Department of Computer Science and Engineering

CSE400C Capstone Project

Smart Clinical Support: A Unique Approach to Healthcare Support in Bangladesh

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Abstract

Bangladesh's healthcare system is underdeveloped and there is a lack of qualified professionals to serve the people. This study primarily focuses on developing smart clinical decision support services in Bangladesh that ensure doctors prescribe accurate medication by systematically reviewing patients' medical records. With access to patients' past medical history through their EHR system, doctors can not only assess potential drug interactions based on current medications but also review previous prescriptions and lab reports to identify any long-term medication risks or recurring issues. This system aims to improve patient safety by ensuring precise prescriptions and minimizing adverse drug reactions through intelligent, technology-driven analysis and recommendation. Previous research on clinical decision support, digital health services, adverse drug interactions, and artificial intelligence-based medical recommendations in different countries, including Bangladesh, is included in the related works section. We will use the HAPI FHIR framework to create the patient database EHR, following the FHIR standard. A large language model (LLM) based on transformer architecture, specifically DialoGPT, has been used to train our medical chatbot, which is capable of understanding and suggesting medical-related problems from clinical data. The paper also presents the research questions, objectives, and methodology. The ultimate aim is to build a smart clinical support service to prevent medical errors among doctors and ensure patient safety in Bangladesh.

Keywords: Medication error, Drug Interaction, EHR, HAPI FHIR, Large language model (LLM), Transformer model, DialoGPT, Chatbot

Chapter 1

Introduction

1.1 Background

A smart clinical support system improves healthcare by offering consultation, assessment, therapy, medication management, and mental and physical health care. The healthcare sector of Bangladesh consists of hospitals, clinics, diagnostic centers, and telemedicine services, which are under four main parts: government, private sector, nongovernmental organizations (NGOs), and donor agencies [1]. In Bangladesh, people are not aware of taking medicine accurately, which leads them to take different types of medicine at a time, and drug interaction occurs. Drug interactions occur when another substance alters a drug's effectiveness or increases the risk of adverse effects [2]. A survey conducted at Kurmitola General Hospital among 100 patients revealed that 29% were taking incorrect medications [3]. Sometimes, doctors prescribe medicines to patients without knowing their medical history, which can later cause side effects. Additionally, most doctors in Bangladesh write prescriptions by hand, which is difficult to understand, and drugstores often hand over the wrong medicine to patients[4]. Zahid et al. highlighted recent healthcare initiatives in Bangladesh, including telemedicine, e-prescription, and health information systems [5]. Providing doctors with access to patients' past and current medications can significantly improve prescription accuracy. With numerous new drugs and increasing adverse reactions, doctors need full access to patients' medical histories to prevent errors and ensure reliable treatment with e-prescription facilities. To ensure safe treatment for the patient, we will implement this smart clinical support service using FHIR, a global standard for digital health data, to enable EHRs(Electronic Health Record)[6] and simplify large-scale health-data analytics [7]. Following FHIR standards, patients' health information can be exchanged between different clinics, allowing doctors to access patients' previous medical records for better care. The application uses HAPI FHIR, a framework to fetch and store healthcare data on an external server [8]. The project's objective is to ensure that doctors can provide safe and reliable care to patients and, therefore, develop a recommendation system by applying various machine learning techniques that can be an impressive solution. To add this medical recommndation system , we will use DialoGPT[9] model due to its ability to generate contextual, human-oriented responses in conversational settings, making it well-suited for simulating medical dialogues and providing relevant suggestions based on patient input. To support our clinical decision-making, we developed a chatbot trained on a medical dataset using the DialoGPT transformer-based language model, enabling it to provide suggestions for medical conditions.

1.2 Problem Statement and Analysis

In Bangladesh, the number of patients compared to per doctor is large enough which increases the risk of medical errors and affects the quality of patient care. Medication errors occur not only due to medical negligence but also due to self-medication, dosage neglect, misinterpretation of prescriptions, and dispensing mistakes. The main goal of this research is to develop a smart clinical support system for clinics, enabling healthcare professionals to access patients' current medications and medical history to prevent adverse drug reactions. However, the question arises of how we can secure patient data in this clinical system following a specific standard. This research seeks to address the challenge of accurately preventing medication errors. A key question is whether checking drug-drug interactions alone is sufficient, or if additional measures are required.

RQ1. How can an AI chatbot, improve doctor-patient communication and deliver medical support within the challenges of Bangladesh's healthcare system?

RQ2. How can a Smart Clinical Support system provide a standardized way for multiple clinics to access and share patient data?

1.3 Project Objectives

The primary objective of this project is to design and implement a Smart Clinical Support System that integrates an AI chatbot to significantly enhance healthcare delivery in Bangladesh. This system aims to improve patient safety, reduce medication errors, and facilitate better access to patient health records through advanced technology and data integration. By leveraging artificial intelligence, the project seeks to create a more efficient, user-friendly, and responsive healthcare environment.

Specific Objectives

1. Enhance Patient Safety

- Develop a comprehensive system that systematically reviews patient medical histories, including past prescriptions, lab results, and allergies. This will help healthcare providers identify potential medication errors and adverse drug interactions before they occur.
- Implement alerts and notifications within the system to inform healthcare professionals of critical issues, ensuring timely interventions and safeguarding patient health.

2. Centralize Patient Health Records

- Create a centralized database using the HAPI FHIR framework, which adheres to the Fast Healthcare Interoperability Resources (FHIR) standard. This will ensure that healthcare providers can access comprehensive and up-to-date patient information across different healthcare facilities, leading to more informed clinical decisions.
- Enable seamless data exchange between various healthcare systems, allowing for a holistic view of patient health and history, which is crucial for effective treatment planning.

3. Integrate an AI Chatbot for Patient Interaction

- Develop an AI-powered chatbot capable of engaging with patients through natural language processing (NLP). The chatbot will assist patients in various ways, including:
  - **Health Queries:** Providing instant responses to common health-related questions, such as symptoms, medication instructions, and general health advice, thus empowering patients with information.

- Ensure the chatbot is designed to learn from interactions, improving its responses over time and providing a more personalized experience for users.

4. Facilitate Efficient Communication

- Develop a user-friendly web interface that allows for secure communication between healthcare providers and patients. This interface will enable:
  - **Direct Messaging:** Allowing patients to communicate with their healthcare providers for follow-up questions or concerns.
  - **Telehealth Services:** Enabling virtual consultations to increase access to care, especially for patients in remote areas.
- Ensure that all communications are secure and compliant with healthcare regulations to protect patient privacy.

5. Promote Data-Driven Decision Making

- Leverage data analytics to support healthcare professionals in making informed decisions regarding patient care. This includes:
  - **Predictive Analytics:** Using historical data to predict patient outcomes and identify at-risk populations, allowing for proactive interventions.
  - **Performance Metrics:** Analyzing system usage and patient outcomes to continuously improve the clinical support system and its functionalities.
- Provide healthcare providers with dashboards and reporting tools that summarize key metrics, enabling them to track performance and make data-driven improvements.

This project aims to create a robust clinical support system that not only addresses current challenges in healthcare delivery but also sets a foundation for future advancements in medical technology and patient care in Bangladesh. The integration of an AI chatbot serves as a key component in enhancing patient interaction and support, ultimately leading to improved health outcomes and a more efficient healthcare system.

Chapter 2

Related Works

Bangladesh has come a long way in healthcare compared to the last few years. As the country struggles with challenges such as a shortage of qualified healthcare professionals and limited access to medical services, various studies have explored innovative approaches to improve healthcare outcomes. A clinical support system (CSS) is introduced to improve healthcare delivery by augmenting medical decisions with targeted clinical knowledge, patient information, and other health information[10]. Clinical Support System can be categorized based on their function, how they recommend, their communication style, human conversation, and decision-making models[11]. The way this system recommends can be inactive or active. Inactive systems require users to manually request advice, while active systems offer real-time guidance[12]. Human-computer interaction is another clinical decision support system characteristic, causing CDS Electronic Health Records (EHR) to become more accessible through integration, voice recognition, pop-up, and messaging alerts. Decision-making models range from simple rules-based decision trees to advanced AI methods such as Beyasian models[13] and neural networks. While AI can improve accuracy, trust issues arise when its recommendations establish the guidelines[14]. To better understand the contributions, we have categorized the existing literature that falls into these characteristics of CDSS into four key areas: (A) FHIR-based EHR Integration, (B) Accurate Diagnosis and Treatment, (C) Doctor-Patient Appointment Systems, and (D) AI in Medical Support. Each of these areas represents a distinct field of study within healthcare-related services with FHIR standards and adverse drug interactions. The following sections summarize key contributions in these areas, highlighting both advances and limitations identified in the existing literature.

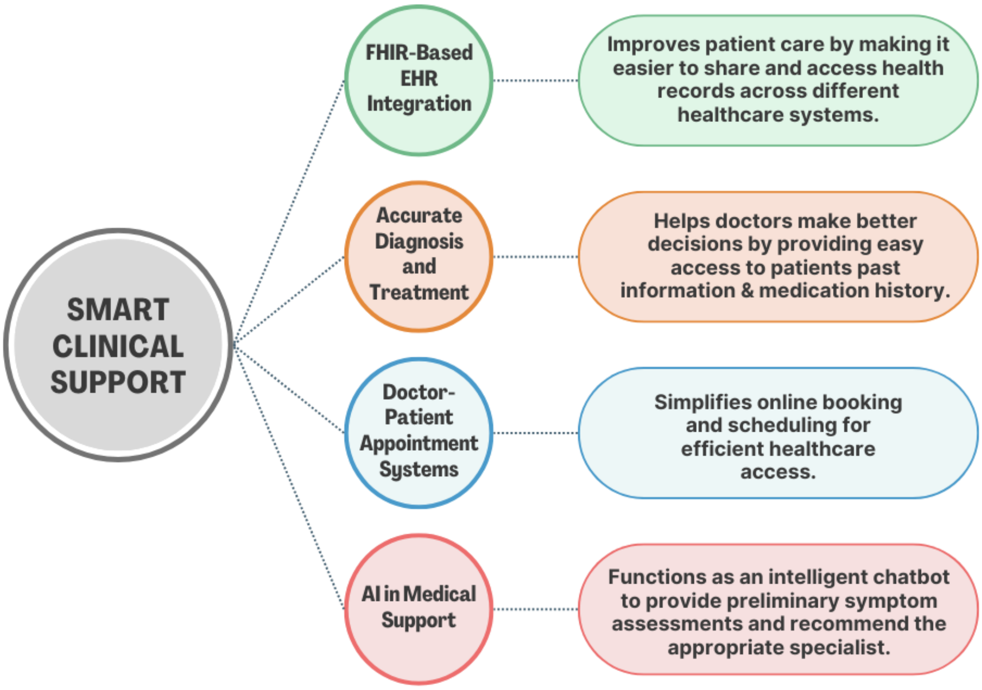

Figure 2.1: Overview of Smart Clinical Support System Components

2.1 FHIR Based EHR Integration

Clinical Support Systems (CSS) are designed to manage patient information, enhance decision-making, and improve communication among healthcare providers, with interoperability being a key component for seamless health data exchange. The AidIT mobile application, developed by Lamprinakos et al., utilizes the Fast Healthcare Interoperability Resources (FHIR) standard to facilitate efficient management of electronic personal health records through a RESTful architecture, thereby enhancing communication among patients, healthcare providers, and pharmacists [15]. Similarly, Sittig and Wright define a framework for interoperability using Electronic Health Records (EHRs) through five essential use cases, which promote improved healthcare delivery and information exchange among stakeholders [16].

In the realm of clinical decision support systems (CDSS), Castaneda et al. emphasize the critical role of integrating electronic health records (EHRs) and bioinformatics to enhance diagnostic accuracy and facilitate precision medicine[17]. Their review highlights the necessity for standardized methodologies to convert vast amounts of unstructured data into actionable knowledge, thereby improving patient care and reducing healthcare costs. The authors argue that existing EHR systems often generate silos of information, which complicates access to valuable clinical insights. They advocate for the development of user-friendly CDSS that can effectively process and present aggregated knowledge to healthcare providers, ultimately aiming to bridge the gap between clinical data and scientific research. However, the paper acknowledges that many current CDSS implementations have not demonstrated significant improvements in clinical outcomes, indicating a need for further refinement and integration of these systems to realize their full potential in clinical practice.

In a comprehensive randomized trial conducted by O'Connor et al. (2011), the effectiveness of an electronic health record (EHR)-based clinical decision support system on diabetes care was evaluated across 11 clinics in Minnesota, involving a total of 2,556 patients diagnosed with diabetes[18]. The primary objective of the study was to assess improvements in key clinical outcomes, specifically hemoglobin A1c, blood pressure, and low-density lipoprotein (LDL) cholesterol levels, among patients whose primary care physicians utilized the EHR-based support system. The findings revealed that physicians in the intervention group utilized the clinical decision support system in 62.6% of office visits, leading to a statistically significant reduction in hemoglobin A1c levels by –0.26% (95% confidence interval, –0.06% to –0.47%; $P = 0.01$) and enhanced maintenance of systolic blood pressure control (80.2% vs. 75.1%, $P = 0.03$). Additionally, 94% of participating physicians expressed satisfaction with the intervention, and notable usage of the system persisted for over a year following the discontinuation of financial incentives. Despite these promising results, the study's limitations include its focus on a single medical group with relatively good baseline diabetes care, which may limit the generalizability of the findings to other healthcare settings, particularly those with different patient demographics or care delivery models. Furthermore, the modest improvements observed may not be sufficient to warrant widespread implementation without further enhancements to the clinical decision support system.

Iqbal et al. proposed a Hybrid Clinical Decision Support System (CDSS) that integrates knowledge-based and data mining approaches to enhance diagnostic precision and reduce costs in healthcare delivery, particularly in resource-limited settings such as rural

Bangladesh[19].

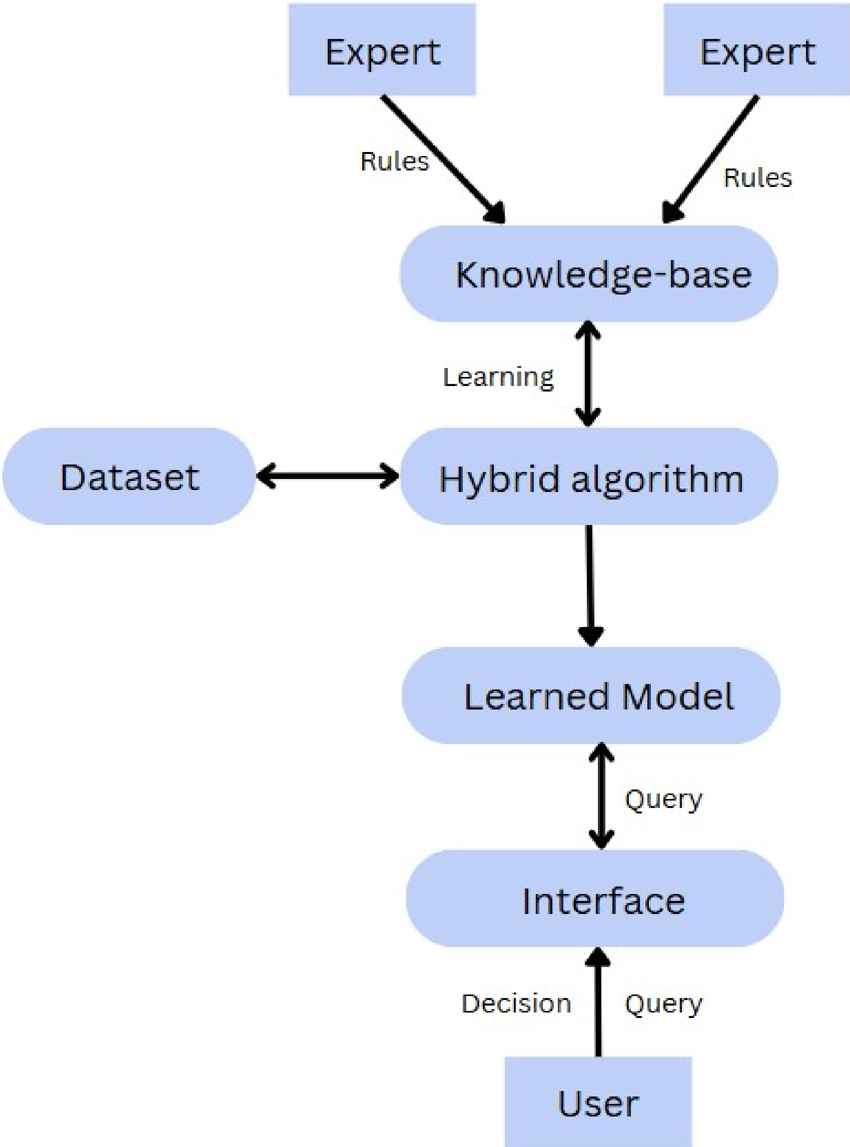

Figure 2.2: Hybrid Decision Support System by Iqbal et al. (Redrawn)[19]

This innovative system leverages the widespread availability of the Internet and mobile technology in Bangladesh to provide diagnostic suggestions based on patient data, thus addressing the critical shortage of qualified healthcare professionals in rural areas. The proposed hybrid algorithm, FOCL, demonstrates improved performance over traditional methods by combining expert knowledge with machine learning capabilities, allowing for a more robust decision-making process. The system is designed to be a learning entity, continuously improving its diagnostic suggestions as it processes more patient data. Furthermore, the study highlights the importance of transparency in the decision-making process, ensuring that the rationale behind diagnostic suggestions is understandable to healthcare providers. However, the study acknowledges limitations, including the reliance on the quality of input data and the potential for over-fitting due to the complexity of the hybrid model. Additionally, the system's effectiveness may be constrained by the availability of accurate and comprehensive medical knowledge, which can vary significantly across different regions and healthcare contexts.

The AidIT mobile application, developed by Lamprinakos et al., leverages the Fast Healthcare Interoperability Resources (FHIR) standard to enhance the management of electronic personal health records through a user-friendly interface accessible by patients, doctors, and pharmacists[15]. This application utilizes RESTful architecture, which is particularly suitable for mobile devices due to its lightweight nature, facilitating efficient data exchange and interoperability among healthcare providers. The AidIT application organizes patient health data into a personal health folder with distinct tabs for personal information, general health history, diagnostic orders, medication, and care plans, thereby promoting seamless communication and reducing medical errors. Furthermore, the application incorporates robust access control mechanisms to ensure the privacy and security of sensitive health information, allowing patients to manage access permissions dynamically. However, the study does not address the integration of wearable health monitoring devices, which could further enhance the application's functionality and real-time health data sharing capabilities.

In recent years, the integration of healthcare systems has gained significant attention, particularly in Asia, where a rapidly aging population and the increasing burden of chronic diseases necessitate efficient healthcare delivery models.

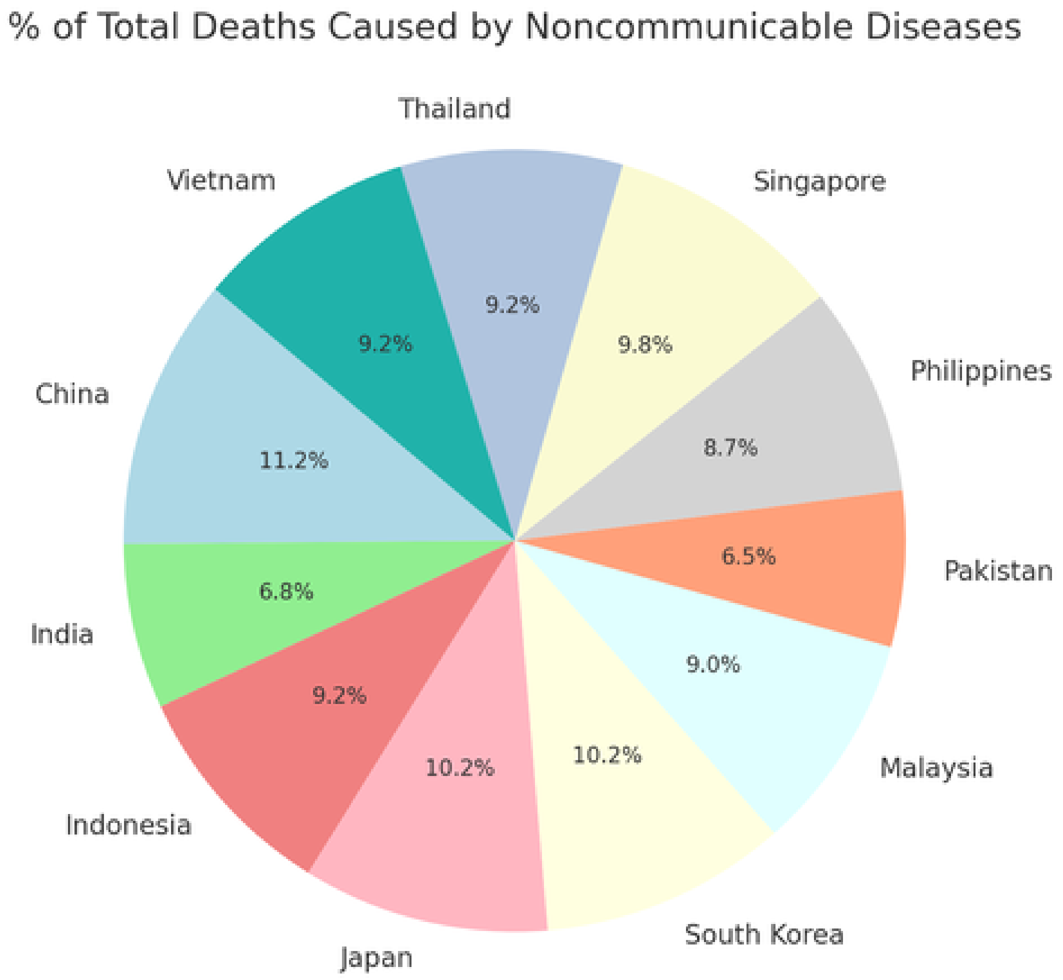

Figure 2.3: Percentage of total deaths caused by non-communicable diseases in Asia in 2014 (Redrawn)[20]

Tham et al. highlight the urgent need for integrated healthcare systems in Asia, emphasizing the fragmentation of care and the lack of robust initiatives to manage chronic conditions such as diabetes, hypertension, and dementia[20]. The authors advocate for a collaborative care model that enhances coordination among health care providers and empowers primary care practitioners to address the complex needs of patients. They propose five key strategies for implementing integrated care, including engaging the population, reinforcing accountability, adapting suitable care models, coordinating services, and building conducive environments. While the paper provides valuable insights into the challenges and strategies for integrated care in Asia, it primarily focuses on the context of various Asian countries, which may limit its applicability to the specific healthcare dynamics and cultural considerations present in Bangladesh.

In recent years, Bangladesh has made significant strides in the realm of digital health services, particularly following its recognition with the United Nations Award for Digital Health Development in 2011. Zahid et al. (2023) provide a comprehensive commentary on the current state of digital health services in Bangladesh, highlighting the various initiatives launched over the past decade, including the implementation of telemedicine, e-prescription, and health information systems[5].

Figure 2.4: Aconceptual design framework for Digital Health Service[5]

Despite these advancements, the authors emphasize that existing digital health services face critical challenges that hinder their effectiveness. Key identified issues include a lack of usability and user centricity, inadequate data privacy and security measures, and insufficient digital infrastructure. The proposed design framework by Zahid et al. aims to address these challenges by focusing on essential elements such as user engagement, data security, interoperability, and scalability, thereby fostering a more sustainable digital health ecosystem. Furthermore, the authors advocate for a people-centered approach to digital health service design, which is crucial for enhancing user trust and participation. However, the limitations of this paper include a lack of empirical data to support the proposed framework and the need for further research to validate its applicability in diverse healthcare settings across Bangladesh, as well as the potential challenges in implementation within the existing healthcare infrastructure.

A notable study titled "Brilliant AI Doctor" in Rural China investigated the deployment of an AI-powered CDSS, revealing critical insights into the complexities of implementing such systems in rural healthcare environments[21]. The research involved ethnographic methods, including observations and interviews with 22 clinicians across six rural clinics, highlighting various tensions between the AI-CDSS design and the local clinical context. Key challenges identified included a misalignment with existing clinical workflows, technical limitations that hindered usability, and significant concerns regarding the transparency and trustworthiness of AI-generated recommendations. Despite these barriers, clinicians expressed optimism about the role of AI-CDSS as a supportive tool that could enhance their diagnostic capabilities rather than replace their expertise. The study emphasized the necessity of tailoring AI-CDSS to fit the unique socio-technical landscape of rural healthcare settings to foster user acceptance and improve system uptake. However, it is important to note that the findings are limited to a specific rural context in China, which may not be directly applicable to other developing countries, including Bangladesh, where different cultural, infrastructural, and healthcare dynamics may influence the effectiveness of AI-CDSS implementations.

The integration of mobile technology into healthcare systems has emerged as a pivotal strategy for enhancing healthcare delivery, particularly in developing countries like Bangladesh. Hossain et al. proposed a comprehensive smartphone-based healthcare application designed to bridge the gap in access to medical services for underprivileged populations[22]. This innovative application incorporates a multitude of features, including online appointment scheduling, cabin booking, a prescription generator, and a robust database of hospital and doctor information.

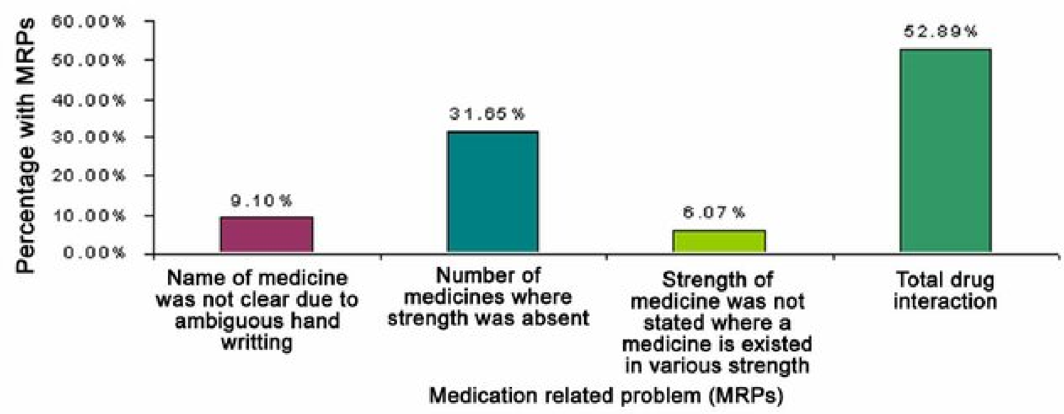

Figure 2.5: MRPs identified from the prescription[22]

Additionally, it facilitates a social networking platform that enables effective communication between patients and healthcare providers, allowing for the sharing of experiences and medical advice. The authors highlighted the critical need for real-time alerts regarding emerging diseases, which can significantly aid in public health surveillance and timely intervention. Furthermore, the application includes a medication reminder system to improve patient adherence to prescribed treatments, thereby enhancing overall health outcomes. Despite these advancements, the study acknowledges several limitations, including challenges related to the scalability of the application and the necessity for continuous updates to ensure the accuracy and relevance of the healthcare information provided. These limitations may hinder the application's effectiveness in adapting to the rapidly evolving landscape of medical knowledge and healthcare practices.

Hussain et al. proposed a Smart CDSS that leverages sensor technologies to monitor the activities of diabetic patients in a home setting[23]. This system utilizes a knowledge base that incorporates diabetes management guidelines, allowing for real-time recommendations and alerts based on patient activities. The architecture of the Smart CDSS is designed to facilitate seamless integration with various healthcare systems through standard interfaces, such as HL7 vMR and Arden Syntax, enhancing interoperability and clinical knowledge sharing. The system's design is based on a layered architecture, comprising hardware, home communication network, autonomous decision-making, and services layers, which enables the provision of safety, remote support, and clinical decision support services. The Smart CDSS has been tested with 100 diabetes patients, demonstrating its potential in providing personalized care and improving disease management outcomes. However, the study primarily focuses on diabetes management and does not address the broader spectrum of chronic diseases, which limits its applicability in diverse clinical scenarios.

Gorham et al. (2024) present the Territory Kidney Care (TKC) initiative, which focuses on enhancing the identification and management of chronic kidney disease (CKD) through an integrated clinical decision support system (CDSS) in the Northern Territory of Australia[24]. This initiative addresses the growing burden of CKD, particularly among populations with complex health needs, by utilizing electronic health record (EHR) data from various health services. The TKC system is designed to provide clinicians with real-time, comprehensive patient information, enabling improved diagnosis, monitoring, and adherence to evidence-based guidelines for care.

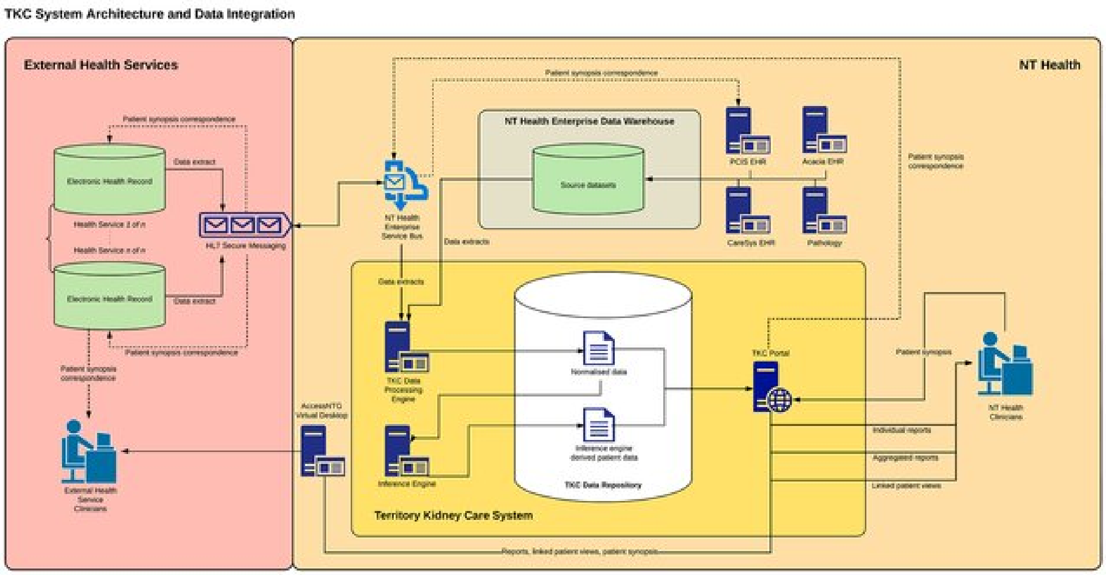

Figure 2.6: System architecture diagram proposed by Gorham et al.[24]

The authors highlight the significance of establishing cross-sectoral partnerships and data sharing agreements, which facilitate better communication and coordination among healthcare providers, ultimately leading to improved patient outcomes. Furthermore, the study emphasizes the importance of user engagement in the design and implementation phases to ensure that the system meets the needs of clinicians and health service providers. However, the authors also recognize that the findings may not be universally applicable, as the unique challenges of implementing such integrated systems can vary significantly across different healthcare environments.

A notable contribution is the work of Ezhil Arasi and Suganthi, who presented a clinical support system that uses magnetic resonance imaging (MRI) for the detection and classification of brain tumors[25]. Their approach involves pre-processing MRI images with a Genetic Optimized Median Filter, followed by tumor region segmentation using a Hierarchical Fuzzy Clustering Algorithm.

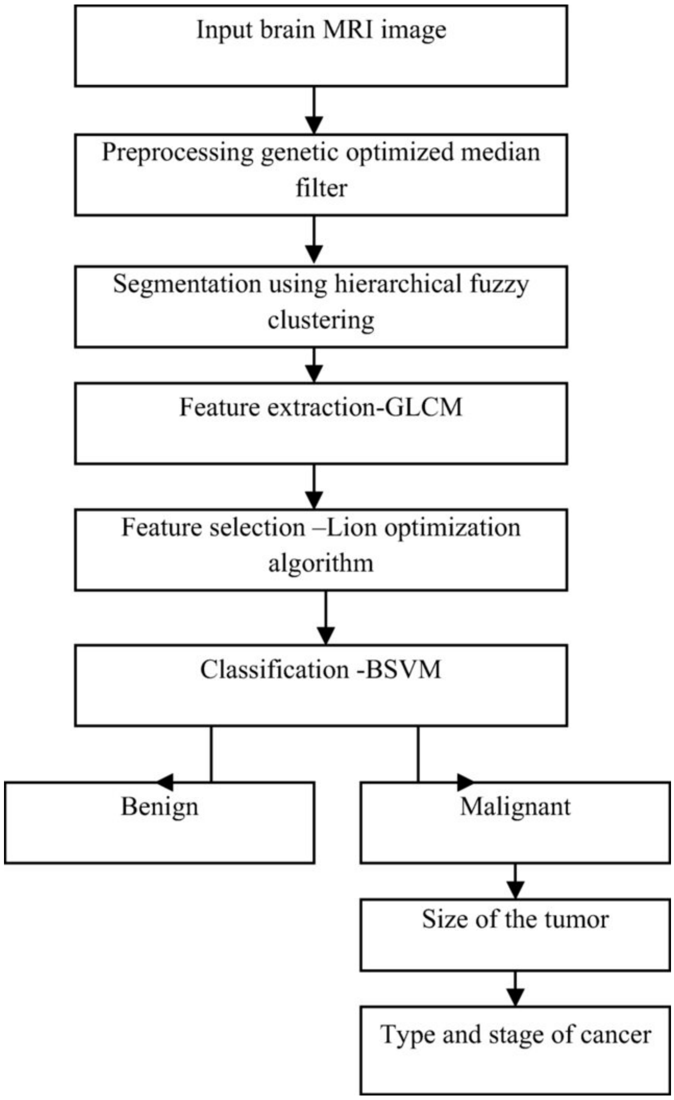

Figure 2.7: Functional Diagram of the Proposed System of Brain Tumor Classification[25]

The system employs the Gray Level Co-occurrence Matrix (GLCM) for feature extraction and integrates a Lion Optimized Boosting Support Vector Machine (BSVM) for classification, achieving an impressive accuracy of 97.69%. This integrated model not only aids in the detection and classification of tumors but also provides insights into the size and stage of cancer, thereby assisting medical professionals in making informed decisions. However, the proposed system primarily focuses on MRI images and may not generalize well to other imaging modalities or tumor types, limiting its applicability in diverse clinical settings.

In clinical decision support systems, Chrimes et al. (2023) introduced a decision tree-based expert system designed to evaluate the severity of COVID-19 infections, emphasizing the complex interactions between viral infections, comorbidities, and physiological responses across various body systems[26]. The research involved the construction of a detailed decision tree comprising 212 nodes, which were stratified by age, body systems, and pertinent medical conditions, ultimately yielding 63,360 potential scenarios for assessing patient outcomes.

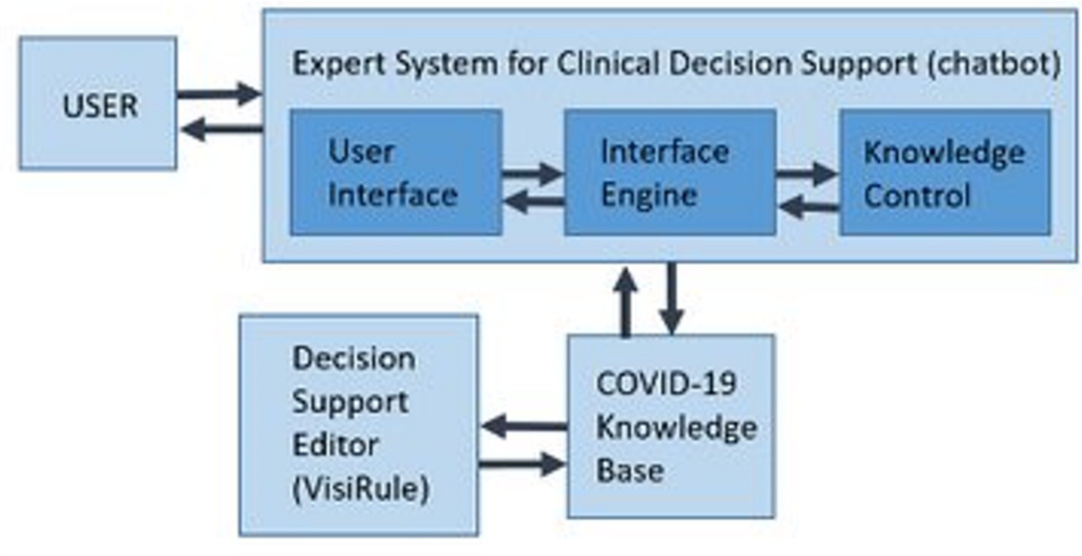

Figure 2.8: Expert system of a COVID-19 decision support web-based (chatbot) tool developed by Chrimes et al.[26]

This innovative framework not only highlights the critical role of integrating medical knowledge into digital health tools but also aims to enhance diagnostic accuracy and treatment efficacy for severe COVID-19 cases. Furthermore, the study illustrates the potential of decision trees to synthesize complex medical data into actionable insights for clinicians. However, the authors acknowledge several limitations, including the exclusion of gender as a variable and the dependence on existing literature rather than primary data collection, which may impact the generalizability and applicability of the findings in diverse clinical settings.

Garcia Valencia et al. (2023) conducted a comprehensive study exploring the potential of AI-powered chatbots to improve various aspects of kidney transplantation, including decision-making, patient communication, and operational efficiency[27]. Their research highlighted the chatbot's capability to provide healthcare professionals with real-time access to medical literature and clinical guidelines, thereby facilitating informed decision-making. Additionally, the chatbot was shown to enhance patient education by delivering personalized and comprehensible information regarding the transplantation process, medication regimens, and post-transplant care requirements. The authors emphasized the transformative possibilities of integrating chatbots into clinical decision support systems (CDSS), which could lead to improved risk stratification and treatment planning, ultimately enhancing patient outcomes. Furthermore, the study discussed the potential for chatbots to assist in medication management by analyzing patient-specific data and offering tailored recommendations. However, the authors also acknowledged the necessity for further studies to validate the effectiveness and safety of chatbots in clinical settings, as well as the importance of addressing ethical considerations, bias mitigation, and the need for transparency in AI applications.

2.2 Accurate Diagnosis and Treatment

Combined use of multiple drugs may cause adverse events. For example, simultaneous administration of a drug metabolized by Cytochrome P450 3A4 (CYP3A4) and the drug that inhibits CYP3A4, e.g., cyclosporine and clarithromycin, respectively, leads to delayed clearance and elevated blood levels of the former drug, which increases and prolongs both the therapeutic and adverse effects[28]. Drug-disease interactions (DDSIs) occur when a drug prescribed to treat one disease may worsen another comorbidity or condition. Clinical decision support systems (CDSS) help by in checking for harmful interactions between medications. This makes it easier for clinical pharmacists or doctors to quickly review a patient's medication history in the electronic health record (EHR) and manage any serious interactions. It's important to check for drug interactions because they can cause harmful side effects.

In the realm of clinical decision support systems, Jung et al. conducted a significant study focusing on the development and deployment of a shared interoperable CDS service for drug-allergy interaction (DAI) checks in Korea[29]. This initiative utilized the CDS Hooks specification and the HL7 Fast Healthcare Interoperability Resources (FHIR) standard to create a national service that enhances patient safety and care quality by allowing healthcare providers, including smaller institutions, to perform DAI checks without incurring high integration costs. The system was successfully launched on G-Cloud, resulting in over one million DAI checks and a warning rate of 3.32% among participating providers.

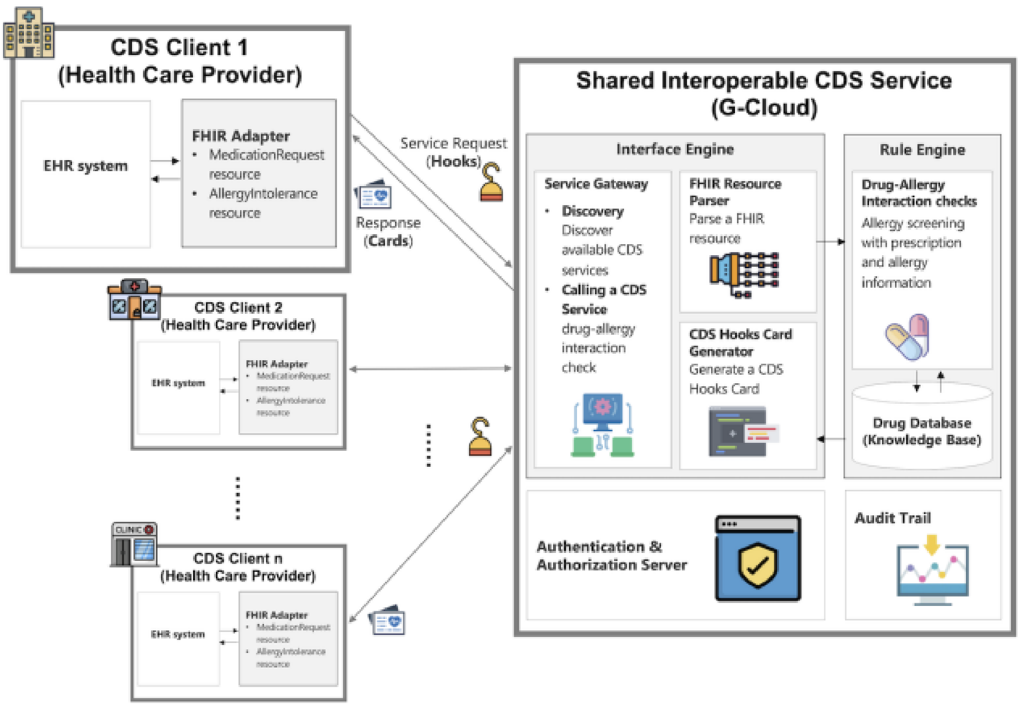

Figure 2.9: The concept architecture for the shared interoperable CDS system is based on CDS Hooks' anatomy. Multiple healthcare providers simultaneously invoke the shared interoperable CDS service deployed on G-Cloud using a hook and receive a card as a response. CDS: clinical decision support; EHR: electronic health record; FHIR: Fast Healthcare Interoperability Resources.[29]

However, a notable limitation of this study is the reliance on a proprietary value set due to the lack of a national allergy code system in Korea, which may limit the applicability of the findings to other healthcare contexts, such as Bangladesh.

In their study, Mamun et al. investigated the incidence of drug-drug interactions (DDIs) in prescriptions from various medical specialists in Bangladesh, analyzing over 21,000 prescriptions across ten different
specializations[30]. The findings revealed that cardiologists had the highest rate of DDIs, with polypharmacy identified as a significant contributing factor, while the study also highlighted the need for improved communication among healthcare providers and the active involvement of pharmacists to mitigate these interactions. However, a limitation of this research is the reliance on prescription data from a limited number of institutions, which may not fully represent the broader healthcare landscape in Bangladesh.

In a comprehensive study by Paul et al., the authors investigated the prevalence and nature of medication errors in a private hospital located in Bogura, Bangladesh[31]. The research focused on analyzing 200 handwritten prescription orders from various medical wards, revealing a total of 692 medication-related problems (MRPs), which translates to an average of 3.46 MRPs per prescription. Notably, the study identified critical issues such as unclear drug names due to ambiguous handwriting, which affected 63 prescribed drugs, and the absence of dose strengths for 219 medications, with 42 of these available in multiple strengths.

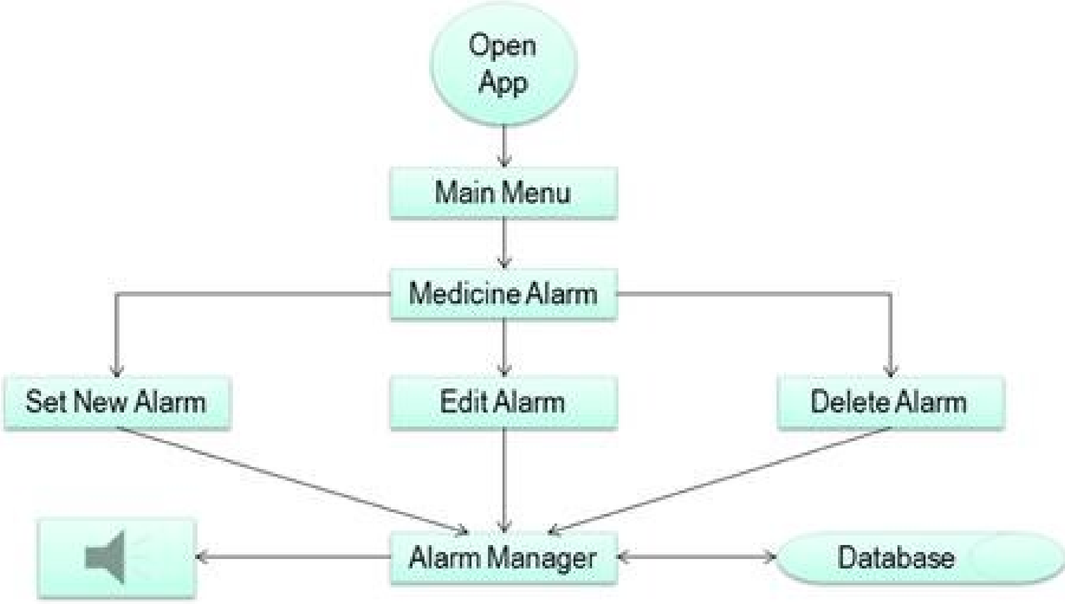

Figure 2.10: System diagram of medicine alarm[31]

Furthermore, the researchers documented a total of 366 drug interactions, categorizing them into serious (12.57%), significant (53.28%), and minor (34.15%) interactions. The findings emphasized the urgent need for enhanced prescribing practices and the integration of clinical pharmacists into healthcare teams to address and reduce the incidence of medication errors. The study also highlighted that approximately 15% of prescriptions were issued for patients with kidney and urinary problems without appropriate dose adjustments, indicating a significant oversight in patient care. However, it is important to note that while the study focused on a private medical facility, similar medication errors are prevalent in public hospitals as well, which limits the validity of the findings to the broader healthcare system.

In the study conducted by Hasan et al. (2020), the critical role of critical care pharmacists (CCPs) in ensuring medication safety through the utilization of free drug-interaction checker mobile apps (DICMA) was thoroughly evaluated within a resource-limited hospital setting in Bangladesh[32]. This observational study was carried out in the intensive care unit (ICU) of Square Hospital, where CCPs screened a total of 2,967 prescriptions. The results were striking, revealing that the pharmacists identified an alarming 11,128 drug-drug interactions (DIs) and 3,932 potential drug-drug interactions (PDIs). The study underscored the correlation between the number of medications in a prescription and the likelihood of encountering DIs and PDIs, with prescriptions containing more than ten medications exhibiting the highest risk. Notably, physicians accepted 95.85% of the PDI suggestions made by the pharmacists, which led to immediate modifications in prescriptions and resulted in positive clinical outcomes for patients. The findings of this research highlight the critical importance of continuous monitoring and intervention by CCPs in enhancing medication safety for critically ill patients. Furthermore, the study demonstrated the potential of mobile health applications to facilitate clinical pharmacy practice, particularly in settings where resources are limited. However, the study had certain limitations, including its focus on a single ICU, the absence of an assessment of clinical outcomes related to the identified DIs, and a lack of analysis regarding the side effects associated with prescribed medications in polypharmacy prescriptions. These limitations suggest the need for further research to explore the broader implications of DICMA usage in diverse clinical settings.

Islam et al. conducted a detailed survey study that examined the pressing issue of medication errors in Bangladesh, highlighting the concerning prevalence of misunderstandings related to prescribed medications among both patients and pharmacy dispensers[3]. The study involved 100 patients and 100 medication dispensers, revealing that a significant 29% of patients were inadvertently taking incorrect medications, with 18% of these individuals facing serious health consequences as a result. The authors pointed out that one of the primary culprits behind these errors was the longstanding problem of illegible handwriting in prescriptions, a challenge that not only affects patient safety but also places an additional burden on healthcare providers. Furthermore, the research highlighted that a staggering 56% of patients reported difficulty in understanding their doctors' instructions, which further complicates their ability to adhere to prescribed treatments. This lack of clarity in communication emphasizes the urgent need for enhanced patient education and better practices in prescription writing to mitigate the risks associated with medication errors. While the findings provide valuable insights into the healthcare landscape in Bangladesh, the study is limited by its relatively small sample size and its focus on specific hospitals and pharmacies in Dhaka, which may not fully capture the diverse experiences of patients across the entire country.

In a comprehensive study conducted by Mamun et al. (2021), the incidence of drug-

drug interactions (DDIs) in prescriptions from general practitioners and specialists in Bangladesh was evaluated, revealing significant findings regarding the prevalence and causes of DDIs across various medical specializations[33]. The study analyzed a total of 21,088 prescriptions collected from 45 medical institutions, encompassing ten different specializations, including cardiology, pediatrics, and gynecology. The results indicated that cardiologists had the highest rate of DDIs at 6.17%, while pediatricians exhibited the lowest rate at 3.29%. The research identified clopidogrel and warfarin as the most common medications involved in interactions, with cardiovascular drugs and antibiotics being the primary categories associated with these DDIs. The authors highlighted that factors such as polypharmacy, a shortage of pharmacists, excessive workload, and miscommunication among healthcare providers significantly contributed to the occurrence of DDIs. Furthermore, the study underscored the necessity for active pharmacist involvement in the verification of prescriptions and the organization of workshops aimed at enhancing physician awareness regarding potential drug interactions. However, the study is limited by its cross-sectional design, which may not capture the dynamic nature of drug interactions over time.

In a comprehensive study by Sultana et al., the authors investigated the prescribing patterns and prescription errors within a tertiary care hospital in Bangladesh, highlighting the critical issue of irrational drug prescribing that plagues many developing countries[34]. The research involved a cross-sectional analysis of 200 patient prescriptions collected over three months, revealing an average of 4.89 drugs per prescription, with a staggering 76.5% of prescriptions characterized by complex regimens.

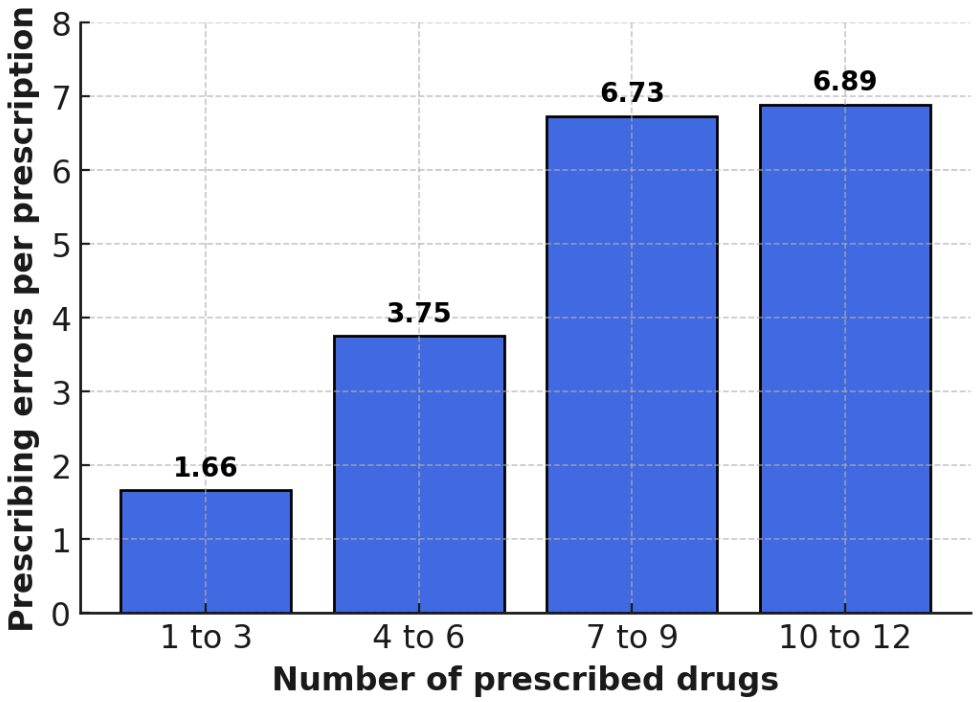

Figure 2.11: Frequency of errors in the prescriptions[34]

Notably, the study found that none of the prescriptions included generic names, which raises concerns about potential confusion and medication errors. Furthermore, a significant 78% of the prescriptions contained antibiotics, far exceeding the World Health Organization's recommended range of 15-25% for developing countries, thus indicating a concerning trend towards polypharmacy. The analysis identified a total of 769 prescription errors, averaging 3.85 errors per prescription, with the most common issues being illegible handwriting and missing dosage strengths. Additionally, the study reported 409 drug interactions and highlighted the lack of dose adjustments for patients with kidney and urinary problems, underscoring the urgent need for improved prescribing practices to enhance patient safety and promote rational drug therapy. However, the study did not explore the severity of the errors, the outcomes of treatment, or the underlying reasons for the prescribing errors, which limits the comprehensiveness of the findings.

2.3 Doctor-Patient Appointment Systems

In recent years, the integration of machine learning techniques into outpatient appointment scheduling has gained significant attention, particularly in addressing the challenges posed by heterogeneous service times. Feng et al. proposed an adaptive decision support system known as Cluster-Predict-Schedule (CPS), which utilizes both supervised and unsupervised machine learning methods to enhance outpatient appointment scheduling efficiency[35].

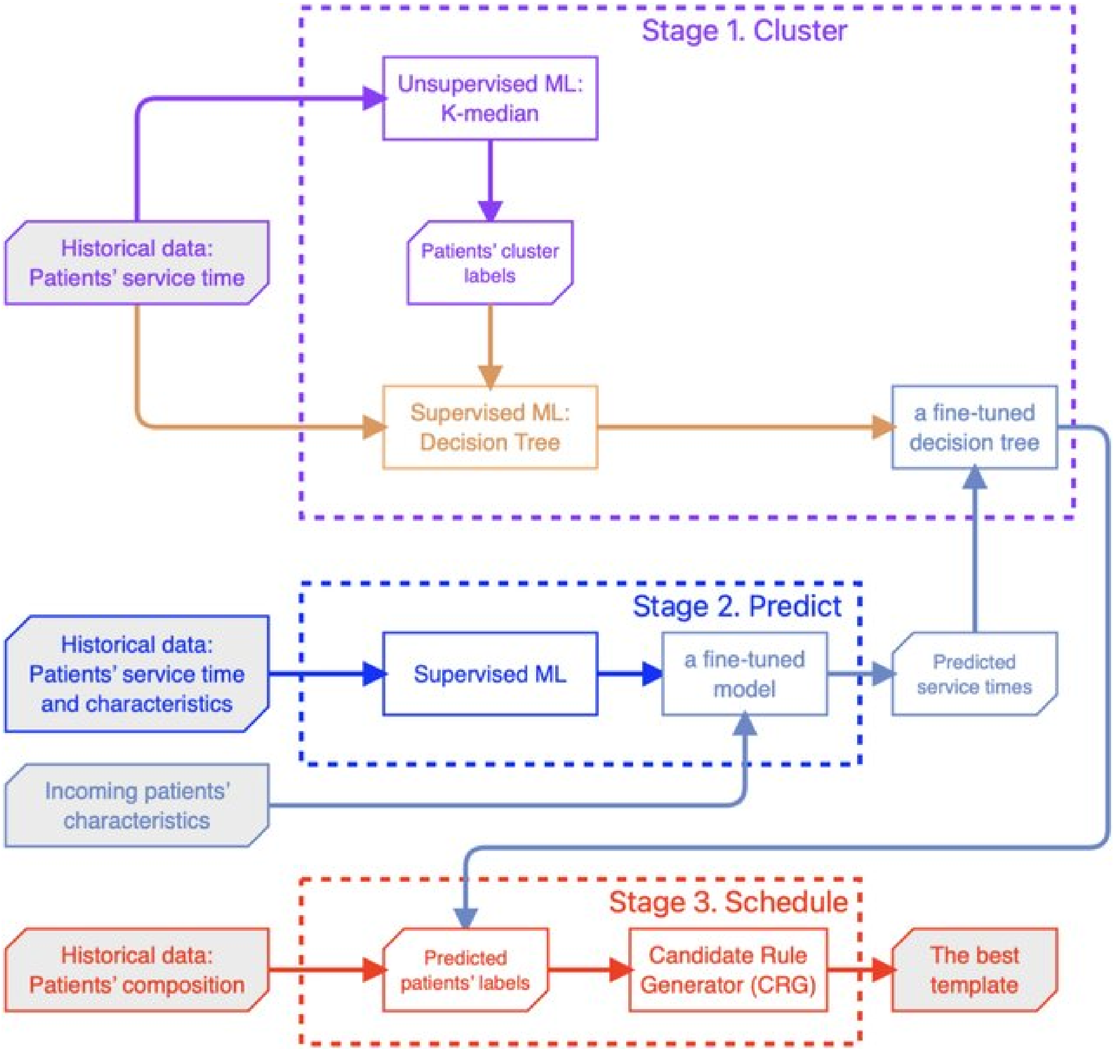

Figure 2.12: A flowchart of the CPS system proposed by Feng et al.[35]

The CPS framework consists of three main components: clustering patients based on historical service times using unsupervised learning, predicting incoming patients' service durations through a supervised learning model, and generating optimal scheduling templates that minimize costs associated with patient wait times, physician idle time, and overtime. Their approach demonstrated a notable cost reduction of up to 15% compared to traditional scheduling methods, such as the first-call, first-appointment (FCFA) scheme, while also improving fairness in patient wait times across different appointment slots. Furthermore, the CPS system's adaptability allows it to dynamically adjust to varying patient characteristics and service times, making it a promising solution for outpatient clinics facing operational inefficiencies. However, the study's reliance on historical data for patient classification and service time prediction may limit its applicability in settings with insufficient data or significant variability in patient characteristics, potentially affecting the robustness of the proposed scheduling framework.

Imteaj et al. present a comprehensive smartphone-based application designed to improve the healthcare system in Bangladesh[36]. This application addresses critical challenges faced by patients, such as the difficulty in finding suitable hospitals, booking cabins, and scheduling appointments with doctors. It offers a range of features including an online cabin booking system, intelligent hospital suggestions based on cost and quality, emergency service calls, and medication reminders.

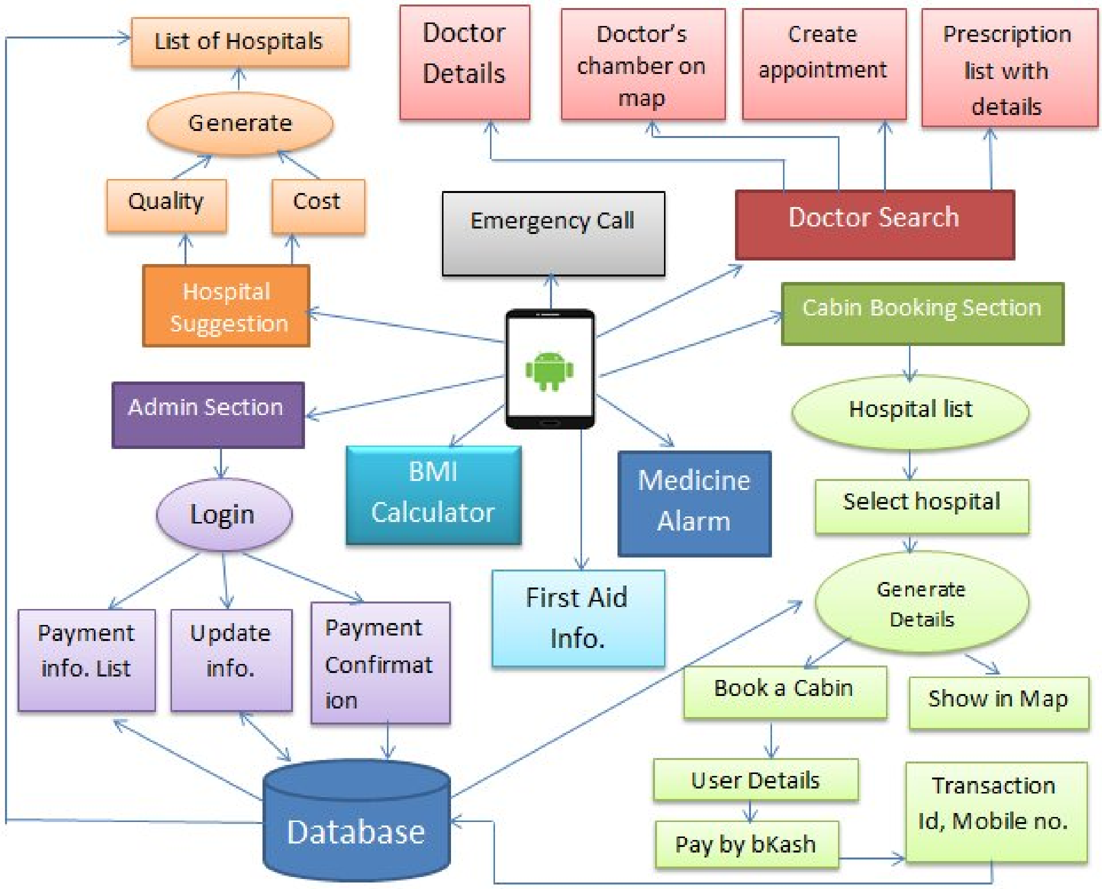

Figure 2.13: System architecture presented by Imteaj et al. [36]

The authors highlight the complexities that patients, especially those from rural areas, encounter when navigating the urban healthcare landscape, where information about hospitals and their services is often scarce and difficult to interpret. By providing a user-friendly interface that consolidates essential healthcare information, the application aims to streamline the process of accessing medical services, thereby reducing the time and effort required in emergencies. However, the study is limited by its focus on a specific geographic area, which may not fully represent the diverse healthcare needs across different regions of Bangladesh.

In Bangladesh, the Aponjon mobile health (mHealth) service has emerged as a significant intervention aimed at improving maternal, neonatal, and infant health care through remote consultations. This service provides subscribers, primarily pregnant women and new mothers, with access to medically trained doctors via a 24/7 call center, alongside regular voice and text messages that offer health information and advice.

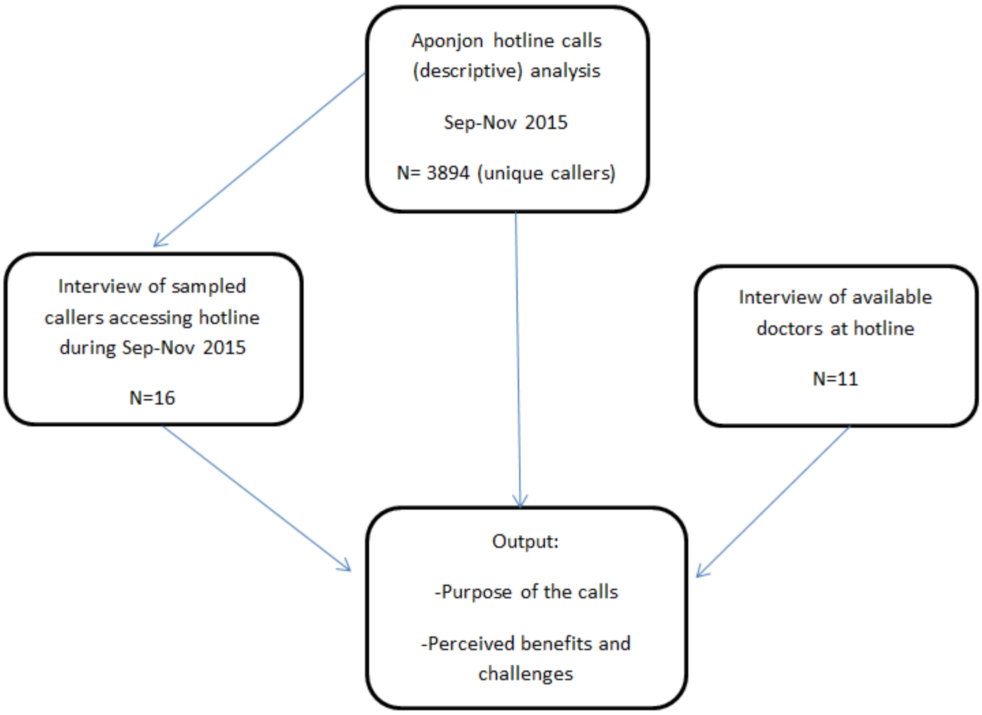

Figure 2.14: Mixed methods data triangulation plan of Aponjon mobile health (mHealth) service[37]

A mixed-methods study conducted by Alam et al. (2019) revealed that approximately 68.36% of the service's users were from rural households, highlighting the potential of mHealth to bridge the gap in healthcare access in underserved areas[37]. The study found that the service was perceived as trustworthy, cost-effective, and convenient, with a majority of calls being nonurgent, indicating a proactive approach to health management among users. However, the research also identified challenges, such as network disruptions and the lack of a structured referral system, which hindered the effectiveness of the consultations. Despite these insights, the study's limitations include a small sample size for qualitative interviews and a lack of comprehensive data on the socioeconomic status of participants, which may affect the generalizability of the findings.

2.4 AI in Medical Support

In the paper titled "A Machine Learning based Drug Recommendation System for Health Care," Mohapatra et al. (2022) propose a drug recommendation system that leverages machine learning techniques to assist users in identifying appropriate medications based on patient reviews and ratings for specific health conditions[38].

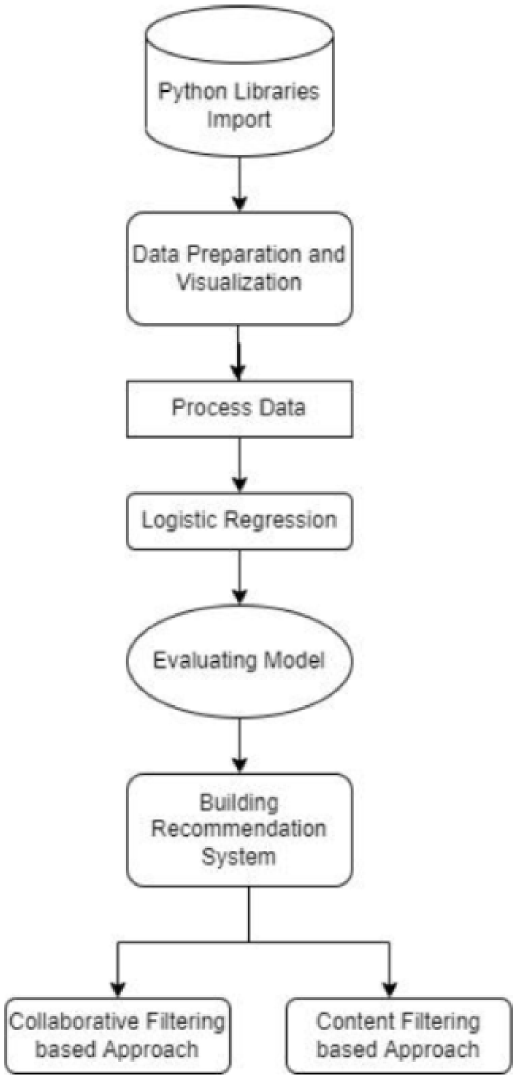

Figure 2.15: A Machine Learning based Drug Recommendation System for Health Care[38]

The authors utilize data mining concepts, sentiment analysis, and both content-based and collaborative filtering approaches to enhance the accuracy and efficiency of the recommendations. Their system is designed to address the challenges posed by the vast amount of health-related information available online, which can lead to misinformation and medication errors. The study highlights the importance of recommendation systems in healthcare, aiming to improve decision-making for both patients and healthcare professionals. However, the paper is limited by its reliance on a specific dataset, which may not encompass the full diversity of patient experiences and drug interactions.

In recent years, the development of medical chatbots has gained significant attention as a means to enhance healthcare accessibility and efficiency. A notable example is the research conducted by Mathew et al., which proposes a medical chatbot that leverages natural language processing (NLP) and machine learning techniques, specifically the K-nearest neighbor (KNN) algorithm, to facilitate disease diagnosis based on user-reported symptoms[39]. The proposed system allows users to engage in conversational interaction with the chatbot, enabling it to identify symptoms and subsequently predict potential diseases while recommending appropriate treatments.

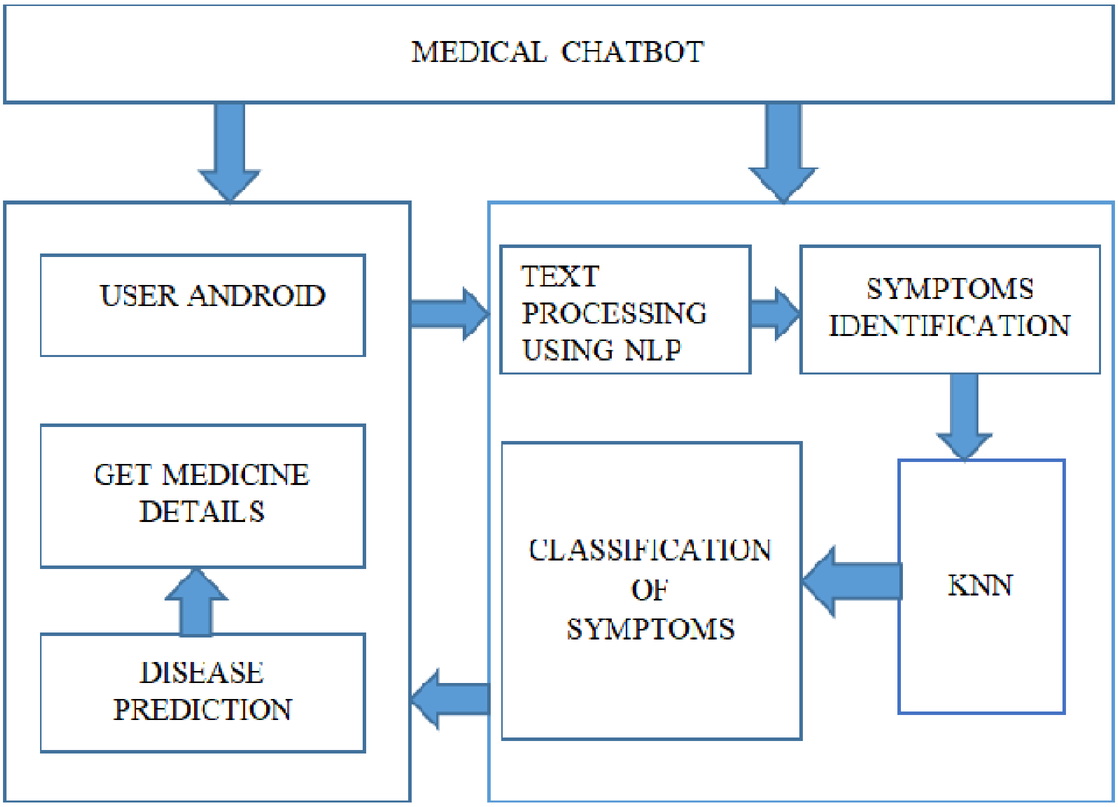

Figure 2.16: Working model of the proposed model conducted by Mathew et al.[39]

This innovative approach aims to alleviate the burden of traditional healthcare systems by providing a free, accessible, and user-friendly alternative for individuals who may find it challenging to visit hospitals due to time constraints or other barriers. The authors highlight the role of the chatbot in promoting health awareness and encouraging users to take proactive measures regarding their health status. Furthermore, the study emphasizes the potential of such technology to reduce the number of individuals neglecting their health due to the cumbersome process of hospital appointments. However, the research also acknowledges certain limitations, including the reliance on the accuracy of the underlying dataset and the potential for misdiagnosis in more complex medical cases, which underscores the necessity for further validation and integration with professional medical services to enhance reliability and effectiveness.

A notable study by Lee et al. developed a smartphone-compatible AI chatbot designed to classify patient symptoms and recommend appropriate medical specialties, addressing the challenges posed by the COVID-19 pandemic[40]. The authors constructed a deep learning-based natural language processing (NLP) pipeline utilizing a dataset of 118,008 sentences, ultimately refining it to 51,134 sentences for model training.

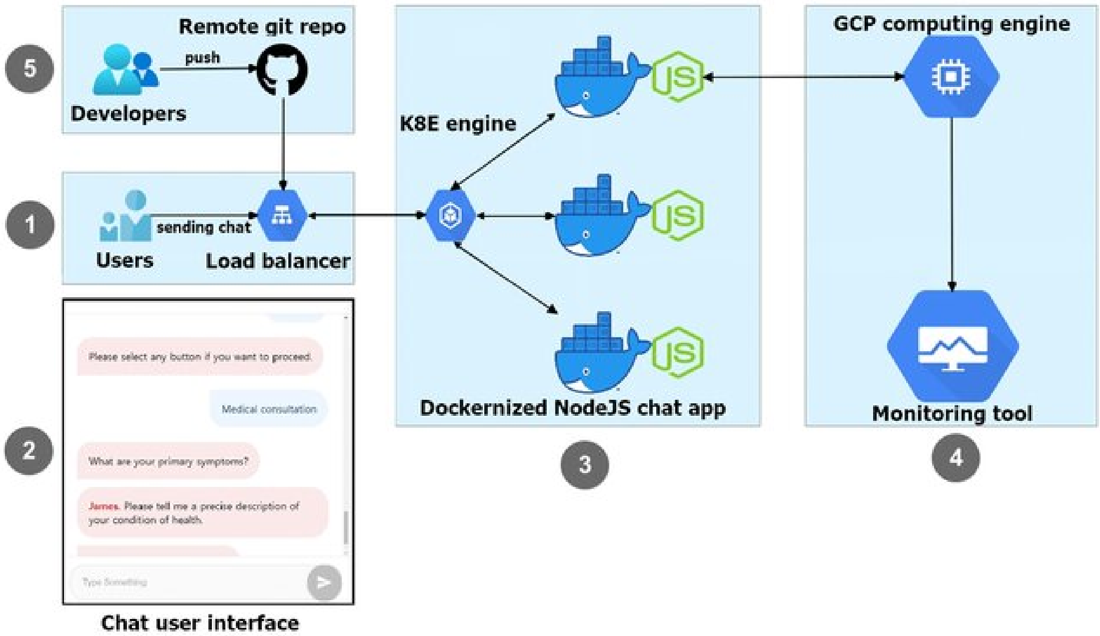

Figure 2.17: Architecture of the chatbot. This figure illustrates the workflow of the developed prototype chatbot[40]

Their findings indicated that the bidirectional encoder representations from the transformers (BERT) model achieved the highest performance metrics, including an area under the receiver operating characteristic curve (AUC) of 0.964 and an F1-score of 0.768. However, due to computational constraints, the authors opted to deploy a lighter long short-term memory (LSTM) model for practical use in their chatbot application. This innovative approach not only facilitates rapid and contactless patient-specialist connections but also highlights the potential of AI-driven solutions in enhancing primary care services. Nonetheless, the study's limitations include the reliance on a single data source, which may affect the generalizability of the findings across diverse patient populations.

The Robotic Medical Support ChatBot (RMSCB) system proposed by Sreedhar Kumar et al. represents a notable advancement in this domain, leveraging machine learning techniques to autonomously predict medical diagnoses and provide temporary solutions[41]. This system specifically addresses the critical lack of 24/7 medical facilities in rural areas, where access to healthcare can be severely limited, especially during non-standard hours. The RMSCB operates through a structured process that includes pre-processing, training, and classification stages.

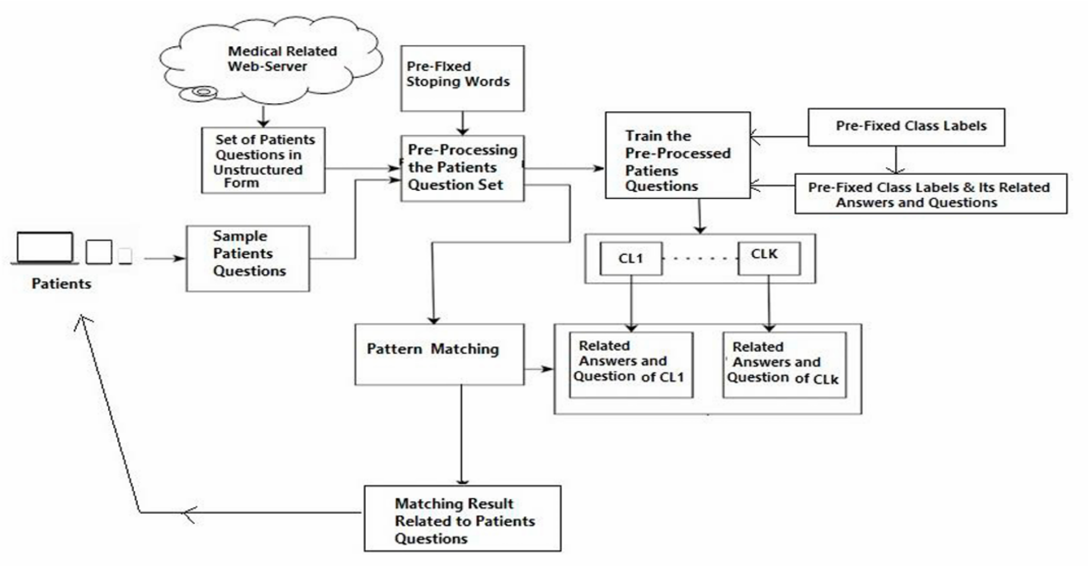

Figure 2.18: Proposed RMSCB System Architecture[41]

It employs models such as the Pre-Fixed Stopping Words Model (PFSWM) to filter irrelevant information and the Pre-Fixed Class Label Model (PFCLM) to categorize medical inquiries effectively. By mapping clinical questions to potential diagnoses and corresponding first-aid solutions, the RMSCB enhances the accuracy and reliability of medical advice provided to users. Experimental results demonstrate the system's efficacy in offering timely first-aid medication information, thereby alleviating the need for immediate physician consultation, particularly in regions with limited access to healthcare services. However, the study acknowledges certain limitations, including the system's potential struggle with complex medical queries and its reliance on pre-defined medical knowledge, which may not encompass all possible health scenarios or account for individual patient variations.

Phooriyaphan et al. designed a comprehensive DSS that employs the Analytic Hierarchy Process (AHP) to assist healthcare organizations in identifying the most suitable chatbot based on a set of critical criteria, including functionalities, multilingual ability, usability, and security and privacy[42]. Their research underscores the growing reliance on chatbots within the healthcare sector, which serve various functions such as facilitating patient interactions, managing appointment scheduling, and disseminating vital medical information.

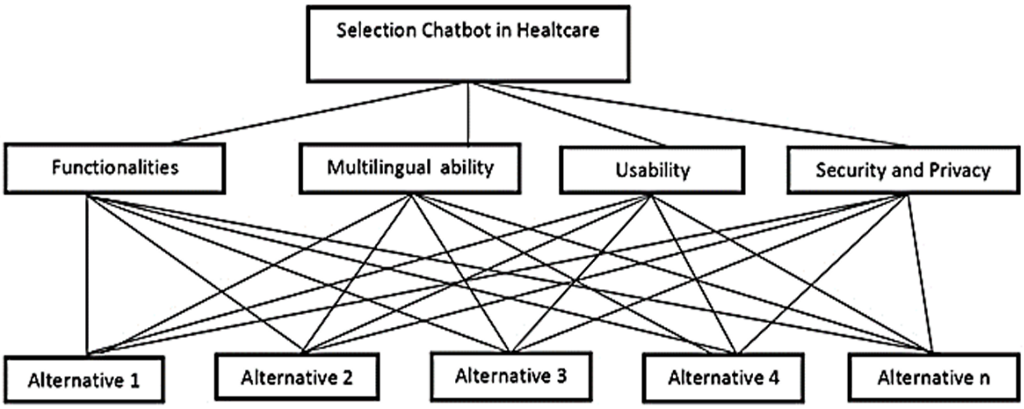

Figure 2.19: AHP structure of selection chatbot in healthcare[42]

By implementing a structured decision-making framework, the DSS aims to enhance patient satisfaction and improve operational efficiency in healthcare settings. The study further illustrates the effectiveness of the DSS in providing reliable and accurate decision-making support, thereby addressing the complexities and challenges associated with selecting appropriate healthcare chatbots. Additionally, the authors conducted a sensitivity analysis to evaluate the robustness of their findings, ensuring that the decision-making process remains adaptable to changing requirements. However, the limitations of this paper include a focus on a specific geographical context (Bangkok, Thailand) and the potential variability in chatbot performance across different healthcare settings, which may affect the generalizability of the findings to other regions or healthcare systems.

S. Venkatesh et al. proposed a Drug Recommendation System in Medical Emergencies utilizing Machine Learning techniques to assist healthcare professionals in making timely and accurate drug selections based on patient symptoms, medical history, and emergency conditions[43]. The system integrates data from various medical databases and employs algorithms such as Decision Trees, Random Forests, and Neural Networks to predict optimal drug choices, thereby enhancing decision-making and reducing human errors in emergency drug prescriptions. The study emphasizes the importance of real-time recommendations and considers factors like contraindications and potential drug interactions to ensure safer drug administration. However, the limitations of this paper include challenges related to data quality and the need for comprehensive integration with existing healthcare systems.

In conclusion, the reviewed literature underscores the transformative potential of digital health solutions, particularly clinical decision support systems (CDSS), in enhancing healthcare delivery in resource-limited settings like Bangladesh. While these systems have demonstrated effectiveness in reducing medication errors and improving diagnostic accuracy, challenges such as data interoperability, user engagement, and the need for standardized methodologies persist. The integration of AI and machine learning further enhances diagnostic capabilities, yet concerns regarding trust and transparency remain. Overall, there is a pressing need for comprehensive, user-friendly, and secure clinical support systems that can effectively address the multifaceted challenges of medication errors and healthcare access, ultimately leading to improved patient outcomes. Our research will focus on refining these systems to adapt to the unique healthcare dynamics of Bangladesh.

2.5 Overview of literature review

This table 3.5.0.1 presents a comprehensive overview of the existing research and methodologies in the field of clinical support system. Through an extensive review of academic literature and studies, various approaches, including different CDSS architectures, machine learning, and dataset sources, have been examined. The table encapsulates critical information such as the models employed, comparative performance, contributions on this field and limitations in those methodologies. This summary serves as a valuable reference for understanding the landscape of research efforts in clinical support system, providing insights into the diverse strategies and their efficacy in this domain.

Table 2.5.0.0.1: Summarization of literature review

Author(s)	**Methods**	**Results**	**Contributions**	**Limitation**
Castaneda et al. [17]	Biostatistical	The development of user-friendly CDSS that can effectively process and present aggregated knowledge to healthcare providers	Emphasize the critical role of integrating electronic health records (EHRs) and bioinformatics to enhance diagnostic accuracy and facilitate precision medicine	CDSS implementations have not demonstrated significant improvements in clinical outcomes, indicating a need for further refinement and integration of these systems to realize their full potential in clinical practice

Author(s)	Methods	Results	Contributions	Limitation
Iqbal et al. [19]	Hybrid algorithm (FOCL)	FOCL, demonstrates improved performance over traditional methods by combining expert knowledge with machine learning capabilities, allowing for a more robust decision-making process	The importance of transparency in the decision-making process, ensuring that the rationale behind diagnostic suggestions is understandable to healthcare providers	The reliance on the quality of input data and the potential for over-fitting due to the complexity of the hybrid model
Lamprinakos et al. [15]	FHIR-based mobile application using RESTful API	AidIT app allows access and management of personal health records by patients, doctors, and pharmacists	Promotes interoperability, reduces medical errors, provides dynamic access control and user-friendly UI	Does not integrate wearable health monitoring devices for real-time data sharing
Zahid et al. [5]	Conceptual framework for Digital Health Services	Highlights gaps in usability, privacy, and infrastructure in Bangladesh's digital health system	Offers a design framework focused on user engagement, data security, interoperability, and scalability	Lacks empirical validation and generalization across different healthcare environments in Bangladesh

Author(s)	Methods	Results	Contributions	Limitation
Hussain et al. [23]	Sensor-integrated Smart CDSS using HL7 vMR and Arden Syntax	Enables real-time monitoring and decision support for diabetes patients in home settings	Provides layered architecture for interoperability, safety, and remote support	Limited focus on diabetes; not generalizable to broader chronic disease management
Chrimes et al. [26]	Decision tree-based expert system	Decision tree with 212 nodes stratified by age, systems, and conditions to assess COVID-19 severity	Enhances diagnostic accuracy and synthesizes complex medical data into actionable insights	Excludes gender as a factor; relies on secondary data, affecting generalizability
Garcia Valencia et al. [27]	AI-powered chatbot	Improves clinical decision-making, patient education, and medication management in kidney transplant cases	Enables real-time access to guidelines and personalized patient communication within CDSS	Requires further studies for validation; potential ethical, bias, and transparency concerns in AI
Jung et al. [29]	CDS Hooks and HL7 FHIR	Implemented a national drug-allergy interaction (DAI) CDS with over 1 million checks	Enabled affordable CDS integration for providers using cloud-based shared services	Dependency on a proprietary value set due to the absence of a national allergy code system

Author(s)	Methods	Results	Contributions	Limitation
Hasan et al. [32]	Observational study with DICMA in ICU	Identified over 11,000 drug interactions, 95.85% of pharmacist suggestions accepted	Highlighted value of clinical pharmacists and mobile apps for medication safety	Single ICU focus and no clinical outcome or side-effect assessment
Feng et al. [35]	Cluster-Predict-Schedule (CPS) using ML	Achieved 15% cost reduction and improved appointment fairness	Demonstrated effectiveness of AI in outpatient scheduling optimization	Limited generalizability due to reliance on historical data and local variability
Alam et al. [37]	Mixed-methods mHealth study	68% rural users found the service trustworthy and cost-effective	Demonstrated mHealth's role in remote maternal care access	Limited qualitative interview sample and lack of socioeconomic data
Lee et al. [40]	NLP using BERT and LSTM	Achieved AUC of 0.964 for symptom-to-specialty chatbot	Improved triage and primary care access using deep learning chatbot	Limited dataset source may restrict generalizability across populations
Mohapatra et al. [38]	Sentiment analysis with collaborative filtering	Designed drug recommender system using patient reviews	Improved drug choices through user-driven recommendation integration	Dataset limitations reduce coverage of patient diversity and interactions

Author(s)	Methods	Results	Contributions	Limitation
Paul et al. [31]	Prescription error analysis	Found 692 medication-related problems with 366 drug interactions	Identified gaps in prescribing practices, stressed need for pharmacists	Single facility focus and excludes outcome tracking for identified errors
Sultana et al. [34]	Cross-sectional prescription study	Found 769 prescription errors and 409 drug interactions	Highlighted irrational drug use and polypharmacy trends in Bangladesh	No exploration of error severity or treatment outcomes
Mathew et al. [39]	KNN-based chatbot with NLP	Enabled interactive disease prediction based on symptoms	Made health screening accessible via conversational AI	Susceptible to misdiagnosis in complex conditions due to dataset dependency

The information in Table 3.5.0.1 offers a comprehensive overview of the current state of research and methodologies within the realm of plant identification using image processing and deep learning techniques. Extensively reviewing academic literature and studies has allowed for the exploration of various approaches, encompassing diverse neural network architectures, feature extraction methods, and dataset sources.

Chapter 3

Materials and Method

3.1 Materials

This study presents the development of a smart clinical support system aimed at improving healthcare data management and interoperability. The system is designed to simplify the exchange of clinical data using international standards and modern Web technologies. To achieve this, HL7 and FHIR standards are employed for messaging and resource-based data exchange, while HAPI FHIR serves as the backbone for our FHIR server implementation. The system also integrates with existing Electronic Health Record (EHR) solutions and uses Django to build a secure, scalable, and user-friendly web interface. To support our clinical decision making for both doctors and patients, a medical recommendation system chat bot has been built and trained on a medical dataset using the DialoGPT open source language model, allowing it to provide suggestions for medical conditions.

3.1.1 Dataset Collection

As our project intends to make a clinical decision support system for the users, we need real-time patient data from them so that it is understandable to train our model on what type of medical help is needed for a user, and what is the solution for those symptoms. But collecting real-time patient data can raise privacy and compliance concerns. So we have used a synthetic medical dataset specifically designed for training our clinical decision support chatbot. We have developed a custom Python script to create 500 structured medical records in JSON format, simulating realistic doctor-patient conversations. Each record includes patient demographics, reported symptoms, and possible medical conditions. As there are many health scenarios in the medical sector, collecting the real solution for a symptom in a dataset is hard. So, we focused on Fever, Diabetes, and Heart-related symptoms and their solutions in our dataset. This synthetic approach allows us to maintain ethical standards and data privacy while still providing high-quality inputs for training and evaluating our AI model.

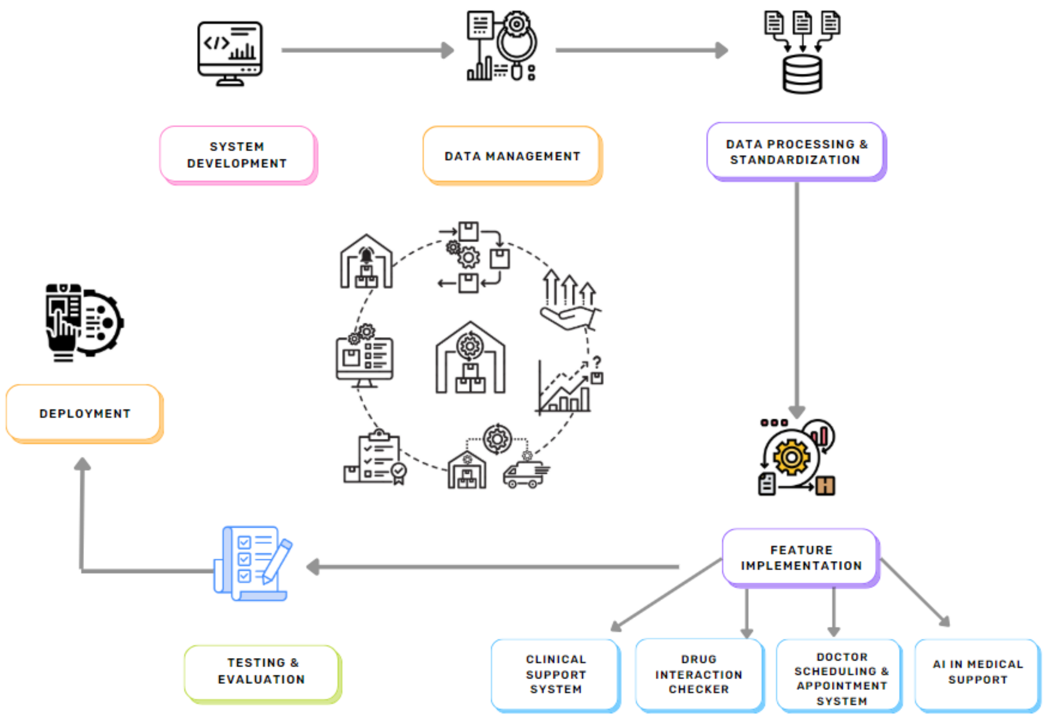

Figure 3.1: Flowchart of the Methodology

3.1.2 Data Processing

To build our medical chatbot more reliably, we first needed a dataset that reflects typical clinical conversations. Since real patient data comes with privacy and ethical concerns, we chose to create synthetic data instead. Using a custom Python script, we generated some synthetic medical dialogue records in JSON format to train our model. Each record simulates an interaction between a patient or doctor and our AI assistant to ask medical suggestion, including information such as symptoms, basic health concerns, and potential follow-up suggestions.

FHIR Compliance: We organized all our medical data according to FHIR (Fast

Healthcare Interoperability Resources) standards. This structure maintain all the health data in a certain structure to maintain a specific standard for sharing their data between health clinic.

Data Cleaning: We reviewed the synthetic dataset to identify any records that were incomplete, inconsistent, or improperly formatted. To handle these errors, missing symptom descriptions or incorrectly structured JSON fields were automatically detected by validation scripts. Minor issues were corrected using automated rules. For more complex errors, such as unclear medical logic or missing context in conversations, the data was flagged for manual review. This step helped ensure that the data the model would learn from was clean, reliable, and meaningful.

Data Normalization: We standardized medical terms and classifications used in the dataset in a specific system. For this step, we created a file in Python that mapped informal or varied symptom names to standardized medical terms. We removed all the data duplication from the dataset. This normalization helps the model to recognize patterns more effectively and makes it easier to search and information while giving a response.

AI Model Training & Optimization: We have prepared the medical dataset to train our conversational AI model. We used the DialoGPT-medium model developed by Microsoft, which is designed to handle natural dialogue. In the training process, we trained the model with the data so that it could learn how to respond when a user asks for medical help. We split the dataset into input (user message) and output (expected response) pairs. The training loop used basic machine learning functions to calculate and minimize error after each batch of conversations. We also adjusted settings like the number of training epochs, batch size, and learning rate to improve performance. As new synthetic data is generated, we plan to retrain the model periodically to keep improving its accuracy in suggesting relevant medical problems.

These preprocessing of the dataset before ensure that the dataset is clean, standardized, and effective for training a reliable medical chatbot that supports accurate clinical decision-making.

3.2 Method

After preparing our dataset, our approach to developing the website maintain FHIR standards and implement a medical assistant to ensure reliable clinical decision making. We propose a clinical decision-making medical assistant using the DialoGPT model with our medical dataset. The user-friendly web application design simplifies real-time decision making in medical help through continuous training, creating a dependable and easily accessible solution. In the subsequent sections, we'll dive into the specifics of our approach, providing detailed insights into the model architecture, system design, algorithmic formulations, and the thorough experiment setup that forms the backbone of our clinical decision-making system framework.

3.2.1 Design/Framework

HL7 Infrastructure

HL7 (Health Level Seven) standards used as the foundation for messaging between healthcare systems, providing established protocols for sharing administrative and clinical data with proper validation and acknowledgment mechanisms. This implementation ensures the reliable transmission of critical healthcare information.

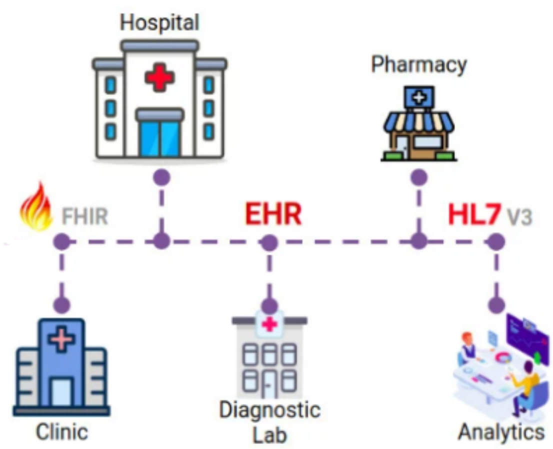

Figure 3.2: Integration of EHR & FHIR in Clinical Services

FHIR Resource Implementation

FHIR (Fast Healthcare Interoperability Resources) standards are utilized to represent healthcare data as modular resources (such as Patient, Observation, MedicationRequest) with clearly defined relationships. This approach provides flexibility while maintaining semantic integrity of clinical information, allowing for granular access to specific health data components.

HAPI FHIR Server Architecture

HAPI FHIR, an open-source Java implementation of the FHIR specification, serves as the backbone for our FHIR server implementation. This framework handles resource parsing, validation, terminology services, and RESTful API operations while ensuring compliance with the FHIR standard and reducing development complexity.

EHR Integration Framework

The system integrates with existing Electronic Health Record (EHR) solutions through standardized interfaces, allowing facilities to maintain their current systems while gaining interoperability benefits. This approach minimizes disruption to clinical workflows while enhancing data exchange capabilities.

DialoGPT Model for Conversational Response

DialoGPT is large-scale pretrained conversational language model developed by Microsoft. To build our medical chat bot we used this model and trained the model with our datasets that have medical data for any disease symptoms so that it can suggests doctor or patients when they ask for any medical related suggestions. This training helped the model how to recognize common symptoms, understand patients queries, and suggest possible medical problems based on the context of the conversation.

Django Web Application Layer

Django web framework is employed to build a secure, scalable, and user-friendly interface, providing robust authentication, authorization mechanisms, and efficient database operations. The framework's MVC architecture enables clean separation of concerns and maintainable codebase for long-term sustainability.

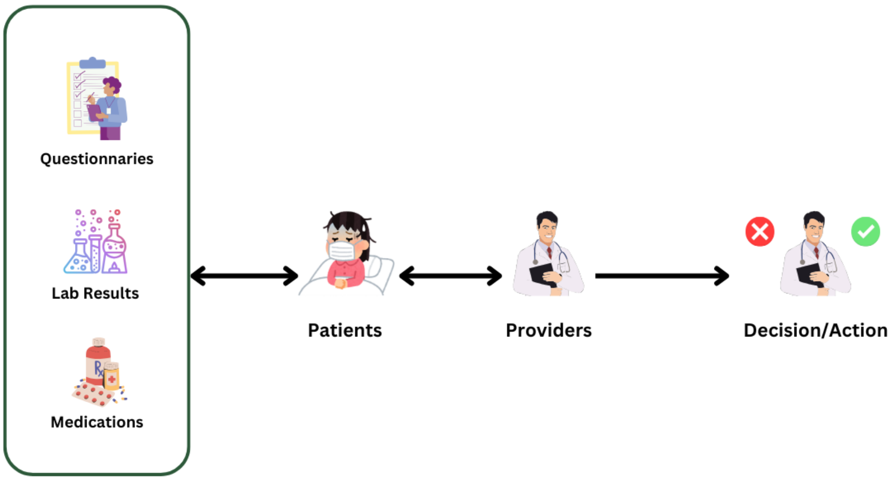

Figure 3.3: Doctor-Patient Interactions

3.2.2 Designing and Building Webpage

We are currently developing the "Bangladesh Clinical Support System" web interface, a user-friendly tool designed to aid in efficient healthcare data management and communication. This web application addresses the need for accessible and reliable clinical information exchange, particularly for healthcare providers working across different facilities.

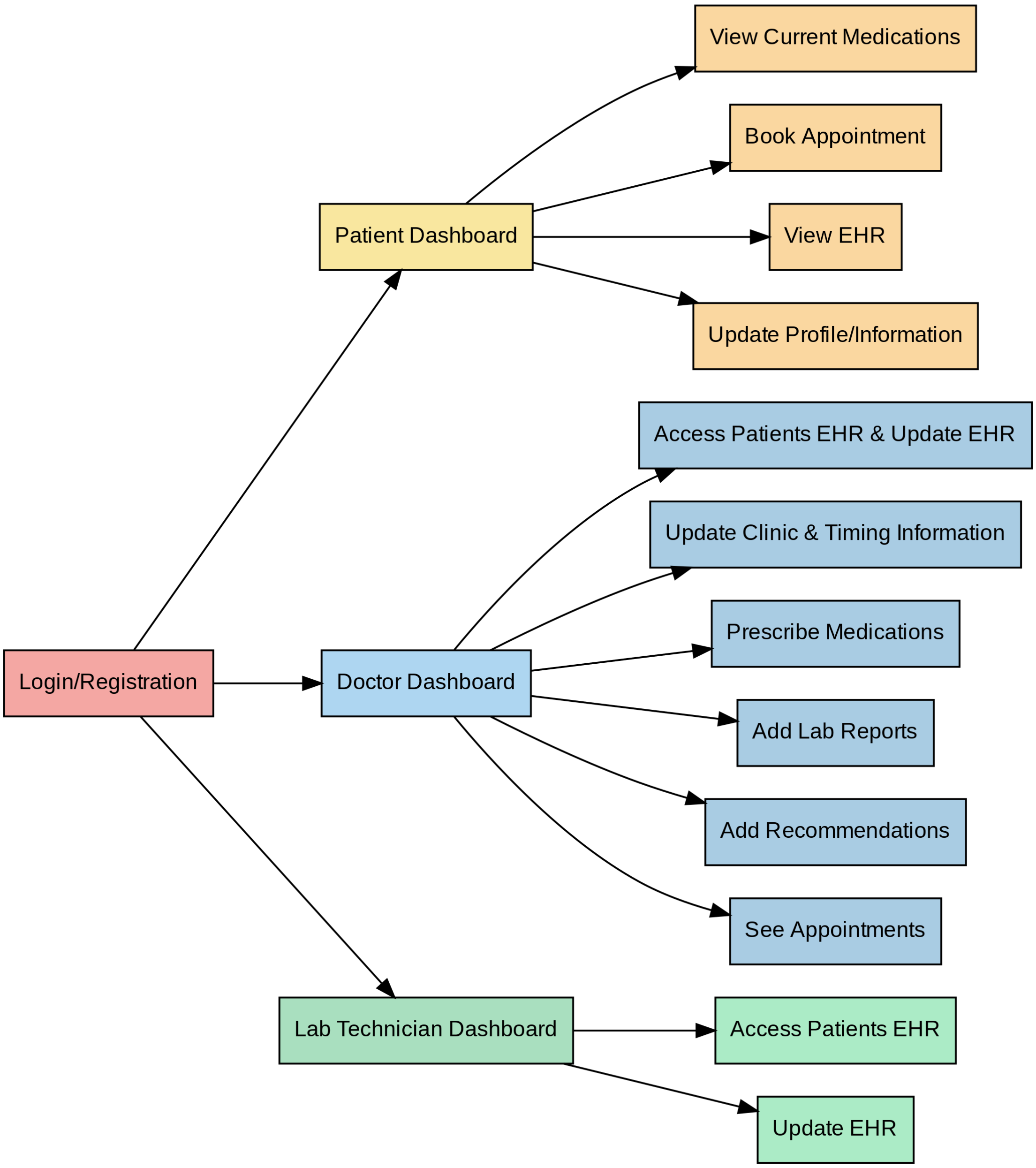

Figure 3.4: Sample Flowchart of Smart Clinical Support System

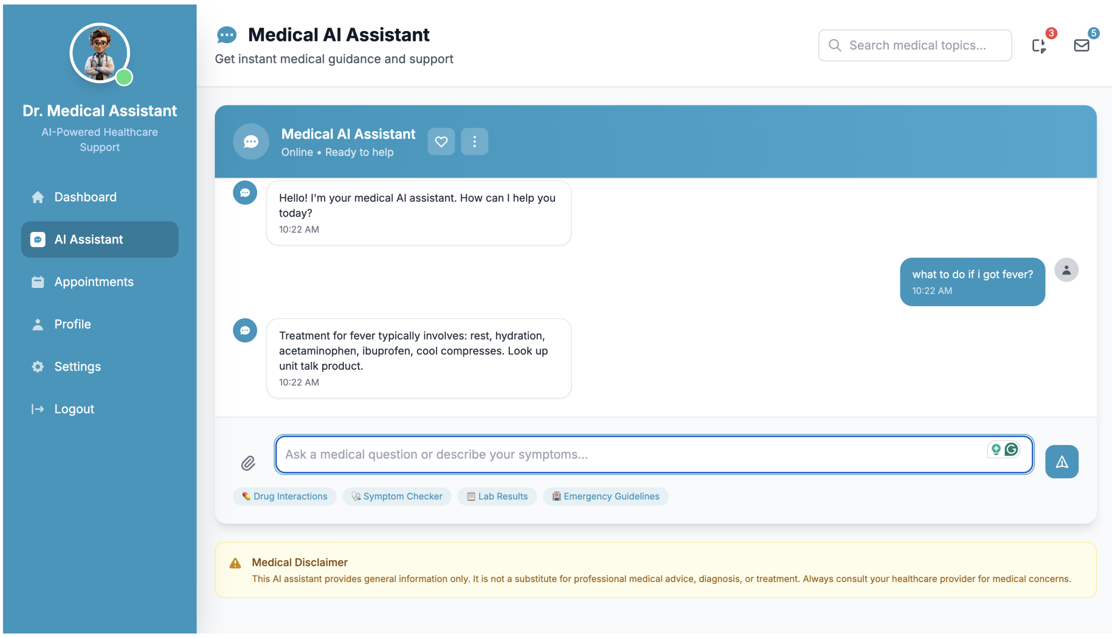

Figure 3.5: Sample Snapshot of our Website

The webpage implements a organized interface prioritizing centralized patient data access. Healthcare providers can search for patients and view their medical records through an intuitive dashboard. The system utilizes FHIR standards to organize clinical information, categorizing it by type for easy navigation. Each patient record will display demographic information, medical history, current medications, and recent diagnostic results, with the ability to access detailed clinical documentation when needed. By integrating HL7 FHIR standards with a user-centered design approach, the interface aims to simplify complex healthcare workflows while maintaining compliance with international data exchange standards.

Chapter 4

Results and Discussion

4.1 Obtained Results

The **Smart Clinical Support** platform has successfully created an integrated online healthcare environment that connects doctors and patients. Patients can now easily book doctor appointments remotely, addressing accessibility challenges, especially in rural areas of Bangladesh. The platform also includes a functional AI chatbot trained on medical terminology, providing basic medical suggestions and guidance while ensuring patient privacy.
Another key achievement is the medication reminder system, which helps patients adhere to their medication schedules through timely notifications. User testing revealed that both patients and doctors found the platform easy to use, with positive feedback regarding its responsiveness and design simplicity. The chatbot demonstrated a satisfactory response accuracy rate when evaluated against predefined medical queries.

4.2 Discussion

The outcomes of this project highlight the significance of digital healthcare solutions in Bangladesh. The online doctor booking and medication reminder features address critical healthcare gaps, improving access and medication adherence. While the chatbot is not a substitute for medical professionals, it provides users with quick, privacy-safe medical suggestions. Some limitations were identified. The chatbot struggled with complex queries that were beyond its training scope, indicating a need for future enhancements in AI capabilities. Additionally, the system requires further scalability testing before large-scale deployment.

Overall, the **Smart Clinical Support** platform represents a promising step toward enhancing healthcare accessibility, efficiency, and patient engagement in Bangladesh.

Chapter 5

Conclusion

The **Smart Clinical Support System** represents a significant advancement in modernizing healthcare support systems in Bangladesh. Bangladesh where people are deprived of reliable medical healthcare service within their financial support, our Clinical Support System opens a new door to the people of Bangladesh where people can get medical service through a medical assistant who is always available. This platform can helps both doctor and patients give One of the system's features is the integration of a chatbot trained on medical data, which ensures privacy protection while providing contextually relevant medical recommendations for healthcare providers. This clinical support tool offers suggestions on medical terminology, treatments, and clinical procedures, making the diagnostic and treatment planning processes more efficient. It also stores healthcare data following a certain standard FHIR which is shareable among the clinics anytime which results in patients don't need to carry medical information like prescription, lab report all the time and ensure a secure treatment to the patients.

5.1 Overall Contributions

The project makes substantial contributions to the field of healthcare solutions, particularly in resource-constrained environments like Bangladesh. This clinical support system provide a new approach to healthcare of Bangladesh where both doctor and patients can take suggestion from a medical assistant. This medical assistant is developed with the help of DialoGPT model which is trained with our medical dataset. Besides, we used FHIR standard to store patient data, medical report related data. As the stored data maintain a certain standard, the data are widely sharable among the clinics. When patient data are accessible among the clinics with proper security, healthcare service become simpler and easier to take from anywhere.

5.2 Limitations and Future Work

In our current project, we have accomplished quite a bit, but there are a couple of considerations. Due to time and budget constraints, we couldn't cover all features we wanted to build. As we could not collect real time data and used certain amount of data, there lack remains in our chatbot while training the model to suggest fully correct suggestion in the conversation. Currently, the chatbot focuses on suggesting medical terms and procedures but does not provide complete diagnostic decisions or patient-specific treatment plans.

In future, we plan to make the dataset medical assistant chatbot more reliable with real time patient data with a security. Also, the clinics and hospital can share the patient data while needed from one clinic to another clinic and patient don't need to store their medical record manually. Another plan is provide our healthcare system nationwide so that people from rural to city, everyone can get healthcare service easily with our cilinal support system.

By addressing these future development areas, **Smart Clinical Support System** has the potential to become a powerful and widely adopted tool in the Bangladeshi healthcare sector, ultimately improving both doctor efficiency and patient outcomes.

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Appendix A

Mapping of Course and Program Outcomes

CSE400-A

Program Outcomes:

PO1 (Engineering Knowledge): Engineering Knowledge (Cognitive): Apply the knowledge of mathematics, science, engineering fundamentals and an engineering specialization to the solution of complex engineering problems.

PO4 (Investigation): Conduct investigations of complex problems, considering design of experiments, analysis and interpretation of data and synthesis of information to provide valid conclusions.

CO	Details	Knowledge Profile (K)	Engineering problem (EP)

CO1	Integrate new and previously acquired knowledge for identifying a real-life complex engineering problem as the capstone project	**(i) Identify a real-life problem** [**K1, K2, K3, K4**] **K1: Theory-based natural Sciences:** A systematic, theory-based understanding of the natural sciences applicable to the discipline **K2: Conceptually-based mathematics, numerical analysis, statistics, and formal aspects of computer and information science:** Conceptually based mathematics, numerical analysis, statistics and the formal aspects of computer and information science to support analysis and modeling applicable to the discipline **K3: Theory-based engineering fundamentals:** A systematic, theory-based formulation of engineering fundamentals required in the engineering discipline **K4: Forefront engineering specialist knowledge for practice:** Engineering specialist knowledge that provides theoretical frameworks and bodies of knowledge for the accepted practice areas in the engineering discipline; much is at the forefront of the discipline	**(i) Identify a real-life problem** [**EP1, EP2, EP3, EP4, EP5, EP6, EP7**] **EP1: Depth of knowledge required:** Cannot be resolved without in-depth engineering knowledge at the level of one or more of K3, K4, K5, K6, or K8 which allows a fundamental-based, first principles analytical approach **EP2: Range of conflicting requirements:** Involve wide-ranging or conflicting technical, engineering and other issues **EP3: Depth of analysis required:** Have no obvious solution and require abstract thinking, originality in analysis to formulate suitable models **EP4: Familiarity of issues:** Involve infrequently encountered issues **EP5: Extent of applicable codes:** Are outside problems encompassed by standards and codes of practice for professional engineering **EP6: Extent of stakeholder involvement and conflicting requirements:** Involve diverse groups of stakeholders with widely varying needs **EP7: Interdependence:** Are high level problems including many component parts or sub-problems

CO2	Examine various problem domains (literature review), define the problems, and formulate the objectives for the capstone project	**(i) Define the problems** [**K8**] **K8: Research Literature:** Engagement with selected knowledge in the research literature of the discipline	**(i) Define the problems** [**EP1, EP2, EP3, EP4, EP5, EP6, EP7**] [**Same as (CO1)**]

CSE400-B

Program Outcomes:

PO2 (Problem Analysis): Identify, formulate, research the literature and analyze complex engineering problems and reach substantiated conclusions using first principles of mathematics, the natural sciences and the engineering sciences.

PO3 (Design/Development of Solutions): Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for public health and safety as well as cultural, societal and environmental concerns.

PO5 (Modern Tool Usage): Create, select and apply appropriate techniques, resources and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

PO6 (The Engineer and Society): Apply reasoning informed by contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to professional engineering practice.

CO	Details	Knowledge Profile (K)	Engineering Problem (EP)

CO3	**Design** hardware and/or software for the finalized project incorporating societal, environmental, and ethical considerations; **build** the proposed system incorporating project management and financial principles and **justify** (test) the deliverable system.	**i) Problem Analysis [K1, K2, K3, K4]** **K1: Theory-based natural Sciences:** A systematic, theory-based understanding of the natural sciences applicable to the discipline **K2: Conceptually-based mathematics, numerical analysis, statistics, and formal aspects of computer and information science:** A systematic, theory-based understanding of the natural sciences applicable to the discipline. **K3: Theory-based engineering fundamentals:** A systematic, theory-based formulation of engineering fundamentals required in the engineering discipline **K4: Forefront engineering specialist knowledge for practice:** Engineering specialist knowledge that provides theoretical frameworks and bodies of knowledge for the accepted practice areas in the engineering discipline; much is at the forefront of the discipline	**(i) Problem Analysis [EP1, EP2, EP3, EP6, EP7]** **EP1: Depth of knowledge required:** Cannot be resolved without in-depth engineering knowledge at the level of one or more of K3, K4, K5, K6, or K8 which allows a fundamental-based, first principles analytical approach **EP2: Range of conflicting requirements:** Involve wide-ranging or conflicting technical, engineering and other issues **EP3: Depth of analysis required:** Have no obvious solution and require abstract thinking, originality in analysis to formulate suitable models **EP6: Extent of stakeholder involvement and conflicting requirements:** Involve diverse groups of stakeholders with widely varying needs **EP7: Interdependence:** Lorem Ipsum is simply dummy text of the printing and typesetting industry.

CO4	**Use** different visualization tools and *write* and **present** (oral and/or poster) technical report incorporating different evaluation matrices including efficiency, cost; and ethical, societal, economic, and environmental impacts.	**(i) Design and Implementation [K5]** **K5: Engineering design:** Knowledge that supports engineering design in a practice area	**(i)Design and Implementation [EP1, EP2, EP4, EP5, EP6, EP7]** **EP1: Depth of knowledge required:** Cannot be resolved without in-depth engineering knowledge at the level of one or more of K3, K4, K5, K6, or K8 which allows a fundamental-based, first principles analytical approach **EP2: Range of conflicting requirements:** Involve wide-ranging or conflicting technical, engineering and other issues **EP4: Familiarity of issues:** Have no obvious solution and require abstract thinking, originality in analysis to formulate suitable models **EP5: Extent of applicable codes:** Involve infrequently encountered issues **EP7: Interdependence:** Are high level problems including many component parts or sub-problems

CO5	Show the skill of being an effective team player.	**(i) Materials and Devices [K6]** **K6: Engineering Practice (technology):** Knowledge of engineering practice (technology) in the practice areas in the engineering discipline	**(i) Materials and Devices [EP1, EP2, EP4, EP5]** **EP1: Depth of knowledge required:** Cannot be resolved without in-depth engineering knowledge at the level of one or more of K3, K4, K5, K6, or K8 which allows a fundamental-based, first principles analytical approach **EP2: Range of conflicting requirements:** Involve wide-ranging or conflicting technical, engineering and other issues **EP4: Familiarity of issues:** Involve infrequently encountered issues. **EP5: Extent of applicable codes:** Are outside problems encompassed by standards and codes of practice for professional engineering

CO6	Demonstrate the capacity to learn beyond classroom lectures and activities	**(i) Social and Environmental Impact of Engineering** [**K7**] **K7: Comprehension of engineering in society:** Comprehension of the role of engineering in society and identified issues in engineering practice in the discipline: ethics and the engineer's professional responsibility to public safety; the impacts of engineering activity; economic, social, cultural, environmental and sustainability	**(i) Social and Environmental Impact of Engineering** [**EP2, EP5, EP6**] **EP2: Range of conflicting requirements:** Involve wide-ranging or conflicting technical, engineering and other issues **EP5: Extent of applicable codes:** Are outside problems encompassed by standards and codes of practice for professional engineering **EP6: Extent of stakeholder involvement and conflicting requirements:** Involve diverse groups of stakeholders with widely varying needs

CSE400-C

Program Outcomes

- **PO7 (Environment and Sustainability):** Develop a Clinical Decision Support System (CDSS) that promotes efficient healthcare resource utilization, minimizes redundant diagnostic procedures, and supports environmentally conscious digital health practices.
- **PO8 (Ethics):** Ensure ethical compliance in handling patient data, including privacy, confidentiality, informed consent, and unbiased algorithm design throughout the development and deployment of the CDSS.
- **PO9 (Individual Work and Teamwork):** Demonstrate the ability to work independently and collaboratively within interdisciplinary healthcare and engineering teams during the design, development, and validation of the CDSS.
- **PO10 (Communication):** Communicate technical and clinical aspects of the CDSS effectively to both healthcare professionals and technical stakeholders, ensuring clarity in decision-making support and system use.
- **PO11 (Project Management and Finance):** Apply sound project planning, timeline management, and cost-effective strategies to successfully deliver

the CDSS while meeting regulatory and clinical requirements.

- **PO12 (Life-Long Learning):** Continuously engage in learning emerging trends in medical informatics, machine learning, and healthcare interoperability standards (e.g., HL7, FHIR) to ensure the CDSS remains current and clinically relevant.

CO	Details	Knowledge Profile (K)	Engineering Problem (EP)
CO7	It is essential to ensure that the CDSS contributes to sustainable and responsible healthcare delivery. The system reduces unnecessary testing, promotes evidence-based clinical practices, and avoids overuse of resources. No negative environmental impact is associated with the digital infrastructure used.	(i) Societal and environmental contexts [K7] **K7:** Comprehension of engineering in society — consideration of environmental, ethical, and sustainability aspects in clinical technology deployment.	(i) Societal and environmental contexts [EP2, EP5, EP6] **EP2:** Addressing conflicting clinical and technical requirements. **EP5:** Use of applicable medical and software development standards (e.g., HL7, ISO 13485). **EP6:** Adapting to feedback from diverse healthcare stakeholders (doctors, patients, IT staff).
CO8	The CDSS respects patient data privacy and security by enforcing encryption, anonymization, and informed consent. Ethical frameworks were applied in algorithm training to reduce bias and ensure fairness in clinical recommendations.	(i) Ethics and equity [K7] **K7:** Understanding ethical principles in healthcare data usage, fairness in algorithms, and transparency.	(i) Legal, health, safety, and ethical issues [EP5, EP6] **EP5:** Compliance with health IT regulations (HIPAA, GDPR). **EP6:** Managing trade-offs between data utility and patient rights.

CO	Details	Knowledge Profile (K)	Engineering Problem (EP)
CO9	All team members contributed according to their expertise in machine learning, medical domain knowledge, or frontend/backend development. Collaboration between developers and healthcare professionals was essential for clinical accuracy.	(i) Teamwork and communication [K6] **K6:** Knowledge of team-based software development in health tech environments.	(i) Interpersonal and organizational issues [EP4, EP6] **EP4:** Need for interdisciplinary collaboration in medical projects. **EP6:** Balancing stakeholder roles from IT and healthcare fields.
CO10	Clear and effective communication with clinical staff and developers was crucial in requirement gathering, feedback collection, and training healthcare professionals to use the CDSS.	(i) Communication [K5] **K5:** Engineering communication skills applied in technical documentation, GUI design, and presentations.	(i) Communication and stakeholder alignment [EP4, EP6] **EP4:** Translating technical decisions into clinically understandable language. **EP6:** Handling varying expectations from clinicians and developers.
CO11	The project followed agile development with defined sprints, regular reviews, and version control. Costs were minimized using open-source frameworks, and resource planning ensured timely delivery.	(i) Project management and financial planning [K4] **K4:** Knowledge of managing software life cycles and estimating healthcare IT costs.	(i) Resource constraints and project delivery [EP5, EP7] **EP5:** Efficient design decisions with cost-benefit trade-offs. **EP7:** Managing interconnected tasks and sub-systems across modules.

CO	**Details**	**Knowledge Profile (K)**	**Engineering Problem (EP)**
CO12	The team remained updated with current trends in FHIR, HL7, LOINC, and clinical informatics. This learning informed improvements in the CDSS and broadened its interoperability and diagnostic intelligence.	(i) Life-long learning [K8] **K8:** Ability to stay current with health tech standards and evolving data-driven care methodologies.	(i) Continuous improvement [EP3, EP7] **EP3:** Updating models and systems with emerging research. **EP7:** Integrating improvements without disrupting existing modules.