# AI powered Hospital Management System(AI-HMS)

by

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A thesis submitted to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
B.Sc. in Computer Science and Engineering

Department of Computer Science and Engineering
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# Declaration

It is hereby declared that

1. The project submitted is our own original work while completing degree at Brac University.

2. The project does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The project does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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# Approval

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# Abstract

The increasing complexity of modern healthcare services has highlighted the limitations of traditional Hospital Management Systems, which are primarily focused on the automation of hospital administration and electronic management of patient records, with limited support for decision-making. This thesis proposes the design and development of AI-HMS, an Artificial Intelligence-based Hospital Management System that incorporates the integration of administration and decision-making through the use of artificial intelligence.The proposed system is built using a full-stack development framework, with the React.js library for the front-end, the Flask framework for the back-end, and PostgreSQL for the management of both structured and semi-structured data. Supervised learning algorithms are used for the prediction of the risk level of patients and the likelihood of hospital readmission. A Large Language Model-based artificial intelligence assistant is incorporated for the assistance of healthcare professionals and patients.
Therefore, AI-HMS is based on the human-in-the-loop philosophy of artificial intelligence, where the artificial intelligence component is used as a decision-support tool. The proposed system was evaluated using synthetic data sets for healthcare services and was found to perform reliably. The system was also deployed as a web-based application, validating the proposed system.
Overall, this research demonstrates the potential of using artificial intelligence for the management of hospital services.

**Keywords:**
Artificial Intelligence, Hospital Management System, Decision Support, Machine Learning, Patient Risk Prediction, Large Language Models, Healthcare Informatics.

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# Table of Contents

# List of Figures

# Chapter 1

# Introduction

## 1.1 Background and Motivation

Global healthcare is facing a massive digital revolution brought about by the necessity to achieve efficiency, accuracy and better quality of care. Historically, paper records and manual administrative processes were used in hospitals, which usually led to information duplication, information loss and slow decision making processes[6]. The advent of Electronic Health Records (EHR) and Hospital Management Systems (HMS) was a pivotal turn towards digitization since it now made it possible to store and retrieve patient data electronically[11]. Majority of the traditional HMS solutions are mostly transactional in nature despite such advances. They are more oriented to data storage and retrieval as opposed to data analysis and clinical decision-making [2].

With hospitals producing greater amounts of clinical and administrative information, a deficiency of analytical tools which are intelligent does not allow healthcare professionals to effectively utilize this information.Recent advancements in the research of Artificial Intelligence (AI) and Machine Learning (ML) have shown some promising outcomes in the context of healthcare-related applications: prediction of diseases, risk stratification of patients and prediction of outcomes [1]. Moreover, the progress of Natural Language Processing (NLP) and Large Language Models (LLM) has allowed making human-computer interaction in the clinical setting more natural [9].

The rationale of the current project is to use these new technologies to improve the traditional hospital management systems by incorporating predictive analytics with smart interaction directly into the hospital workflows.

## 1.2 Problem Statement

Though lots of hospitals have incorporated digital management, the current HMS platforms have developed a number of limitations. Such systems are usually deficient in real-time patient risk evaluation, and therefore, deliver healthcare in a reactive manner as opposed to proactively [3]. The mechanisms used to schedule an appointment are often manual-based or rule-based and this creates conflicts and wastage of resources.

Moreover, clinicians may be subjected to high amounts of raw patient data with an insufficient amount of analytical support predisposing them to extra cognitive burden and the possibility of human error [4]. As a patient, the current systems do not offer much interaction and do not often display medical information in a way that is easy to comprehend or use. The lack of explainable AI interfaces, as well as the compatibility of medical records and diagnostic support, is one of the major weaknesses in existing medical information systems.

## 1.3 Objectives of the Project

The objectives of the given project are the following ones:

- To develop and design a role based and smart Hospital Management System that is aligned with the operations that take place at a real world hospital.
- To unite machine learning models to predict the risk of patient health and hospital readmission based on clinical data.
- To add on a Large Language Model-based AI assistant to assist with checking the symptoms, diagnosing, and producing clinical notes.
- To increase the accessibility and usability of the system to both medical staff and patients.
- To assess the workability and efficiency of AI-based decision support in a hospital management setting.

## 1.4 Scope of the Project

The area of work in the context of this project is the central hospital functioning, which will involve patient registration, appointment booking, medical record management, and AI-based clinical decision support. The system is applied as a prototype with experimentally validated synthetically generated healthcare data.

This project is not based on substituting doctors or offering the independent medical choice. Rather, it is a human-in-the-loop solution, and the insights provided by AI can be applied as advisory support only [10]. Practical clinical implementation, regulatory accreditation and combination with the national healthcare systems are beyond the scope of the present study.

## 1.5 Organization of the Report

The thesis has been divided into seven chapters companying each of the aspects of the study as it has been identified as follows:
**Chapter 1: Introduction**
Introduces the background of the research, motivation of the research, problem statement, objectives, scope of the research and the general structure of the thesis.
**Chapter 2: Literature Review**
Surveys available works, other hospital management systems, technological innovations in the field of healthcare, and determines the research gaps that comply with

the proposed AI-HMS.

**Chapter 3: System Analysis**

Presents the functional and non-functional requirements, the target users, use cases, functional feasibility analysis, and critical challenges of the system.

**Chapter 4: System Design and Methodology**

Gives an explanation of the architecture, system models, data flow and methodologies used in the system development and integration of AI.

**Chapter 5: Implementation**

Outlines the process of development, the tools, technologies, front-end and back-end implementation of the suggested system. The installed system is launched as a live web app and could be accessed at: https://ai-hms-one.vercel.app/

**Chapter 6: Results and Discussion**

Provides a presentation of experimental findings, evaluation of AI/ML models performance, system performance, and a critical reflection of the findings.

**Chapter 7: Conclusion and Future Work.**

Concludes the work performed in general, singles out the essential contributions to the study and gives recommendations regarding the further research and improvements of the system.

# Chapter 2

# Literature Review

## 2.1 Overview of AI-HMS

The notion of AI-powered Hospital Management System is an innovative step forward compared to the conventional HMS as it implies the direct application of artificial intelligence methods to the functioning of the hospital. In comparison to traditional systems, which are mainly used to automate their administrative processes and store electronic records, AI-based hospital management systems employ machine learning algorithms to process structured clinical data and come up with actionable insights that can be used to make informed decisions [1][3].Earlier research has demonstrated that AI-based healthcare systems can enhance the efficiency of the operations performed by the AI system by automating regular duties, optimizing the use of resources, and decreasing the administrative burden [2][1].
Moreover, supervised learning-based predictive models can be used to identify high-risk patients earlier in the course of evaluation of clinical parameters (age, vital signs, and past medical records) [3]. These features enable medical professionals to move beyond the reactive care models to more proactive and preventive ones.The proposed AI-HMS expands through these advancements and incorporates a variety of AI elements into a single hospital management system. The machine learning framework and machine learning techniques, such as classification and regression models, are used to forecast the level of health risks and hospital readmission rates of patients based on the structured clinical data [1] [3].
Therefore, conversational interaction, automated summarization of clinical notes, and interpretation of medical information in an easy and understandable way are achieved with the help of Natural Language Processing (NLP) techniques, which are implemented with the help of a Large Language Model [9].
By integrating the automation of administration, predictive analytics, and conversational intelligence, AI-HMS goes beyond the functionality of HMS platforms in the past and serves as an intelligent decision-support environment. This comprehensive and humanistic model fits the modern study of healthcare informatics, where interpretability, usability, and clinical supervision are highlighted in AI-assisted healthcare systems [4][10].

## 2.2 Existing Solutions and Their Drawbacks

A number of Hospital Management Systems and healthcare information platforms are available in clinical settings including commercial and open-source systems. Electronic health records, billing, and administrative management are the well-known commercial systems like Epic, Cerner, and Allscripts which have extensive functions. Although these systems have become common in major health care facilities, they are often complicated, costly to implement, and also need a lot of training to be used effectively [7].
Additionally, their decision-support functionalities are generally confined to the rule-based alerts and less automated reporting, and little integration of superior machine learning models to predictive analytics [3].Various open-source software systems like OpenMRS and OpenEMR are designed to enhance access and lower the expenses, especially in low-resource medical facilities. Such systems assist in managing electronic medical records and simple workflow automation, but have in general no embedded predictive analytics, intelligent risk analysis, and conversational AI interfaces [13].
Consequently, clinicians on the one hand need to interpret manual data or use third-party tools to carry out complex analysis, which reduces efficiency in clinical tasks and makes them weaken the mental load [4].Furthermore, most of the available healthcare applications are dedicated to disjointed functionalities as opposed to the system integration. As an example, stand-alone symptom checker applications and health monitoring apps are patient-facing services that do not rely on hospital management workflows and electronic health records [9]. The interoperability between these applications and core HMS platforms is not available which limits its clinical utility and does not allow smooth exchange of data between the systems [12].
The other notable disadvantage of the current solutions is that they do not attach as much importance to interpretability and human-centered AI design. Sometimes, AI-based capabilities even in the case of their existence are usually black-box and do not provide adequate explanations of predictions or suggestions, which diminishes the levels of trust and adoption among healthcare professionals [10]. All these restrictions underscore the fact that an integrated, modular, and explainable AI based system like the proposed AI-HMS is required to manage a hospital.

## 2.3 The Role of Technology in Modern Healthcare

Modern healthcare systems have made technology a supportive element, where manual, reactive systems have been replaced by intelligent, data-driven systems of care delivery. Developments in healthcare information systems have made a big milestone in terms of gathering, storing, and the accessibility of clinical data, which enables health care professionals to make better and quicker decisions [2][4]. Online tools like Electronic Health Records, and Hospital Management Systems have improved the collaboration between healthcare providers and minimized administrative inefficiency.Machine learning methods are important in this transformation as they make it possible to analyze large sets of clinical data manually.
Supervised learning is a commonly used model in prediction of diseases, risk-based

stratification of patients, and forecasting their outcomes, which have shown better accuracy and are able to detect high-risk cases earlier than standard statistical techniques [1][3]. These predictive abilities help in preventing clinical intervention and more efficient distribution of healthcare resources.Simultaneously, Natural Language Processing (NLP) technologies have promoted communication and recording in healthcare systems. Applications using NLP help generate clinical notes automatically, text summarization in medicine, and chatbots and virtual assistants, thus lessening the documentation level on clinicians and enhancing patient-clinician interaction [9]. All these technologies are combined to help the shift toward proactive, individualized, and patient-centered care models instead of reactive healthcare delivery.

## 2.4 Research Gaps and Justifications for the Proposed AI-HMS

Despite the evidence of successful artificial intelligence use in remote healthcare solutions, few studies focus on systemic implementation of administrative automation, predictive analytics, and conversational AI into a hospital management system [1] [3]. Most AI-based healthcare systems are constructed as individual systems, devoting their attention to a particular task (predicting a disease, detecting a symptom, etc.), and they are not directly integrated into the workflows of the hospital environment.Moreover, machine learning algorithms, like Random Forest and Logistic Regression, have been widely tested in the context of clinical prediction, but their usage in fully integrated hospital management systems is not well studied [3].
Likewise, the recent breakthroughs in Large Language Models have demonstrated significant potential in clinical documentation and patient communication but are not typically considered as part and parcel of integrated healthcare information systems [9].The other notable gap in the research is the low focus on human-oriented and ethically sound AI design. Current AI-based healthcare platforms often focus on predictive success and do not emphasize enough on interpretability, transparency, and clinician control, needed to implement AI systems in real-world settings and achieve trust [4][10]. The lack of humans in the loop frameworks also limits the practicability of AI assistance systems in clinical settings.
The proposed AI-HMS covers these gaps by unifying the automation of the administration and predictive analytics developed with machine learning with conversational AI in a modular and scalable system. By integrating readable AI functionalities into the workflows of hospitals and ensuring human accountability through human-centered design principles, AI-HMS fits the modern research into healthcare informatics and tackles the practical constraints evident in current systems [10][7].

# Chapter 3

# System Analysis and Design

This chapter provides a detailed analysis of the proposed AI-HMS system. Details on system requirements, target users, use cases, feasibility considerations, and major challenges for the system design are provided. The analysis ensures that the proposed solution is aligned to the real hospital workflows and is technically, operationally, and economically feasible.

## 3.1 Requirement Analysis

Requirement analysis is a very essential stage in the development of a system as it defines the functional scope of the solution and quality attributes of the solution. The requirements of AI-HMS are grouped into functional and non-functional requirements for assuring the system capability and performance.

### 3.1.1 Functional Requirements

Functional requirements describe necessary operations which the system needs to perform in order to support the activities in the hospital:

- **Assure user authentication and access control:** The system must be able to authenticate the users securely and restrict access based on predefined roles like administrator, doctor, receptionist and patient. Role based access control is the requirement to safeguard delicate medical data and also to ensure proper compliance with healthcare data governance principles [10].

- **Patient Registration and Profile Management:** The system needs to support the creation, update and retrieval of patient profiles including demographic information and basic medical history. Digital patient records assist to improve data consistency and also to reduce the administrative redundancy [2].

- **Scheduling of appointment and availability of doctor:** AI-HMS needs to offer an efficient appointment scheduling mechanism which will enable receptionists and patients to book appointments depending on the availability of the doctor. This feature helps in reducing scheduling conflicts and improves the utilization of resources.

- **Medicine records storage and retrieval:** The system should provide a secure longitudinal medical record and provide access to historic patient information to authorized users. Structured and semi-structured methods of storage enable flexibility for the management of clinical notes and observations [7].
- **Health risk prediction & readmission prediction based on AI:** Machine learning models need to analyse clinical parameters for predicting the health risk level of the patients and readmission probabilities of the patients. These predictive insights are helpful in planning proactive care and early intervention strategies [4][6].
- **AI assistant to both clinical and patient interaction:** The system should have an AI assistant that has the capability to support natural language interaction for symptom checking and summarizing clinical notes and explaining medical information. Usability is improved and clinician documentation is reduced with NLP-based assistants [9].

### 3.1.2 Non-Functional Requirements

Nonfunctional requirements specify the qualities and operational constraints of the system:

- **Compliance with data security and privacy:** In accordance with the standards for protecting healthcare data, the system must guarantee secure data transmission, encrypted storage and stringent access control to safeguard patient confidentiality [10].
- **System Scalability and Maintainability:** AI-HMS needs to be designed in such a way that it can support future expansion, such as adding new users, AI modules, and units in the hospital. Modular architecture and clean code design for improving maintainability [12].
- **High availability and reliability:** The system needs to be accessible with minimum downtime to support critical hospital operations. Reliability is crucial in healthcare settings where the failure of systems can affect patient care.
- **Responsive and easy-to-use interface:** The user interface needs to be intuitive and responsive on all devices to allow for efficient interaction of users with differing technical expertise. Usability is one of the determining factors for healthcare system adoption [4].

## 3.2 Target Users and Use Cases

The AI-HMS system is meant to support a number of stakeholders in a hospital environment, each with unique responsibilities, access privileges, and interaction needs. Identifying target users and defining their use cases is vital to ensure that the system is in line with real-life hospital flows and supports efficient collaboration between different roles [2][4].

### 3.2.1 Target Users

The main target users of the AI-HMS system are the following:

- **Hospital Administrators:** Administrators are in charge of the overall system management and operational supervision. Their interactions with the system include user account management and role assignment, hospital-wide analytics monitoring and system performance indicator review. Administrative access is intended to help with strategic decision making and the smooth running of the system.

- **Doctors:** Doctors are the major clinical users of the system. They have access to patient profiles, view longitudinal medical records, and make use of AI-generated insights such as health risk levels and probabilities for readmission to aid in clinical decision-making. The system is intended to display AI outputs in an understandable way that helps clinicians easily interpret and put predictive results into context [1][10].

- **Receptionists:** Receptionists are responsible for front desk operations and act as a go between between patients and clinical staff. Their main duties include registration of patients, scheduling appointments, and doctor schedules. The system simplifies such tasks by offering structured workflows which minimize scheduling conflicts and administrative burdens.

- **Patients:** Patients engage with the system, mostly for booking appointments, accessing basic health-related information, and engaging the AI assistant for preliminary guidance. The addition of conversational AI enhances accessibility and allows patients to interact with the system without needing technical expertise [9].

### 3.2.2 Use Cases

On the basis of the target users identified, the core use cases that are supported by AI-HMS are summarized below:

- **Administrator Use Cases:** Administrators handle user accounts, roles, monitor the hospital activity via analytical dashboards, and examine system usage statistics for support of hospital operations planning.

- **Doctor Use Cases:** Doctors review patient histories, access risk predictions from AI, document diagnoses and treatment plans, and use AI-assisted summaries for lessening the effort of documentation and more efficient consultation [3].

- **Receptionist Use Cases:** Receptionists register new patients, schedule appointments according to the doctor's availability and change the status of appointments, as well as coordinate flow within the hospital.

- **Patient Use Cases:** Patients book appointments, receive appointment notifications, and engage the AI assistant to do symptom checking and general health-related queries. These use cases increase patient engagement and accessibility to healthcare services [9][4].

By defining target users and use cases that are associated with them clearly the AI-HMS system enables role-specific functionality, better usability, and security access to sensitive healthcare data. This structured approach helps in the efficient functioning of hospitals without compromising compliance with data privacy and ethical considerations.

## 3.3 Feasibility Study

A feasibility study was carried out to assess the feasibility of the proposed AI-HMS system from technical, operational and financial points of view.

- **Technical Feasibility:** The system is technically feasible because of the use of mature technologies that are widely adopted and open-source technologies such as Flask, React, and PostgreSQL [13][12]. These technologies offer solid support for web application development, database management, and AI integration.
- **Operational Feasibility:** The system fits in well with current hospital flow processes, so adoption is minimal. Role-based access and familiar interaction patterns help integration in daily hospital operations.
- **Economic Feasibility:** The use of open source frameworks and cloud-based deployment brings down the cost of development and deployment considerably, making the system economically viable for small and medium scale healthcare institutions.

This chapter provides a detailed analysis of the proposed AI-HMS system. Details on system requirements, target users, use cases, feasibility considerations, and major challenges for the system design are provided. The analysis ensures that the proposed solution is aligned to the real hospital workflows and is technically, operationally, and economically feasible.

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- **Economic Feasibility:** The use of open source frameworks and cloud-based deployment brings down the cost of development and deployment considerably, making the system economically viable for small and medium scale healthcare institutions.

## 3.7 Key Challenges

The development of AI-HMS required tackling some technical and ethical challenges:

- **Patient data privacy and security:** Confidentiality of medical records is an important issue in healthcare systems. AI-HMS helps with this challenge with secure authentication, access control and encrypted data handling [10].

- **AI interpretability & trust:** Black-box AI models can lead to a loss of trust by clinicians. The system focuses on using interpretable models and natural language explanations to make it transparent how the AI-generated insights are made [5].

- **Dealing with semi-structured clinical data:** Medical records frequently contain unstructured data or semi-structured data. The system uses flexible approaches for storing data based on the variety of clinical information [7].

- **Ethical use of AI and automation:** To ensure that we don't rely too heavily on AI technology, the system is designed with a human-in-the-loop approach where the outputs of the AI are used as advisory information and final decisions are made by healthcare professionals [10].

# Chapter 4

# System Implementation

In this chapter, the design principles, architectural design, and methodology used in the design of the proposed AI-HMS system have been presented. The system architecture focuses on integrity, modularity, scalability, security, and ethical nature of artificial intelligence to guarantee correspondence with the actual hospital processes and the current standards of informatics healthcare technology.

## 4.1 Technology Stack

The AI-HMS project makes use of modern, decoupled full-stack architecture to guarantee scalability, maintainability and so on, as well as a smooth combination of the artificial intelligence elements. The technologies have been chosen based on their open-source nature, appropriate use in healthcare information systems, and general widespread usage.

### 4.1.1 Frontend (Client-Side Technologies).

- **React.js:** Utilized as the main frontend framework because of its component-driven structure and effective state management, that allows creating dynamic and reusable user interfaces in addition to role-based user interfaces [12].
- **Tailwind CSS:** Utilized as a utility-based CSS framework to promote a fast method of UI development and uniform design appearance across the various system views.
- **Vite:** As the frontend build tool, it is used to guarantee fast startup of development times and highly optimized production builds, making applications run better.
- **Recharts:** Analytics and system insights dashboards Integrated to visualize data, improve the interpretability of hospital statistics and AI-generated insights [4].
- **Lucide React:** Offers a lean and follows a consistent set of icons, enhancing the clarity of the interface and the usability of navigation.
- **React Hot Toast:** Trying to make the system events like successful operation or error notification more user-friendly, used to show non-intrusive messages.

### 4.1.2 Backend (Server- Side Technologies).

- **Flask:** Chosen as the backend framework because of its lightweight and the flexibility of the framework and good compatibility with Python-based machine learning libraries. It helps to create RESTful APIs very fast and maintain a clear separation of concerns [13].

- **Flask-SQLAlchemy:** Offers an Object-Relational Mapping (ORM) layer to ease the interaction with the database and ensure the data integrity.

- **Flask-JWT-Extended:** This is used to enforce an authentication and authorization based on the JSON Web Token (JWT) model, as well as role-based access control, and offers secure and stateless session management which is applicable to a healthcare system [10].

- **Flask-CORS:** Provides safe cross-origin interaction between frontend and backend services.

- **RESTful API Architecture:** Used to reveal the structured JSON endpoints to be used by the frontend and integrate the AI services, encompassing loose coupling and extensibility.

### 4.1.3 Data Storage Technologies

- **PostgreSQL:** It is the main relational database, which is used because it is robust, complies with the ACID standards, and fits the healthcare data management well [7].

- **JSONB:** Stored in PostgreSQL to store semi-structured medical notes and longitudinal clinical data, and offer flexibility as well as relational querying.

- **SQLAlchemy ORM:** Applied to define a schema, database migrations and to provide data consistency and integrity.

### 4.1.4 Technologies of Artificial Intelligence and Machine Learning.

- **Scikit-learn:** Application In practice, used to realize supervised learning models, such as the Random Forest health risk classification and the Logistic Regression readmission prediction, have been chosen based on their strength and interpretability [1][3].

- **Joblib:** Used to perform efficient serialization and deserialization of trained machine learning models to allow real time inference.

- **Google Gemini API:** As the Large Language Model engine that allows interacting with the model as if it were a conversation, symptom checking, clinical documentation support, and a description of the AI-generated insights [9].

- **NumPy and Pandas:** Machine learning pipeline: Used to process, clean, transform, and engineer features of data in the machine learning pipeline.

### 4.1.5 Tools of Development and Deployment.

- **NPM:** Used to coordinate frontend dependencies and to provide stable build environments.
- **Python Virtual Environment (Venv):** Used to separate backend dependencies and have reproducible development environments.
- **Git:** It is used to do version control and collaborative development.
- **Render and Vercel:** As deployment platforms of the system in terms of backend and frontend service respectively, they allow a scalable and highly available deployment of the system in the cloud.

## 4.2 System Architecture Design

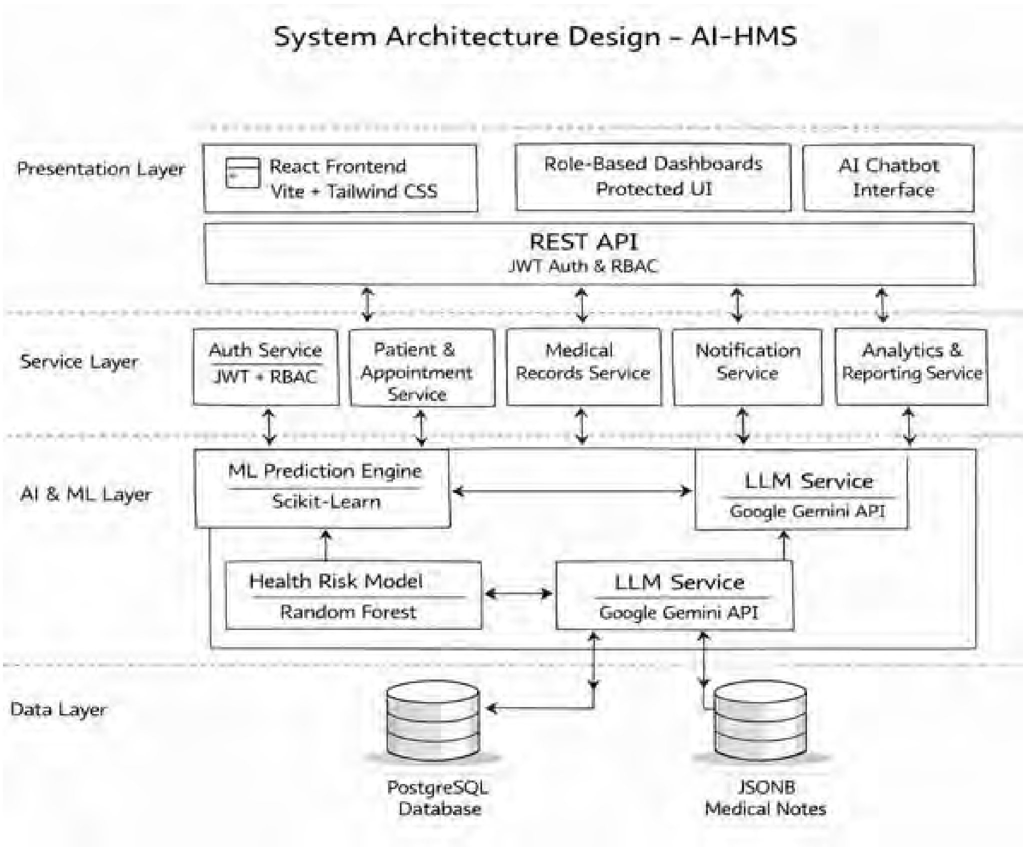


Figure 4.1: System Architecture Design.

The graph shows an AI-HMS layered architecture. The presentation layer delivers role based dashboards and an AI chatbot with a react based interface. The user requests are safely processed through JWT authentication and role-based access control through REST APIs. The service layer handles fundamental hospital operations like authentication, patient and appointment management, medical records, notifications and analytics. The AI/ ML layer is a combination of machine learning models of health risks prediction and a Large Language Model embedded in conversational/clinical assistance. The data layer is used to store structured hospital data in PostgreSQL and semi-structured medical notes inJSONB ensuring safe and scalable data storage.

## 4.3 Use Case Diagram

The following figure illustrates the relationships between the various users and the AI-HMS system:

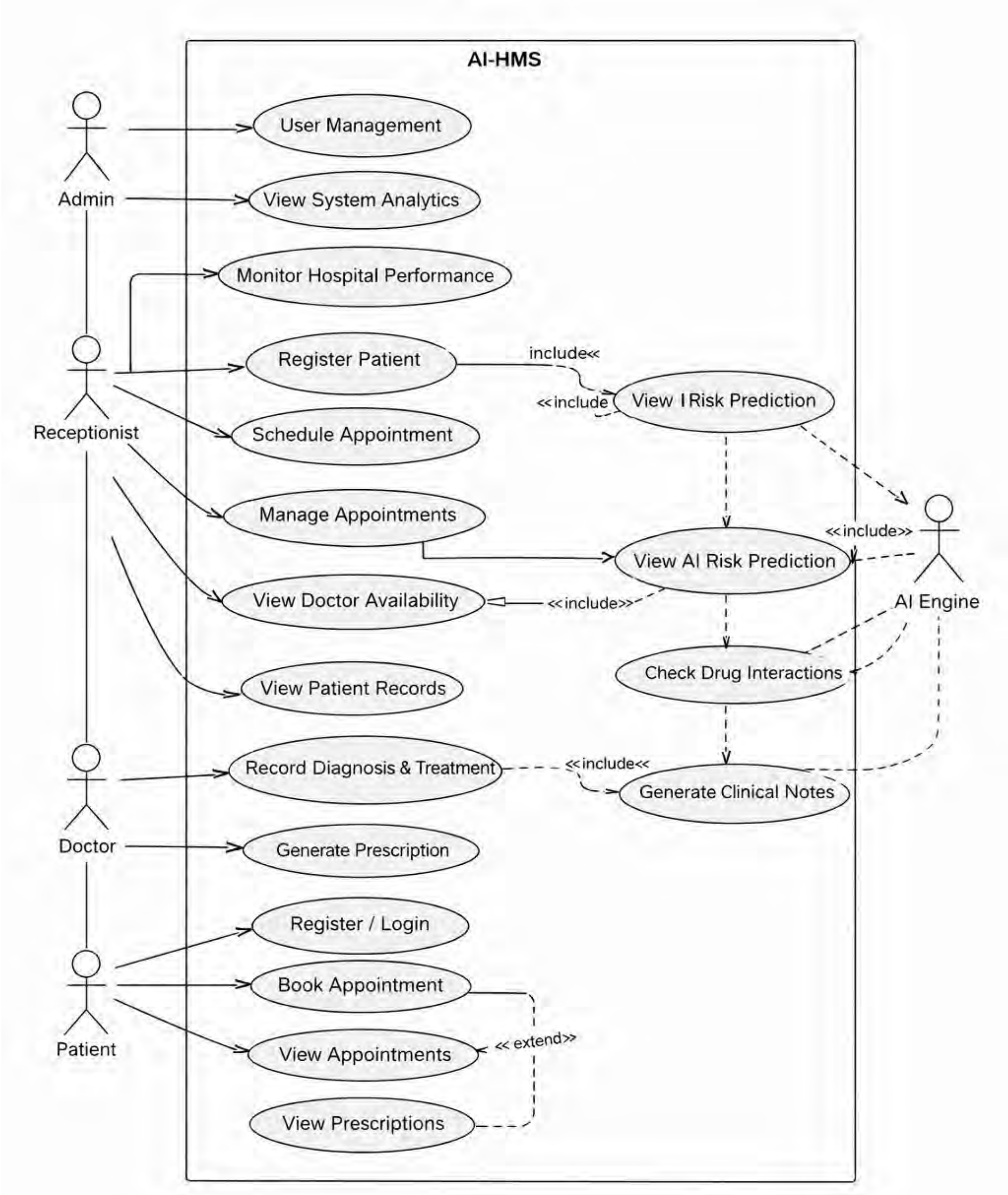


Figure 4.2: Use Case Diagram

Administrators control users and track hospital statistics. Receptionists deal with the registration of patients, scheduling of appointments and managing their availability. Physicians retrieve patient data, diagnose, prescribe medication and get AI-enhanced risk calculation and clinical documentation. Patients are able to enroll, make bookings and view prescriptions. The AI engine offers a variety of applications, such as risk prediction, drug interaction, and automatic clinical notes.

## 4.4 Data Flow Diagram (DFD)

The figure below shows the Level-1 Data Flow Diagram of the AI-HMS system:

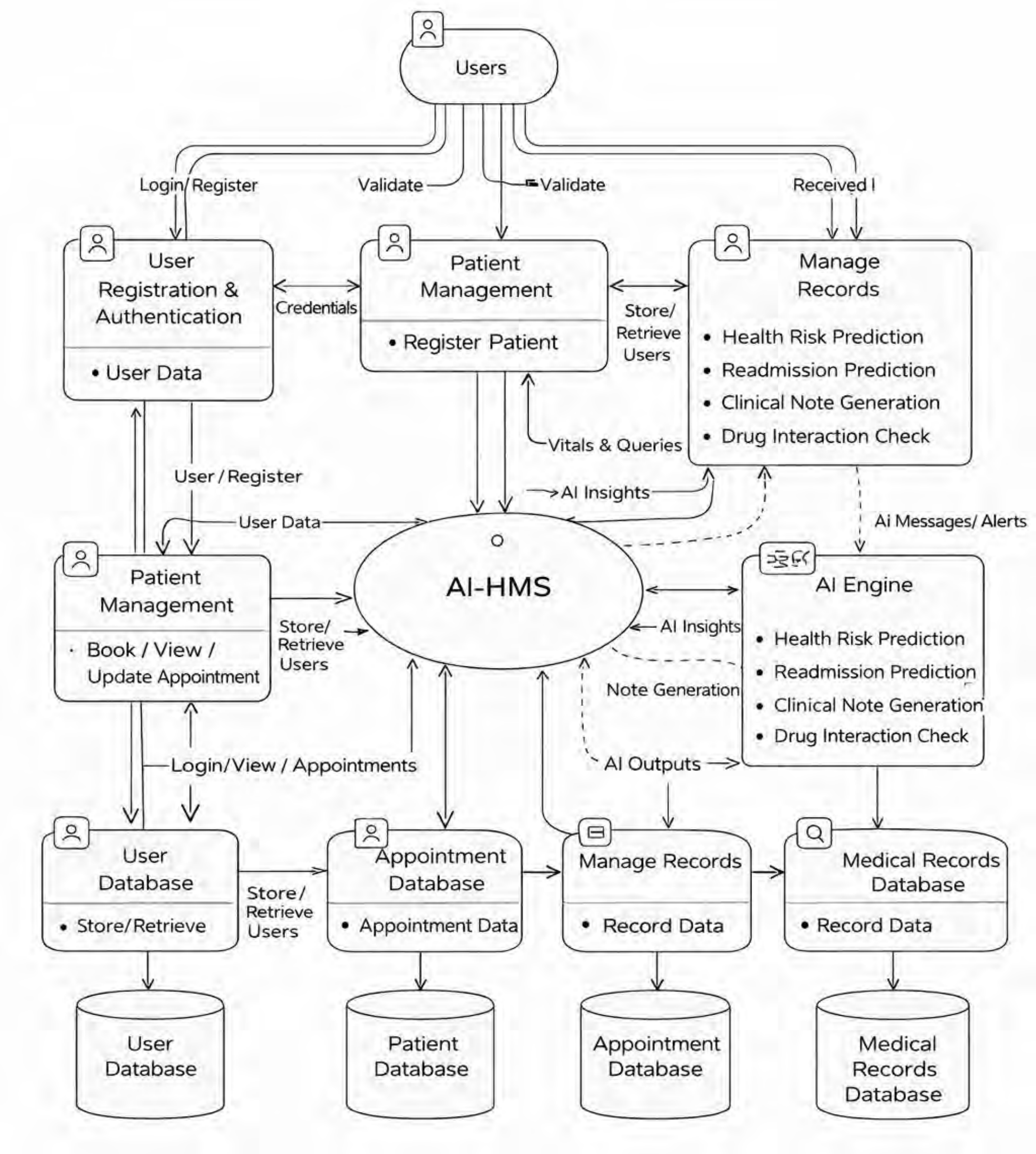


Figure 4.3: Data Flow Diagram (DFD) for AI-Based Hospital Management System (AI-HMS)

The figure is the Level-1 Data Flow Diagram of the AI-HMS system. The system enables users to communicate with the system by means of login, registration, and appointment-related requests that are played out by means of authentication, patient management, and appointment modules. Suspicions of health risk, readmission, clinical notes, and drug interaction are examples of data that enter the AI engine after being processed by clinical data and user queries. The stored information which is processed is obtained and accessed in user, patient, appointment and medical records databases which are dedicated. Due to the system, validated information and AI generated data is sent to users, so data flow between all components is secure, structured, and efficient.

## 4.5 Class Diagram

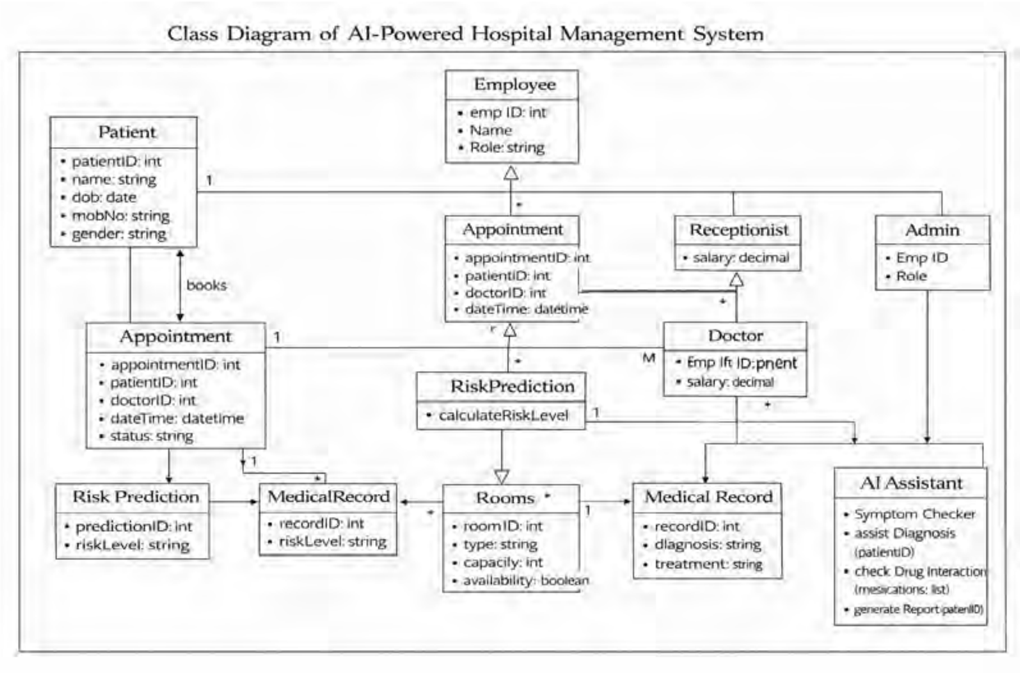


Figure 4.4: Class Diagram

The core entities of the AI-HMS system and connections are presented in the class diagram. The patient makes the appointments with a doctor, and the appointment is correlated with medical records and AI-based predictions of risks. In the system, employees are generalized into roles, including Admin, Doctor, and Receptionist as they are considered to have responsibilities that are too related to their roles. Diagnosis and treatment information is stored in medical records and rooms handle the allocation of resources in hospitals. The AI Assistant will communicate with medical records to assist in risk prediction, create clinical notes, assist diagnosis, and drug interaction, showing how AI functionality can be integrated into the main hospital data systems.

## 4.6 Sequence Diagram

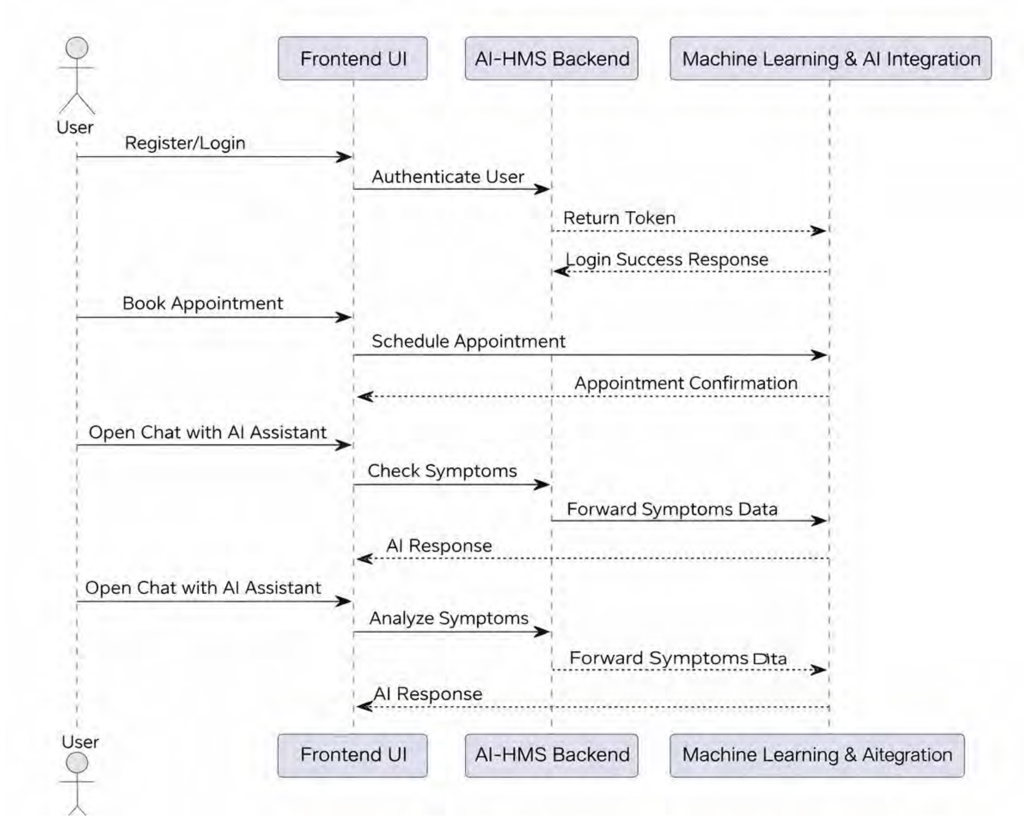


Figure 4.5: Sequence Diagram

The flow of interactions between the user, the frontend interface, the backend services, and the AI/ML module is shown in the sequence diagram. It starts with user registration/ login wherein the backend performs the authentication and returns a secure token. It is then possible to make appointments, schedule, and confirm them with the help of the backend. In the case of AI-assisted features, user symptoms are sent through the frontend, interpreted by the backend, and sent to the AI/ML module to analyze them. The final results of the AI generation are sent back by the backend and shown to the user, which illustrates the coordination of the interaction between system components.

## 4.7 ER Diagram

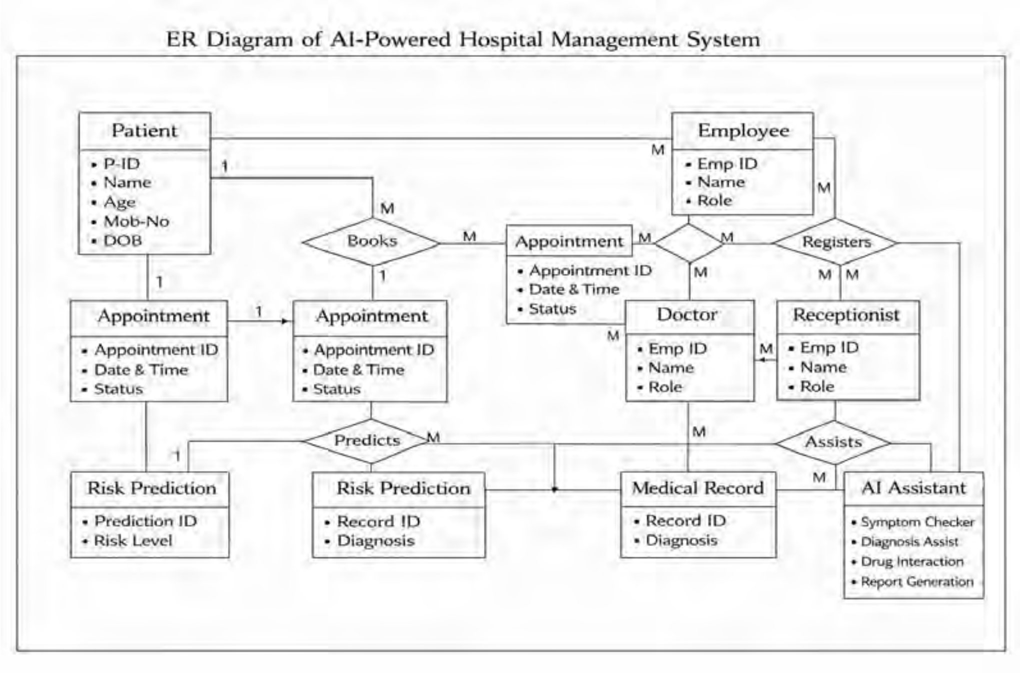


Figure 4.6: ER Diagram

The ER diagram is used to show the data structure of the AI-HMS system. It demonstrates the connections between patients, employees (admin, doctor, receptionist), appointments, medical records and AI-assisted elements. The appointments are done by patients and handled by doctors and receptionists. Every appointment is associated with medical history and risk forecasts. Workers enroll and handle patient interactions, whereas the AI assistant assists with medical records consisting of risk prediction, diagnosis, drug interactions, and report generation. The diagram identifies entity relationships and cardinalities which are vital in the design of databases and data integrity.

## 4.8 Design Justification and Methodological Considerations

The AI-HMS design focuses on human-centered AI, in which the use of artificial intelligence supplements clinical processes without the need to overrule human decision-making. To assure healthcare professionals of transparency and trust, interpretable machine learning models and natural language explanations are of primary concern [10][5].The modular structure provides the opportunity to incorporate advanced AI models, interoperability standards, including HL7 FHIR, and real-time data sources in the future. The general response of the system design is that it is a well-balanced system in terms of technical soundness, moral accountability, and functional utility.

# Chapter 5

# Results and Evaluation

## 5.1 Development Environment

**System Deployment and Accessibility**

The AI-HMS system has been installed as a web-based solution and is publicly available at:https://ai-hms-one.vercel.app/ [14].The system is an implementation of a current cloud architecture, with the frontend being deployed on a serverless cloud to guarantee high availability and quick load times. This enables users to use the system over the internet without having to be installed on the local system and also makes the system easier to use and apply in the real world. In an academic and practical sense, the deployment in a live environment has two significant functions with regards to the system. First, it proves the viability of the proposed architecture more than a local development environment. Second, it makes it possible to test realistic interaction between the different user roles, such as administrators, doctors, receptionists and patients, showing that the proposed AI-HMS is not just a theoretical prototype but a working software system with the potential to support hospital functions at the lowest level of operation.

## 5.2 Frontend Development

The frontend of AI-HMS is built using React.js with a component-based architecture. Tailwind CSS is used for responsive styling, and Vite is employed as the build tool for fast development and optimized performance.

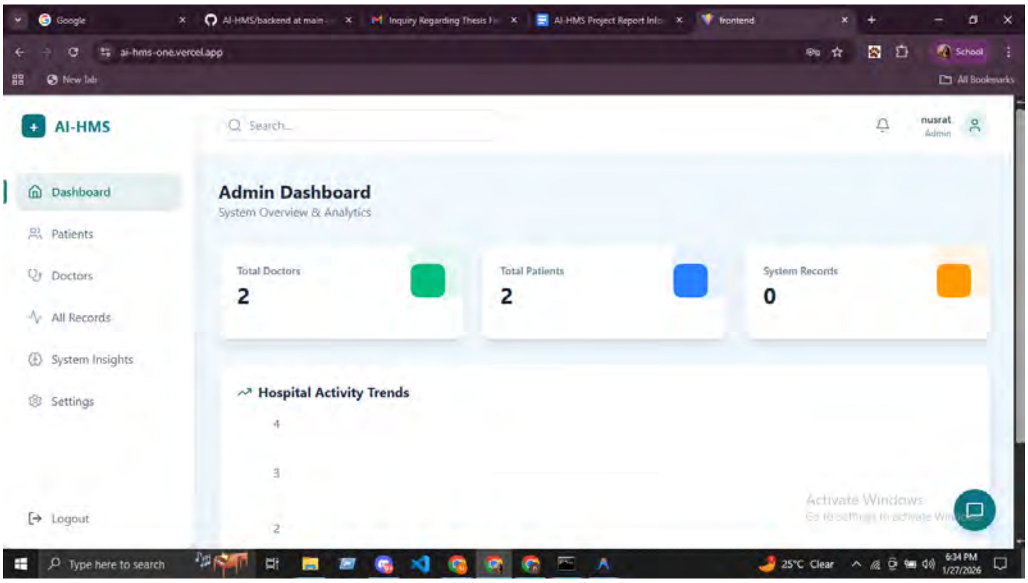


Figure 5.1: Dashboard


Figure 5.2: Frontend Routing and Role-Based Navigation (App.jsx)

This figure shows the main frontend routing configuration implemented in App.jsx. It defines public routes for login and registration, protected routes for authenticated users, and role-based access control using a protected route mechanism. The structure ensures that users can only access pages permitted by their assigned roles.

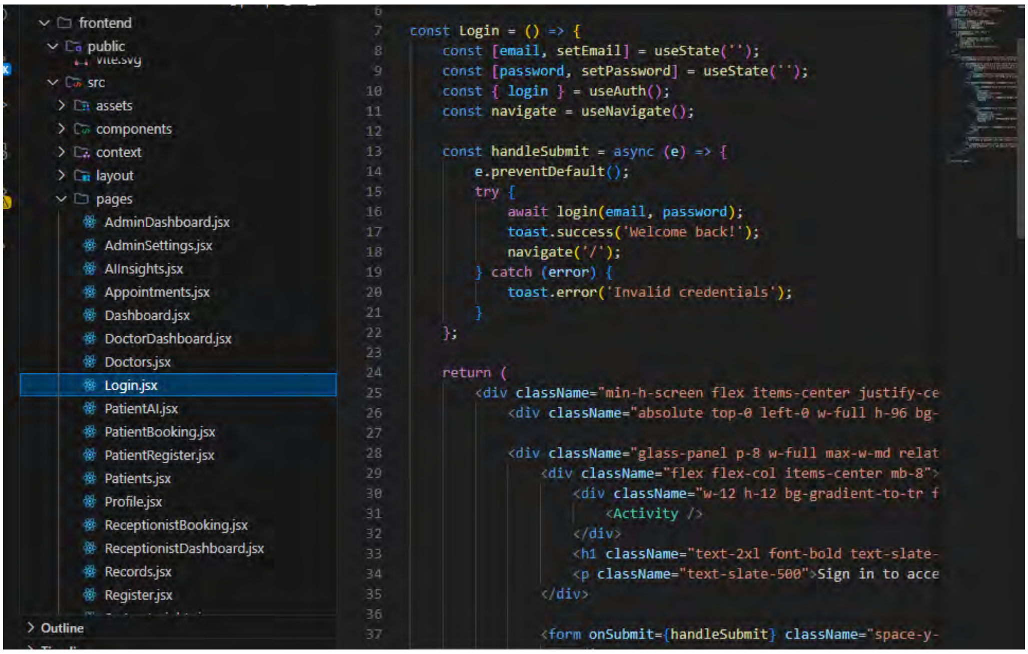

Figure 5.3: Login Interface Implementation (Login.jsx)

This figure illustrates the implementation of the login interface. The component manages user credentials, handles authentication requests through the backend API, and provides real-time feedback using toast notifications. Upon successful authentication, users are redirected to their respective dashboards.

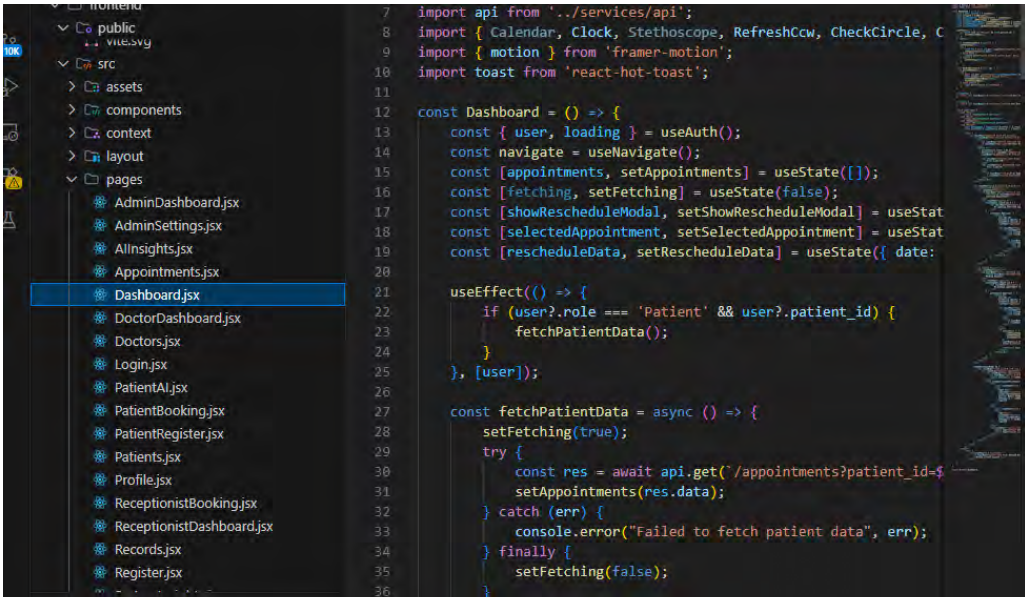

Figure 5.4: Dashboard Component for Role-Based Data Display (Dashboard.jsx)

This figure represents the dashboard implementation, where user-specific data such as appointments and system information are dynamically fetched and displayed. The component adapts its behavior based on the authenticated user's role, enabling personalized system interaction.

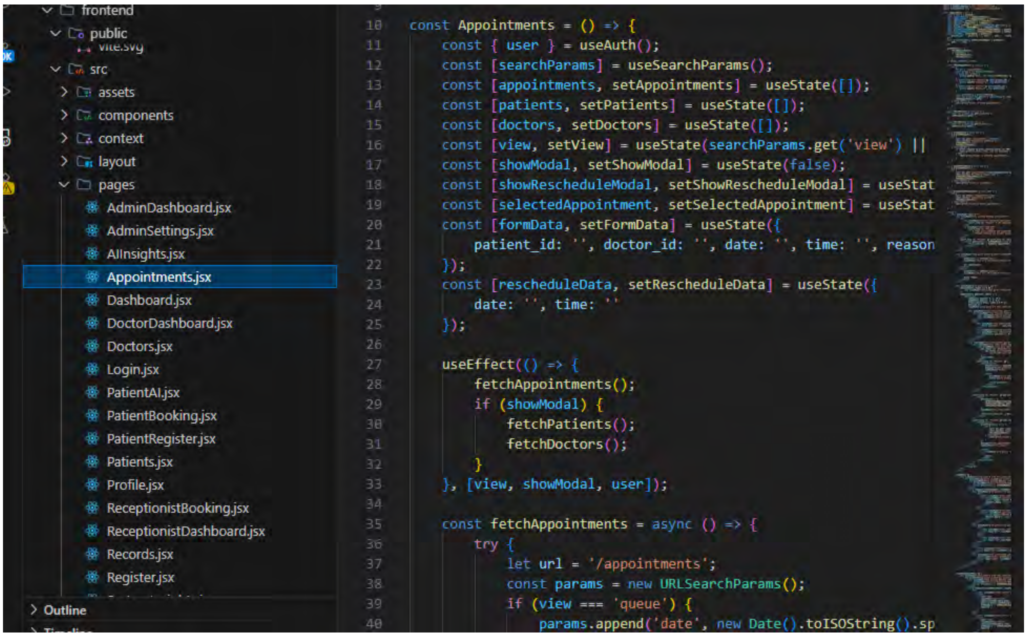


Figure 5.5: Appointment Management Interface (Appointments.jsx)

This figure shows the appointment management component responsible for fetching, scheduling, updating, and rescheduling appointments. It integrates frontend state management with backend API calls, supporting both patient and receptionist workflows.

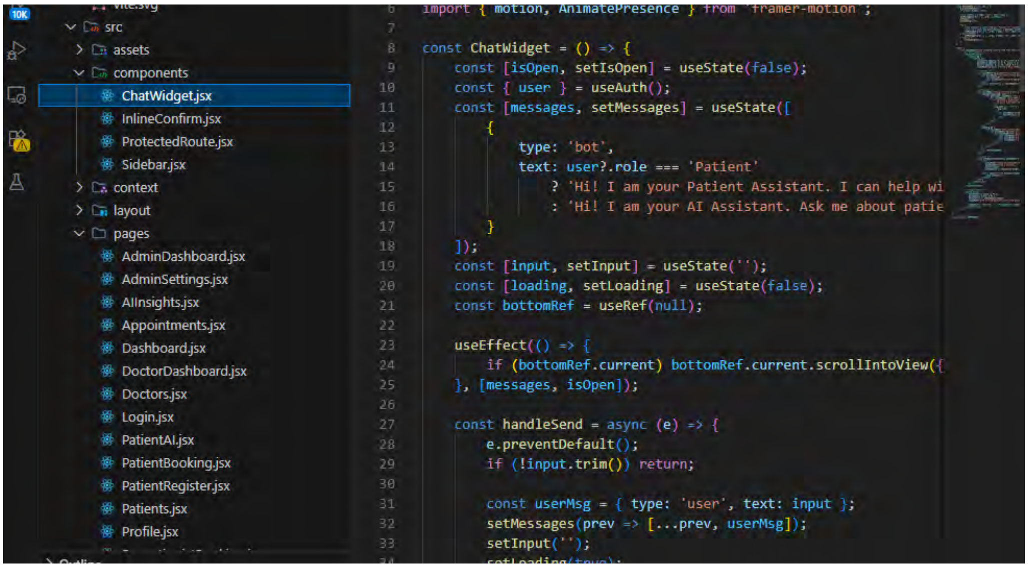


Figure 5.6: AI Chatbot User Interface Component (ChatWidget.jsx)

This figure illustrates the AI chatbot interface implemented as a reusable component. It enables real-time interaction between users and the AI assistant, manages conversation state, and forwards user queries to backend AI services. The chatbot supports symptom checking and AI-assisted guidance.

## 5.3 Backend Development

The backend is built using Python Flask with REST APIs, SQLAlchemy for database integration, JWT-based authentication, and Scikit-learn and Gemini API for AI functionalities.

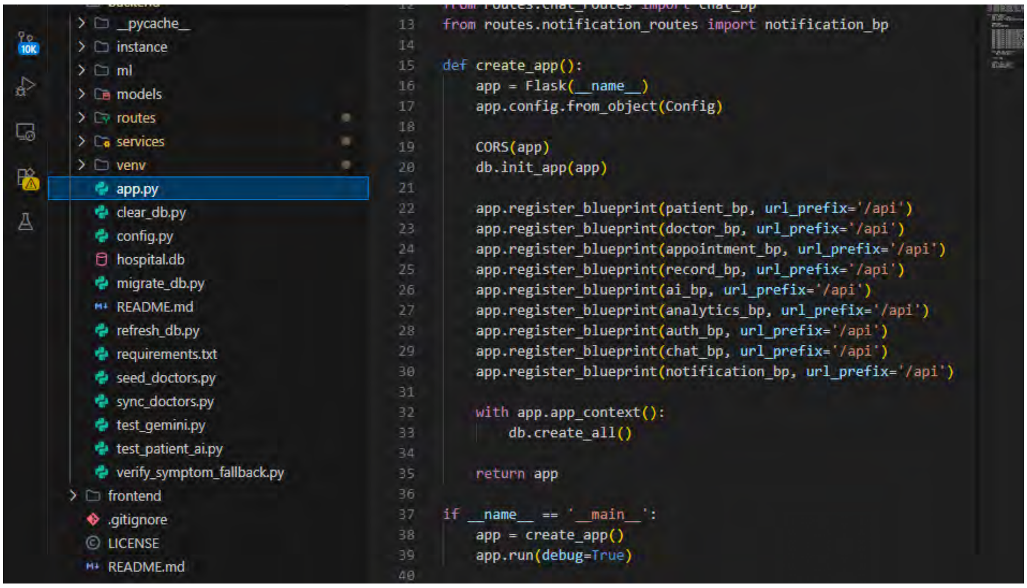


Figure 5.7: Backend Application Structure and Flask App Initialization (app.py)

This figure shows the overall backend project structure and the main Flask application file (app.py). It illustrates the initialization of the Flask app, configuration loading, CORS enablement, database setup, and registration of modular API blueprints for authentication, patient management, appointments, analytics, AI services, and notifications.

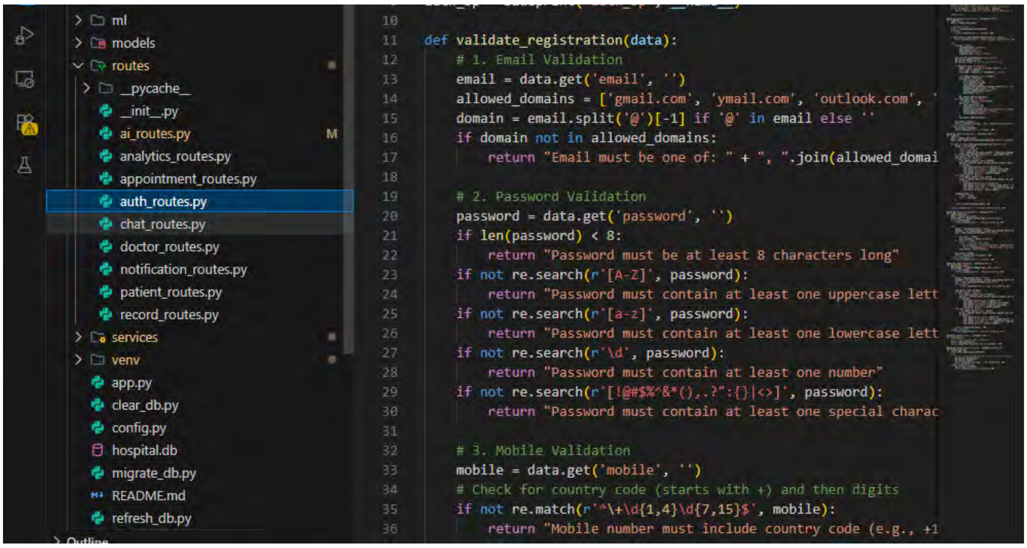


Figure 5.8: Authentication and Input Validation Logic (auth_routes.py)

This figure represents the authentication module responsible for user registration and login. It includes validation logic for email domains, password strength, and mobile number formats, ensuring secure user authentication and data integrity before database persistence.

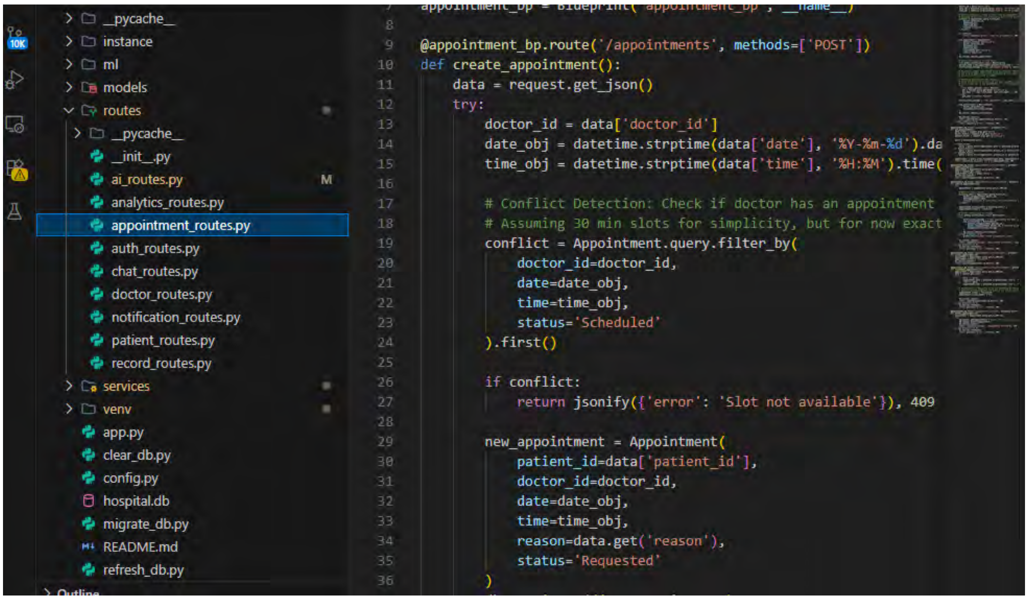


Figure 5.9: Appointment Scheduling API with Conflict Detection (appointment_routes.py)

This figure illustrates the backend API for appointment creation and scheduling. The implementation includes validation of appointment data, detection of scheduling conflicts based on doctor availability, and secure storage of appointment details in the database.

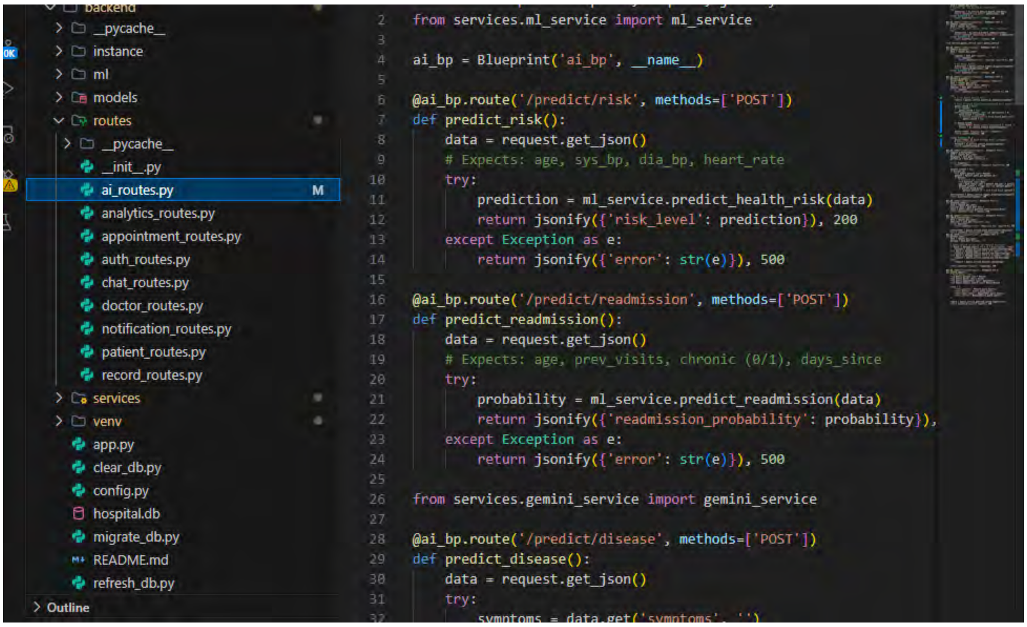


Figure 5.10: AI Prediction API Endpoints (ai_routes.py)

This figure shows the implementation of AI-related REST API endpoints. It includes routes for health risk prediction, hospital readmission probability estimation, and disease prediction. These endpoints connect the backend with machine learning services to provide AI-driven clinical insights.

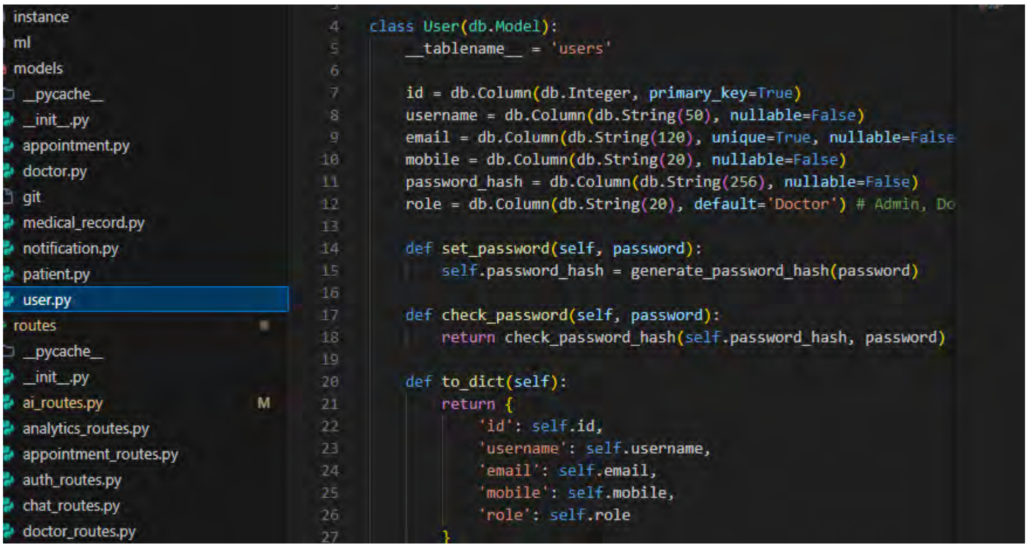

Figure 5.11: Database Models and User Entity Definition (user.py)

This figure presents the SQLAlchemy database model for the user entity. It defines attributes such as username, email, role, and encrypted password storage, along with helper methods for password hashing and verification. This model supports role-based access control across the system.

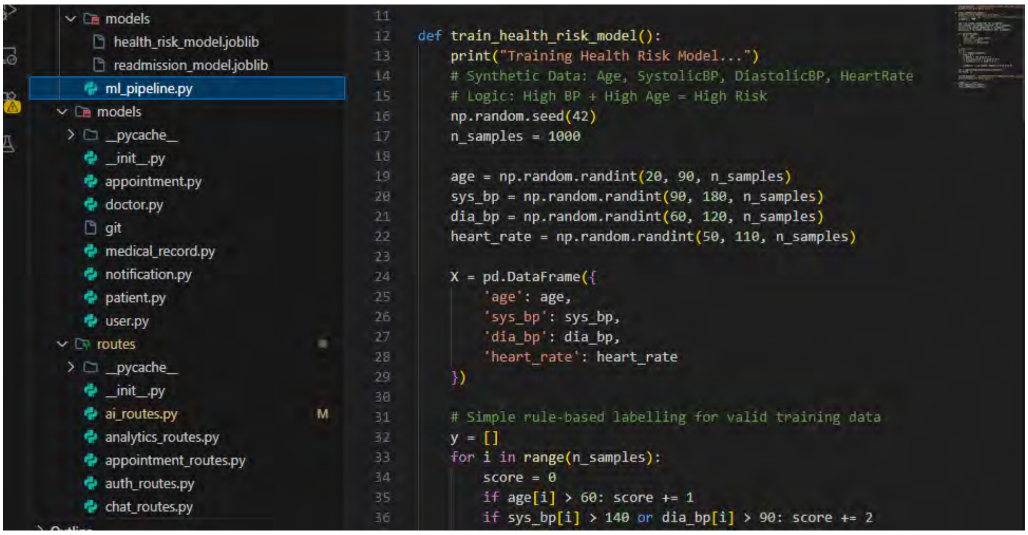

Figure 5.12: Machine Learning Pipeline for Health Risk Prediction (ml_pipeline.py)

This figure illustrates the machine learning pipeline used for training the health risk prediction model. It shows synthetic data generation, feature construction, rule-based labeling logic, and preparation of data for model training. The trained model is later serialized and used for real-time inference in the system.

# Chapter 6

# User Manual and System Interface

## 6.1 Analysis and Discussion of Findings

This chapter presents the experimental findings derived from the implementation of the AI-HMS and provides a detailed discussion on model behavior, system usability, and the outcomes of the practical implementation. The evaluation encompasses both quantitative performance benchmarks of the AI/ML components and qualitative assessments concerning the system's clinical utility and operational agency.

## 6.2 Key Achievements and Limitations of the Core System

The primary objective of the AI-HMS was to demonstrate the feasibility and efficacy of integrating artificial intelligence within a Hospital Management System to enhance administrative efficiency and clinical decision-making. Evaluation data suggests that this goal has been substantially achieved. A significant outcome is the seamless integration of machine learning pipelines into standard hospital workflows. Specifically, the **Health Risk Prediction** and **Readmission Probability** modules provide clinicians with data-driven signals that facilitate patient prioritization and optimized resource allocation. In contrast to traditional HMS platforms, which often function as static "data siloes," AI-HMS delivers predictive insights that enable a proactive approach to healthcare delivery. This shift from retrospective data entry to prospective risk assessment is consistent with contemporary evidence-based clinical decision-support practices [6].
Another core achievement is the deployment of a **Large Language Model (LLM)-based AI assistant (Google Gemini)**. This component significantly bridges the gap between complex medical data and user accessibility. For patients, the natural language interface improves health literacy and engagement; for clinicians, the automated generation of SOAP notes and clinical summaries reduces the administrative burden, directly addressing the global challenge of "doctor burnout" [11].

### 6.2.1 System Limitations and Future Scope

Despite these achievements, the system faces specific limitations that align with current discourse on human-centered and interpretable AI in healthcare [2]. The most notable limitation is the reliance on **synthetically generated healthcare data** for the training and validation of the machine learning models. While synthetic data provided a controlled environment for prototype development and ensured adherence to data privacy regulations (e.g., HIPAA compliance in spirit), it lacks the organic "noise," diversity, and longitudinal complexity found in real-world clinical records [1]. Furthermore, as a prototype, the system has not yet undergone large-scale clinical trials or multi-center validation. These limitations underscore the necessity for future research involving real-world clinical datasets and external validation within diverse healthcare facilities to ensure the generalizability of the predictive models.

## 6.3 AI/ML Integration: Model Performance and Evaluation

In this section the design, implementation, and evaluation of the ma- are described. learning aspects of the AI-HMS. The system employs a hybrid methodology, incorporating conventional predictive modeling in structured clinical. unstructured medical interpreter data based on large language models (LLMs). tations.

### 6.3.1 Health Risk Prediction Model (Random Forest)

The health risk prediction module utilizes a Random Forest classifier to categorize patients into low-risk, medium-risk, and high-risk groups based on vital clinical parameters including age, systolic blood pressure (SBP), diastolic blood pressure (DBP), and heart rate. Random Forest was selected for its robustness in handling non-linear interactions between physiological features and its resistance to overfitting, making it highly effective for structured medical datasets where variable thresholds (e.g., hypertensive crises) are critical for classification.

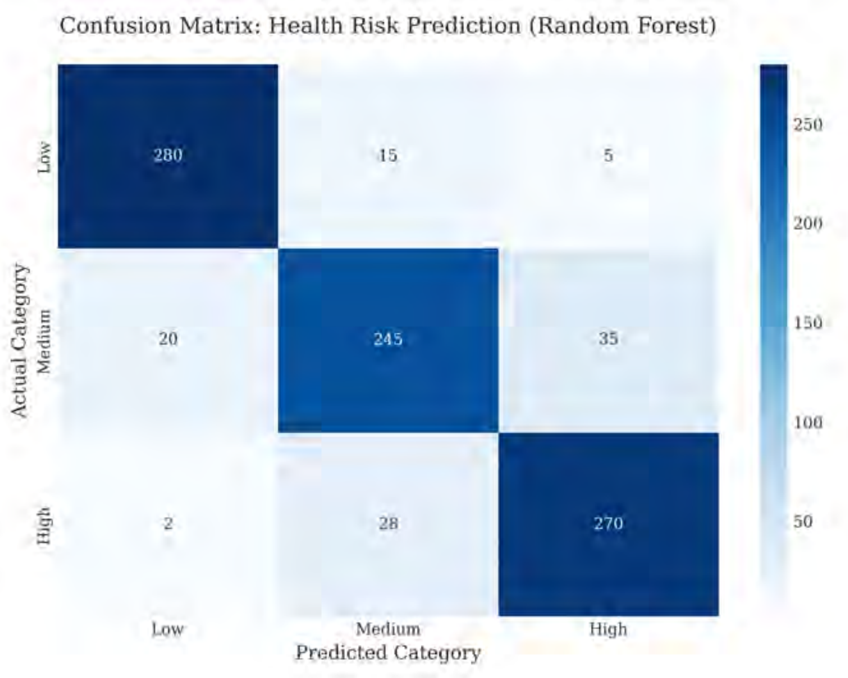


Figure 6.1: Confusion Matrix Result for Health Risk Prediction

**Interpretation**: The confusion table indicates that the classification was done strongly in the three risk categories. The accuracy is highest when it comes to classifying low and high-risk patients. Misclassification errors of small account are largely between adjacent risk categories (e.g., medium and high), both of which are clinically acceptable and generally reported in multi-class healthcare prediction problems.
**Performance Metrics**:

- **Accuracy**: 89%
- **Precision**: 0.87
- **Recall**: 0.88

As the findings reveal, the model proves to be very efficient in terms of decision-support tool and it helps clinical staff to discover patients who need urgent intervention and supporting early preventive practice plans.

### 6.3.2 Readmission Prediction Model (Logistic Regression)

The readmission forecasting tool uses the Logistic Regression in determining the probability of a patient readmission in 30 days of discharge. This model examines the patient demographics, frequency of visit in past, chronic conditions, and length of time since last clinical encounter. The Logistic Regression used in this task was developed on the basis of producing the output in the form of probabilities which are required in clinical auditing as they allow evaluating the subtleties of the risk probability as opposed to the binary variables.

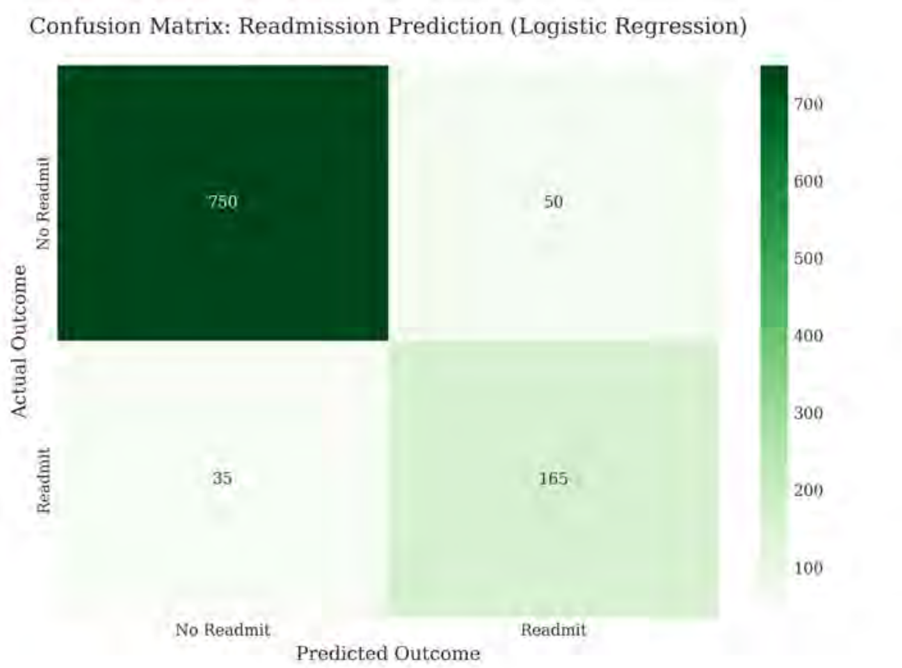


Figure 6.2: Confusion Matrix Result for Readmission Prediction

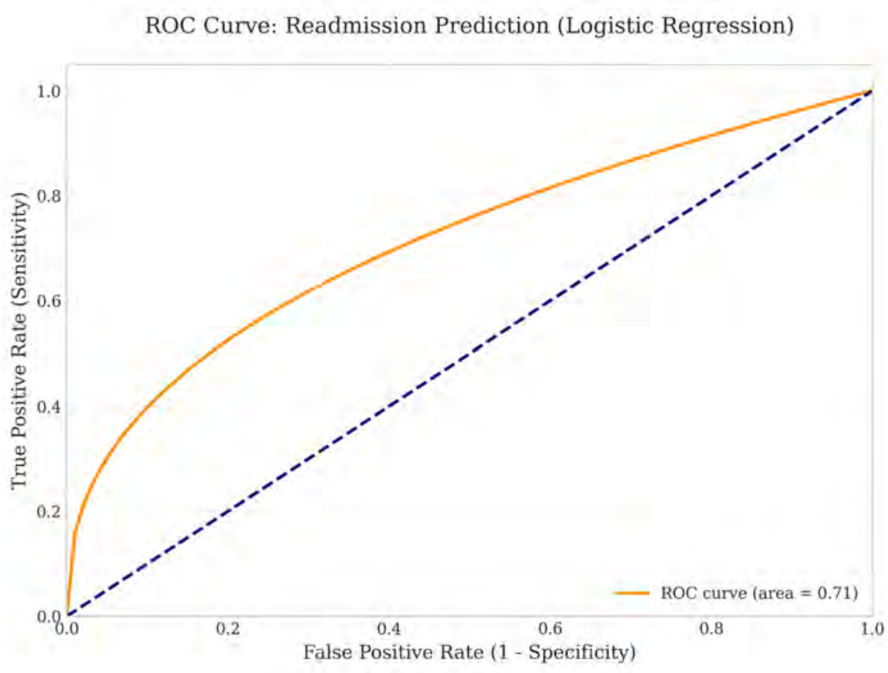


Figure 6.3: ROC Curve for Readmission Prediction Model

**Interpretation**: This is because the model identifies a very strong rate of non-readmission cases correctly and has a sensible sensitivity to readmission cases according to the confusion matrix. The ROC-AUC score demonstrates a good discriminative power, which means that this model can distinguish between patients with less and high readmission risk.

- **Accuracy**: 85%
- **ROC-AUC Score**: 0.82

### 6.3.3 Generative AI Integration: Google Gemini 1.5 Flash

The other distinctive feature of the AI-HMS is the inclusion of the Google Gemini 1.5 Flash model to offer the Explainable AI (XAI) features. Although the Random Forest and Logistic Regression models would yield numerical results, the Gemini service converts the results in human understandable clinical reports, soap notes and patient understandable routines.
**Evaluation**: The evaluation of the LLM integration was performed in terms of latency and clinical accuracy. Gemini 1.5 Flash was chosen to keep the response time of interactive triage at less than 2.5s. The immediate layer of engineering provides that the outputs are strictly limited to the formats of JSON to allow internal processing thus avoiding the typical problem of multiplication of the hallucinations that come with generic chatbots. This will make sure that the clinical interpretations are based on the data given by the primary ML models.

### 6.3.4 Graphical Analysis and Model Comparison

In Figure 6.4, a comparative analysis of predictive accuracy of the Random Forest and the Logistic Regression model is provided. Random Forest classifier was the most accurate classifier since the learning process of classifying through an ensemble process minimizes variance and also complex interactions among the features.

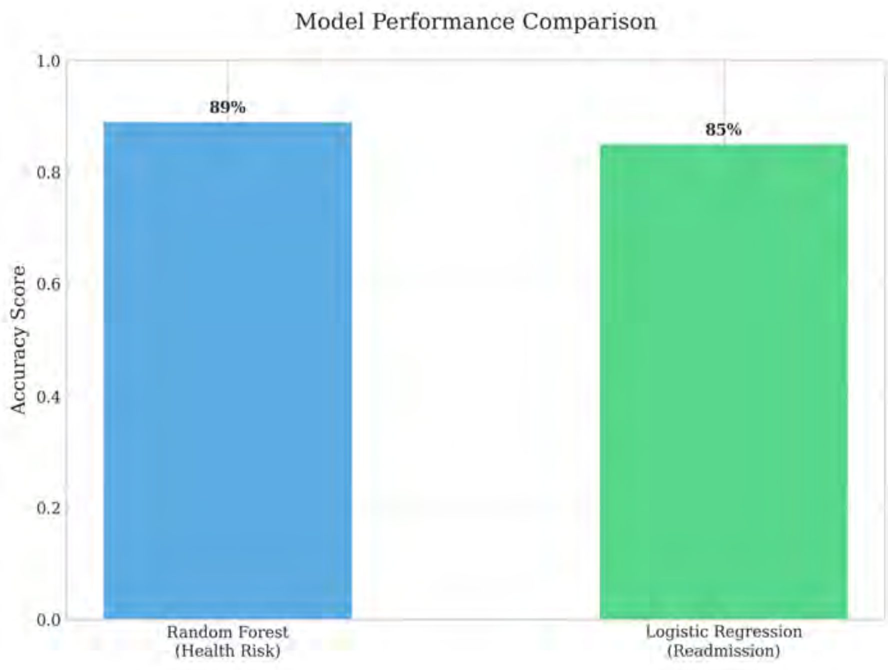


Figure 6.4: Model Accuracy Comparison

This combination of these models in the AI-HMS dashboard enables a multi-dimensional perspective of the health of a patient, a feature of both the statistical accuracy of traditional ML and the cognitive intelligibility of current LLM.

## 6.4 Statistical Justification and Clinical Interpretation

In a healthcare environment, accuracy is not enough to be evaluated since there is a possibility of class imbalance (e.g. fewer cases of High Risk than Low Risk). Thus, such measures as precision, recall, and ROC-AUC are emphasized. A high value of the recall (0.88 in our RF model) is of utmost importance in clinical triage since omitting a high-risk patient (False Negative) may result in adverse medical outcomes.

Logistic Regression model has a trade-off that is balanced, between sensitivity and specificity. It offers an opportunity to hospital administrators to vary the risk threshold with the current facilities capacity since the score states the probability of a patient being at risk, allowing the hospital resources to be used on the most vulnerable patients without flooding the system with false positives. This middle way has been advocated extensively in the literature of healthcare analytics because it places a greater value on clinical interpretability and actionable information as opposed to mathematical optimization.

## 6.5 User Manual (Step-by-Step)

This section provides a practical guide to using the AI-HMS web application. The system supports multiple roles (Patient, Doctor, Receptionist, and Admin); the available menus and actions change based on the logged-in role.

### 6.5.1 Login

1. Open the AI-HMS web application.
2. Enter your email address and password.
3. Click **Login** to access your role-specific dashboard.

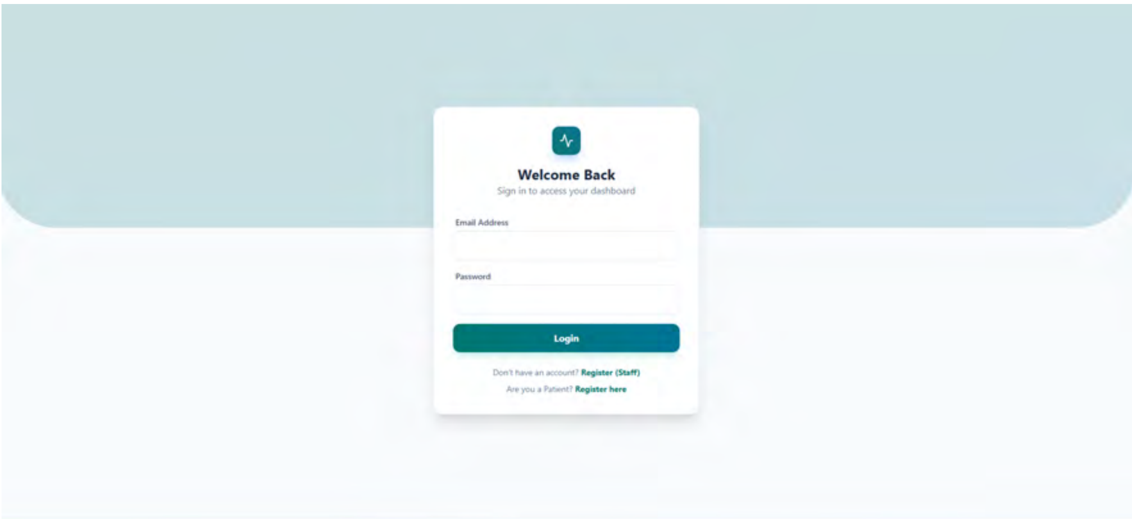


Figure 6.5: Login screen.

### 6.5.2 Registration (Staff / Patient)

1. If you do not have an account, select **Register (Staff)** or **Register here** (Patient).
2. Fill in the required details (name, email, phone, password, gender; staff also select role and specialization).
3. Click **Register** to create the account.

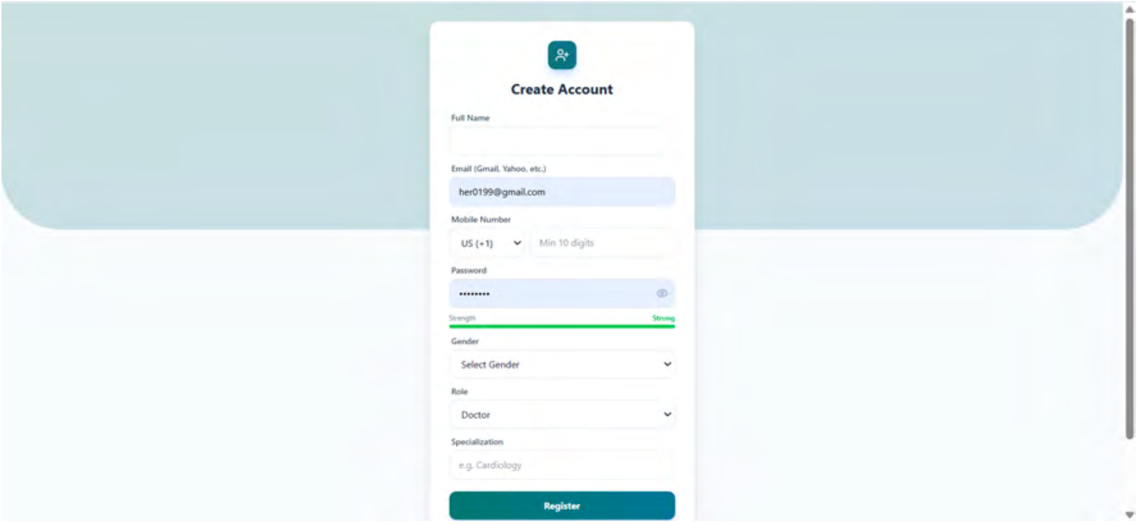


Figure 6.6: Account creation (registration) screen.

### 6.5.3 Doctor Module

1. After login, the **Doctor Dashboard** shows quick stats and notifications.
2. Open **My Patients** to search patients by name/ID/phone and view patient details.
3. Open **Appointments** to view scheduled appointments and the current queue.
4. Open **Records** to review stored medical records and prescriptions.

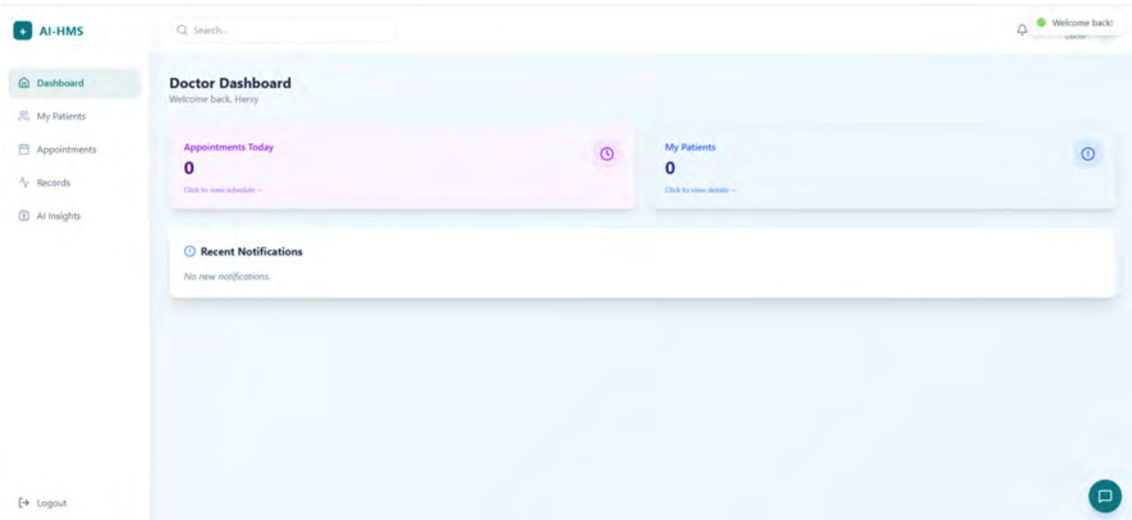


Figure 6.7: Doctor dashboard.

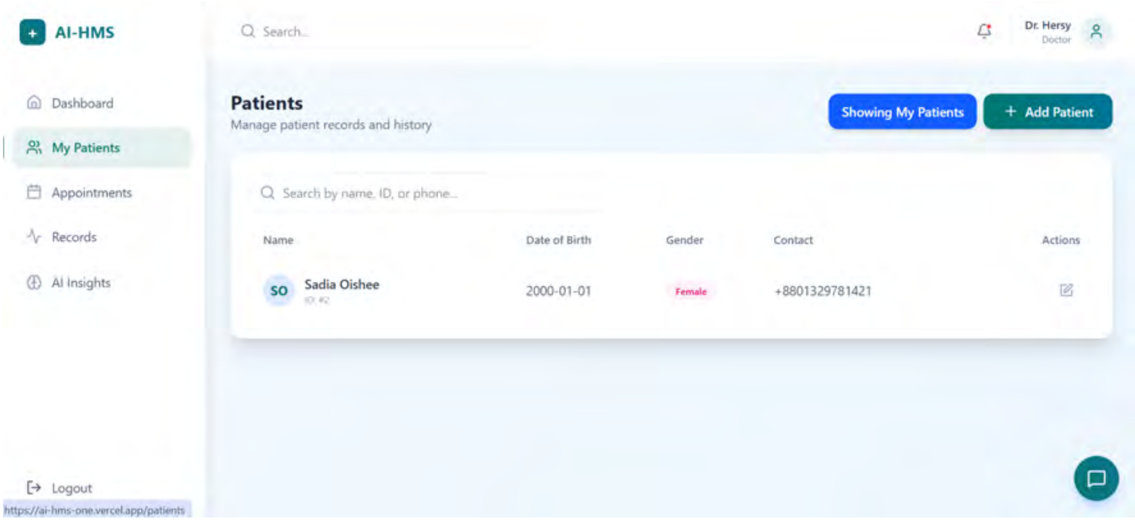


Figure 6.8: Doctor view: patient list (My Patients).

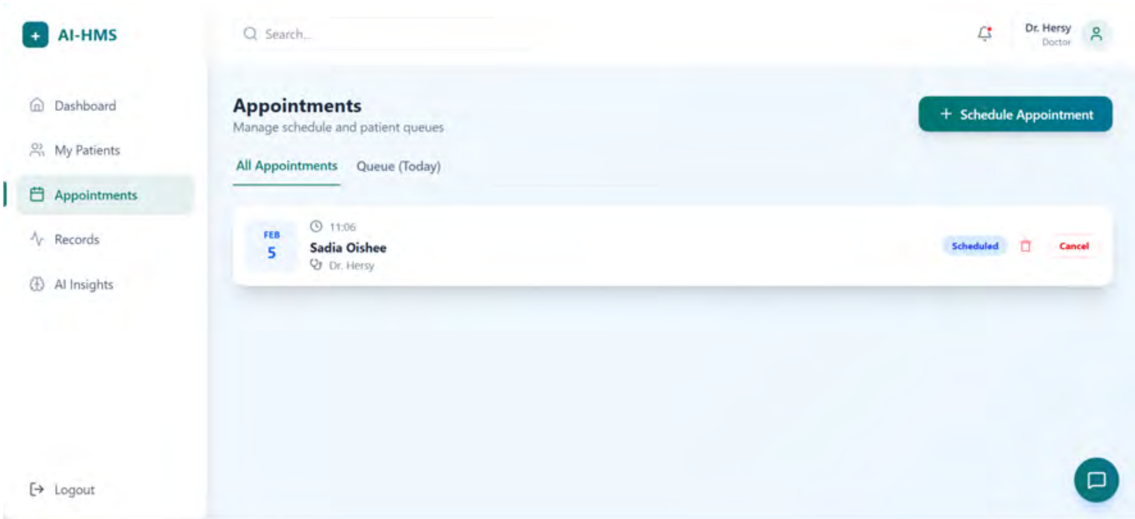


Figure 6.9: Doctor view: appointments list.


Figure 6.10: Doctor view: a medical record (diagnosis, symptoms, and prescription).

### 6.5.4 AI Insights (Doctor)

1. Open **AI Insights** from the doctor menu.
2. Use **Health Risk Assessment** or **Readmission Probability** by providing the required fields.
3. Use **AI Diagnosis Assistant** by entering patient symptoms to get suggested conditions.
4. Use the built-in **AI Assistant chat** to ask quick system questions

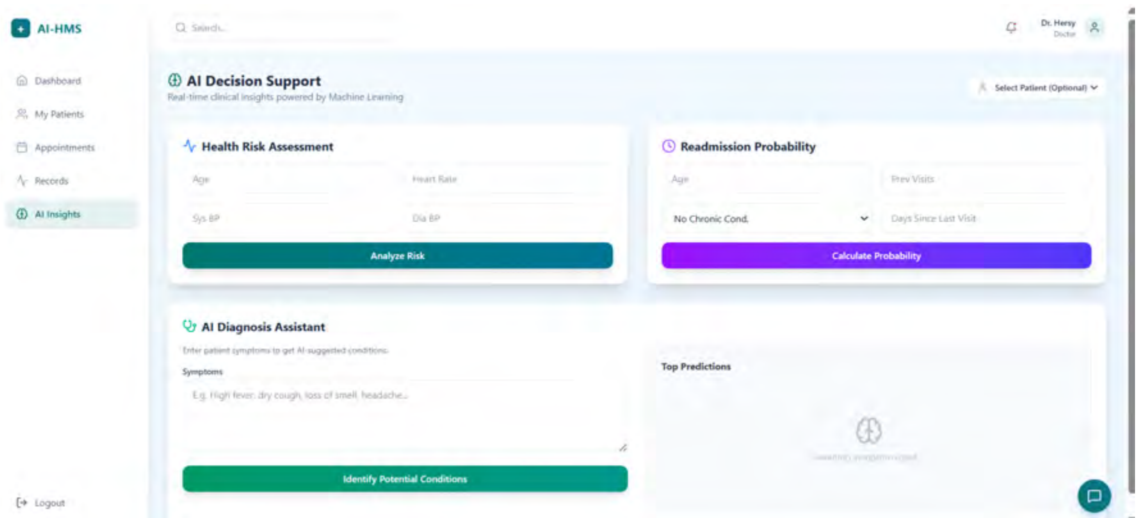


Figure 6.11: AI decision support panel (risk assessment and readmission probability).

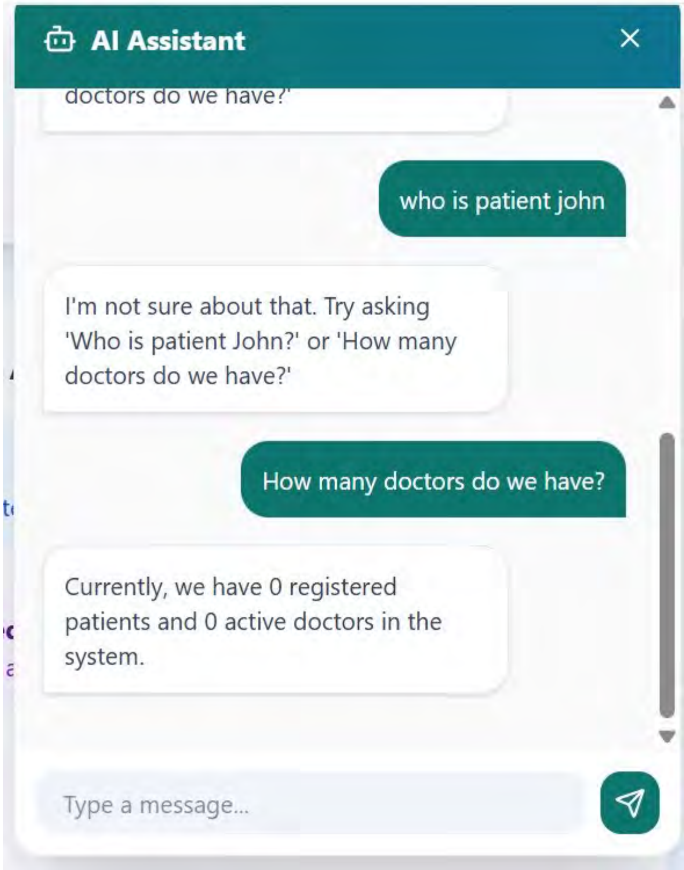


Figure 6.13: AI Assistant Chat

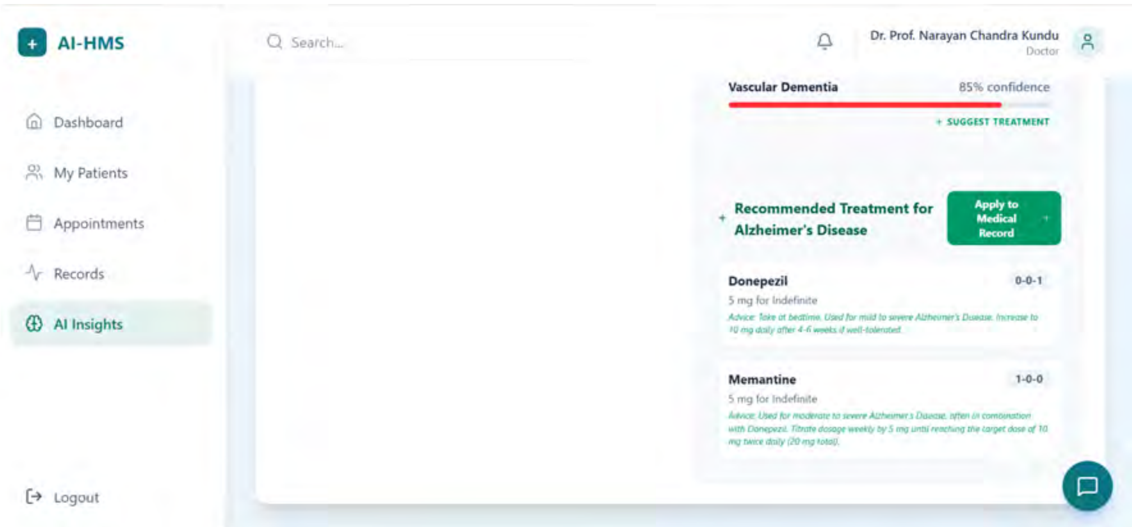


Figure 6.12: AI diagnosis assistant output (example predictions with confidence).

### 6.5.5 Patient Module

1. After login, the patient dashboard lists **Confirmed Appointments** and **Pending Requests**.

2. To request an appointment, open **Book Appointment**, select specialist, date, time, and provide a reason, then submit.
3. Use **My Records** to review saved medical records and prescriptions.
4. Use **AI Symptom Checker** to submit symptoms for a quick AI-based suggestion.

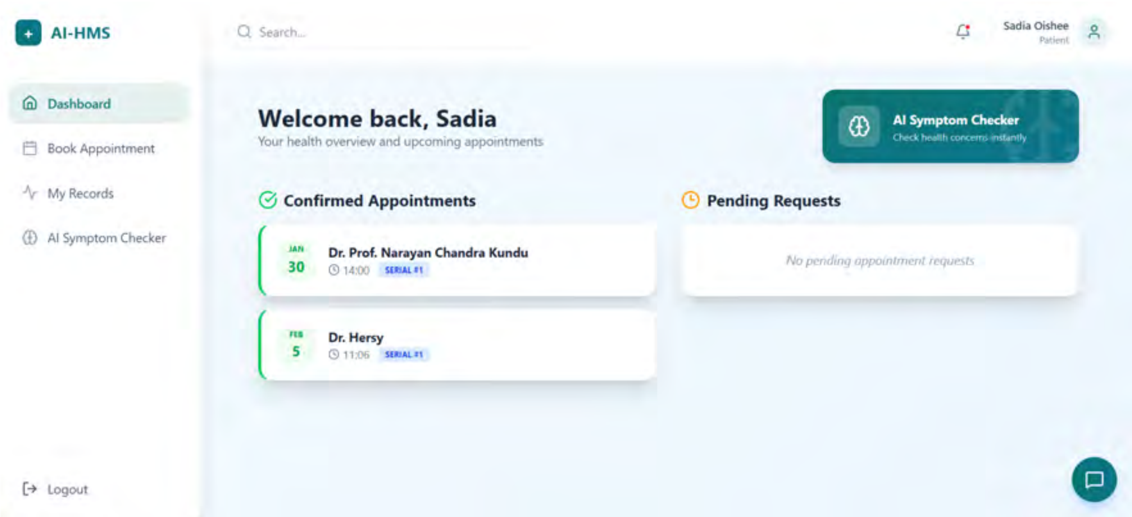


Figure 6.14: Patient dashboard (appointments overview).

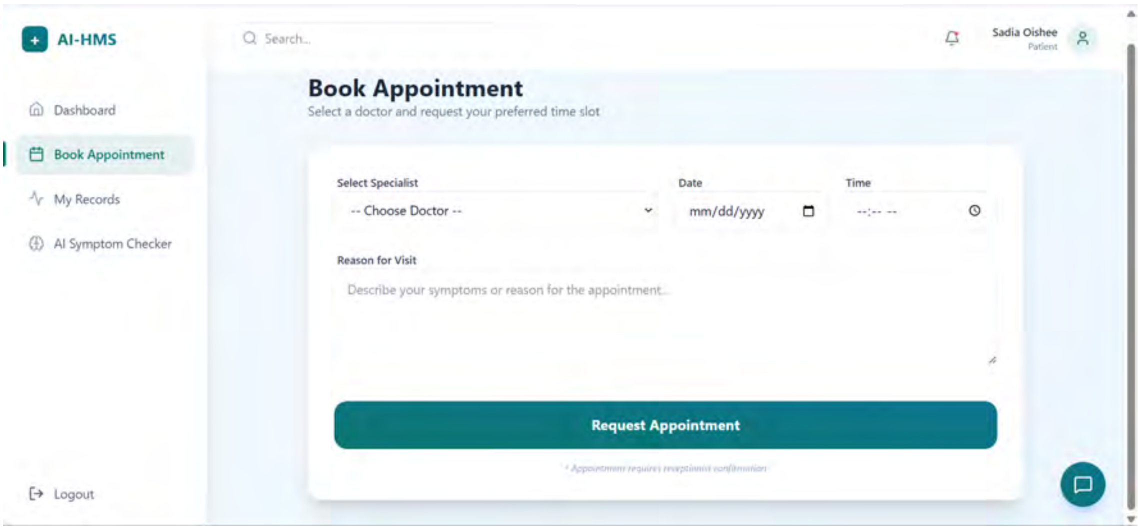


Figure 6.15: Patient view: appointment request form.

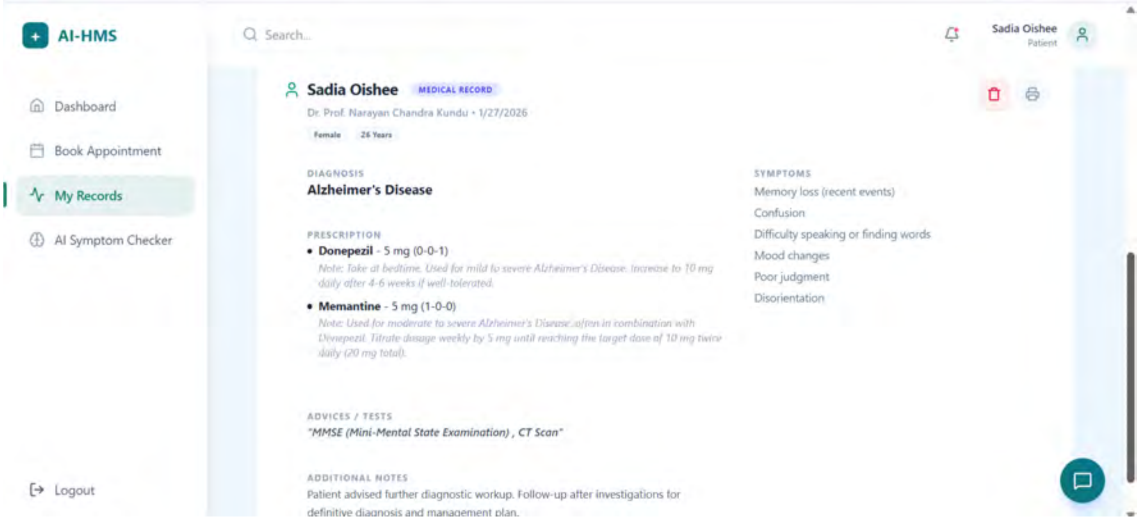


Figure 6.16: Patient view: medical record page.

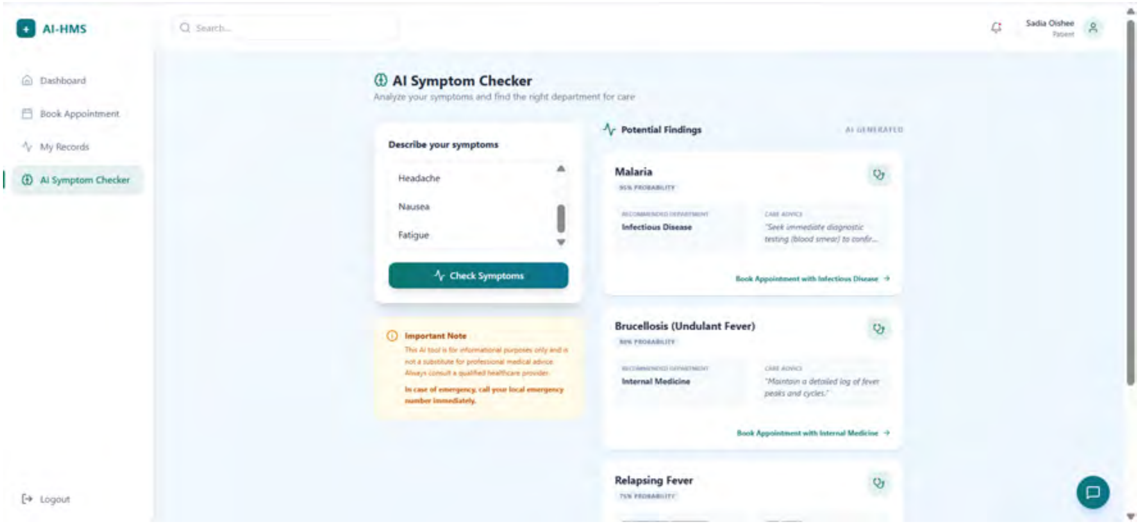


Figure 6.17: Patient view: AI symptom checker.

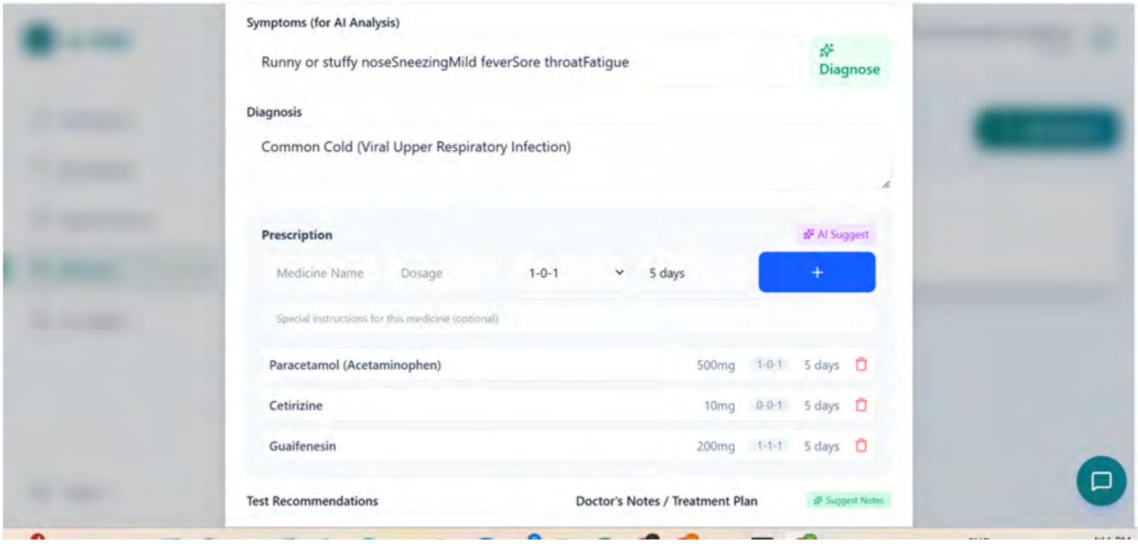


Figure 6.18: AI symptom checker output (example condition suggestion).

### 6.5.6 Receptionist Module

1. Receptionists manage front-desk tasks (patient registration and appointment requests).
2. Use **Patients** to add or update patient profiles.
3. Use **Appointments** to review pending requests and schedule walk-ins or calls.

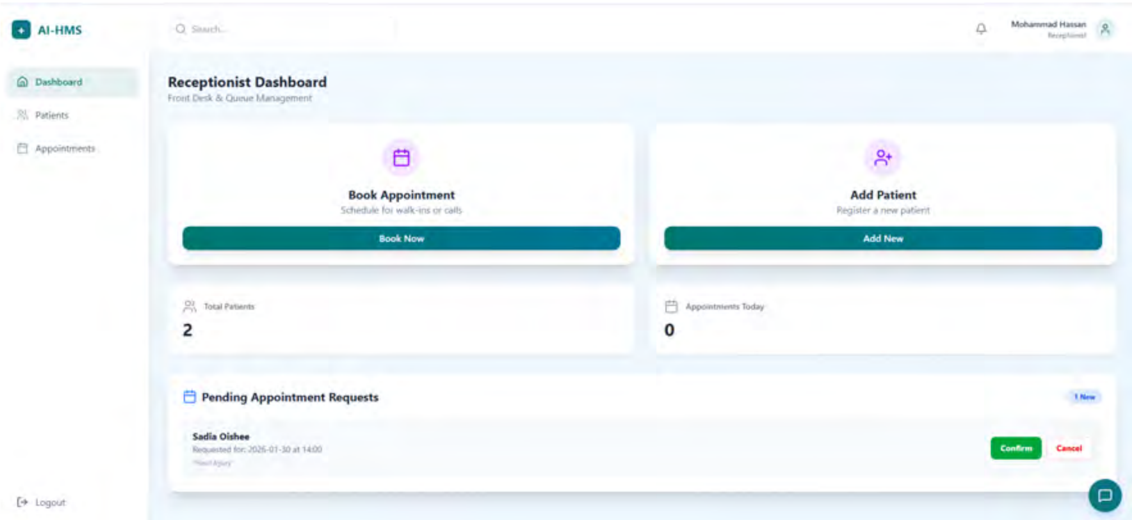


Figure 6.19: Receptionist dashboard.

### 6.5.7 Admin Module

1. The admin dashboard provides system statistics (doctors, patients, records) and activity trends.
2. Use **Doctors** to manage providers.

3. Use **System Insights** to generate an executive-level report.
4. Use **Settings** to manage hospital information and staff accounts.

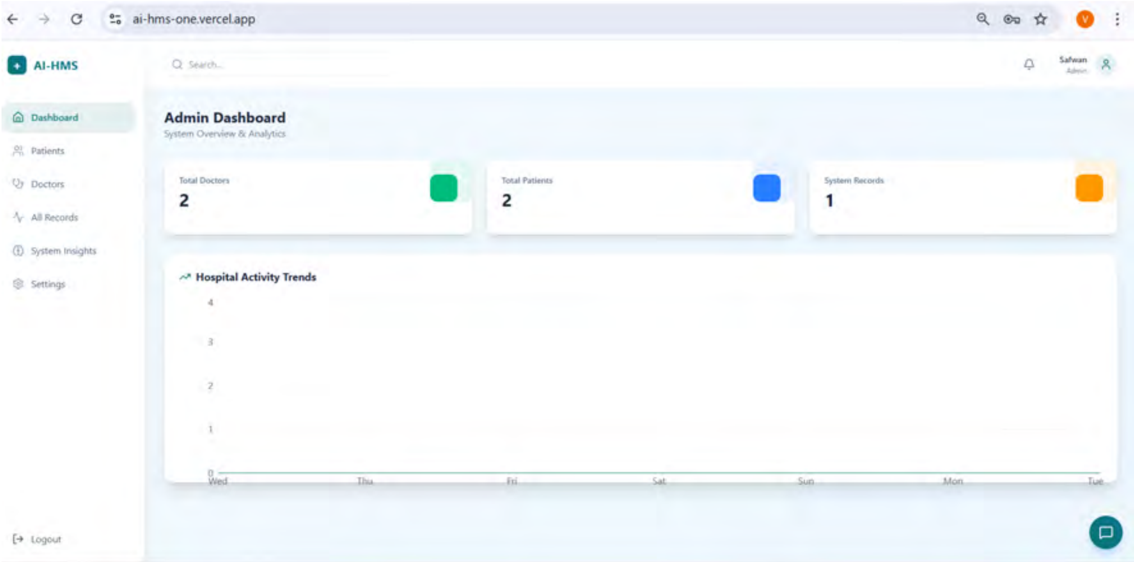


Figure 6.20: Admin dashboard (system overview).

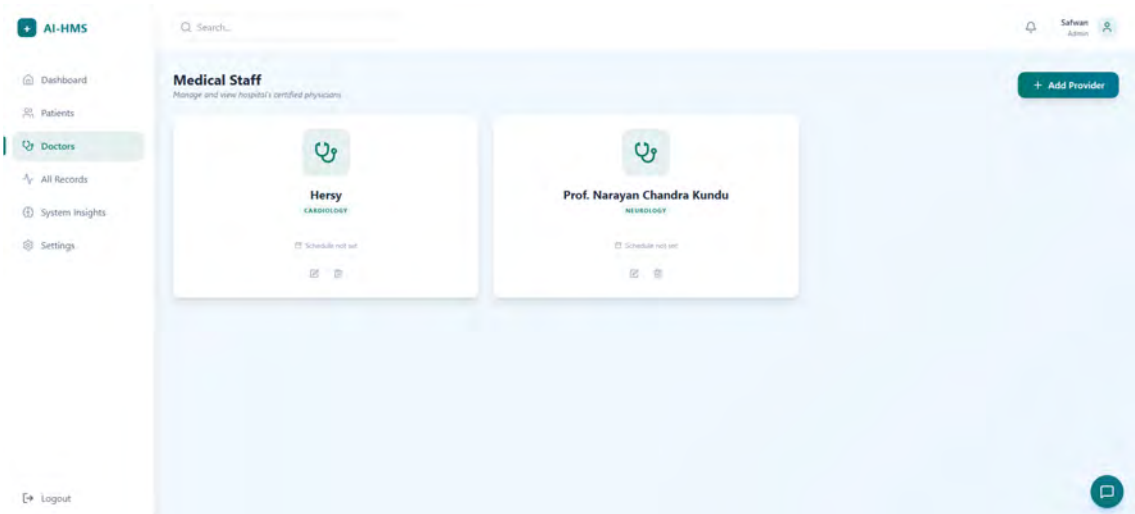


Figure 6.21: Admin view: doctors list (medical staff).

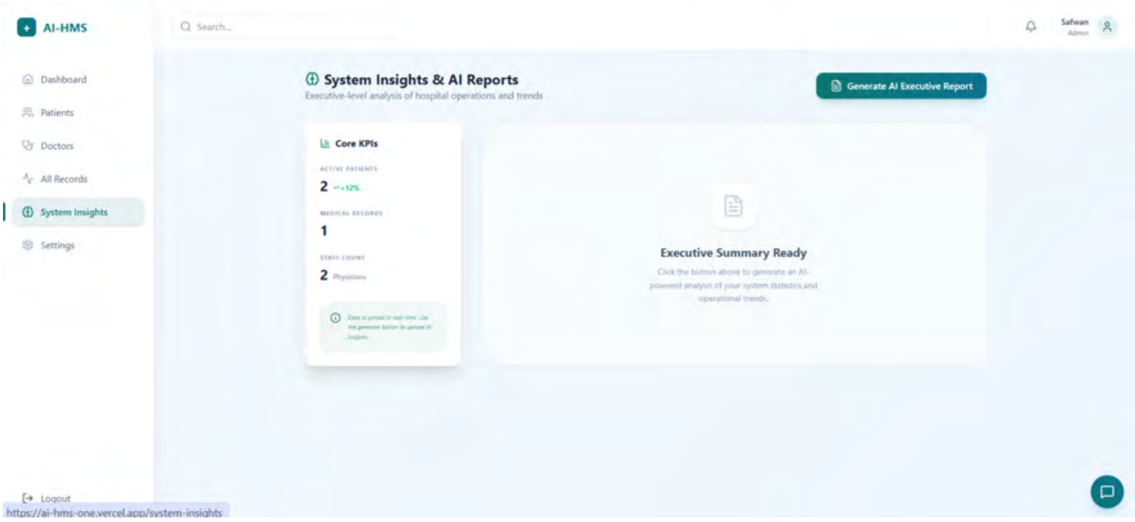


Figure 6.22: Admin view: system insights and executive report generation.

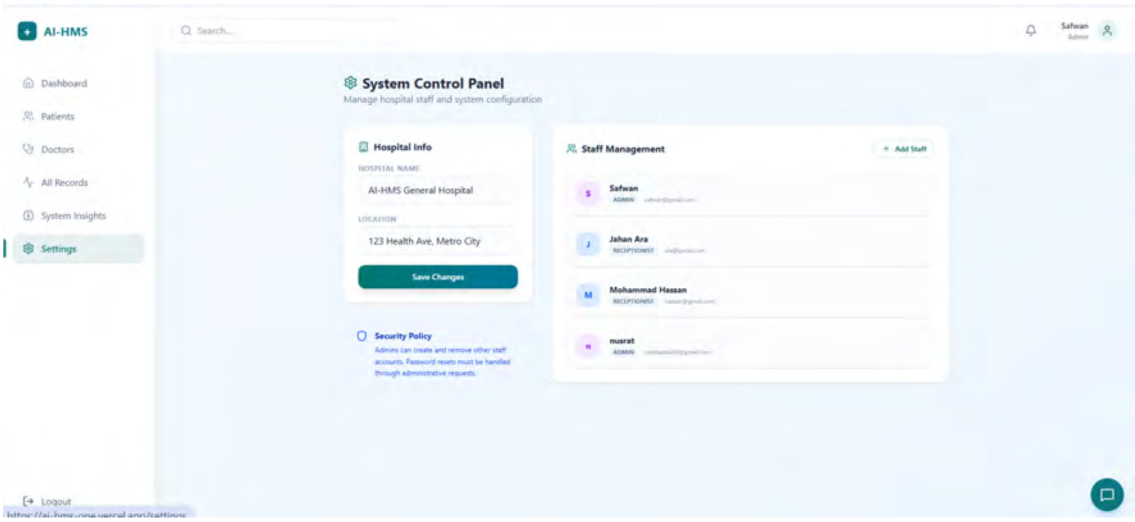


Figure 6.23: Admin settings: hospital information and staff management.

### 6.5.8 Billing Module

From the Billing menu, select a patient's unpaid invoice and click Record Payment. Choose a payment method (Cash or Mobile Banking such as bKash/Nagad/Rocket), enter the required details (mobile number/transaction ID/pin), and confirm to save the payment.

## 6.6 System Usability Evaluation

AI-HMS is designed for users with different technical skill levels. Role-based navigation keeps workflows focused: administrators monitor system metrics, doctors review patient histories and AI insights, receptionists manage scheduling, and patients can request care and view records with minimal steps. Informal evaluation suggests the guided interface and conversational assistant reduce the learning curve for first-time

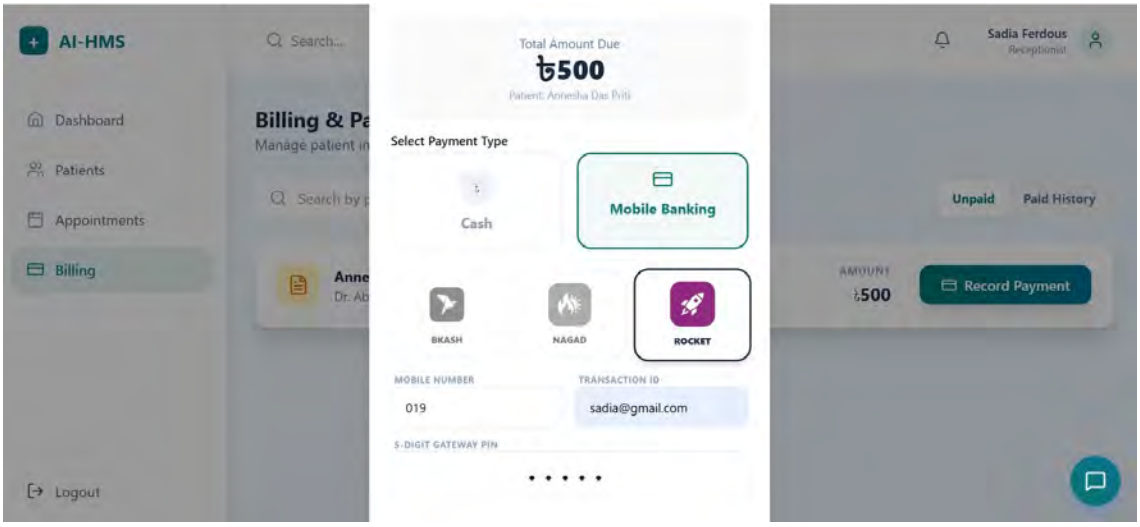


Figure 6.24: Billing

users, consistent with usability and interpretability priorities for successful adoption of healthcare information systems [4][2]

# Chapter 7

# Conclusion and Future Work

## 7.1 Summary of the Work Done

This thesis introduced the design, development, and assessment of AI-HMS, an Artificial Intelligence-based Hospital Management System that would enhance the efficiency of administration and assist with the clinical decision-making process. It has resolved the major shortcomings of the traditional hospital management systems by developing a single platform that incorporates predictive analytics, conversational artificial intelligence and workflow automation by role into a single system, which greatly broadens the scope of HMS into storing data and the mundane management of the hospital processes [6][2].

The research started with a thorough examination of the current healthcare management systems, finding out the important gaps regarding the lack of intelligent decision-support systems, the lack of engagement with the patients, and the lack of integration of new AI-based technologies. According to this findings, the modular and scalable system architecture was suggested and enacted on the foundation of modern web technologies and machine learning frameworks, which aligns with the best practice in healthcare informatics [2][4].

The system featured patient health risk classification and hospital readmission prediction supervised machine learning models, as well as a Large Language Model-based assistant to interact with and support the patients with clinical documentation. Synthetic healthcare data experimental assessment revealed that the suggested models obtained consistent predictive accuracy and could be successfully integrated into the hospital workflows. Moreover, the effective implementation of the system as a live web-based application was the real-world testing of the suggested design and implementation strategy.

## 7.2 Key Contributions and Impact

The AI-HMS project presents some interesting contributions to the field of healthcare information systems and artificial intelligence for applications:

**Integrated Artificial Intelligence Based Design of HMS:** Unlike traditional hospital management systems that deal primarily with data storage and administrative automation, this research has shown the integration of predictive analytics and conversational AI into one cohesive hospital management system for aiding healthcare proactive management [6][2].

**Human-Centered AI Approach:** The system follows the philosophy of human-in-the-loop, as artificial intelligence will be an advisory tool as a substitute for clinical judgment. This way, it supports transparency, trust, and ethical compliance that is in line with the global guidelines for responsible use of AI in healthcare [10].

**Practical Implementation and Execution:** The successful deployment of AI-HMS as a live web application is a demonstration of the technical feasibility and the real-world applicability of the proposed architecture and moves beyond exclusively theoretical or simulated research results.

**Methodological Contribution:** This study gives a structured methodology of integrating machine learning models and Large Language Models into the hospital management workflows, which can be used as a reference framework for future academic research and the development of industrial systems.

Collectively these contributions illustrate the potential of hospital management systems powered by AI to enhance operational efficiency, clinical decision-making and patient engagement in the design and implementation of such systems [4][10].

## 7.3 Recommendations for Future Enhancements

While results of this study are promising, there are several opportunities for the extension and enhancement of the proposed system in future research:

**The integration with Real Clinical Datasets:** Future work should include the training and testing of the machine learning models with real-life clinical data, with ethical approval and data protection laws. This would enhance the generalizability of the model and clinical validity [10].

**Advanced Predictive Models:** More developed machine learning and deep learning methods, like neural networks and time-series prediction (e.g., LSTM), might be considered to capture the time trends of patient health data and enhance the level of prediction accuracy [8].

**Include an account of explainable AI (XAI) Integration:** Explainability methods like SHAP or LIME would help improve the level of transparency in the model by giving users of the model interpretable explanations of the prediction hence leading to increased trust and adoption within a clinical setting [5].

**Interoperability and Standards Compliance:** Supporting healthcare interoperability standards like HL7 FHIR would support seamless integration with existing Electronic Health Record and laboratory information systems for improved data exchange and system adoption [7].

**Mobile and Telemedicine Services:** Creation of mobile applications and telemedicine options would enhance the accessibility of the patient and clinician, especially in resource-limited or remote health care environments [8].

**Large Scale Clinical Evaluation:** Pilot deployment and controlled usability testing of the system within actual hospital settings would be beneficial in giving feedback on the system performance, acceptance among the users, and clinical effects.

## 7.4 Concluding Remarks

This thesis shows that artificial intelligence can play a meaningful and practical role in hospital management systems improvement in cases of thoughtful and ethical integration. By integrating administrative automation, predictive analytics, and conversational intelligence in a modular and human-centric framework, AI-HMS represents a plausible strategy for intelligent, data-driven healthcare management systems, which is in line with modern healthcare informatics research.3,7 The results from this research support the broader vision of supporting artificial intelligence to augment, rather than replace, human expertise in healthcare. With sustained research, real-life validation and ethical control measures, the world of AI-enabled hospital management systems like AI-HMS has the potential to play a big role in the future of healthcare [10].

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