration of data analytics with algorithms in blood donation management has been transformative. For example, Predictive Analytics Algorithms analyze historical blood donation data to forecast future demand patterns and predict blood availability during critical times (Zhao et al., 2021). These data-driven approaches help blood banks make informed decisions about when and where to mobilize donation drives, optimize donor outreach strategies, and maintain an adequate supply of blood components.

Advanced algorithms like the Lévy Flight-based Grey Wolf Optimizer (LSGWO) are gaining attention in solving complex blood supply chain problems. The LSGWO algorithm uses a flowchart methodology to address the intricacies of the Blood Platelet Supply Chain Network

(BPSCN), involving the identification of critical variables, evaluation of possible solutions, and the selection of optimal strategies for supply chain operations. Its approach allows for efficient management of platelet inventory levels, reducing both the wastage of perishable blood products and the risk of shortages during peak demand periods (Shokouhifar, 2020).

In the developed solution, Smart Donor Search algorithm was used to enhance donor matching processes by analyzing donor profiles, blood types, and location data to identify the most suitable donors for specific patient needs. This precise matching reduced the waiting time for patients requiring blood transfusions, thereby improving treatment outcomes, and potentially saving lives. The figure 2.6 shows a flowchart of the LSGWO Algorithm for Solving the Blood Supply Chain Network.

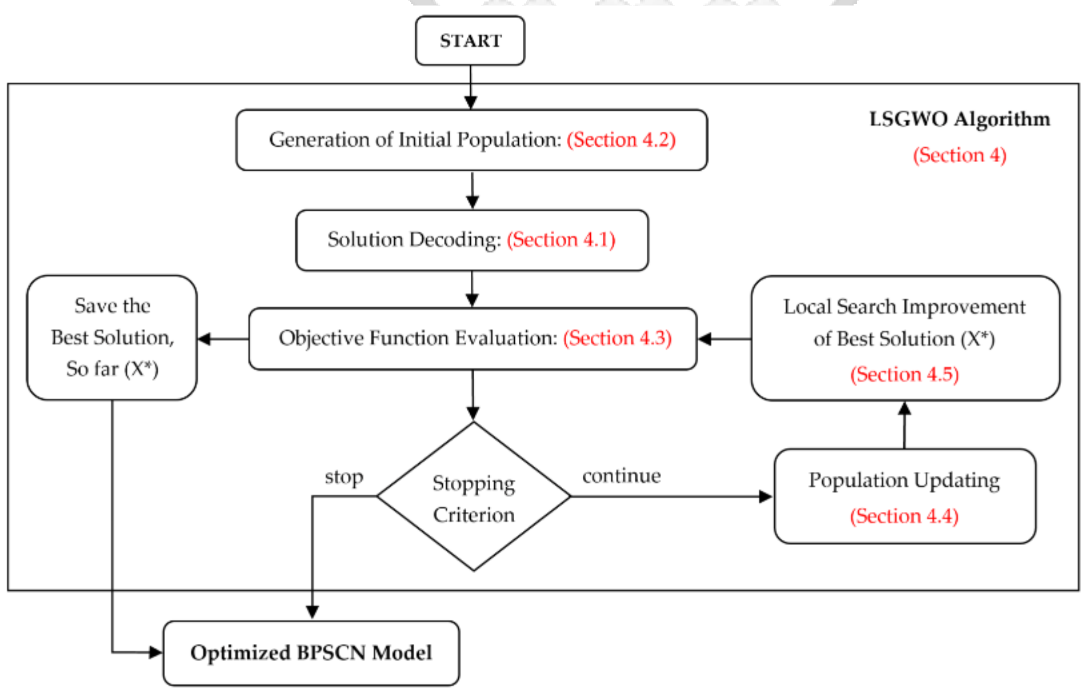

Figure 2.6: Flowchart of the LSGWO Algorithm for Solving the BPSCN Model (Shokouhifar, 2020)

2.8 Research Gap

The existing literature highlights various advancements in blood supply chain management, particularly in the use of technology, optimization algorithms, and mobile applications. However, significant gaps remain that underscore the need for further research and innovative solutions. One critical gap is the lack of a comprehensive, integrated system that not only optimizes the logistics of blood supply but also effectively links patients in need with potential donors instantly, particularly in the context of Mombasa, Kenya.

While studies have explored the use of blockchain technology and IoT in managing blood supply chains, they often fail to address the real-time needs of blood donors and recipients. Current systems typically operate in silos, focusing either on supply chain optimization or on donor engagement without a holistic approach. Also, many existing solutions do not leverage predictive analytics to forecast demand effectively or utilize geofencing technologies to improve donor mobilization.

The literature does not adequately address the unique socio-cultural and logistical challenges faced in developing countries, where the infrastructure for health data management is often lacking. This creates an opportunity to develop a machine learning-powered mobile application that can facilitate real-time patient-donor linkage, incorporating features such as geolocation, predictive analytics, and user-friendly interfaces tailored to the local context.

By addressing these gaps, this research aimed to provide a robust solution that not only enhances operational efficiencies in blood supply management but also improves patient outcomes through timely and effective donor mobilization. This integrated approach represents an important step forward in optimizing blood donation processes in Mombasa, ensuring that no patient is left without the necessary blood supply due to logistical challenges.

2.9 Conceptual Framework

The conceptual framework for this study is grounded in the development of a machine learning-powered mobile application designed to enhance the linkage between patients and blood donors in Mombasa, Kenya. It was shaped not only by the identified research gaps but also significantly informed by insights gathered from the reviewed literature on blood donation systems, digital health interventions, and predictive analytics. Previous studies revealed critical challenges in traditional blood donation systems, including delays in locating suitable donors, low donor retention, and inefficiencies in responding to emergency blood needs. Literature also emphasized the value of technology in improving healthcare delivery—especially the integration of mobile apps, predictive algorithms, and user-centric designs to streamline processes and encourage donor participation.

Drawing from such literature, the framework integrates predictive analytics to forecast the most suitable and nearest available donor based on factors such as location, blood group, donation history, and availability. This design decision was guided by research supporting the effectiveness of machine learning in health resource allocation and emergency response. The literature further highlighted the importance of user engagement in sustaining digital health initiatives. As a result, features such as gamification through virtual 'LIFESAVER' points, real-time notifications, and personalized donor profiles were included to improve donor retention and responsiveness.

Secure data handling and compliance with ethical standards also emerged as a critical theme in the reviewed literature. In response, the application emphasizes privacy and adheres to relevant data protection laws, including Kenya's Data Protection Act. The technical design ensures secure data collection, storage, and sharing protocols while maintaining transparency and user control over personal information. Additionally, the reviewed literature underscored the importance of agile and iterative development in the success of digital health applications. This informed the adoption of an agile development approach, enabling continuous refinement of the system based on user feedback, pilot testing, and collaboration with healthcare professionals and blood bank staff.

The framework integrates historical donor data, real-time user input, and cloud-based infrastructure to power the machine learning model and ensure the scalability of the system. Mobile technology is employed to improve accessibility, especially in urban and peri-urban areas where smartphones are prevalent. The result is a conceptual and technical design that directly responds to gaps identified in both the problem statement and literature review, ensuring a robust, user-friendly, and contextually relevant solution. This holistic approach ultimately aims to save lives by enabling faster and more reliable access to blood donations in emergency situations, as illustrated in Figure 2.7.

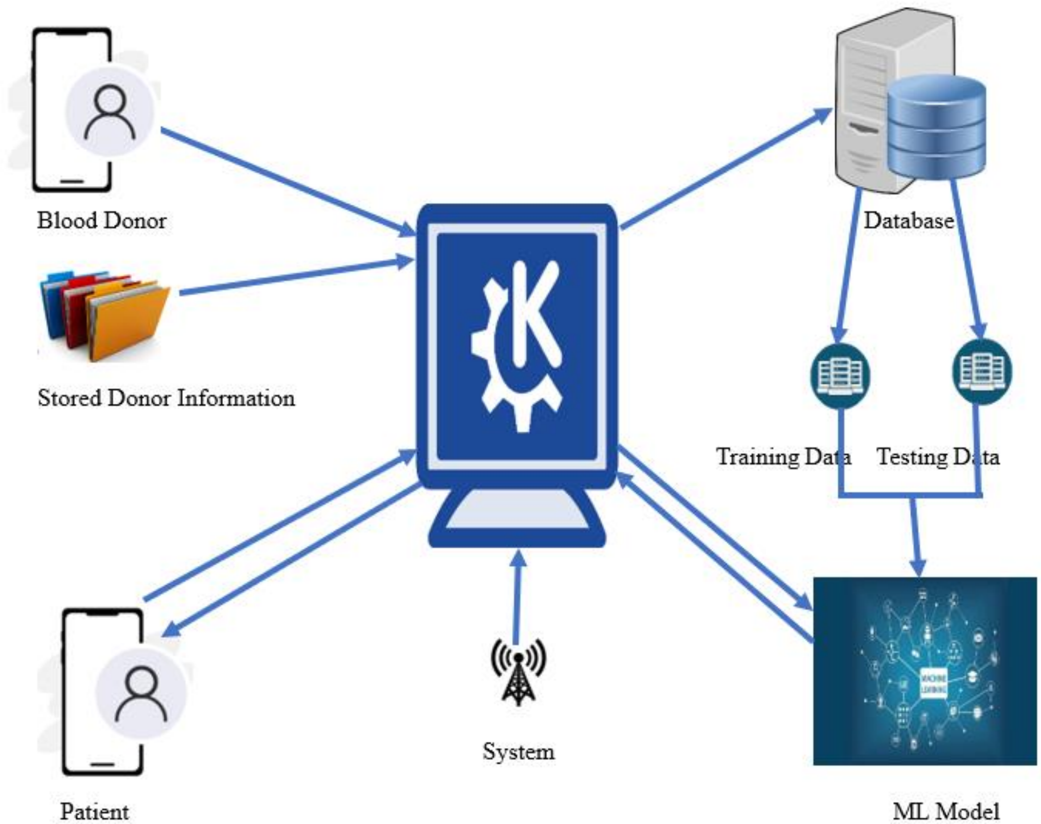

Figure 2.7: Conceptual Framework

Chapter 3: Research Methodology

3.1 Introduction

Research methodology refers to the systematic process of identifying and applying appropriate techniques for collecting and analyzing data to achieve the research objectives (Sreekumar, 2023). This study aimed to develop a machine learning-powered mobile application that is designed to improve the efficiency of linking patients requiring blood transfusions to the nearest potential blood donors in Mombasa. The main focus was on employing data collection methods, machine learning algorithms, and geolocation technology to create a reliable solution that solved the challenges in the patient-donor matching.

3.2 Research design

The research design for this study was descriptive, exploratory, and experiential. The descriptive research helped us understand the existing blood donation and distribution system in Mombasa, while the exploratory research was utilized to develop the ML powered solution to predict suitable donors for raised blood requests. The experiential component focused on engaging users and observing how they interacted with the application to refine its design and functionality. This study employed a mixed-methods design, combining both qualitative and quantitative approaches. The qualitative approach collected insights from interviews and surveys while the quantitative approach focused on analyzing data obtained through questionnaires and existing databases related to blood donors and recipients. This approach ensured that both the technical development and the user experience were fully addressed.

3.3 Population

The population for this study consisted of two groups within Mombasa, which had a population of approximately 1.5 million (Kenya National Bureau of Statistics, 2024).

i. Patients – These are the main users of the mobile application; this group included individuals who require blood for transfusions. Patients or their representatives would be able to use the system to post a blood appeal request and search for the nearest compatible blood donors. Understanding their needs, preferences, and challenges in finding blood donors was essential for designing a user-friendly and effective application.

ii. Blood Donors - This group comprised of individuals who are eligible and willing to donate blood. Both regular and potential new donors who had not previously donated blood but are interested were included. The details collected from these donors such as their blood type, donation history, and geographical location were used to live-test the machine learning model.

These two groups represented the key stakeholders in the blood donation process, and therefore their engagement in the study provided a comprehensive understanding of the requirements, expectations, and possible barriers related to the adoption of the mobile app solution in Mombasa.

3.3.1 Sampling

The study used stratified random sampling to ensure representation from key stakeholders who were patients and blood donors. This technique allowed a better generalizability of results by ensuring different sectors of the population were represented proportionately. According to Madam Grace Nzilani, who was the then technical director of Mombasa's Regional Blood Transfusion Center (RBTC), 10,000 patients require blood components annually in Mombasa. For a region to have sufficient blood supply, 1% of the population is required to be active blood donors (WHO, 2016). Mombasa with a population of 1.5 million people will need a regular pool of 15,000 blood donors. To find the sample size, Cochran's equation was used for both the patients and blood donors**.**

3.3.1.1 Cochran's Equation

$$\text{Sample Size (n)} = \frac{Z^2 p(1-p)}{e^2}$$

Equation 3.1: Cochran's Equation

Where:

Z = Z-score (based on the desired confidence level, that is, 1.96 for a 95% confidence level)

p = estimated proportion of the population that has the attribute of interest (if unknown, 0.5 is used to maximize the sample size)

E = margin of error (or confidence interval, that is, 5% or 0.05)

3.3.1.2 Calculating Initial Sample Size n0

$$n0 = \frac{Z^2 p(1-p)}{e^2}$$

$$n0 = \frac{(1.96)^2 \times 0.5 \times (1-0.5)}{(0.05)^2}$$

$$n0 = \frac{3.8416 \times 0.25}{0.0025}$$

= 384.16

Before population correction, each group required **384** samples.

3.3.1.2 Adjusted Cochran's Equation

The total population of Mombasa was 1.5 million, but only a fraction were eligible blood donors and patients who need blood for transfusion.

Therefore, we estimated the following:

i. Donors Population N1 = 15,000

ii. Patients Population N2 = 10,000

Applying the finite population correction:

$$n1 = \frac{n0}{1 + \frac{n0 - 1}{N}}$$

Equation 3.2: Adjusted Cochran's Equation

Sample Size for Blood Donors (N1=15,000)

$$n1 = \frac{384}{1 + \frac{384 - 1}{15,000}}$$

$$n1 = \frac{384}{1.0255} = 374.4$$

= 374

Sample Size for Patients (N2=10,000)

$$n1 = \frac{384}{1 + \frac{384 - 1}{10,000}}$$

$$n1 = \frac{384}{1.0383} = 369.8$$

= 370

Therefore, using Cochran's Equation with a 95% confidence level and a 5% margin of error, the sample sizes for blood donors was **374** while that of patients was **370**. These were the numbers of participants required to obtain statistically significant results for the study.

3.4 Data collection

Data was collected using a combination of primary and secondary data sources.

3.4.1 Primary Data

Primary data was collected from blood donors and patients through using a structured questionnaire administered to both blood donors and patients, or their representatives.

3.4.1.1 Blood Donors

A structured questionnaire was administered to blood donors. It captured key variables such as blood group, donation frequency, preferred time and location for donation, total number of donations, and willingness to be contacted for future donations. Demographic information, including age, gender, location, and contact details, were also gathered. This data was instrumental in achieving the objective iv of testing the developed mobile application. Real-world matching between patients and donors using collected data validated the system's effectiveness.

3.4.1.2 Patients

A structured questionnaire was also administered to patients or their representatives. It gathered information on the challenges they faced when searching for blood donors, their experiences with existing systems, and their expectations for an improved donor-matching application. Key variables collected included blood type needed, urgency, hospital location, and past experiences with donor matching. In addition to this, name, age, gender, and contact details were also gathered. This data was critical in evaluating the effectiveness of the developed mobile application in meeting patients' needs.

3.4.2 Secondary Data

Secondary data was collected from the Mombasa Regional Blood Transfusion Centre (Blood Bank) to support the development of the blood donor-patient matching model. This data helped analyze donation patterns, donor characteristics, and trends in blood demand.

Datasets containing historical donation records and blood request trends from the blood bank was used to train and test the machine learning model. This data contributed to objective iii, which focused on developing a mobile application that efficiently links patients to potential blood donors. The key variables collected and analyzed from the blood bank included:

i. Donor demographics - Gender, Age, Occupation

ii. Donation history - Nature of last donation, Times donated, Days since last donation, Reaction.

iii. Donation preferences - Preferred donation frequency, Convenient time, Convenient locality.

iv. Experience and feedback - Rate of service, Reaction to donation, Encouragement to donate.

v. Blood group information - Blood group of the donor.

vi. Blood donor score – This is the measure of a blood donor's likelihood to donate blood when required. This will be the target feature that the model will be aiming to predict.

Even though no personal identifiable information was collected here, this data was very crucial in understanding donor behavior, predicting donor availability, and improving the accuracy of patient-donor matching.

3.5 Design

The system development followed the Agile software development methodology. This is a flexible and iterative approach that focuses on delivering small, incremental improvements through continuous feedback which allows for flexibility in incorporating feedback from users.

3.5.1 Agile Development

According to Beck et al. (2021), Agile development is a flexible and iterative approach to software development that emphasizes collaboration, customer feedback, and small, incremental changes. Instead of delivering a complete product at once, Agile teams work in short cycles called sprints or iterations, allowing for continuous improvement and adaptation to changing requirements (Highsmith, 2009). The figure 3.1 shows Agile development cycle.

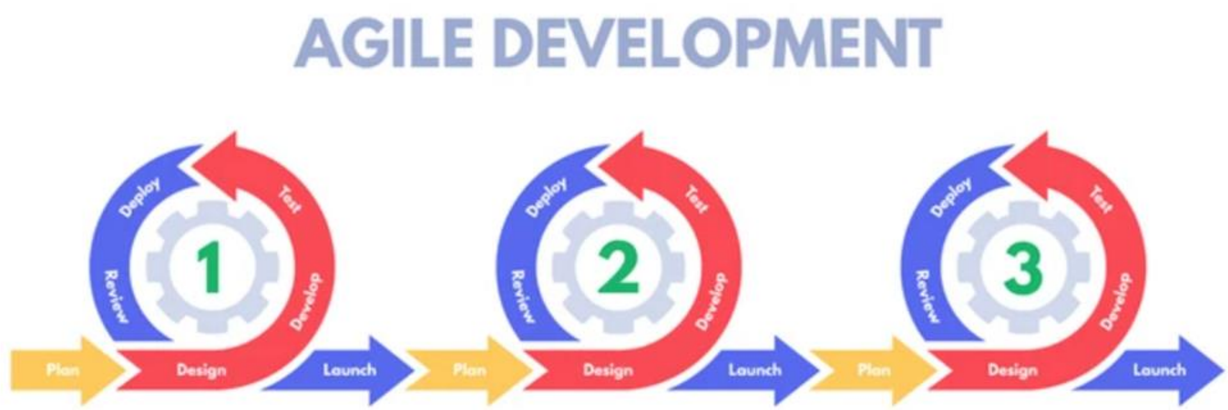

Figure 3.1: Agile Development Cycle (Concas et al., 2008)

In planning phase, the primary focus was on collecting detailed requirements for the mobile application. This phase identified objectives, key features, and functionalities that the app must include, the likes of real-time blood requests, donor matching algorithms and location tracking.

This phase involved stakeholders, including healthcare professionals and regular blood donors to ensure that the solution meets their needs.

For design phase, the architecture of the system was created and the user interface (UI) and user experience (UX) of the mobile application designed. This included planning how users would interact with the app, the layout of the screens, and how the machine learning algorithms would be integrated. Wireframes and prototypes were developed to visualize the application and get some feedback from users before moving to development.

During development, building of the actual mobile application started using the planned design and architecture. This was where coding takes place, with a focus on implementing core features like donor registration, blood request handling, machine learning algorithms, and the integration of data points like blood group and location. Because Agile development encourages iterative progress, what was released here were small, functional increments of the application for user testing.

Testing is a continuous process in Agile development. Once a new feature or component was developed, it was tested for bugs, usability issues, and compatibility. In the developed system, this meant checking whether the machine learning model accurately predicted the nearest and most suitable blood donor based on real-time blood requests and that the app ran smoothly on different devices. User feedback during this phase helped identify areas for improvement.

Deployment to the real-world environment came after successful testing. Healthcare providers, donors, and patients in Mombasa had early access to the app, and initial feedback was collected to identify areas for improvement. Deployment was done in a controlled manner, starting with a pilot phase in specific centers like the Regional Blood Bank to ensure everything functioned as expected.

For Review phase, what was collected was the continuous feedback from users to understand how well the app was meeting their needs and to identify any new requirements or change. Feedback on the machine learning model's accuracy and the efficiency of the donor-patient matching process were also important in this phase. Based on this, more iterations of the app were planned and developed.

The last phase was launch. Once all issues from the review phase were resolved, the full-scale launch of the app would follow. The app would be made available to all intended users in Mombasa. Afterwards, continuous monitoring and maintenance would ensure the app's performance remains optimal. Future updates would be based on user feedback and evolving needs.

3.5.2 Key Components

The proposed solution was designed to automate the process of matching patients with blood donors by using machine learning algorithms. It consisted of the following key components:

3.5.2.1 User Interface Design

A simple, user-friendly interface was developed for the mobile application platform. Donors were able to register and update their details, and patients/relatives or healthcare providers were able to post blood requests. Approvals will be by system admins or authorized healthcare administrators.

3.5.2.2 Database Design

A centralized database was implemented to store donor profiles, patient blood requests, and historical data on donations. The database was designed to ensure data integrity, security, and scalability.

3.5.2.3 Machine Learning

The predictive model was integrated into the system to automate the process of finding the most suitable blood donor based on criteria such as proximity, blood group, and donor availability. XGBoost was the primary model used for prediction due to its exceptional accuracy, efficiency, and robustness, making it ideal for predictive tasks involving donor-patient matching. Its ability to handle missing data and provide feature importance simplified preprocessing and enhances model interpretability, and its computational efficiency ensured faster training and real-time predictions, aligning with the system's goal of instant and reliable donor-patient linkage.

The performance of the machine learning model was validated using a combination of evaluation metrics and testing methods to ensure it was both accurate and reliable. Dataset was split into training and testing subsets. While 70% of the data was used for training, the other 30% was reserved for testing. Validation metrics like Mean Absolute Error (MAE), Mean Squared Error

(MSE), and Root Mean Squared Error (RMSE) were used to measure the accuracy of the predictions.

K-fold cross-validation was also used to assess the model's generalizability. This was done by splitting the dataset into k subsets and iteratively training and testing the model on different combinations of the subsets. The model's ability to match donors to patients was also evaluated using metrics like precision, recall, and F1-score. This was to ensure that it performed effectively in real-world scenarios. These validation methods confirmed the capability of the model to deliver reliable matches with very little or no errors.

3.5.2.4 Geolocation

The geolocation feature uses GPS data to determine the real-time location of donors and the patient/hospital. When a blood request is initiated, the system calculates the distance between the requester and all available donors using their geolocation coordinates. A geofencing mechanism then filters donors within a predefined radius (10 kilometers) to ensure only nearby donors are considered first.

The system also checks donor availability based on the collected data such as preferred place o donate, preferred donation times and willingness to donate. Notifications are sent only to donors who meet the proximity and availability criteria. This approach greatly reduces response time while optimizing the matching process.

3.5.2.5 Notifications

The system features an alert system that ensures effective communication between donors and recipients. When a blood request is initiated, the system notifies nearby blood donors who have the option to confirm or deny based on their circumstances. Once a donor confirms their availability, the patient/hospital is notified of the successful match, including relevant details like phone number, and expected time of arrival. If a donor declines or does not respond, the system automatically notifies another eligible donor. This real-time notification process enhances the speed and reliability of the donor-patient linkage, ensuring that patients receive timely blood transfusions.

3.5.3 Role of Blood Banks in the Proposed Solution

Currently, blood banks play the important role of collecting, screening, and storing blood, as well as distributing it to healthcare facilities based on demand (World Health Organization, 2017). They, however, rely on traditional methods for donor recruitment, such as blood drives and public campaigns, and use manual or semi-digital systems to manage donations and inventory data. Despite their sincere efforts, inefficiencies in matching blood supply with patient needs and delays in communication often hinder their effectiveness.

With the developed solution, blood banks can be integrated into a streamlined system powered by ML and geofencing. The mobile app can be made to assist in matching available blood to patients in need and support targeted donor recruitment through predictive analytics. Also, the solution enhances communication between blood banks, donors, and healthcare facilities, which ensures quicker response times. By leveraging detailed analytics and optimized logistics, blood banks can transition from reactive operations to proactive, data-driven entities, greatly improving the efficiency and impact of blood donation processes.

3.6 Deliverables

The deliverables for this project include:

i. Machine Learning-Powered Mobile Application - A fully functional mobile application that links blood donors to patients in Mombasa, Kenya. Key features here include donor registration, blood request handling, location tracking, and a ML patient-donor matching algorithm.

ii. System Documentation - Comprehensive documentation of the application's design, development process, and deployment. This also include user manuals, technical specifications, and guidelines for future maintenance or updates.

iii. Data Analysis Reports - Reports on the collected data, including donor and recipient statistics, usage patterns, and insights derived from testing the machine learning model.

3.7 Ethical Considerations

In the development and deployment of the mobile application, ethical considerations are important to ensure that the rights and privacy of all users are respected. One of the major concerns here is data privacy and security, since the application handles personal information from both blood donors and recipients, including locations and contact information. To address this, strict measures are implemented to comply with data protection regulations, such as the General Data Protection Regulation (GDPR). The data is securely stored and encrypted to prevent unauthorized access. Consent was obtained from users before any personal information was collected or processed.

Transparency and fairness are central to the design of the ML algorithm used for patient-donor matching. The algorithm was developed to not have biases and ensure that all patients have equal opportunities to receive blood donations based on medical needs and availability, rather than any discriminatory factors. This created a fair system that prioritizes the urgency of matches which improved response times during emergencies.

Finally, the ethical use of technology in this project involved ensuring that the application is used only for its intended purpose: to facilitate and streamline blood donation processes in Mombasa. Misuse of the app or the collected data for any unauthorized activities was strictly prohibited. The goal was to promote trust and confidence among users, which encouraged greater participation in blood donation while safeguarding their personal information.

3.8 Utilization of Research Results

The findings from this research will be used to enhance the efficiency of blood donation processes in Mombasa. The developed mobile application will serve as a practical tool for healthcare facilities to improve the linkage between patients requiring transfusions and blood donors. By providing real-time data on patient needs and donor availability, the application intends to streamline the blood donation process, ensuring timely access to blood supplies. The insights gained from this research will inform policymakers and health organizations about the current challenges and opportunities in blood donation systems, which will guide them in making data-driven decisions to improve outcomes of public health.

3.9 Dissemination of Research Results

The dissemination of research results will be done through different channels to reach a diverse audience, which include healthcare professionals, policymakers, and the public. Strategies will include publishing findings in peer-reviewed journals and presenting at conferences and workshops that are focusing on public health and technology in healthcare. Community outreaches will be organized to educate the public about the importance of blood donation and the functionalities of the developed mobile solution. Social media campaigns and partnerships with local health organizations will further help the visibility of the research findings, promoting awareness and encouraging participation in blood donation activities.

Chapter 4: System Analysis and Design

4.1 Introduction

This chapter discusses the system analysis and design that was implemented in the system. The chapter also highlights the system requirement analysis, the functional requirements and non-functional requirements. The chapter highlights the system narrative and finally it highlights the system design diagrams.

4.2 Analysis of Primary Data Collected

This provides insights into the existing methods used to link blood donors to patients, their effectiveness, and the limitations associated with traditional approaches. The data was gathered through questionnaires administered to patients or their representatives and blood donors within Mombasa.

The collected data revealed that most hospitals and blood donation centers rely on manual processes such as maintaining handwritten donor lists, excel sheets, utilizing outdated hospital databases, or making urgent blood requests via uncoordinated social media posts. These methods have proven to be inefficient, especially during emergencies where immediate response is critical.

According to the findings, approximately 60% of respondents acknowledged that the existing systems are slow and lack proper donor engagement mechanisms. Also, most hospitals reported experiencing challenges in locating suitable donors due to outdated contact information and inadequate communication channels. Sometimes, it could take more than 3 days just trying to find a suited blood donor. Figure 4.1 shows responses from the questionnaire.

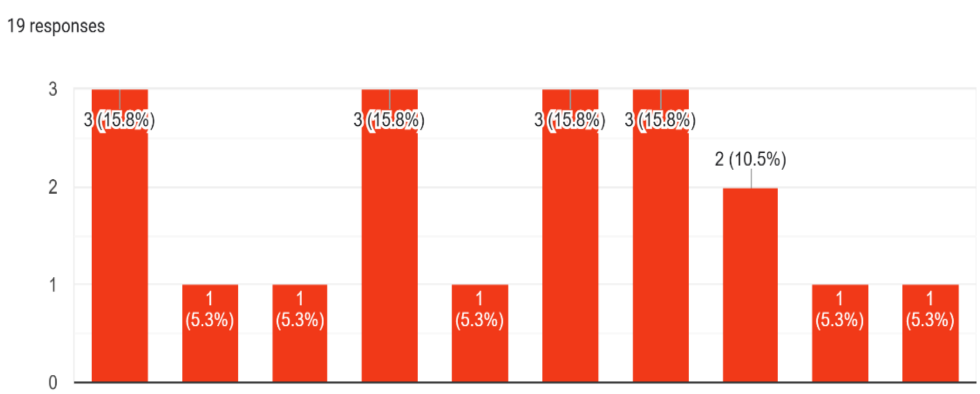

Figure 4.1: Questionnaire Responses

The data also highlights the absence of modern technological integration in the systems. Over 70% of the participants expressed interest in mobilization using a more streamlined process that involves automated notifications, localized donor searches, and machine learning-based matching mechanisms. Figure 4.2 proves the interest in mobilization using modern technology.

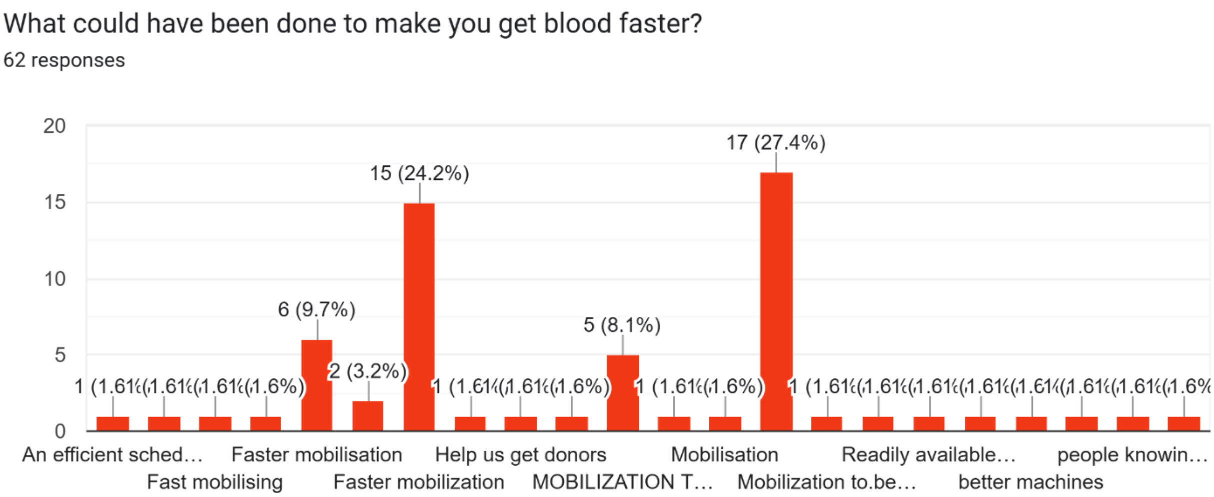

Figure 4.2: Responses on What Could Improve Blood Acquisition

4.3 System Requirement Analysis

System requirements analysis is a structured, or organized, methodology for identifying an appropriate set of resources to satisfy a system need and the requirements for those resources that provide a sound basis for the design or selection of those resources. It acts as a transformation between the customer's system need and the design concept energized by the organized application of engineering talent. (Jeffrey O. Grady, 2020).

4.3.1 Functional Requirements

The functional requirements for the proposed machine learning-powered mobile application are designed to ensure efficient and accurate matching of blood donors to patients. The key functional requirements include:

i) User Registration and Authentication - The system allows donors to create accounts using their emails. The system authenticates users to ensure only authorized individuals can access own profiles.

ii) Donor Management - The system allows donors to provide their personal information, blood group, location, and donation history. The system allows donors to update their profiles, including availability for future donations.

iii) Blood Request Management - The system allows patients, their representatives or hospitals to place blood requests by specifying blood type, units needed and hospital location. The system also provides real-time status updates on blood requests.

iv) Machine Learning-Based Matching - The system utilizes XGBoost to predict suitable donors based on blood group, donation history, and other relevant features. The system then generates a ranked list of potential donors most likely to donate.

v) Geolocation and Geofencing - The system identifies donors within a specified radius of the patient's location. The system utilizes geofencing to ensure only users within Mombasa County are allowed access. Geolocation helps to locate potential donors when they are within proximity to hospitals or blood request points.

vi) Notifications and Alerts - The system sends notifications to potential donors when a matching blood request is identified. The system also allows donors to accept or decline donation requests, after which feedback will be sent to the source of the request.

vii) Data Management and Storage - The system stores donor and patient information securely in a MySQL database. The system ensures data integrity and privacy during storage and retrieval.

viii) Analytics and Reporting - The system provides reports on successful donations, donor availability, and request fulfillment rates. The system allows administrators to visualize data trends and generate reports.

ix) Feedback Collection - The system allows users to provide feedback on the mobile application usage for continuous improvement.

4.3.2 Non-functional Requirements

The non-functional requirements of the proposed system ensure its efficiency, security, and usability. These requirements include:

i) Performance - The system provides responses to user requests within 2 second. The system approves and process blood donor-patient matching within 15 seconds. Overall, anyone who makes a request should know of donor availability in less than 15 seconds.

ii) Scalability - The system can support a growing number of users without significant performance degradation. The system architecture allows easy integration of additional features in the future. Some of the features are already marked for future updates is redeeming virtual points earned from reward program.

iii) Security - The system ensures data encryption during transmission and storage to protect sensitive user information. The system implements user authentication and authorization to restrict access to unauthorized individuals.

iv) Availability - The system is available to users 99.9% of the time, ensuring uninterrupted access to services. The system has a backup and recovery mechanism to prevent data loss.

v) Maintainability - The system is modular-based to allow easy updates and maintenance. The system documentation is kept up to date to facilitate troubleshooting and enhancements.

vi) Portability - The system, being a PWA, is accessible via both Android devices, iOS platforms and desktop.

4.4 System Narrative

The developed blood donation system is a machine learning-powered mobile application designed to enhance the efficiency of linking blood donors to patients in need. The system targets Mombasa County, Kenya, where the demand for blood transfusions is high, and the existing systems are inefficient in connecting patients to potential blood donors as quickly as it should be. The primary users of the system are patients seeking blood, donors willing to donate blood, and system administrators who manage the application.

The application allows patients to create blood appeal requests by specifying their blood requirements based on blood type and location. Using geolocation and geofencing technologies, the system identifies and lists nearby most potential blood donors who match the required blood type. The machine learning model predicts the likelihood of a donor responding positively to a blood request based on factors such as past donation history, preferred donation times, and willingness to donate in the future.

Blood donors can create accounts, log in, and update their availability status. They receive notifications when their blood type is requested and can choose to accept or decline the request. The system stores and maintains user details securely, ensuring data integrity and privacy.

The application includes an administrator module for managing users, requests, monitoring the system's performance, and ensuring data security. The system architecture is designed to be scalable, supporting multiple simultaneous users with minimal latency. Also, the user interface is optimized for usability, providing a seamless experience on mobile devices.

The overall objective of the system is to minimize the time taken to connect patients with compatible blood donors, thereby enhancing emergency response efficiency and improving healthcare outcomes. The successful implementation of this system addresses the inefficiencies in the current blood donation process and provide a reliable, fast, and user-friendly platform for blood donation management.

4.5 System Design Process

The System Design Process focuses on creating a structured plan that defines the architecture, components, interfaces, and data flow of the proposed blood donation system. The design process is divided into various subsections to comprehensively cover the system's structure and functionalities.

4.5.1 System Architecture Diagram

The System Architecture Diagram depicts the overall structure of the system, detailing the interactions between various components such as the mobile application, server, database, and machine learning model. The figure 4.3 shows interactions of the various components in the mobile application.

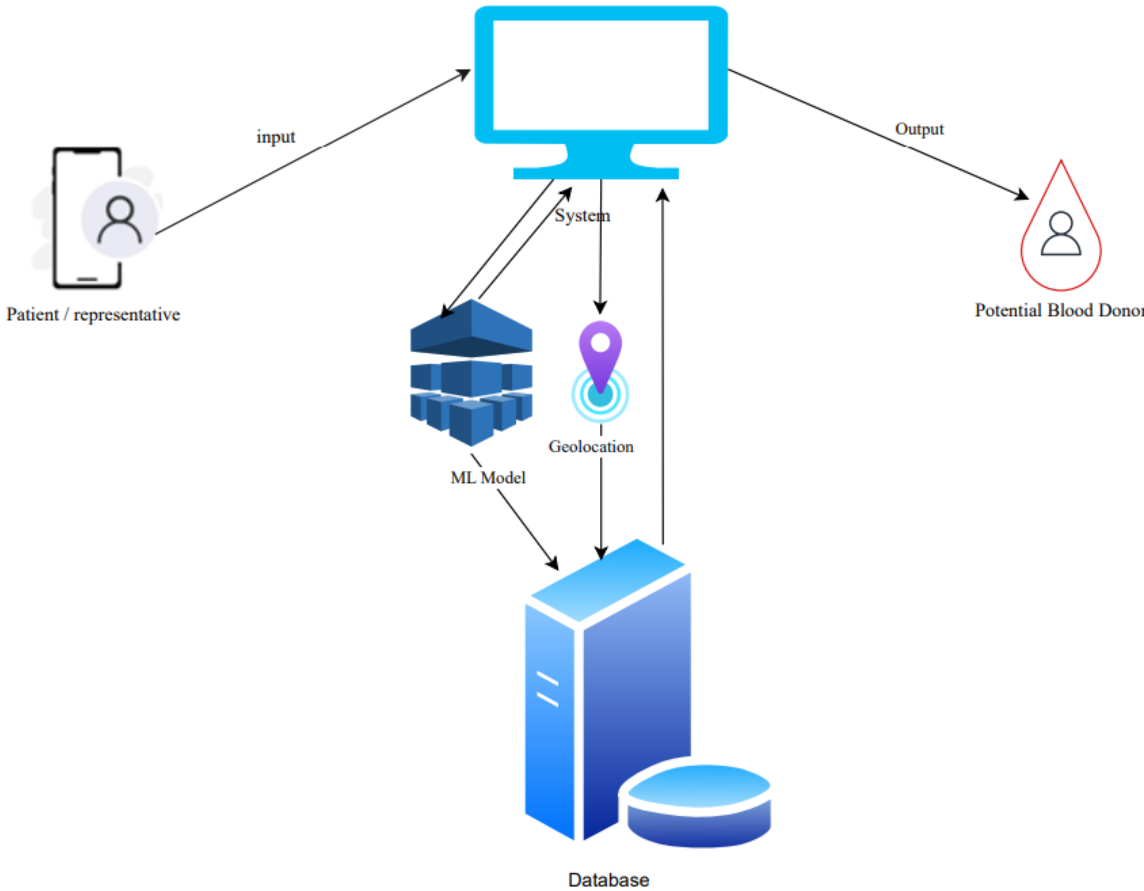

Figure 4.3: System Architecture

4.5.2 Flowchart of The Developed System

Figure 4.4 shows a flowchart of the proposed solution, from registration to transfusion.

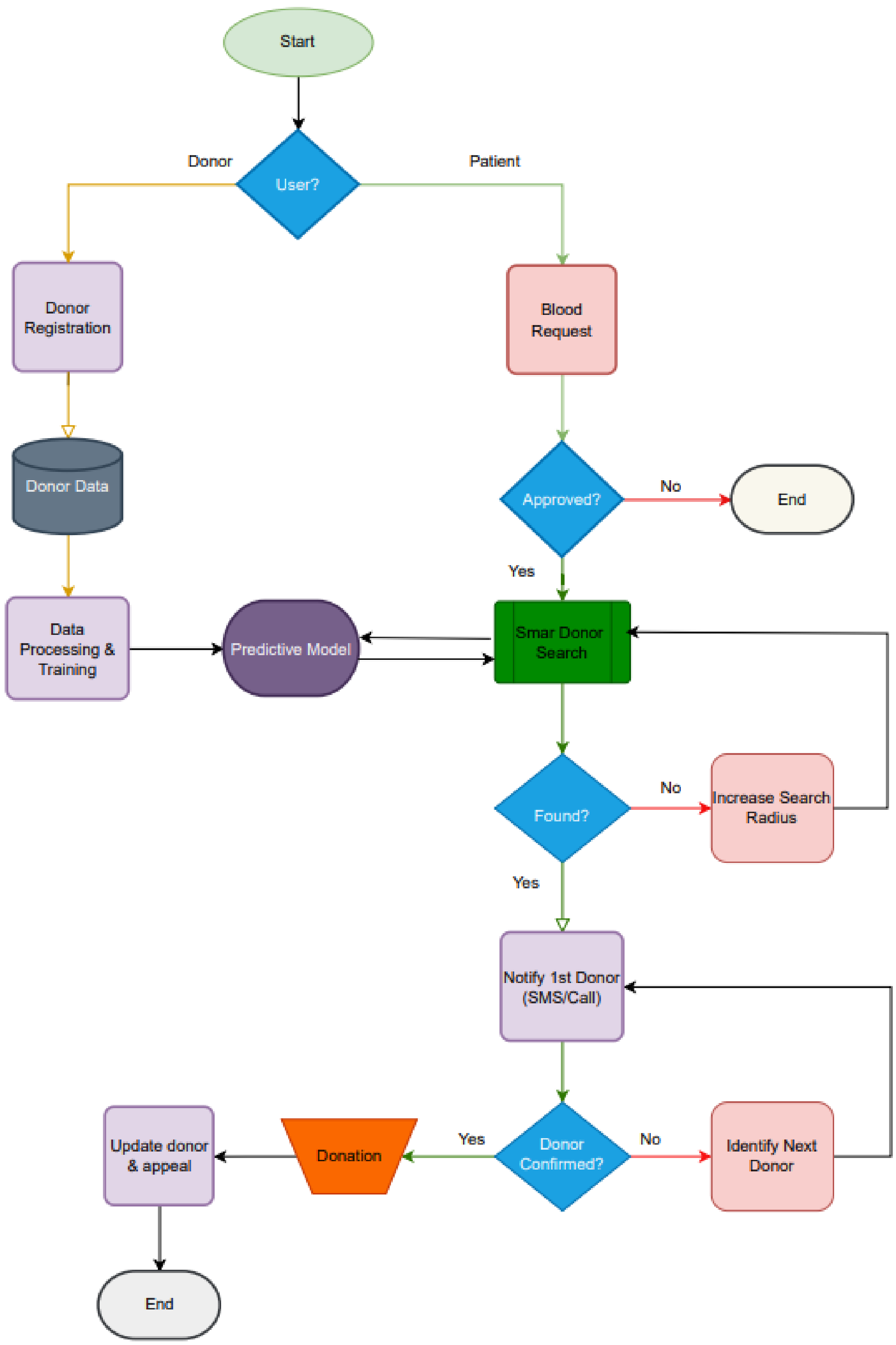

Figure 4.4: A Flowchart of The Developed System

4.5.3 Use Case Diagram

The Use Case Diagram illustrates the interactions between users (patients, donors, and administrators) and the system. It highlights the various functionalities offered by the system and how different users interact with them. Figure 4.5 illustrates the same.

Figure 4.5: Use Case Diagram

4.5.4 Sequence Diagrams

Sequence Diagrams illustrate how objects interact in a particular scenario of the system. This helps to understand the flow of events in the blood request and donor matching processes. Figure 4.6 shows the sequence diagram.

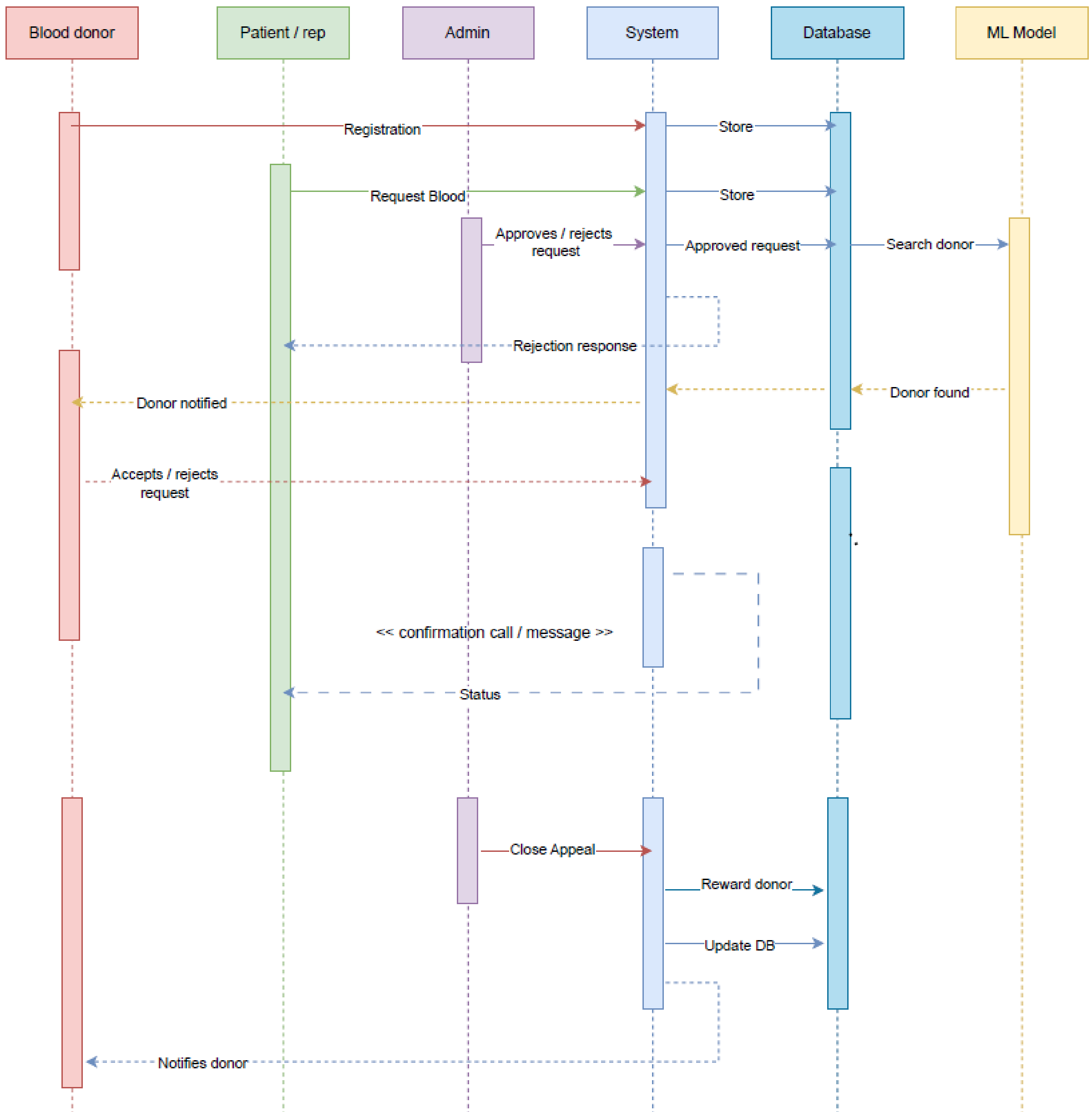

Figure 4.6: Sequence Diagram

4.5.5 Activity Diagrams

The Activity Diagrams describe the dynamic aspects of the system, showing the workflow of various processes including donor registration, blood request creation, and blood request fulfillment. Figure 4.7 illustrates the same.

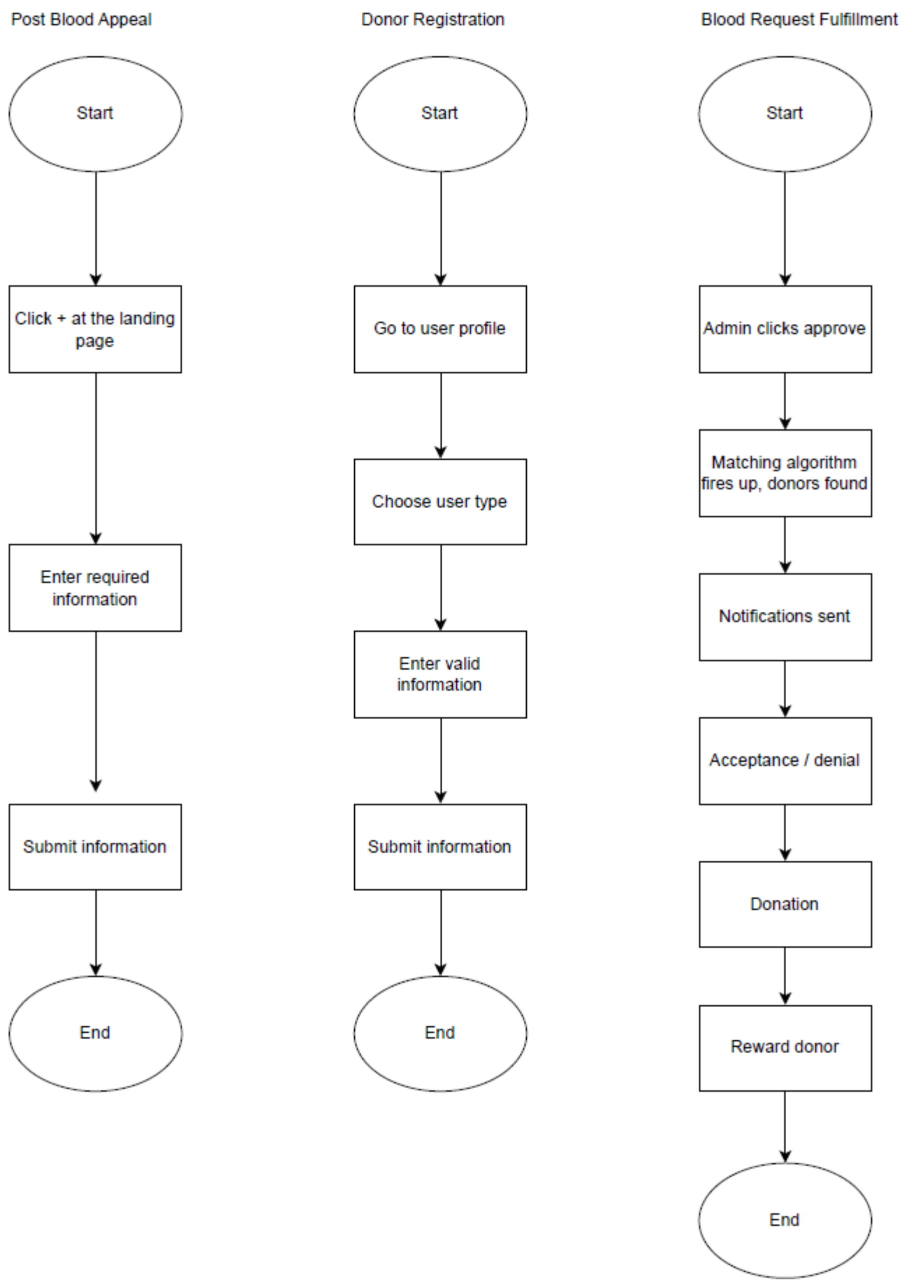

Figure 4.7: Activity Diagram

4.5.6 Entity-Relationship Diagram

The Entity Relationship (ER) Diagram displays the relationships between different entities in the database such as Admins, Donors, Patients and Blood Requests. Figure 4.8 shows the entity-relationship diagram.

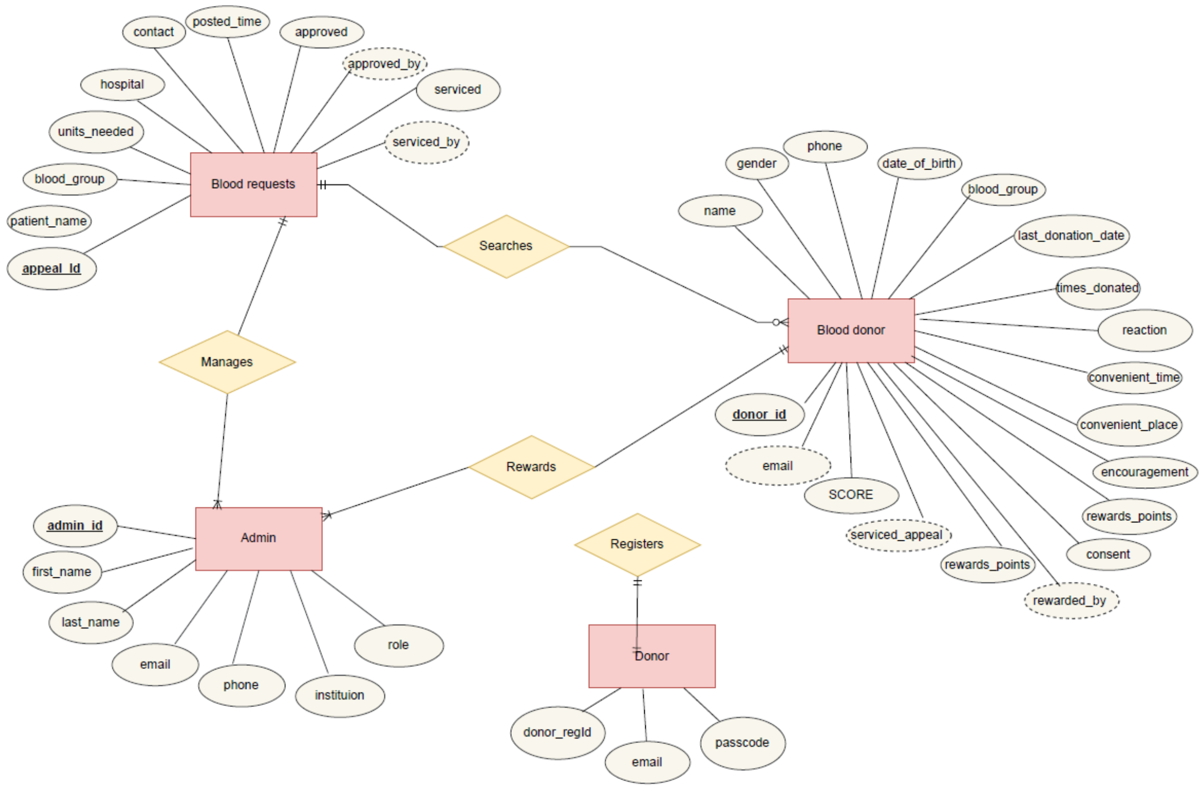

Figure 4.8: An Entity Relationship Diagram

4.5.7 Database Schema (D2 Schema)

The Database Schema presents a detailed structure of the database, including tables, fields, primary keys, foreign keys, and relationships. Figure 4.9 shows DB schema of the mobile application.

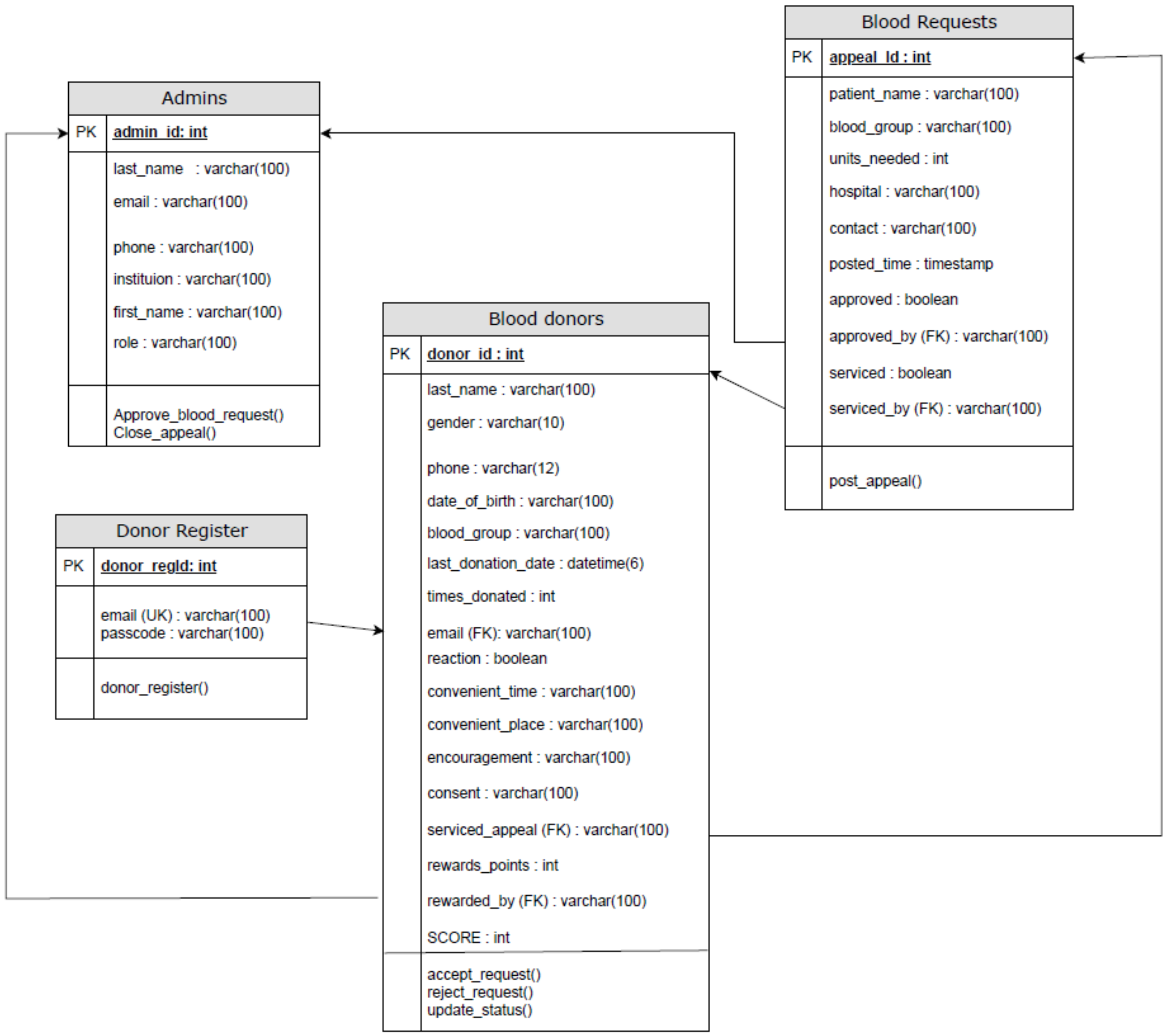

Figure 4.9: Database Schema

Chapter 5: System Implementation and Testing

5.1 Introduction

This chapter provides a detailed description of the implementation of the blood donor-patient linkage mobile application and the testing process carried out to ensure the system's functionality, reliability, and efficiency. The implementation phase involves the development of the system using appropriate tools and technologies, which was followed by testing to validate the requirements.

5.2 Set Up Description

This section describes the setup environment required for the development and implementation of the Smart Donor App. It includes the hardware specifications of the devices used, and the software tools utilized to build, test, and deploy the application.

5.2.1 Hardware Specifications

The hardware specifications required for the development and testing of the Smart Donor App are shared in the table. Table 5.1 shows the hardware specifications.

Table 5.1: Hardware Specifications

Hardware	**Development Machine**	**Mobile Devices (for testing)**
Processor	Intel Core i7 10th Gen	Quad-core 1.8 GHz
RAM	8GB	4 GB
Storage	512 GB SSD	256 GB
Operating System	Windows 10	Android 10 & iOS 18
Display	1080p resolution	1080 x 2340 pixels
Network Connectivity	4G, 5G and Wi-Fi.	4G, 5G and Wi-Fi.

5.2.2 Software Description

The software requirements for developing and deploying the Smart Donor App in the table 5.2 shown below.

Table 5.2: Software Description

Programming Languages	Frameworks and Libraries	Database Management System	Development Environment	Deployment Tools	Other Tools
Python HTML JavaScript CSS PHP	Fast API Bootstrap Scikit-Learn XGBoost Pandas Numpy Google Maps API	MYSQL	Visual Studio Code Colab Android Studio Git	Nescom Render Streamlit Apache Web Server	Swagger UI Postman Microsoft Word Zotero

5.3 Machine Learning Model

The machine learning model is trained to match blood donors to patients based on various features. The model is developed using Python's Scikit-Learn library and deployed within the Render framework to provide real-time predictions. The machine learning model used in this system is based on prediction algorithms aimed at efficiently linking blood donors to patients based on compatibility criteria. The dataset was obtained, cleaned and analyzed.

5.3.1 Dataset Overview

The dataset consisted of features related to blood donation. The dataset contains information on blood donors, including their blood group, which identifies their blood type and occupation, indicating their job or profession. It also includes age, measured in years, and timesDonated, which records the number of times a donor has given blood. The daysSinceLastDonation feature gives how many days have passed since the donor's last donation, while convTime captures their preferred time for donation. PreferedFreq represents how often the donor prefers to donate. The dataset also includes rateService, a rating given by donors on their experience, and reaction, which notes whether they had any side effects after donating. The encouragement feature indicates whether the donor was encouraged by someone to donate, while convLocality records their preferred donation location, this has missing values. Lastly, SCORE is the target feature that represents the donor's likelihood to donate blood. Figure 5.1 shows the features and their data types.

```
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 501 entries, 0 to 500
Data columns (total 19 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Name                    500 non-null    object
 1   DoB                     493 non-null    datetime64[ns]
 2   Gender                  500 non-null    object
 3   Phone                   500 non-null    float64
 4   Blood_Group             500 non-null    object
 5   Date_of_Donation        493 non-null    object
 6   Willing_Future_Donation 497 non-null    object
 7   Nature_Last_Donation    497 non-null    object
 8   Times_Donated           479 non-null    float64
 9   Preffered_Freq          497 non-null    float64
 10  Rate_Service            497 non-null    float64
 11  Reaction                497 non-null    object
 12  Convenient_Time         500 non-null    object
 13  Convenient_Locality     486 non-null    object
 14  Encouragement           500 non-null    object
 15  Consent                 497 non-null    object
 16  Age                     500 non-null    float64
 17  DaysSinceLastDonation   501 non-null    int64
 18  Score                   501 non-null    int64
dtypes: datetime64[ns](1), float64(5), int64(2), object(11)
memory usage: 74.5+ KB
```

Figure 5.1: Features used by Smart Donor App Prediction Model

5.3.2 Data Cleaning and Preprocessing

Missing entries in the features were handled using imputation techniques. Non-numeric features like Blood group and preferred frequency were converted to numeric values. Features like Times_Donated were scaled to improve model performance.

5.3.3 Exploratory Data Analysis

EDA was conducted to understand the distribution of data and relationships between variables.

Figures 5.2 shows distribution of score which was the target feature. The distribution shows the maximum number of donors have a score of the range 86 to 90.

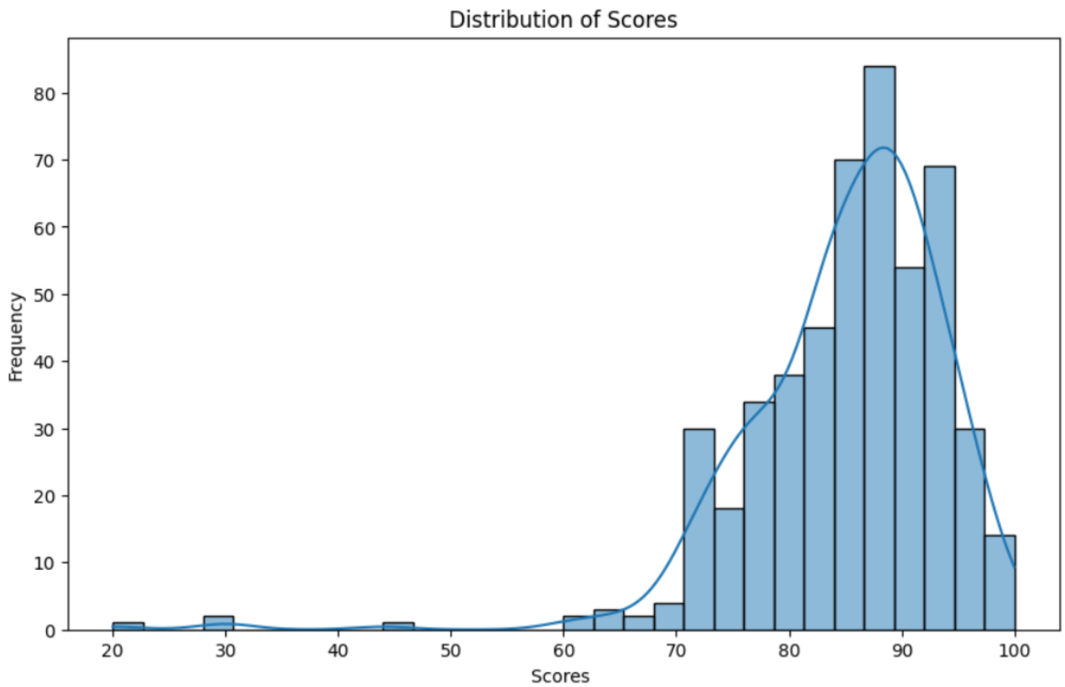

Figure 5.2: Distribution of The Target Feature

Another important analysis was getting count of score by the blood groups. Figure 5.3 illustrates the same. Blood group O+ had the highest number of blood donors followed by A+. A- had the least number of blood donors.

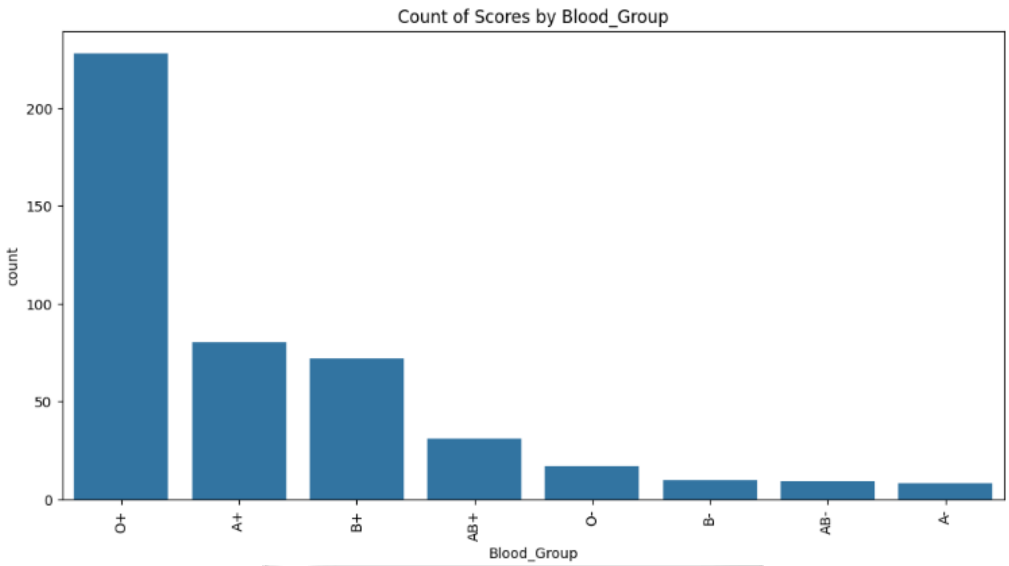

Figure 5.3: Count of Scores by Blood Group

It was followed by distribution by gender and encouragement. Figure 5.4 illustrates gender and encouragement distribution.

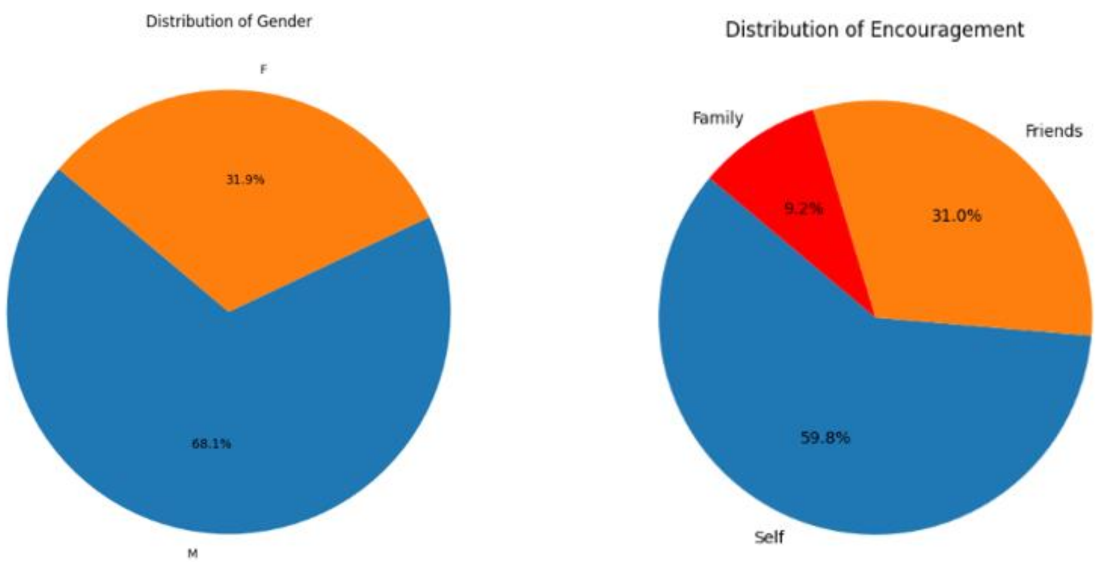

Figure 5.4: Distribution of Gender and Encouragement

Next was a correlation heatmap to determine relationships between features such as donation frequency and future willingness. Figure 5.5 captures different correlations. Strongest positive correlation to the score was with rating service of previous donation at 0.72.

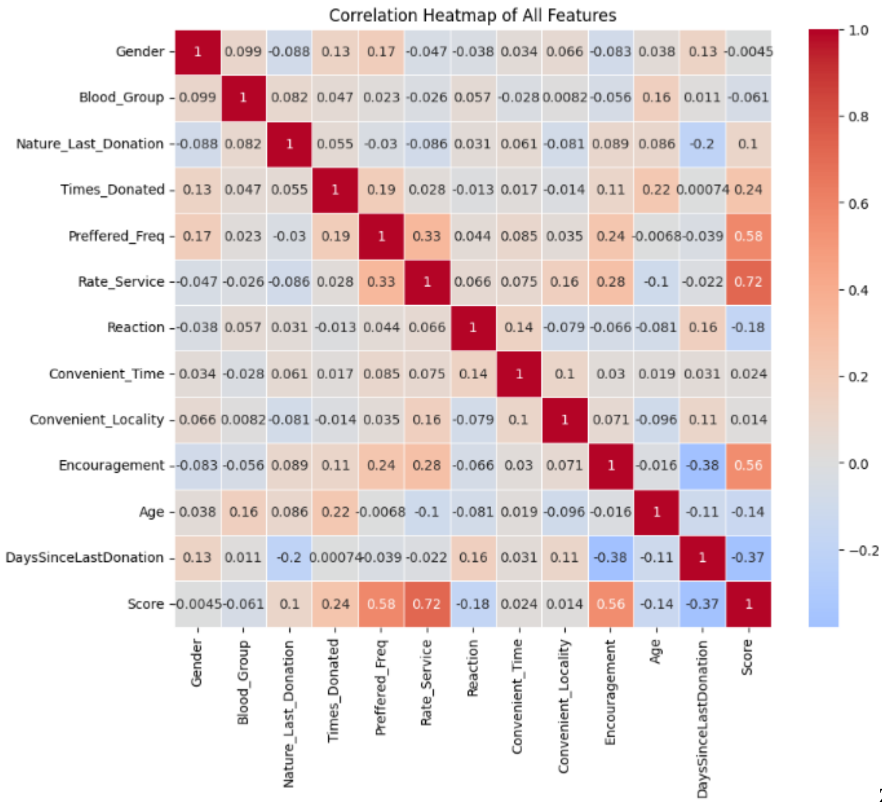

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Figure 5.5: Correlation Heatmap

5.3.4 Model Selection and Training

In developing the prediction component of the Smart Donor App, three regression models were evaluated: Linear Regression, Decision Tree Regressor, and XGBoost Regressor. These models were selected to compare both linear and non-linear approaches, as well as to evaluate performance trade-offs between simplicity, interpretability, and predictive power.

Linear Regression was chosen as a baseline model due to its simplicity and ease of interpretation. However, it assumes linear relationships between input features and the target variable, which may not capture complex interactions in real-world data.

Decision Tree Regressor was considered next as it is capable of modeling non-linear patterns and interactions between features without requiring feature scaling. However, it is prone to overfitting, especially with small datasets, which can reduce its generalization ability.

XGBoost Regressor emerged as the preferred model due to its high accuracy, scalability, and ability to handle missing data and feature interactions effectively. It combines the predictions of multiple weak learners (decision trees) through gradient boosting to minimize error iteratively. XGBoost is also equipped with regularization mechanisms (L1 and L2), which help in preventing overfitting and improving generalizability.

5.3.4.1 Module Tuning

This was performed to optimize the XGBoost model's performance, hyperparameter tuning was conducted using Grid Search and Cross-Validation (5-fold). Key hyperparameters that were tuned included:

i. n_estimators which is the number of boosting rounds

ii. learning_rate which controls the step size at each iteration

iii. max_depthn which limits the maximum depth of each tree

iv. subsample which is a fraction of training data used for each tree

v. colsample_bytree which is a fraction of features used for each tree

The final model configuration balanced accuracy and generalizability, as measured by key performance metrics:

Mean Absolute Error (MAE) – to minimize prediction error magnitude

Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) – to penalize larger errors

R-squared (R^2) – to assess how well the model explains variance in the target variable

5.3.4.2 Implications of Data Biases

Despite the model's strong performance, the training data may contain inherent biases which can influence the predictions:

i. For Selection Bias, if donor records were skewed towards certain age groups, locations, or blood types, the model may disproportionately favor those demographics in matching predictions.

ii. For Response Bias, self-reported information (e.g., willingness to donate, donation history) could be inaccurate or influenced by social desirability, leading to distorted model training.

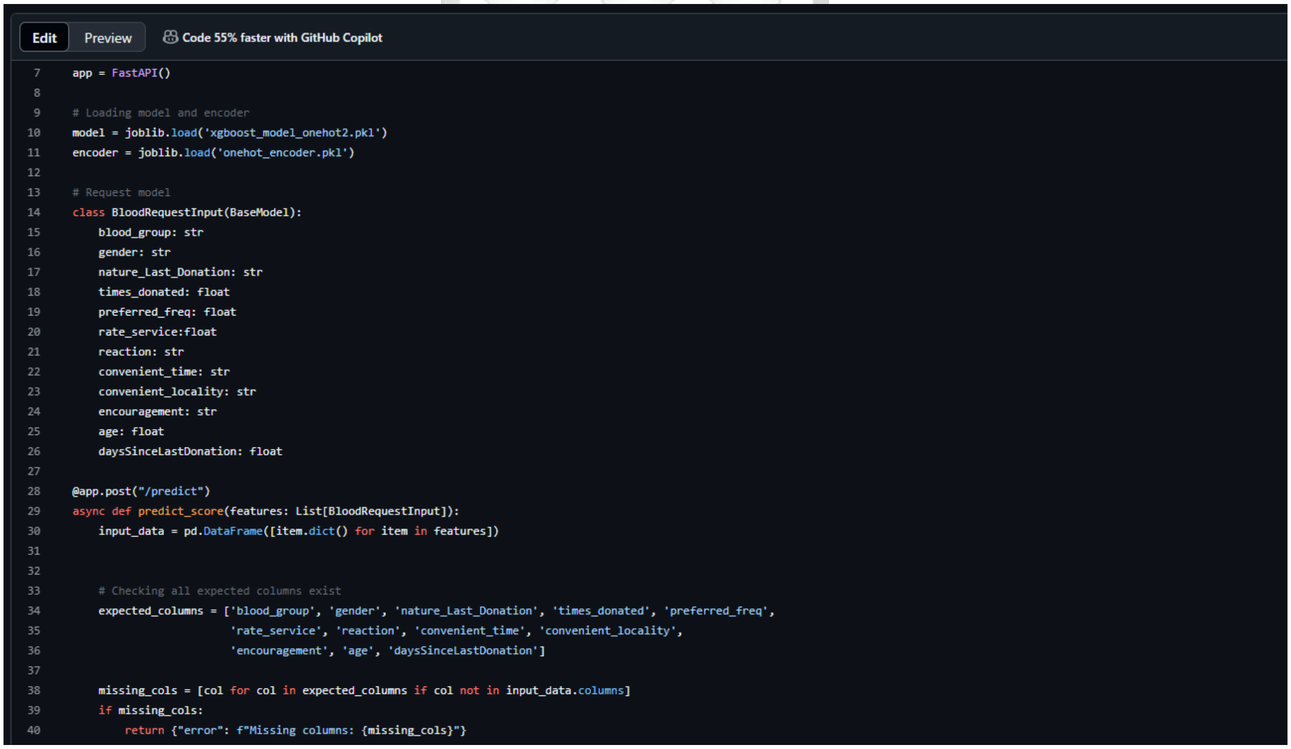
iii. For Temporal Bias, if the dataset spans a limited time range, seasonal trends in blood donation behavior may not be adequately captured.

To address these concerns, data preprocessing included outlier detection, imputation for missing values, and stratified sampling where feasible. However, future work should include continuous monitoring of model predictions in real-world usage to detect and correct for emerging biases.

.

5.3.5 Integration with Backend

The trained model was integrated into the backend of the system using FastAPI, enabling real-time donor-patient matching upon request submission. Swagger UI and Postman were used to test and interact with the API. Figure 5.9 shows creation and 5.10 consummation of the API.




```python
app = FastAPI()

# Loading model and encoder
model = joblib.load('xgboost_model_onehot2.pkl')
encoder = joblib.load('onehot_encoder.pkl')

# Request model
class BloodRequestInput(BaseModel):
    blood_group: str
    gender: str
    nature_Last_Donation: str
    times_donated: float
    preferred_freq: float
    rate_service:float
    reaction: str
    convenient_time: str
    convenient_locality: str
    encouragement: str
    age: float
    daysSinceLastDonation: float

@app.post("/predict")
async def predict_score(features: List[BloodRequestInput]):
    input_data = pd.DataFrame([item.dict() for item in features])


    # Checking all expected columns exist
    expected_columns = ['blood_group', 'gender', 'nature_Last_Donation', 'times_donated', 'preferred_freq',
                        'rate_service', 'reaction', 'convenient_time', 'convenient_locality',
                        'encouragement', 'age', 'daysSinceLastDonation']

    missing_cols = [col for col in expected_columns if col not in input_data.columns]
    if missing_cols:
        return {"error": f"Missing columns: {missing_cols}"}
```

Figure 5.6: FastAPI Code Segment

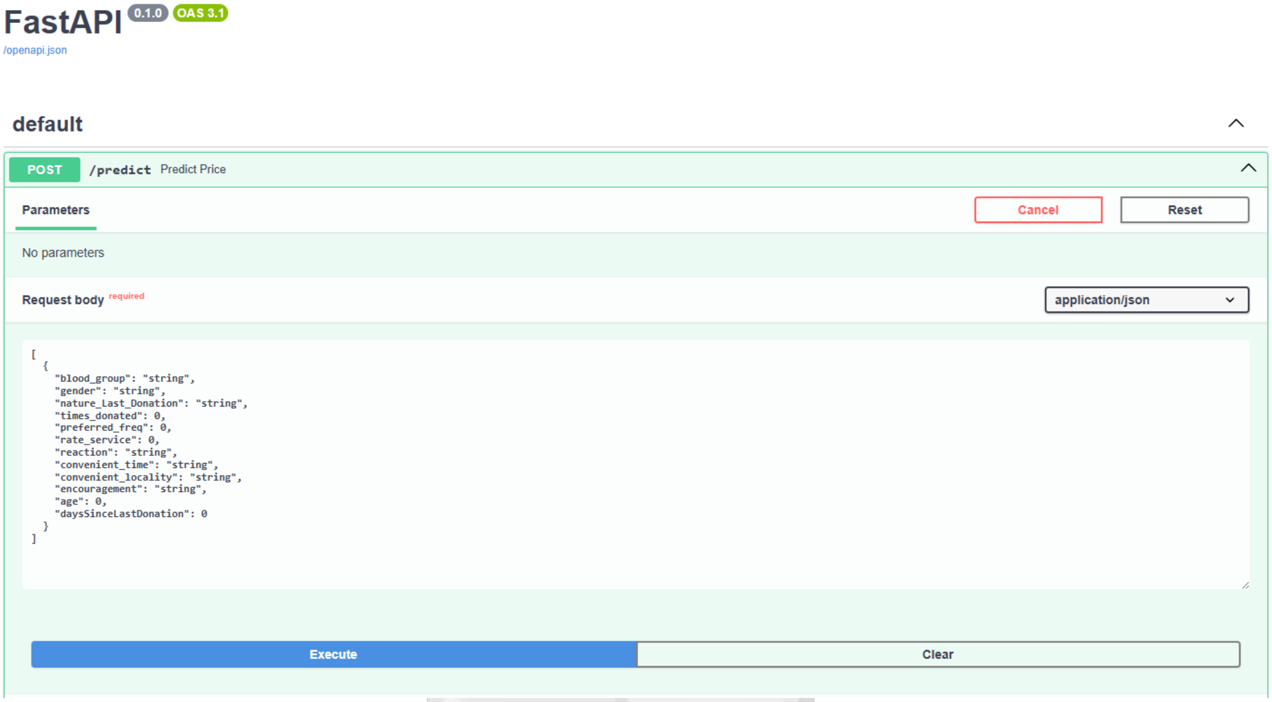


Figure 5.7: Swagger UI Consummation of the API

5.3.6 Deployment

The model was deployed on both streamlit and Render to ensure redundancy.

Figures 5.8 and 5.9 show the code segment and Streamlit deployment of the ML model.

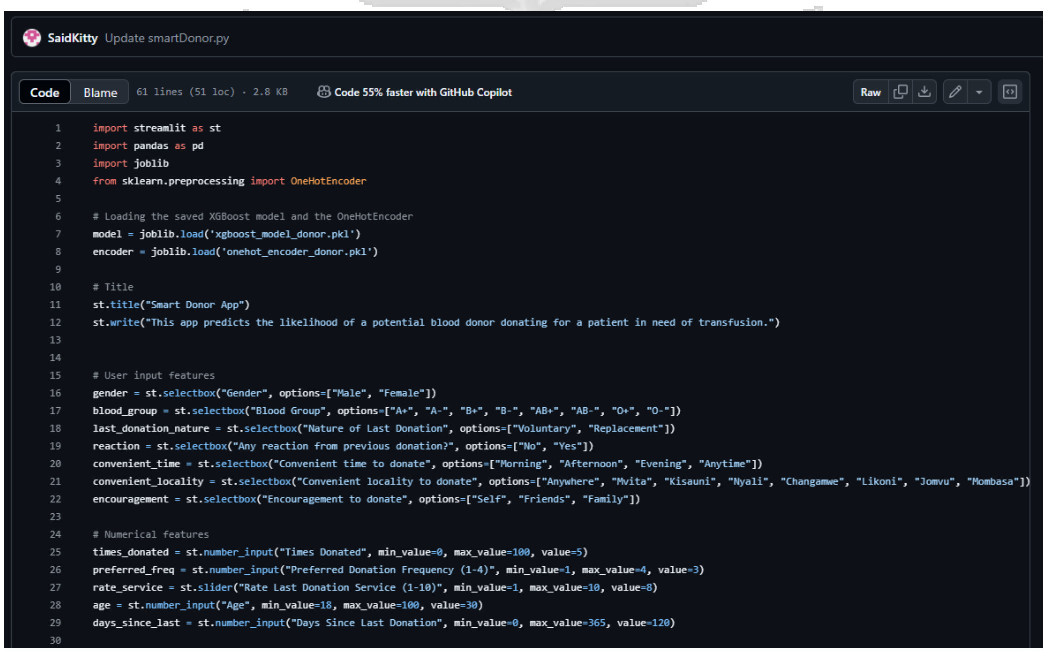


Figure 5.8: Code Segment in GitHub Repository

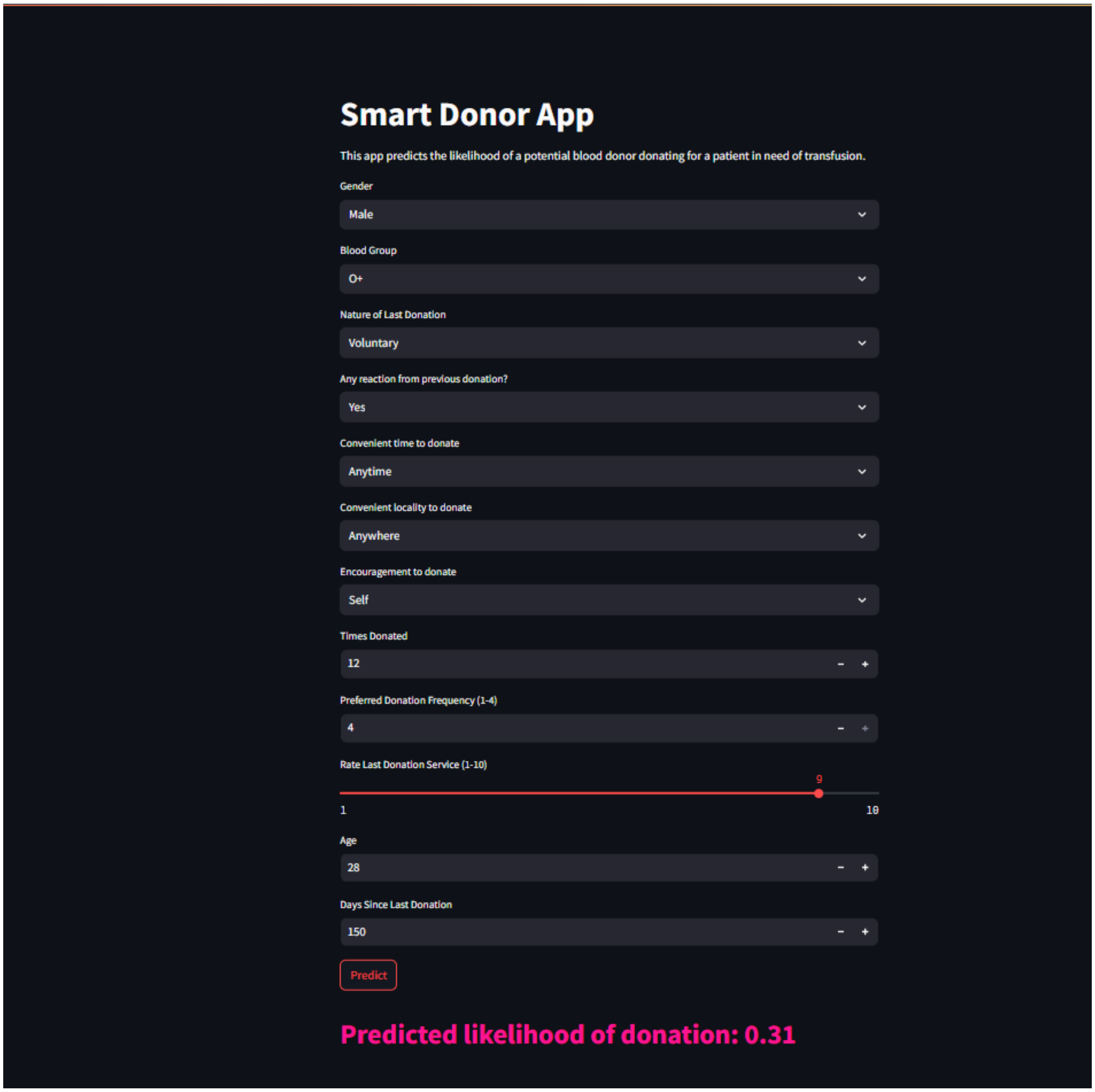


Figure 5.9: Donor Score Predicting Model Deployed on Streamlit.

5.4 System Implementation

System implementation involves the actual construction of the system. The implementation of this system is divided into the following modules which fall under front-end or back-end design:

5.4.1 Front-End Design

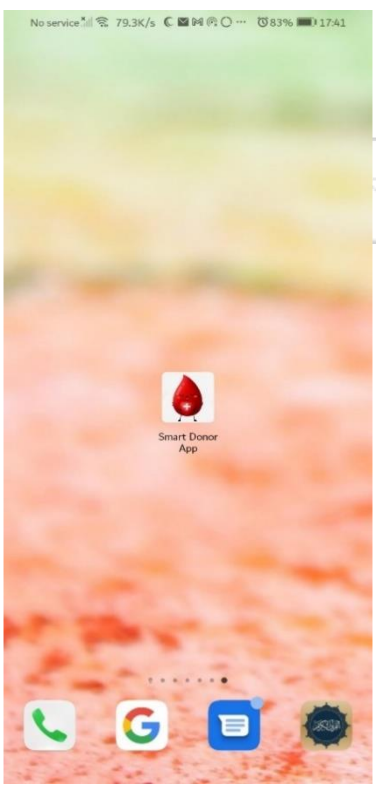
The front-end of the system is designed to provide an intuitive and user-friendly interface for patients and donors. The interface was built using HTML, CSS, JavaScript, and Ajax for a responsive and interactive user experience. CSS 5 and bootstrap was employed to enhance the styling and layout of the application.

5.4.1.1 Navigation Module

The Navigation Module provides the user interface elements that facilitate navigation throughout the application. It includes the following stages:

i. Opening the Application **-** Users start by launching the application, which displays a series of splash screens showcasing the application's name and logo, providing a smooth introductory experience.

ii. Landing Page – After the splash screens, the landing page is displayed, presenting users with a clear view of all active blood appeal requests that have not been fulfilled. Users can click on the call icon to call and volunteer to donate for that specific appeal. Figure 5.10 shows navigation interfaces.



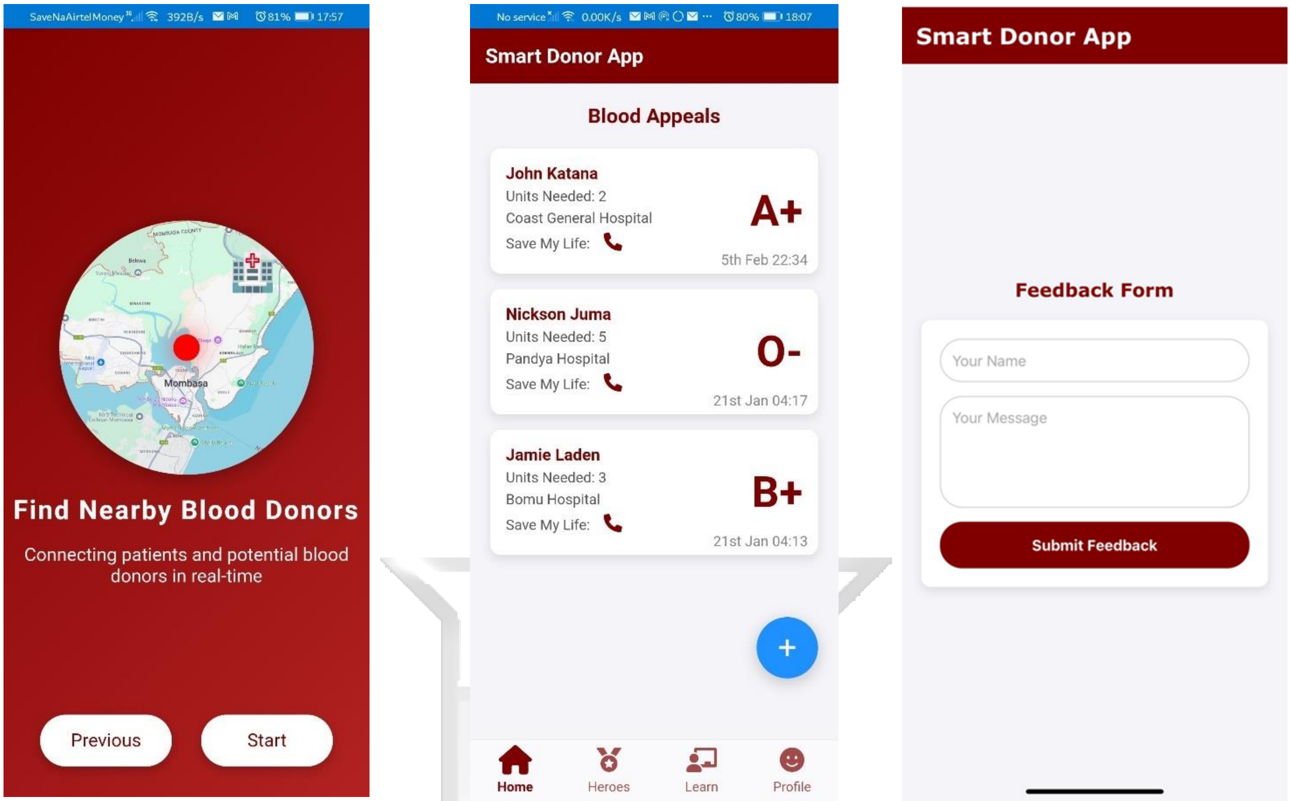


Figure 5.10: Images Showing Navigation

5.4.1.2 Blood Request Module

The Blood Request Module allows patients to request blood and receive suitable donor suggestions. To post a new blood appeal request, the patient clicks the + button located on the landing page. This action directs the user to a form where they can fill in the details of their blood request, such as blood group, urgency, and preferred location.

Upon submitting the request, the system processes the input and provides donor suggestions based on compatibility criteria. The successful creation of a blood request is confirmed with a notification, and the new blood appeal request appears on the landing page for potential donors to view and respond to. Figure 5.11 shows blood appeal request.

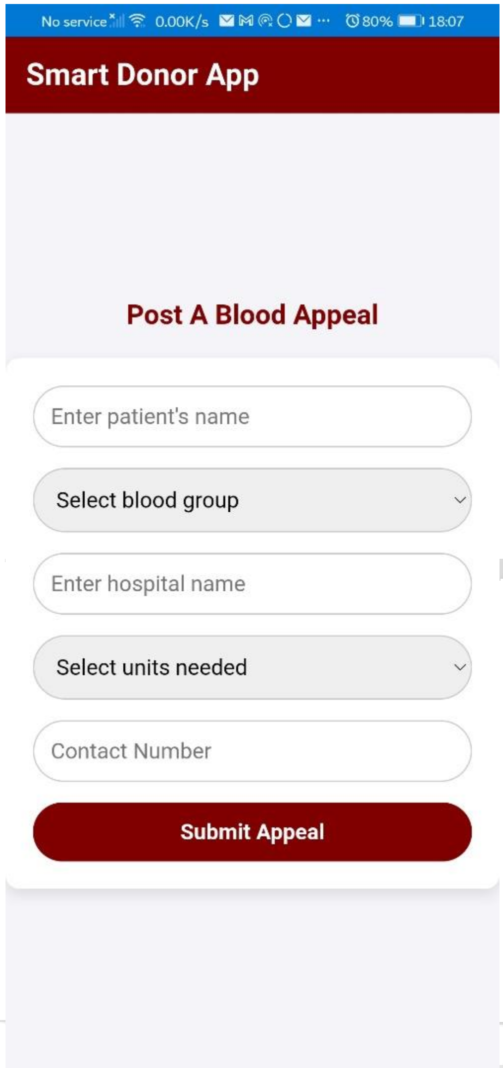


Figure 5.11: Blood Appeal Request Interface

5.4.1.3 User Module

The user module manages donor registration, authentication, and user profile management. This module provides an interface for users to create accounts, log in, and manage their profiles. It includes functionalities for updating availability and accepting or rejecting donation requests. Donors can also view their donation history and update their willingness to donate in the future. Figure 5.3 illustrates the same.

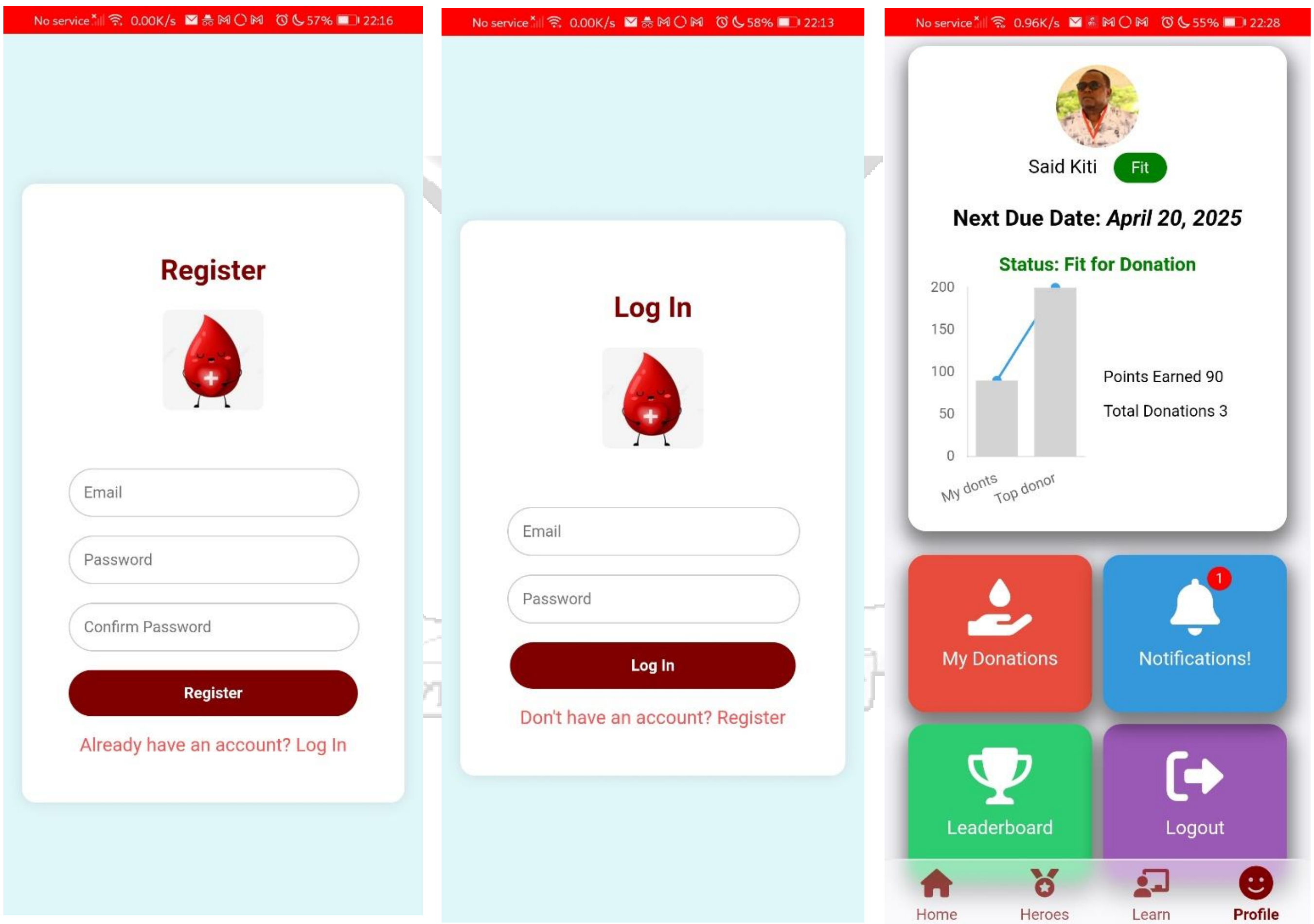


Figure 5.12: Registration, Login and Blood Donor Profile Interfaces

5.4.1.4 Admin Module

The Admin Module allows administrators to manage the platform effectively. It provides functionalities such as managing user accounts, approving blood requests, monitoring the status of donations, and generating reports for system performance analysis. The module offers role-based access control to ensure only authorized personnel can access sensitive features. Figure 5.13 shows the functionalities.

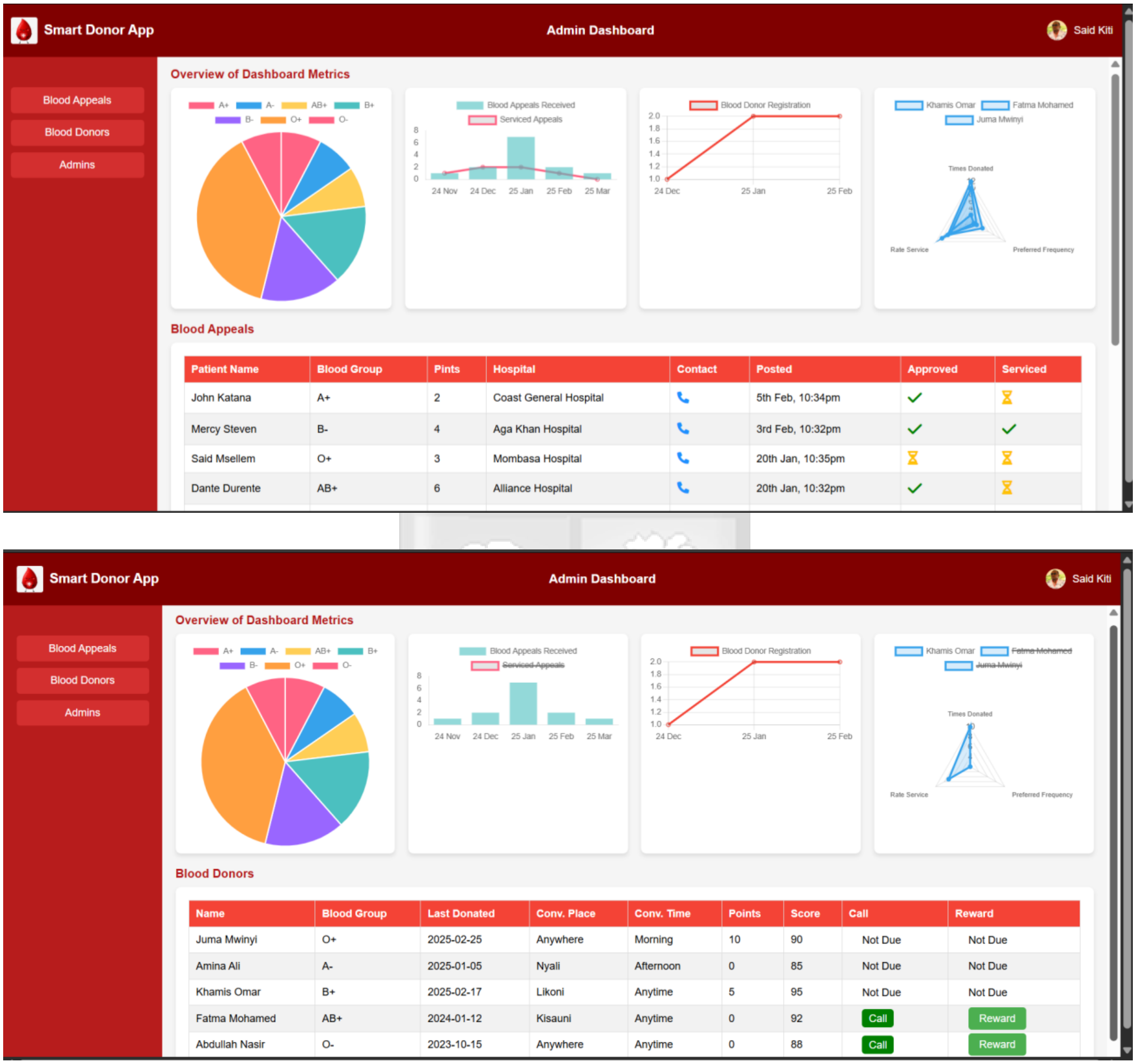


Figure 5.13: Admin Platform Showing Different Functionalities

5.4.1.5 Donor Reward Module

The Donor Reward Module aims to encourage blood donors to participate actively. It keeps track of donors' contributions and provides them with rewards or recognition based on their donation history. The module includes a point-based system where donors earn points each time they donate. Top 6 blood donors are displayed on *Heroes board* as shown in figure 5.14 where all users can see and get motivated to donate.

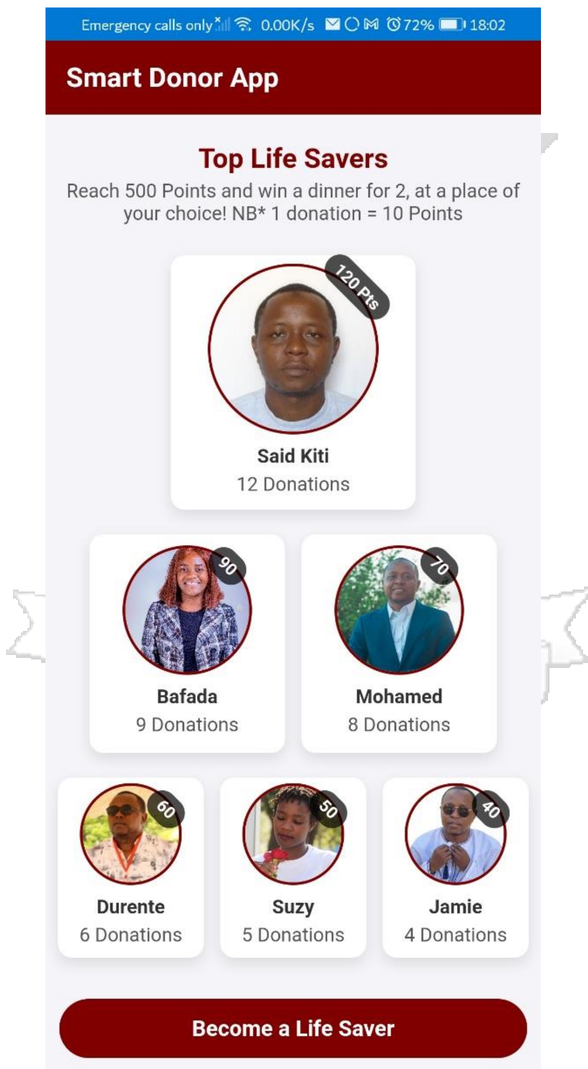


Figure 5.14: Screenshot of Top 6 Blood Donors

5.4.1.6 Notification Module

The Notification Module is designed to send alerts to blood donors and patients for successful matches and blood requests. This backend component ensures timely communication via push notifications, SMS, and calls, depending on the user's preferences. Figure 5.9 shows notifications received by the donor.

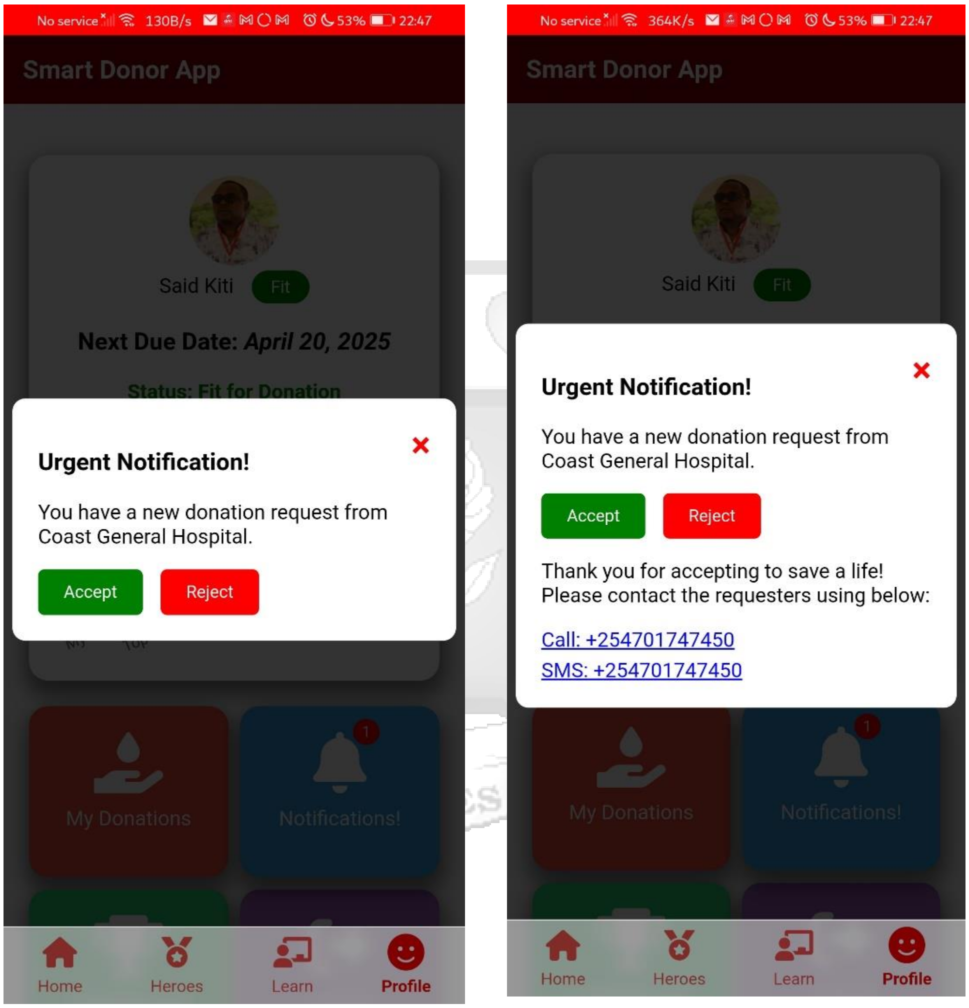


Figure 5.15: Notifications and Actioning on Them

5.4.1.7 Learn Module

The Learn Module provides educational content to raise awareness about blood donation. It includes an animated video explaining blood group compatibility, live feeds from X on blood donation topics, and informative articles on the importance of donating blood. This module is designed to educate users and encourage more people to participate in blood donation. Figure 5.5 shows the user interface of the Learn Module.

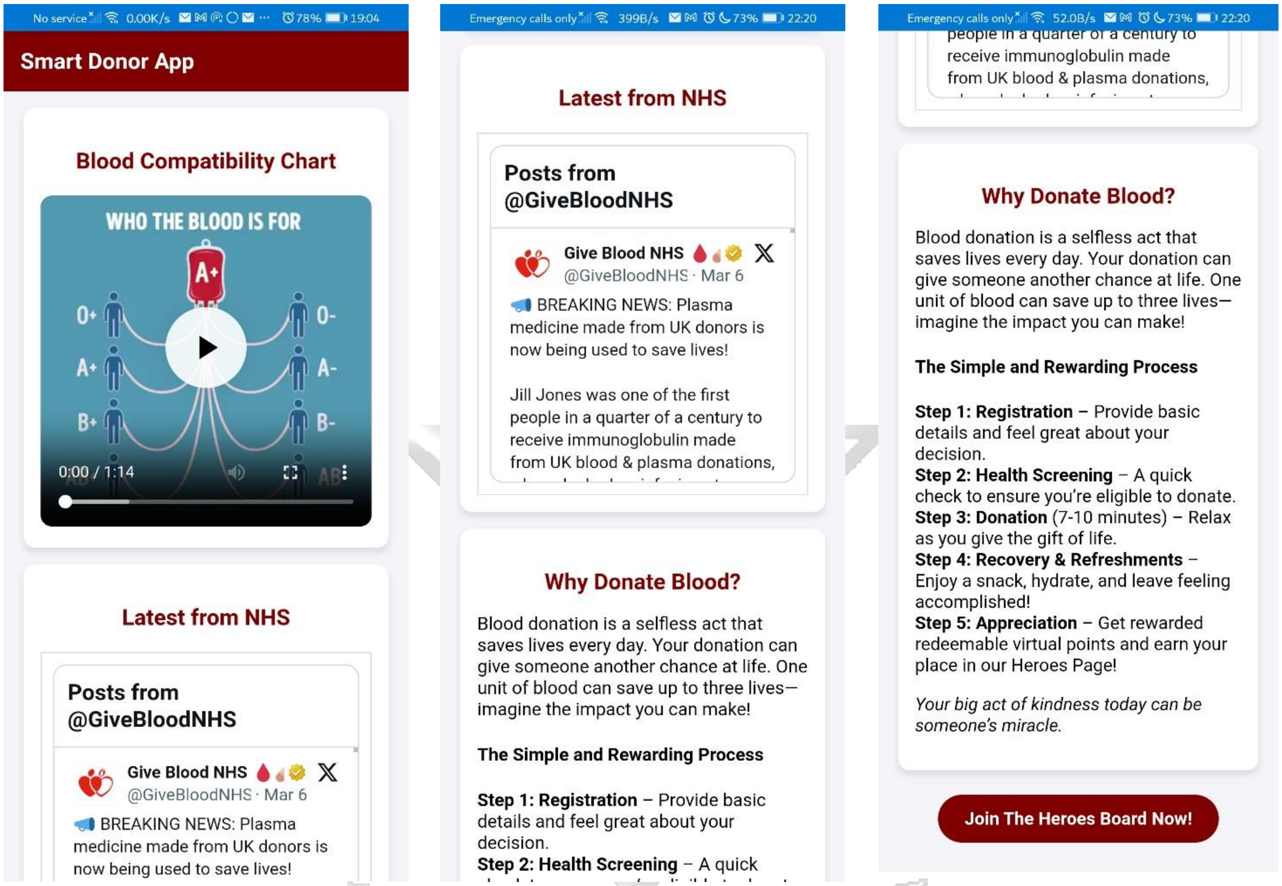


Figure 5.16: Screenshots of the Learn Module Interface

5.4.2 Back-End Design

The back end of the system handles server-side logic, database management, and machine learning model integration. It was built using php, JavaScript and Python to handle requests, process data, and communicate with the MySQL database.

5.4.2.1 System Backend

This is responsible for handling all server-side logic, request processing, and data management. It serves as the core component that interacts with the front end, processes business logic, and communicates with the database.

The backend was developed using PHP, JavaScript, and Python, each serving specific roles: PHP manages server-side operations, handles authentication, and processes API requests. JavaScript facilitates real-time processing and asynchronous operations where necessary. Python is used for integrating machine learning models and processing data-intensive operations.

5.4.2.2 Database

The database is implemented using MySQL, which serves as the central data repository for storing user details, donor information, and transaction records. The database follows D2Schema, ensuring a structured and organized data management approach. To ensure security, passwords are stored using hashing techniques to prevent unauthorized access. Figure 5.8 shows donor registration with hashed passwords.

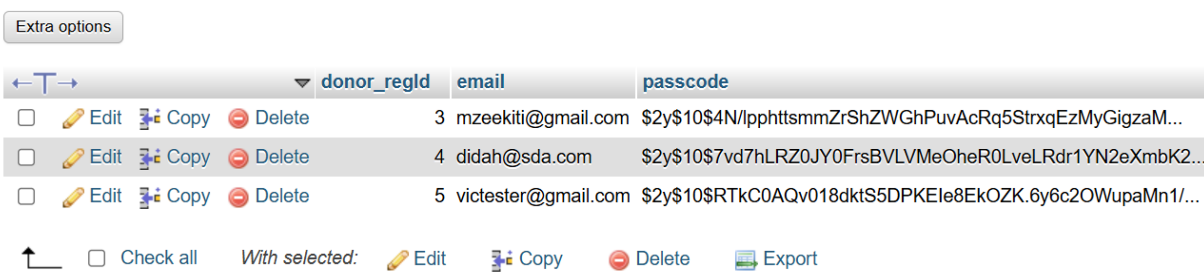


Figure 5.17: Database Table Showing Hashed Passwords

5.5 System Testing

The entire system was tested to verify that all functionalities work correctly when combined. Test cases were developed based on the system requirements and use cases.

5.5.1 Unit Testing

Each module of the system was tested individually to ensure correctness and functionality. Test cases were created for the front-end, back-end, and machine learning components. Table 5.1 shows the outcomes of the tests conducted.

Table 5.3 Unit Testing Results

Test Case ID	**Module**	**Test Description**	**Expected Outcome**	**Actual Outcome**	**Status**
UT-01	Front-End	Testing user login functionality	Successful login	Successful	Passed
UT-02	Front-End	Testing donor ability to change availability status	Successful changing	Successful	Passed
UT-03	Back-End	Testing API response for donor search	Correct data retrieved	Accurate Data	Passed
UT-04	ML Component	Testing donor matching accuracy	Correct matching	Accurate Match	Passed
UT-05	Notification Component	Testing notifications	Notifications Sent	Successful	Passed

5.5.2 Integration Testing

Integration testing was conducted to ensure that various modules work together seamlessly. This includes testing the communication between the front-end, back-end, database, and machine learning model. Table 5.2 shows the test results.

Table 5.4 Integration Testing Results

Test Case ID	Module	Test Description	Expected Outcome	Actual Outcome	Status
IT-01	API Integration	Testing data exchange between client and server	Data sent successfully	Data Received	Passed
IT-02	ML Integration	Testing ML model integration with API	Predictions retrieved	Accurate Output	Passed
IT-03	DB Integration	Checking data retrieval and update functionality	Data correctly updated	Success	Passed

5.5.3 User Acceptance Testing (UAT)

User acceptance testing was carried out to ensure that the system meets the expectations of end-users. Feedback from various users was collected, and necessary adjustments were made to enhance user experience. Table 5.3 shows the results after testing.

Table 5.5 UAT Results

Test Case ID	Scenario	Test Description	Expected Outcome	Actual Outcome	Status
UAT-01	Usability Testing	Checking ease of navigation	Smooth navigation	User-friendly	Passed
UAT-02	Performance Testing	Checking system responsiveness	Quick response	Fast and reliable	Passed
UAT-03	Functional Validation	Verifying data accuracy on profile page	Correct data shown	Accurate display	Passed

Chapter 6: Discussions

6.1 Introduction

This chapter provides a comprehensive discussion of the findings from the development, testing and deployment of the Smart Donor App. The discussion includes a comparative analysis of the application with existing methods of linking blood donors to patients, evaluation of the strengths and weaknesses of the application, implications of the study, and how the research objectives and questions have been addressed.

6.2 Analysis of Findings

The Smart Donor App has been developed with functionalities that are aimed at improving the patient-donor linkage process. The implementation of machine learning, geofencing, and predictive analytics provides an innovative approach compared to traditional systems and other applications. The results from testing the application indicate that it effectively matches patients with suitable donors based on various criteria, including blood type, availability, location, and donor willingness to donate.

6.3 Comparison with Existing Systems

The Smart Donor App demonstrates significant improvements over conventional blood donation systems and related applications. These improvements include:

6.3.1 Machine Learning-Powered Matching

The application leverages machine learning algorithms for optimized donor-patient linkage. This feature is superior to existing systems that only match donors based on simple criteria such as blood group. A good case is current systems used by all blood banks in Kenya where an administrator goes through stored excel list of blood donors, determine those of the same blood group as that required, and give them a call to persuade them to donate. This is despite not knowing their current health or availability status and how fit they are for a blood donation. Smart Donor App's model considers factors such as preferred place of donation, preferred time of donation, frequency, reaction and donor availability among others which provide a more accurate and efficient matching process. Another close comparison can be made with a model created by Karina that predicted whether a blood donor donated in March. In addition to having very few features, the model does not consider the most realistic features like donor's preferred time, availability and place of donation. This poses a challenge of inconveniencing blood donors reducing the likelihood of positive matches. Figure 6.1 shows the 4 features used in making the model as compared to 18 used for Smart donor App as shown by Figure 6.2.

Notebook Input Output Logs Comments (0)

Out[2]:

	Recency (months)	Frequency (times)	Monetary (c.c. blood)	Time (months)	whether he/she donated blood in March 2007
0	2	50	12500	98	1
1	0	13	3250	28	1
2	1	16	4000	35	1
3	2	20	5000	45	1
4	1	24	6000	77	0

Figure 6.1: Features Used by Karina's Blood Prediction Model

```
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 501 entries, 0 to 500
Data columns (total 19 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Name                   500 non-null    object
 1   DoB                    493 non-null    datetime64[ns]
 2   Gender                 500 non-null    object
 3   Phone                  500 non-null    float64
 4   Blood_Group            500 non-null    object
 5   Date_of_Donation       493 non-null    object
 6   Willing_Future_Donation 497 non-null   object
 7   Nature_Last_Donation   497 non-null    object
 8   Times_Donated          479 non-null    float64
 9   Preffered_Freq         497 non-null    float64
 10  Rate_Service           497 non-null    float64
 11  Reaction               497 non-null    object
 12  Convenient_Time        500 non-null    object
 13  Convenient_Locality    486 non-null    object
 14  Encouragement          500 non-null    object
 15  Consent                497 non-null    object
 16  Age                    500 non-null    float64
 17  DaysSinceLastDonation  501 non-null    int64
 18  Score                  501 non-null    int64
dtypes: datetime64[ns](1), float64(5), int64(2), object(11)
memory usage: 74.5+ KB
```

Figure 6.2: Features Used by Smart Donor App Prediction Model

6.3.2 Accuracy

Although Karina's model is a classification model, which is evaluated using ROC AUC of 0.7890, and the Smart Donor App model is a regression model which is evaluated using an R^2 score of 0.8906, the two metrics are not directly comparable. However, the high R^2 score suggests that the Smart Donor App model makes accurate predictions. Figure 6.3 shows a Receiver Operating Characteristic score of 0.7890 which means that the classification model has a 78.90% chance of correctly distinguishing between the positive and negative classes while figure 6.4 shows Coefficient of Determination of 0.8906 which means that 89.06% of the variation in the target variable is explained by the regression model.

```
logreg_auc_score = roc_auc_score(y_test, logreg.predict_proba(X_test_no
rmed)[:, 1])
print((logreg_auc_score))
```

```
0.7890178003814368
```

Figure 6.3: Roc_auc_score of Karina's Model

```
XGBoost Regressor

Mean Absolute Error: 0.055214678424935035
Mean Squared Error: 0.00538641849305489
Root Mean Squared Error: 0.07339222365519994
R^2 Score: 0.8906323434919423
['onehot_encoder.pkl']
```

Figure 6.4: R^2 Score of Smart Donor App's Model

6.3.3 Localized Matching

While the current system used by Damu Kenya selects a donor based on their place of birth details, the Smart Donor App employs geofencing technology to prioritize donors who are currently within a reasonable distance from where the patient or representative has raised the blood appeal request. This ensures timely matching, especially during emergencies.

For example, if a potential blood donor's place of birth is Kisumu but they are currently in Nairobi, the existing system would be unable to consider this person as a potential donor. However, the Smart Donor App, through geofencing, can accurately identify the donor's current location and facilitate an efficient match for that place.

6.3.4 Matching Speed

The system's user-friendly interface is designed to be very easy to navigate. It allows patients to search for donors based on their needs and provides donors with a simple way to indicate their availability by clicking fit/unfit button. This usability feature enhances user experience compared to traditional systems.

Tests conducted have shown that it takes an average of 15 seconds to make a request, get it approved, search and find the nearest most potential blood donor with the highest likelihood to donate blood for the request raised.

On the contrary, the legacy Damu Kenya system used in blood bank is largely manual, time-consuming and significantly slower.

6.3.5 Reward Program for Donor Retention

The current system used by Damu Kenya does not incentivize blood donors, which may contribute to lower donor retention rates. The Smart Donor App addresses this gap by implementing a structured reward program aimed at enhancing donor motivation.

Through the reward program, donors earn 30 points for every successful blood donation and can accumulate these points for which can later be redeemed for other benefits or recognition badges. By acknowledging and rewarding donors' contributions, the app fosters a culture of consistent blood donation and strengthens donor loyalty.

6.3.6 Enhanced Donor Engagement

The application captures information about donors' willingness to donate in the future and provides personalized notifications to encourage blood donation. This retention mechanism is absent in existing systems, giving the Smart Donor App a unique advantage.

6.3.7 Data Security and Consent Handling

All personal data is securely managed. Sensitive data is encrypted, maintaining user privacy and compliance with ethical standards unlike in many current systems where even passwords are sometimes stored as plain texts.

While the current system in many Regional Blood Transfusion Centers overlook consent, the Smart Donor App ensures donor consent is obtained prior. In addition to this, a blood donor can switch status to unfit anytime for whatever reason by just tapping a button that will exempt them from being found as potential blood donors during matching. Figures 6.5 shows the status switch.

Figure 6.5: Fit and Not Fit Buttons to Change Availability

6.4 Strengths and Weaknesses

The Smart Donor App presents several strengths that make it a valuable solution for linking blood donors to patients efficiently. Some of the strengths are:

i. Effective matching through machine learning and predictive analytics.
ii. Enhanced user experience due to simple interface design.
iii. Better donor engagement and retention mechanisms.
iv. Improved response time through geofencing.
v. Secure handling of user data and consent.

While the Smart Donor App demonstrates significant potential in bridging the gap between patients in need of blood and available donors, it is not without challenges. Below are the primary technical, ethical, and user-experience-related limitations observed during development and testing:

i. Internet Dependency

The app relies on stable internet connectivity, which may limit its effectiveness in remote or underserved areas with poor network coverage.

ii. User Input Reliability

The system depends heavily on users to provide accurate and up-to-date information. Inaccuracies in user data—such as falsified donation history or unavailable contact information—can compromise the system's efficiency.

iii. Data Privacy and Consent

Ethical concerns were raised around storing and handling sensitive personal and health-related data. Although users gave consent during registration, long-term data protection measures need further reinforcement in accordance with data privacy regulations such as Kenya's Data Protection Act (2019).

iv. Validation and Scalability

The app's performance and scalability were tested only in a limited context. Further validation is required to assess how well it functions with a larger user base, under high load, and in emergency situations.

v. Limited Integration with Health Facilities

At this stage, the app is not fully integrated with existing hospital or blood bank systems, which limits real-time tracking of blood demand and supply.

To enhance validity and reliability, future iterations of the app should include automated data verification features, stronger encryption protocols, and integration with official health data systems.

6.5 Implications of the Study

The Smart Donor App addresses the inefficiencies associated with traditional blood donor-patient linkage systems. Its implementation could significantly improve the availability and accessibility of blood donors, particularly during emergencies. The application also provides a practical framework for developing similar systems in other regions facing similar challenges.

6.6 Linking to Objectives and Research Questions

The research aimed to identify existing methods of linking blood donors to patients, evaluate their effectiveness, and develop a superior mobile application to enhance the process. The Smart Donor App successfully meets these objectives by providing functionalities that address the limitations of traditional systems. The objectives have been achieved as follows:

i. To evaluate challenges faced in linking patients to blood donors.

   The findings from primary data collection reveal that traditional systems mainly rely on manual donor lists, hospital databases, or scattered social media posts, which are inadequate during emergencies. From the analyzed results, most hospitals and blood banks experience delays in finding suitable blood donors, leading to negative health outcomes. The lack of proper coordination and communication channels also makes the existing methods unreliable and inefficient.

ii. To analyze existing technologies used in systems for linking patients to potential blood donors.

   From the data gathered, traditional methods are almost always ineffective due to slow response times, poor data management, and insufficient donor engagement. Based on the analyzed results, approximately 60% of the respondents indicated that existing systems which largely depend on using excel lists, are outdated, very manual and lack intelligent matching mechanisms and modern technological integration. 70% indicated it can take up to 3 days to get a matching donor.

iii. To develop a mobile application that instantly links patients to potential blood donors.

The Smart Donor App has been successfully developed, incorporating features such as machine learning-powered donor-patient matching, geofencing for locality-based searches, user consent handling, and personalized donor engagement mechanisms. These functionalities address the identified weaknesses of existing systems by providing a more streamlined and effective approach to blood donor linkage.

iv. To test the developed mobile application

Testing results indicate that the Smart Donor App offers a faster, more accurate, and user-friendly system for connecting patients with the nearest potential blood donors.

7: Conclusion, Recommendations and Future works

7.1 Conclusion

This research aimed to develop a Smart Donor App that leverages machine learning and geofencing technologies to optimize blood donor-patient linkage. The findings demonstrated that the proposed system effectively addresses the limitations of the current approach employed by Regional Blood Transfusion Centers through Damu Kenya, which relies on place of birth details rather than real-time location. By utilizing predictive analytics, the Smart Donor App enhances the efficiency of the matching process, ensuring that patients can access compatible blood donors within a reasonable distance, especially during emergencies.

The incorporation of a reward program promotes donor engagement and retention, fostering a consistent supply of regular blood donors. Overall, the Smart Donor App proves to be a promising solution for enhancing blood donation processes in Mombasa, Kenya.

7.2 Recommendations

To further improve the effectiveness of the Smart Donor App, the following recommendations are proposed:

i. Implementing a Predictive Blood Appeal Model which can predict blood appeal requests before they are raised. Early predictions will allow the system to proactively notify donors, minimizing delays and enhancing response times.

ii. Integrating with National Blood Donation Systems like the one used by Kenya Tissue and Transplant Authority and Damu Kenya to enhance donor-patient linkage on a broader scale.

iii. Enhancing Data Security and Privacy mechanisms through end-to-end encryption to safeguard donor and patient information.

7.3 Suggestions for Future Works

Future work should focus on expanding the application's capabilities by incorporating additional features such as:

i. Implementing advanced deep learning models to enhance donor-patient matching as well as prediction of blood appeal requests.
ii. Extending the application to cover other regions beyond Mombasa, making it a nationwide solution.
iii. Providing local language options to cater to diverse user groups, improving usability.

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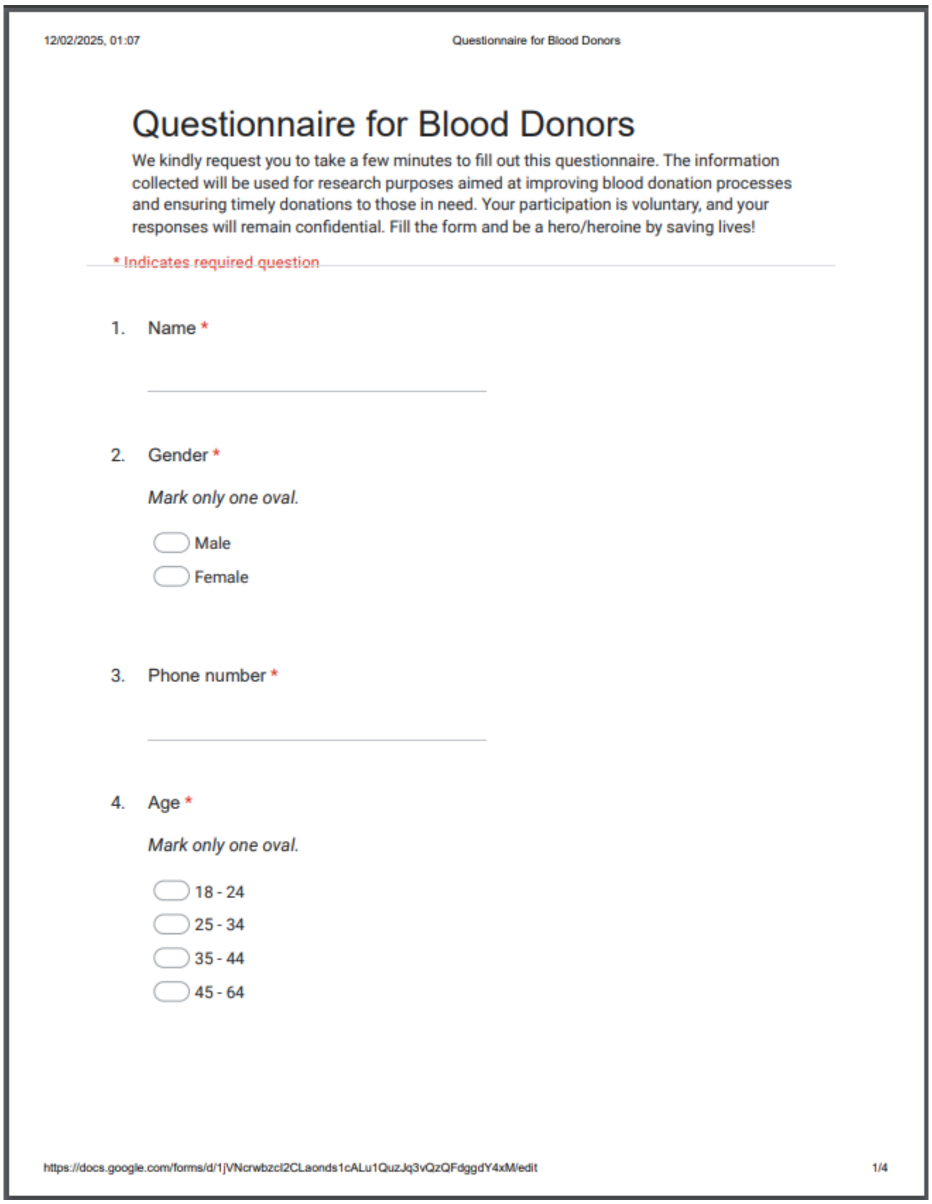
Appendices

Appendix A: Questionnaire for Blood Donors

Below appendix provides a picture of the Google form questionnaire that will be used to collect data from possible blood donors in Mombasa. It collects information such as respondent's name, age, gender, location, and blood group, in addition to details that are related to their donation frequency and preferences. Responses will be used to understand donor behavior, patterns and what they like, and this will inform the development of the patient-donor linkage system.



12/02/2025, 01:07 Questionnaire for Blood Donors

Questionnaire for Blood Donors

We kindly request you to take a few minutes to fill out this questionnaire. The information collected will be used for research purposes aimed at improving blood donation processes and ensuring timely donations to those in need. Your participation is voluntary, and your responses will remain confidential. Fill the form and be a hero/heroine by saving lives!

* Indicates required question

1. Name *

2. Gender *

Mark only one oval.

- Male
- Female

3. Phone number *

4. Age *

Mark only one oval.

- 18 - 24
- 25 - 34
- 35 - 44
- 45 - 64

https://docs.google.com/forms/d/1jVNcrwbzcI2CLaonds1cALu1QuzJq3vQzQFdggdY4xM/edit 1/4

Appendix A.1: Page 1 of The Donor Questionnaire

5. Blood group *

Mark only one oval.

- ◯ A+
- ◯ A-
- ◯ B+
- ◯ B-
- ◯ AB+
- ◯ AB-
- ◯ O+
- ◯ O-
- ◯ I don't know

6. How many times have you donated blood in total? *

Mark only one oval.

- ◯ 0
- ◯ 1 - 10
- ◯ 11 - 20
- ◯ 21+

7. What is your preferred place to donate? *

Mark only one oval.

- ◯ Changamwe
- ◯ Jomvu
- ◯ Kisauni
- ◯ Likoni
- ◯ Mvita
- ◯ Nyali

Appendix A.2: Page 2 of The Donor Questionnaire

03/10/2024, 11:18 Blood Donation Questionnaire

8. What time of the day do you prefer to donate? *

Mark only one oval.

- ◯ Morning (7am - 12pm)
- ◯ Afternoon (12 pm - 4 pm)
- ◯ Evening (4 pm - 11 pm)

9. Are you willing to be contacted in future donations? *

Mark only one oval.

- ◯ Yes
- ◯ No

10. Any other comments

____

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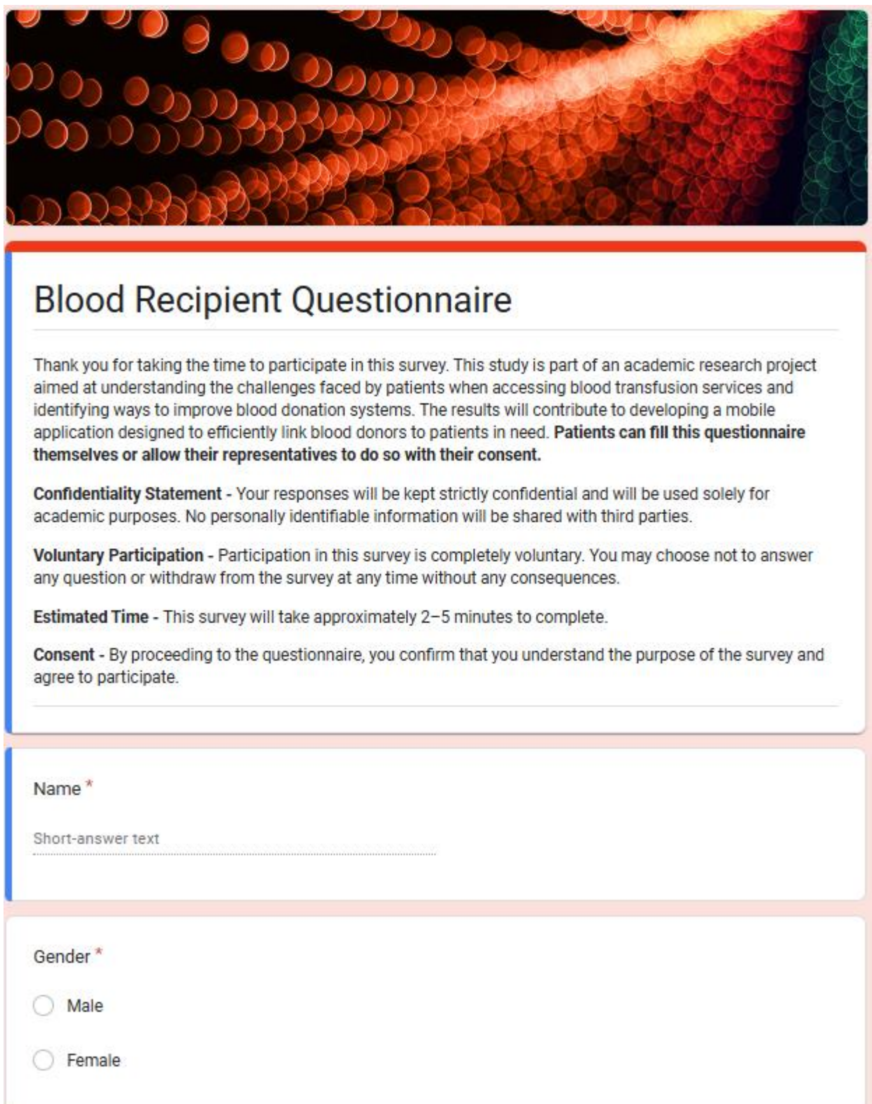
Google Forms

https://docs.google.com/forms/d/1jVNcrwbzcl2CLaonds1cALu1QuzJq3vQzQFdggdY4xM/edit 3/4

Appendix A.3: Page 3 of The Donor Questionnaire

Appendix B: Blood Recipient Questionnaire

Appendices B.1, B.2 and B.3 shown below provide pictures of the Google form questionnaire that will be used to collect data from people who require blood for transfusion. This one collect information such as the respondent's name, age, gender, and blood group, where they were admitted and how long it took them to get blood/blood donor. The responses will be used to understand the challenges recipients face when accessing blood transfusions, including delays, accessibility issues, and systemic inefficiencies, to inform the development of an optimized donor-patient matching system.



Blood Recipient Questionnaire

Thank you for taking the time to participate in this survey. This study is part of an academic research project aimed at understanding the challenges faced by patients when accessing blood transfusion services and identifying ways to improve blood donation systems. The results will contribute to developing a mobile application designed to efficiently link blood donors to patients in need. **Patients can fill this questionnaire themselves or allow their representatives to do so with their consent.**

Confidentiality Statement - Your responses will be kept strictly confidential and will be used solely for academic purposes. No personally identifiable information will be shared with third parties.

Voluntary Participation - Participation in this survey is completely voluntary. You may choose not to answer any question or withdraw from the survey at any time without any consequences.

Estimated Time - This survey will take approximately 2–5 minutes to complete.

Consent - By proceeding to the questionnaire, you confirm that you understand the purpose of the survey and agree to participate.

Name *

Short-answer text

Gender *

- Male
- Female

Appendix B.1: Page 1 of the blood recipient's questionnaire

Phone number *

Your answer

Age *

- 18 - 24
- 25 - 34
- 35 - 44
- 45 - 64

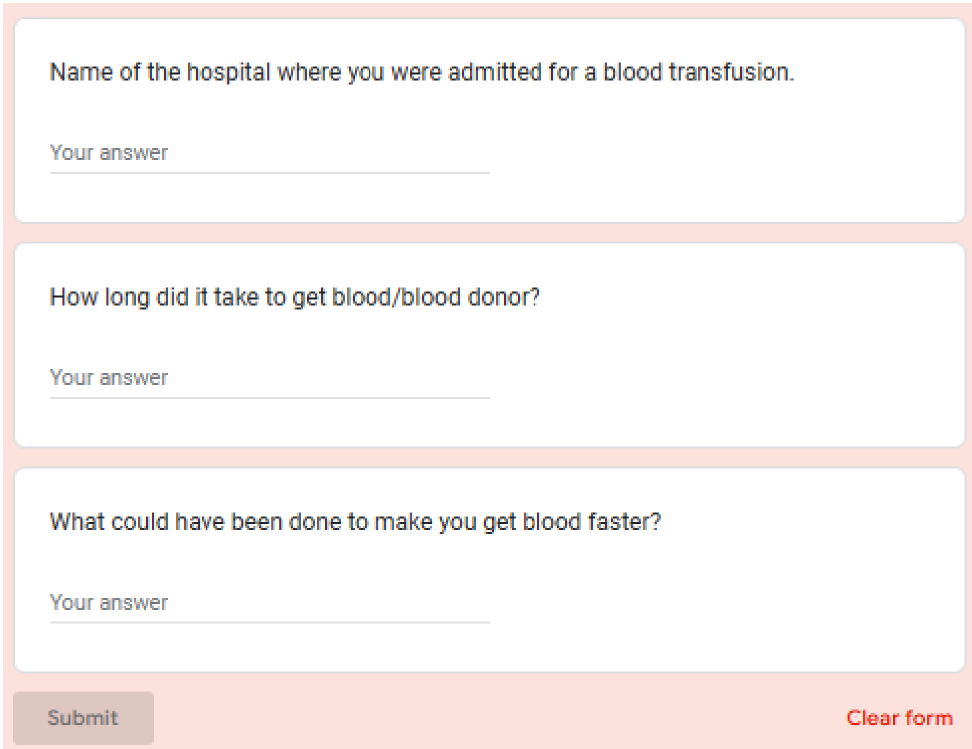
Blood group *

- A+
- A-
- B+
- B-
- AB+
- AB-
- O+
- O-

When did you require blood for transfusion ?

- 2024
- 2021- 2023
- 2015 - 2020
- Before 2015

Appendix B.2: Page 2 of the blood recipient's questionnaire



Name of the hospital where you were admitted for a blood transfusion.

Your answer

How long did it take to get blood/blood donor?

Your answer

What could have been done to make you get blood faster?

Your answer

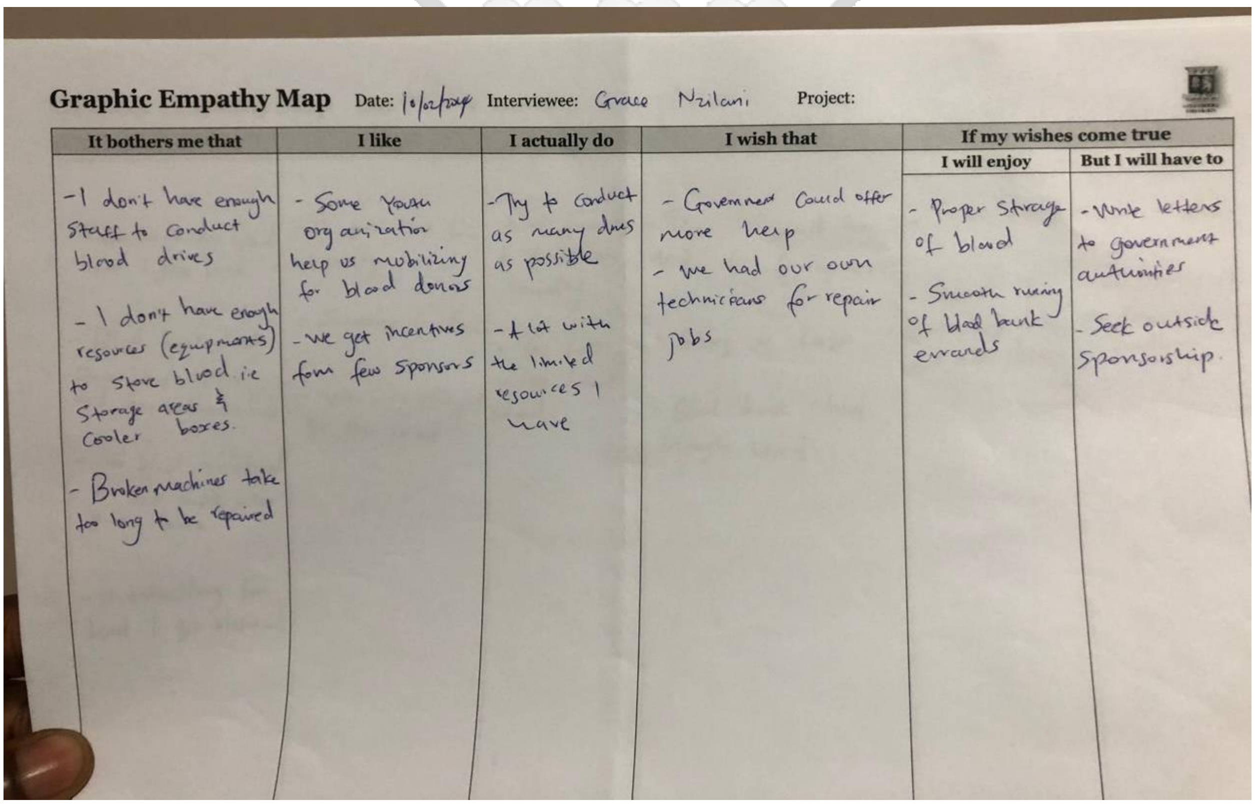
Submit

Clear form

Appendix B.3: Page 3 of the Blood Recipient's Questionnaire

Appendix C: Interview Responses

The appendix B.1 below shows responses of an interview conducted with the director of the Kenya Tissue and Transplant Authority (KTTA) Blood Bank in Mombasa. The interview highlighted the challenges faced by the blood bank in maintaining adequate blood supply and efficiently connecting donors to patients in need. The director emphasized the difficulty in tracking potential donors and the delays experienced during emergencies, which can lead to preventable health complications. The insights from this interview strongly validated the necessity for a solution, such as the proposed machine learning-powered mobile application, to streamline donor-patient linkage and improve the efficiency of the blood supply chain in Mombasa.



Graphic Empathy Map Date: 10/02/2024 Interviewee: Grace Nzilani Project:

It bothers me that	I like	I actually do	I wish that	If my wishes come true	
				I will enjoy	But I will have to
- I don't have enough staff to conduct blood drives - I don't have enough resources (equipments) to store blood i.e storage areas & cooler boxes. - Broken machines take too long to be repaired	- Some youth organization help us mobilizing for blood donors - we get incentives from few sponsors	- Try to conduct as many drives as possible - A lot with the limited resources I have	- Government could offer more help - we had our own technicians for repair jobs	- Proper storage of blood - Smooth running of blood bank errands	- Write letters to government authorities - Seek outside sponsorship.

Appendix C.1 Interview Responses with Technical Director of Coast RBTC

Appendix D: Motivators and Barriers for Blood Donation

Appendix D.1 below shows results of a study that was conducted by Atiyeh Abdallah at Qatar University in July 2021 and published on ResearchGate. It explored the knowledge level, motivators, and barriers related to blood donation among students. The results showed that even though many students had a basic understanding of the need for blood donation, still there were quite some gaps in awareness, especially regarding the impact of their donations on healthcare. This emphasizes even more the need for targeted awareness and patient-donor matching.

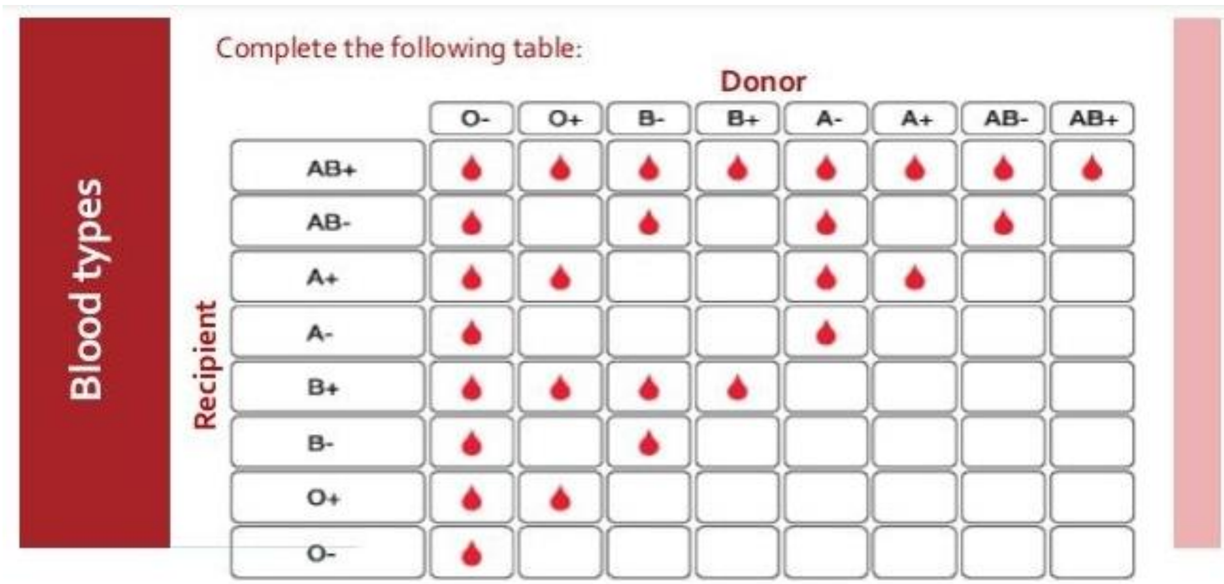
Items	Strongly Agree (%)	Agree (%)	Neither Agree nor Disagree (%)	Disagree (%)	Strongly Disagree (%)
(a) I do not think there is a need to donate blood	1.3%	2.0%	7.0%	26.3%	63.5%
(b) I might get HIV or AIDS from giving blood	1.5%	8.8%	20.0%	26.5%	43.5%
(c) No one ever asked me to give blood	13.8%	31.3%	22.5%	18.3%	14.2%
(d) Failing to meet the requirements (body weight, blood pressure, hemoglobin, etc.)	26.3%	18.8%	19.3%	18.3%	17.5%
(e) Fear (needles, feeling dizzy, etc.)	12.8%	19.8%	9.8%	26.0%	31.8%
(f) I do not have time to donate blood	7.5%	17.8%	24.3%	24.5%	26.0%
(g) I do not know where to donate blood	10.5%	21.8%	12.3%	26.5%	29.0%
(h) Inconvenient hours for blood donations sites	5.3%	11.8%	36.3%	23.3%	23.5%
(i) Inconvenient locations for blood donations sites	6.5%	14.2%	31.5%	24.5%	23.3%
(j) Limitation of activities after donation	2.8%	9.5%	35.8%	26.0%	26.0%
(k) Others (open-ended question)	11.7%				

Barriers toward blood donation (N = 400).

Appendix D.1: Motivators and Barriers for Blood Donation (Atiyeh, 2021)

Appendix E: Blood Donor-Recipient Matching

Knowing blood group compatibility is crucial in developing an effective blood donor-patient matching solution (Ahmed et al., 2022). According to World Health Organization (2021), incompatible blood transfusions can lead to serious health complications that may be life-threatening. Including blood group compatibility into the matching process will ensure that patients receive blood from donors whose blood type is compatible, minimizing risks and improving the success rate of transfusions and the matching algorithm. Appendix E.1 below shows blood group compatibility.



Recipient \ Donor	O-	O+	B-	B+	A-	A+	AB-	AB+
AB+	●	●	●	●	●	●	●	●
AB-	●		●		●		●	
A+	●	●			●	●		
A-	●				●			
B+	●	●	●	●				
B-	●		●					
O+	●	●						
O-	●							

Appendix E.1: Blood Group Compatibility. (WHO, 2021)

Appendix F: NACOSTI License

Figure F.1 and F.2 show the NACOSTI License and Ethical Review Approval letter obtained for the purpose of collecting primary data.

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: 264992

Date of Issue: 27/February/2025

RESEARCH LICENSE

This is to Certify that Mr.. MZEE SAID KITI of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Mombasa on the topic: A Machine Learning-Powered Mobile Application That Links Blood Donors to Patients in Mombasa, Kenya for the period ending : 27/February/2026.

License No: NACOSTI/P/25/416242

264992

Applicant Identification Number

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See overleaf for conditions

Appendix F.1: NACOSTI License.

Strathmore
UNIVERSITY

14th February 2025

Mr Kiti Mzee,
mzee.kiti@strathmore.edu

Dear Mr Kiti,

RE: A Machine Learning-Powered Mobile Application that Links Blood Donors to Patients in Mombasa, Kenya

This is to inform you that SU-ISERC has reviewed and **approved** your above SU-masters proposal. Your application reference number is **SU-ISERC2577/25.** The approval period is from **14th February 2025 to 13th February 2026.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, MTA) will be used.
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification.
iv. Any changes anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours.
v. Clearance for the export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

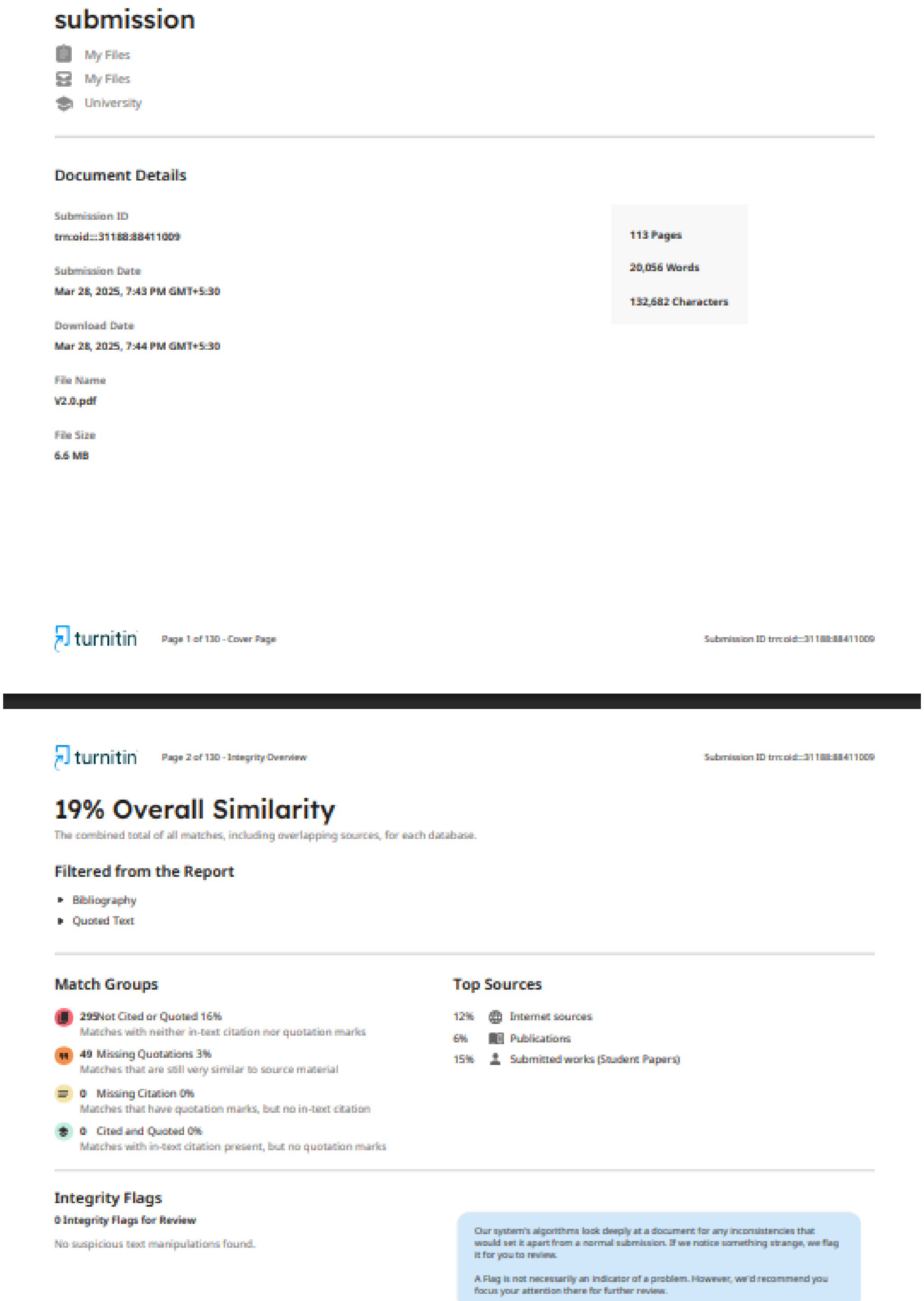
Mr Ambrose Rachier,
Chairperson; SU-ISERC

Ole Sangale Rd, Madaraka Estate. PO Box 59857-00200, Nairobi, Kenya. Tel +254 (0)703 034000
Email admissions@strathmore.edu www.strathmore.edu

Appendix F.2: Ethical Approval Letter.

Appendix G: Plagiarism Check

Plagiarism check was conducted using Turnitin and the result was 19% as shown in the figure below.



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Appendix G.1: Plagiarism Check