Department of Computer Science and Engineering

CSE400B Capstone Project

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

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1 Abstract

Medication errors are a major public health concern in Bangladesh. 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 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. Standard machine learning techniques, including K-Nearest Neighbors (KNN), decision trees, and random forests, will be used to provide an automatic medicine recommendation system in our clinical service. 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-Drug Interaction, EHR, HAPI FHIR, Decision Trees, Random Forests, SVM, Logistic Regression, Neural Networks

2 Background

A smart clinical support system provides healthcare, including 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 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 medications 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. We will implement this smart clinical support service using FHIR, a global standard for digital health data, to enable EHRs, support mobile health technologies, and facilitate large-scale health-data analytics [6]. FHIR uses XML and JSON for data exchange, supporting both server and client applications. The application uses HAPI FHIR, a framework to fetch and store healthcare data on an external server [7]. In our clinical service, we will utilize artificial intelligence for medicine recommendation systems by employing various machine learning techniques, which include decision trees, random forests, support vector machines (SVM), logistic regression, and neural networks. This smart clinical support system allows doctors to prescribe medications more accurately and appropriately.

3 Related Work

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 decision support system (CDSS) is introduced to improve healthcare delivery by augmenting medical decisions with targeted clinical knowledge, patient information, and other health information[8]. CDSS can be categorized based on their function, how they recommend, their communication style, human conversation, and decision-making models[9]. Functionally, some CDS determine that 'what is true?' by diagnosing the conditions, while others focus on "what to do?" by suggesting testing or treatment. Most modern systems do both. The way they recommend can be inactive or active. Inactive systems require users to manually request advice, while active systems offer real-time guidance[10]. 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[11] and neural networks. While AI can improve accuracy, trust issues arise when its recommendations establish the guidelines[12]. To better understand the contributions, we have categorized the existing literature that falls into these characteristics of CDSS into four key areas: FHIR Based EHR Integration, Accurate Diagnosis and Treatment, Doctor-Patient Appointment Systems, and AI in Medical Support. The following sections summarize key contributions in these areas, highlighting both advances and limitations identified in the existing literature.

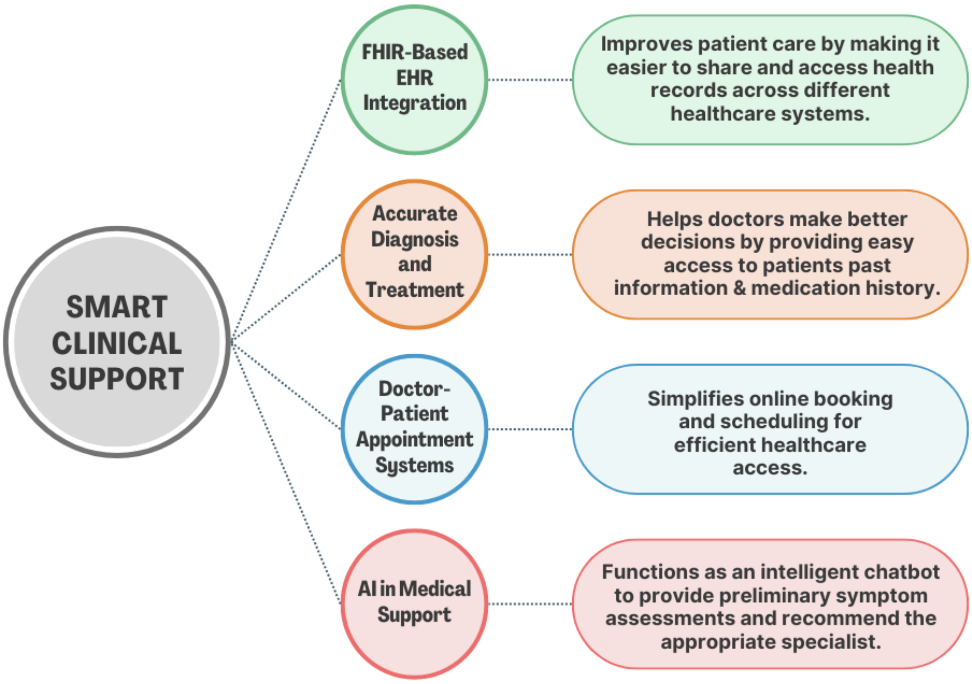

Figure 1: Overview of Smart Clinical Support System Components

3.1 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 [13]. 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 [14].

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[15]. 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[16]. 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[17].

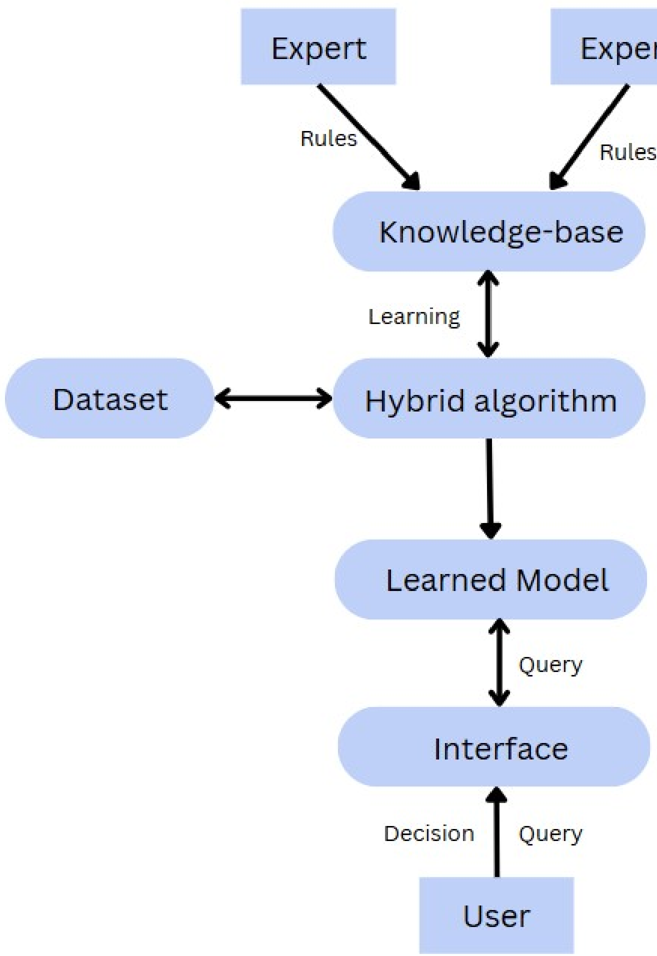

Figure 2: Hybrid Decision Support System by Iqbal et al. (Redrawn)[17]

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.

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.

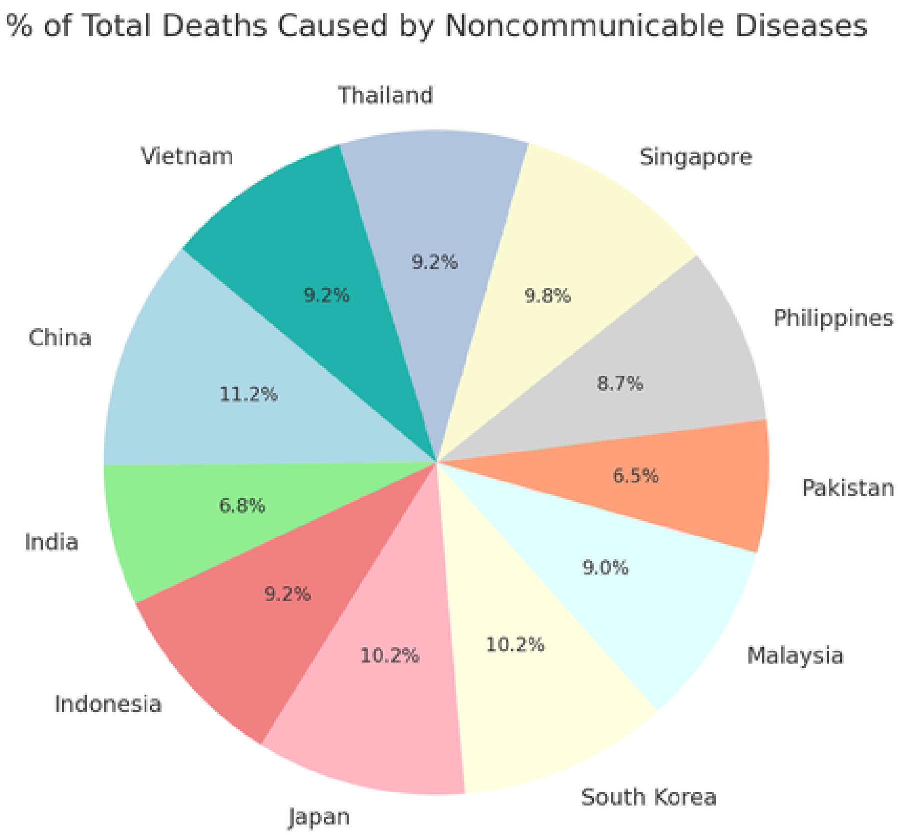

Figure 3: Percentage of total deaths caused by non-communicable diseases in Asia in 2014 (Redrawn)[18]

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[18]. 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 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[19]. 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[20]. 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.

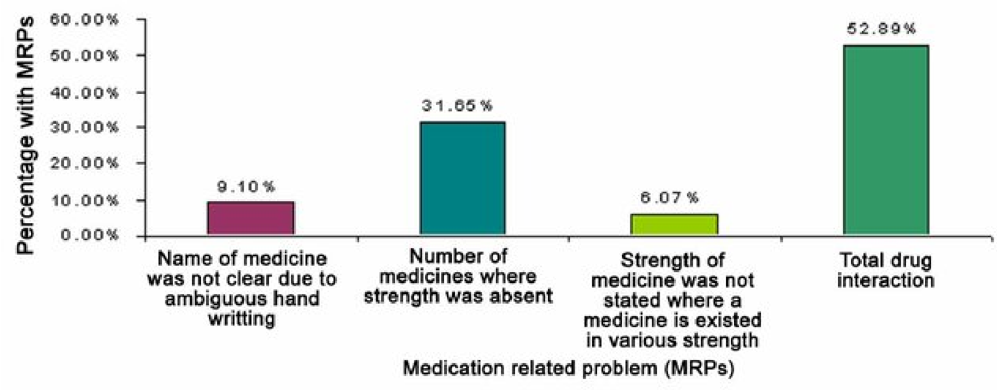

Figure 5: MRPs identified from the prescription[20]

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[21]. 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[22]. 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.

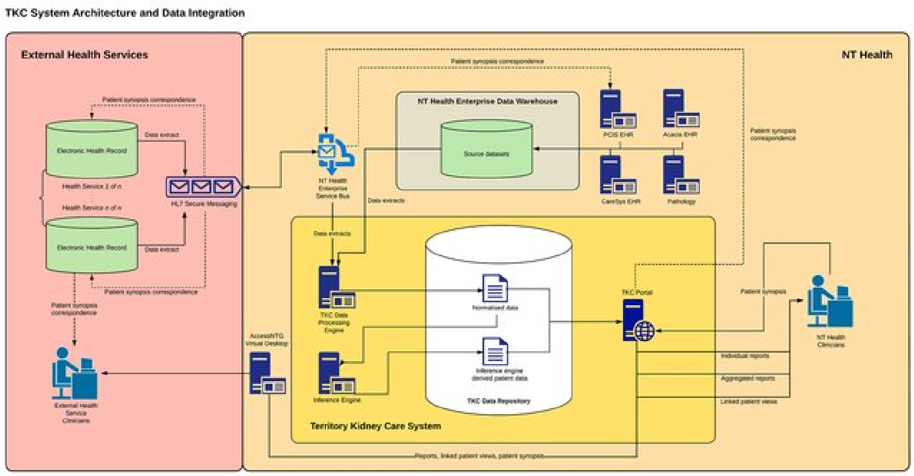

Figure 6: System architecture diagram proposed by Gorham et al.[22]

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[23]. Their approach involves pre-processing MRI images with a Genetic Optimized Median Filter, followed by tumor region segmentation using a Hierarchical Fuzzy Clustering Algorithm.

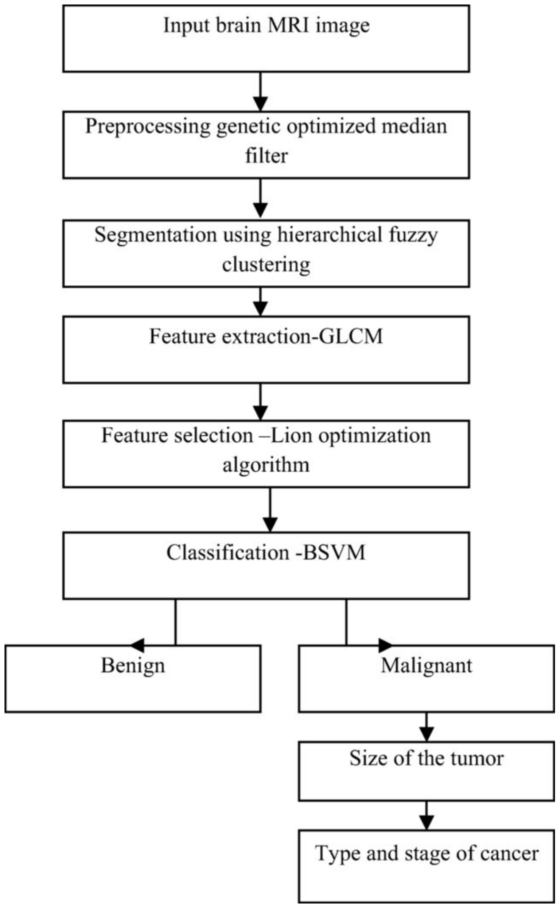

Figure 7: Functional Diagram of the Proposed System of Brain Tumor Classification[23]

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[24]. 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.

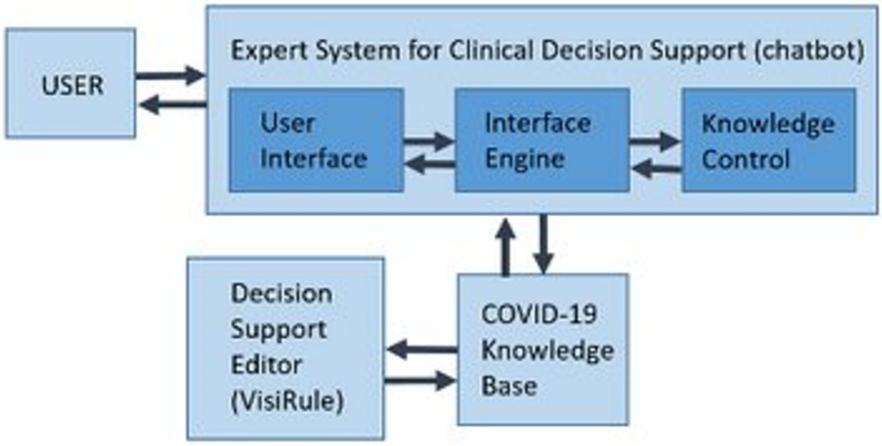

Figure 8: Expert system of a COVID-19 decision support web-based (chatbot) tool developed by Chrimes et al.[24]

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[25]. 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.

3.2 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[26]. 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[27]. 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.

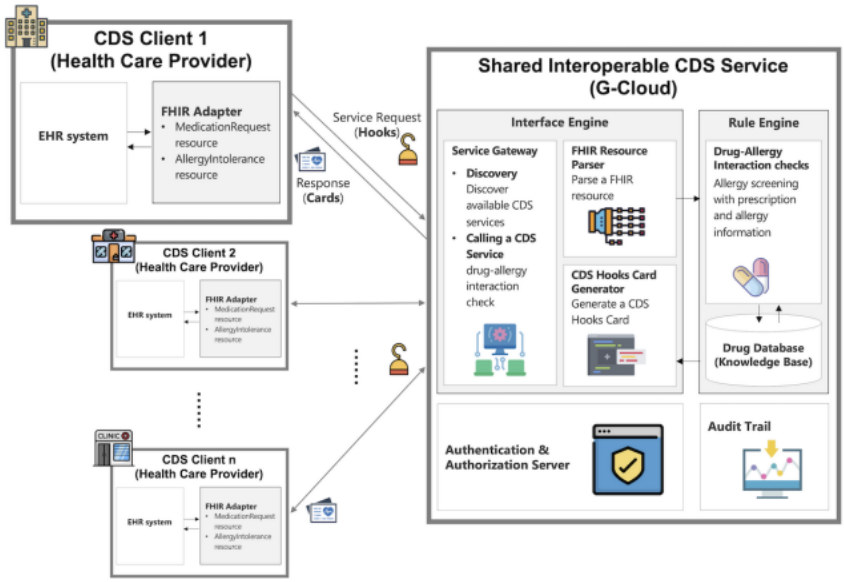

Figure 9: The concept architecture for the shared interoperable CDS system is based on CDS Hooks' anatomy. Multiple healthcare providers simultaneously invoke the shared interoperable CDS service deployed on G-Cloud using a hook and receive a card as a response. CDS: clinical decision support; EHR: electronic health record; FHIR: Fast Healthcare Interoperability Resources.[27]

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[28]. 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[29]. 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.

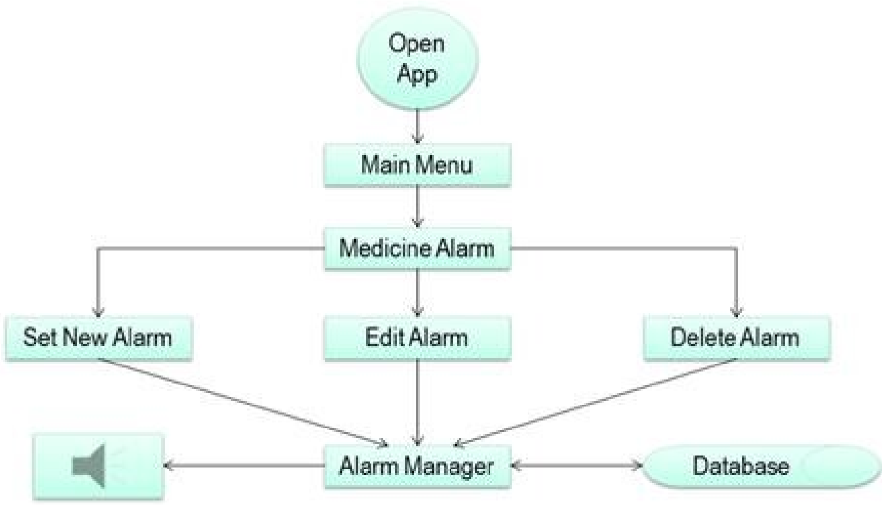

Figure 10: System diagram of medicine alarm[29]

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[30]. 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[31]. 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[32]. 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.

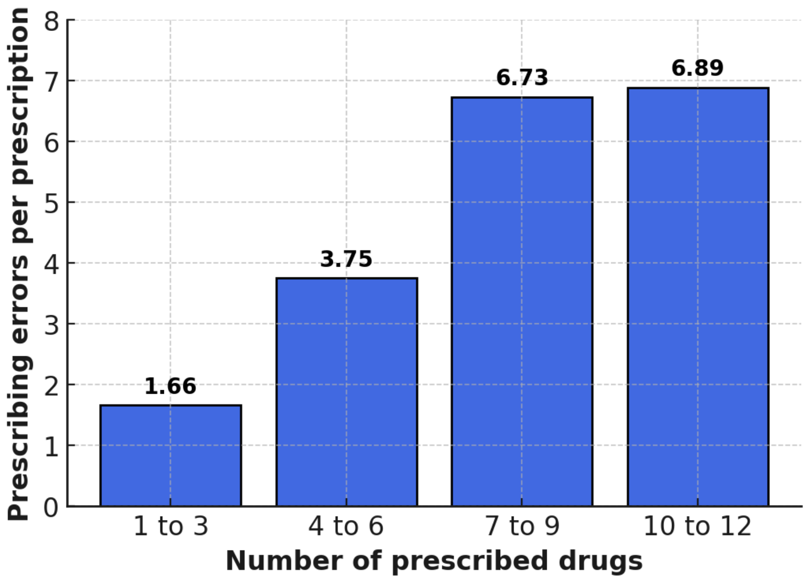

Figure 11: Frequency of errors in the prescriptions[32]

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.

3.3 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[33].

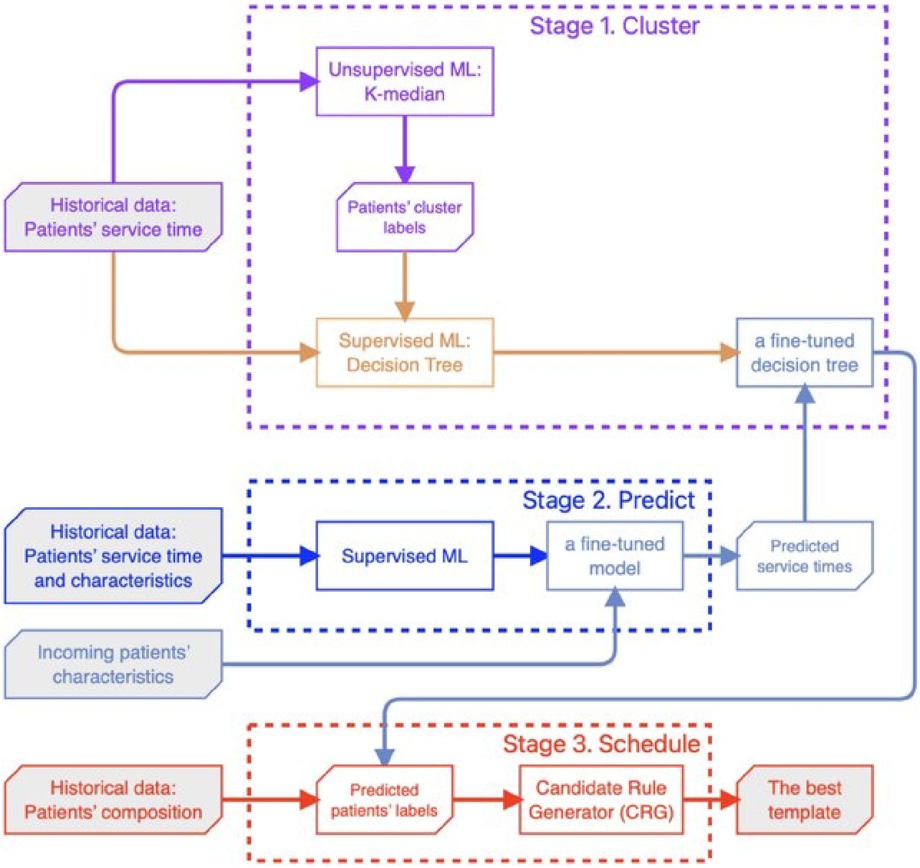

Figure 12: A flowchart of the CPS system proposed by Feng et al.[33]

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[34]. 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.

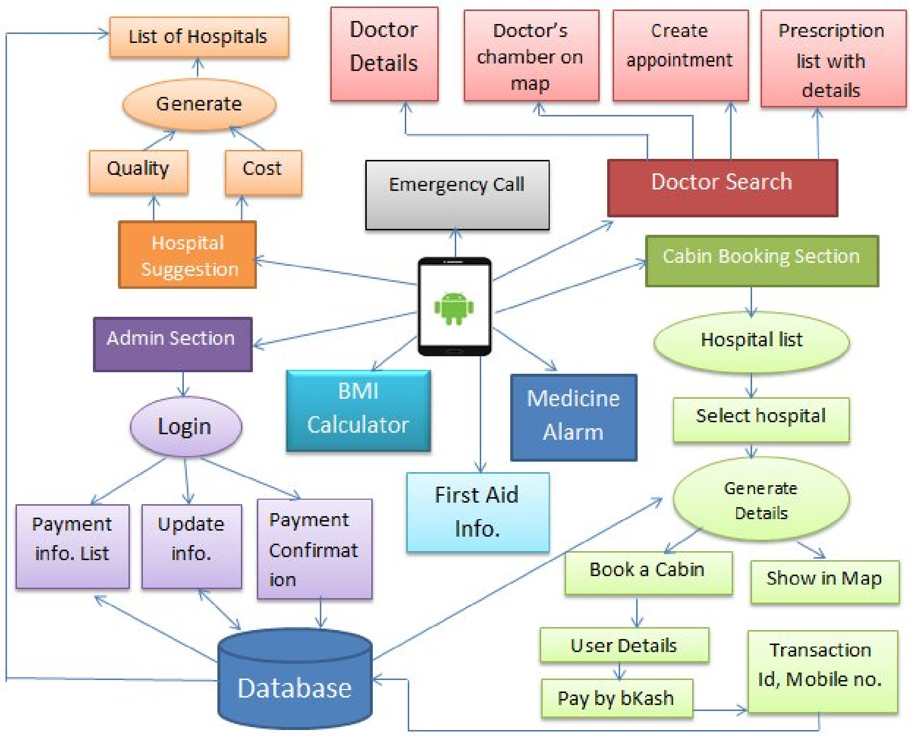

Figure 13: System architecture presented by Imteaj et al. [34]

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.

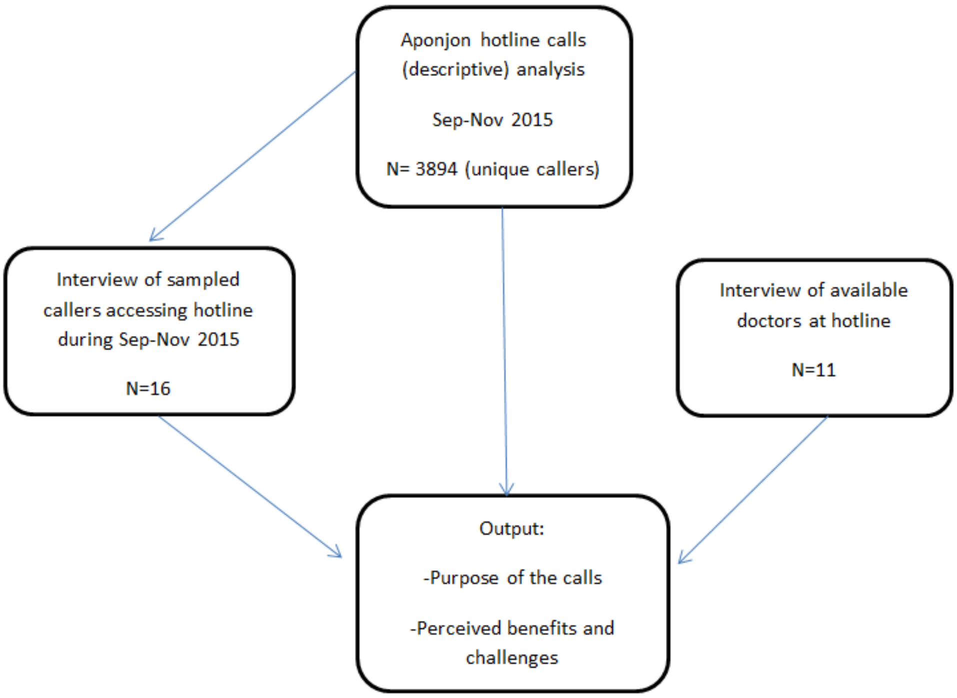

Figure 14: Mixed methods data triangulation plan of Aponjon mobile health (mHealth) service[35]

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[35]. 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.

3.4 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[36].

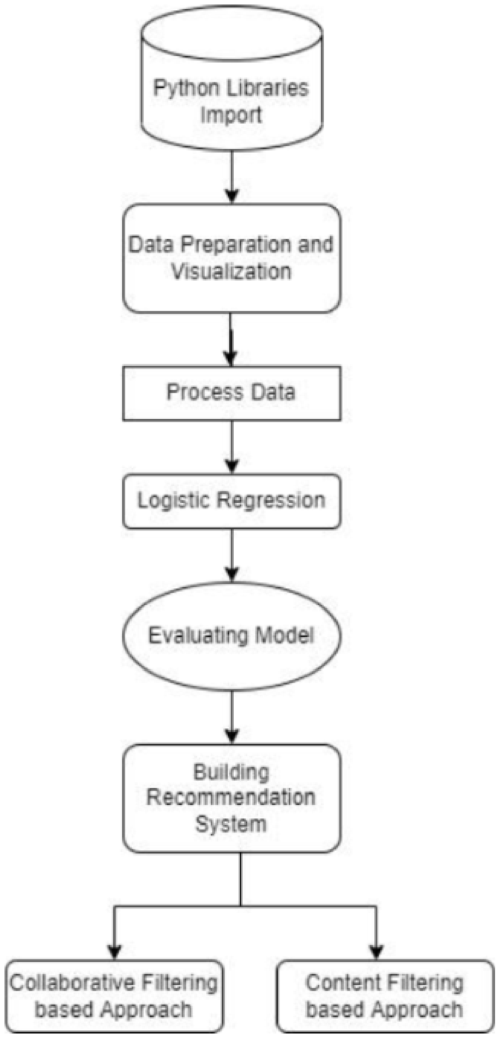

Figure 15: A Machine Learning based Drug Recommendation System for Health Care[36]

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[37]. 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.

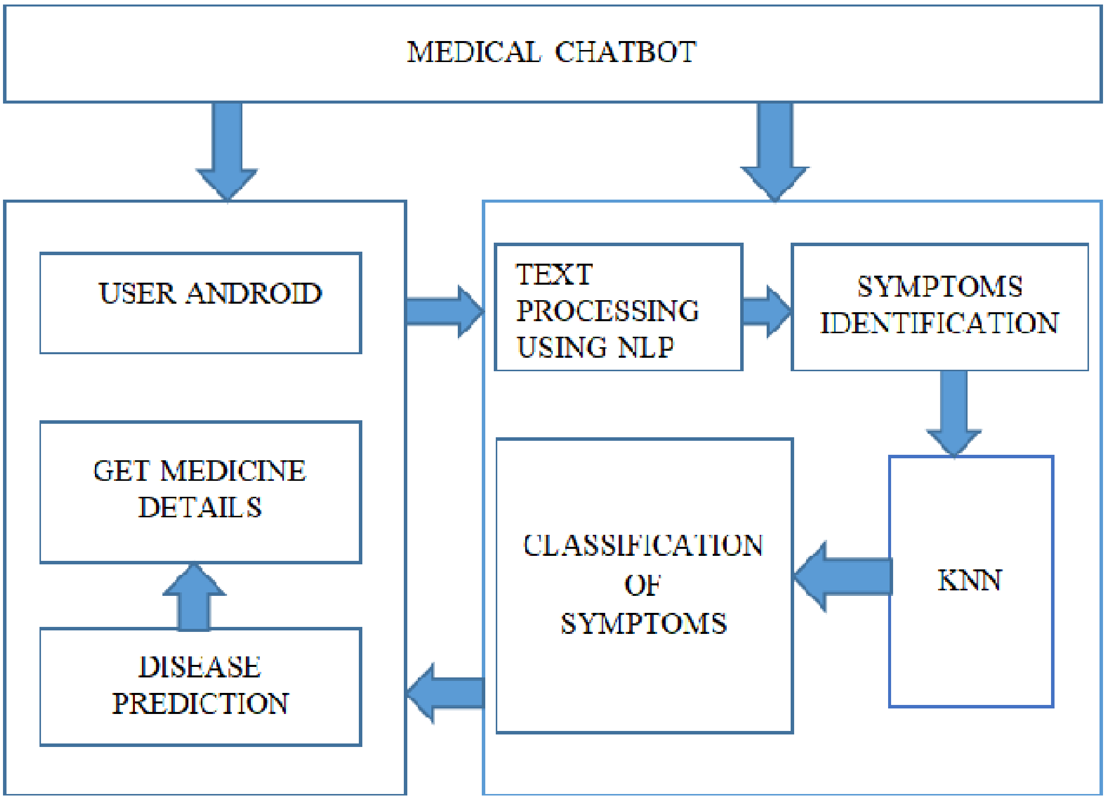

Figure 16: Working model of the proposed model conducted by Mathew et al.[37]

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[38]. 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.

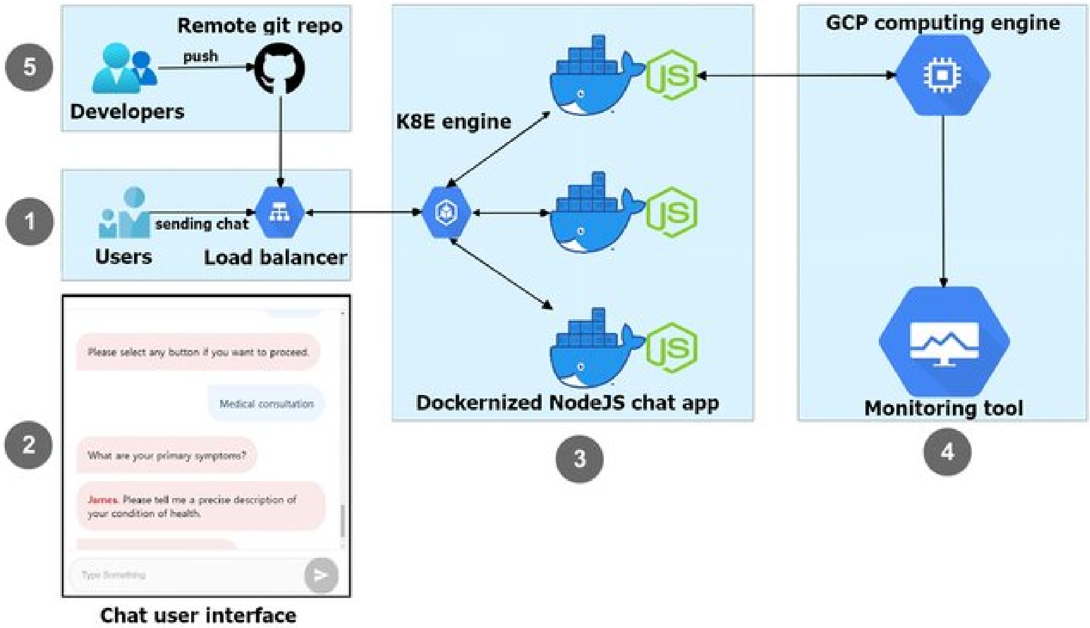

Figure 17: Architecture of the chatbot. This figure illustrates the workflow of the developed prototype chatbot[38]

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[39]. 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.

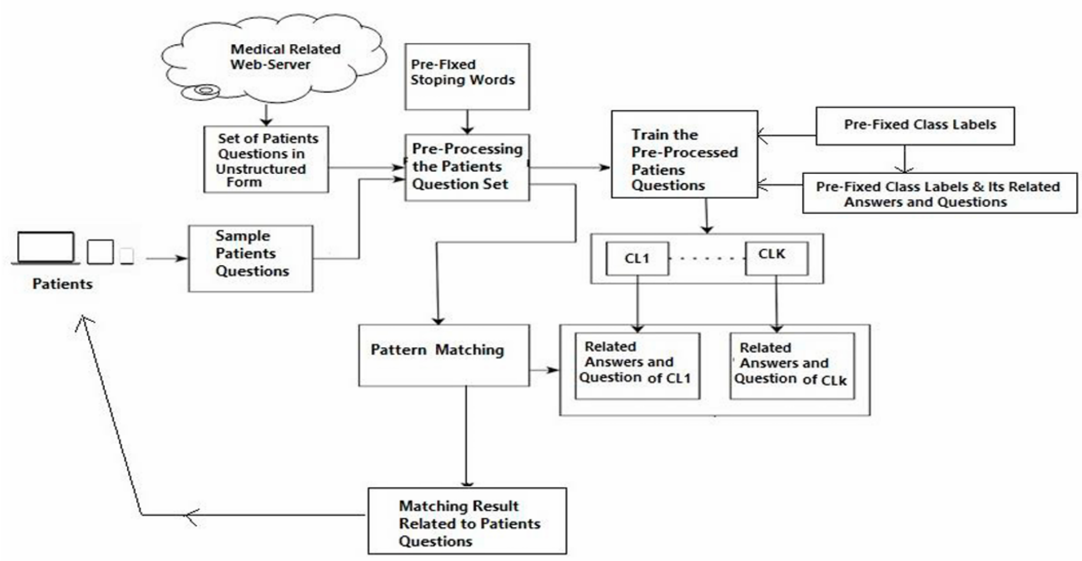

Figure 18: Proposed RMSCB System Architecture[39]

It employs models such as the Pre-Fixed Stopping Words Model (PF-SWM) 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[40]. 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.

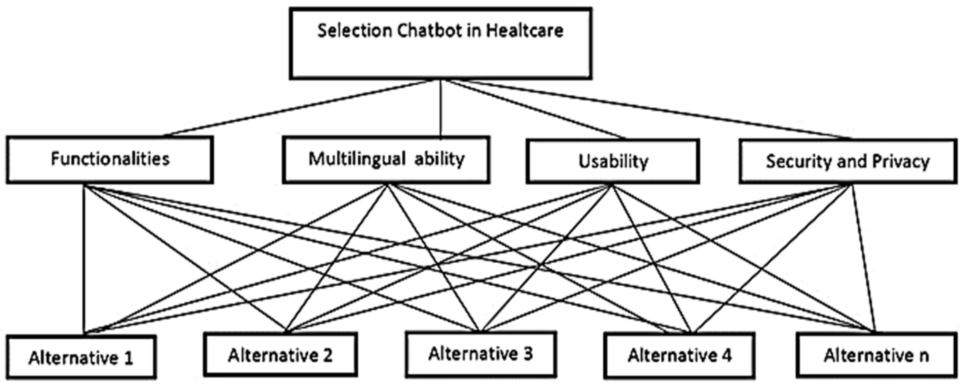

Figure 19: AHP structure of selection chatbot in healthcare[40]

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[41]. 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.

4 Problem Statement

The healthcare industry is currently facing several challenges that significantly impact both patients and healthcare providers.

a. **Access and Sharing of Patient Data:** Another major challenge is the difficulty in accessing and sharing patient data among clinics and healthcare providers. Patient information is often stored in disparate systems that lack effective communication, resulting in delayed treatment, repeated tests, and fragmented care.

b. **Medication Errors:** One of the most pressing issues is the occurrence of medication errors, which can happen when patients receive the wrong prescription, incorrect dosage, or fail to recall their past medications, leading to unintended drug interactions. Without access to complete medical records, doctors may struggle to ensure safe prescriptions, highlighting the need for a system that provides accurate patient history to prevent errors and improve safety.

c. **Healthcare Access in Remote Areas:** Additionally, patients living in remote or underserved areas face significant barriers to accessing healthcare. Many individuals encounter long travel distances to see a doctor, endure long wait times for appointments, and struggle to receive timely medical advice, further exacerbated by a shortage of healthcare professionals in these regions.

Given these challenges, there is a clear need for a comprehensive clinical support system to address these problems. Imagine a system that connects patients with doctors remotely, securely stores patient data in one centralized location, sends medication reminders, and helps prevent prescription errors. While technology has made significant advances in healthcare, many existing systems still fall short in terms of usability, security, and efficiency qualities that are essential for both patients and medical staff.

This paper will explore the development of such a system and evaluate how it could improve the quality, safety, and accessibility of healthcare services. It will also examine the technological, security, and usability challenges involved in creating and implementing a solution like this.

5 Research Objectives

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.

5.1 Research Question

The primary research question of our Capstone Project aims to investigate the key aspects of implementing such a system, ensuring the accuracy of medical prescriptions, and promoting secure and effective communication among healthcare providers. The primary research question of our Capstone Project is given below:

RQ1. Can a Smart Clinical Support system prevent medication errors among healthcare professionals in Bangladesh?

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

6 Methodology

6.1 System Development

The proposed smart clinical support system is designed to enhance the efficiency of medical services in Bangladesh clinics by providing an integrated platform for appointment scheduling, clinical decision support, drug interaction checking, and AI-driven medical assistance. The system will be developed as a web application, ensuring accessibility for both doctors and patients.

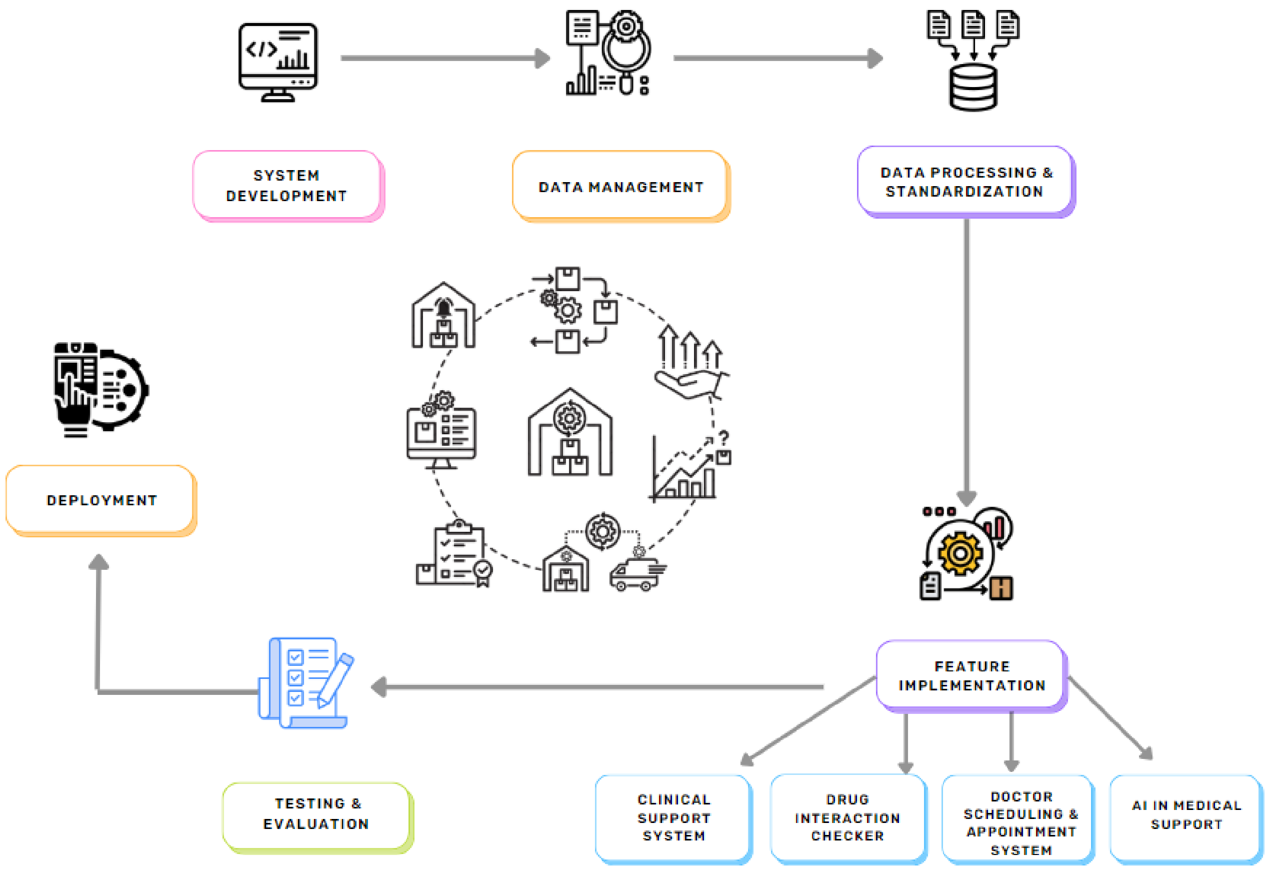

Figure 20: Flowchart of the Methodology

6.2 Data Management

The system will require various data sources to function effectively:

- **Electronic Health Records (EHRs):** Structured patient records will be formatted according to FHIR standards, ensuring interoperability with other healthcare systems. These records will include patient history, diagnoses, prescribed medications, and test results.
- **Doctor & Appointment Data:** The system will store doctors' schedules, patient bookings, and consultation records, enabling efficient appointment management.
- **Drug Interaction Database:** A curated dataset containing known drug interactions will be integrated to provide real-time safety checks during prescription. This database may be sourced from open medical repositories or manually compiled based on international pharmaceutical guidelines.
- **AI Training Data:** Patient interactions, symptom reports, and medical literature will be used to train AI models for disease prediction and medical recommendations.

All collected data will be securely stored and processed to ensure compliance with healthcare data privacy standards.

6.3 Data Processing & Standardization

To maintain data integrity and usability, the following preprocessing steps will be applied:

- **FHIR Compliance:** Data will be structured using predefined FHIR resource models, ensuring compatibility with existing healthcare infrastructures.
- **Data Cleaning:** Inconsistent or incomplete records will be flagged for review, with automated validation processes correcting minor errors where possible.
- **Data Normalization:** Standardized medical terminologies and classifications will be adopted to improve searchability and accuracy.

- **AI Model Training & Optimization:** Machine learning algorithms will be continuously trained with updated clinical data to improve decision-making accuracy.

These preprocessing steps ensure high-quality data inputs for the system's decision-making components.

6.4 Feature Implementation

The system will integrate multiple functional modules to support medical professionals and patients efficiently:

Smart Clinical Support System

- The system will analyze patient records and suggest treatment options based on clinical guidelines and best practices.
- Rule-based logic will be implemented to flag potential risks, such as contraindications or missing tests before prescribing medications.
- Decision recommendations will be aligned with established medical protocols to support healthcare providers in making informed choices.

Drug Interaction Checker

- A built-in drug interaction module will verify prescriptions against a database of known adverse interactions.
- The system will provide alerts for high-risk combinations, offering alternative medication suggestions when possible.
- Doctors can override flagged interactions with justification, ensuring flexibility while maintaining safety.

Doctor Scheduling & Appointment System

- Patients will be able to browse available doctors, view their schedules, and book appointments.
- Doctors can manage their availability, confirm or reject appointments, and reschedule if necessary.
- Automated appointment reminders will be sent to patients and doctors to reduce no-show rates.

AI in Medical Support

- The system will integrate **AI-driven chatbots** to assist patients with symptom-based diagnosis and preliminary treatment recommendations.
- **Machine learning models** will analyze patient symptoms, medical history, and treatment outcomes to enhance diagnostic accuracy.
- **Natural language processing (NLP)** will be used to improve human-computer interaction, making AI-assisted decision-making more accessible to healthcare providers.
- AI will continuously learn from **real-world patient data** to refine disease prediction and treatment suggestions.

These features collectively enhance the system's ability to support doctors in delivering effective patient care.

6.5 Testing & Evaluation

A multi-stage evaluation process will be conducted to ensure system reliability and effectiveness:

- **Unit Testing:** Each module will be individually tested to verify correct functionality.
- **Integration Testing:** Different system components will be tested together to ensure seamless interactions between features.
- **AI Model Validation:** The performance of AI-driven recommendations will be assessed using real-world case studies and expert evaluations.
- **User Acceptance Testing (UAT):** Healthcare professionals will participate in testing to provide feedback on usability and workflow integration. Adjustments will be made based on real-world user experiences.
- **Security & Performance Testing:** The system will undergo stress testing to assess its handling of concurrent users, as well as security audits to ensure data protection compliance.

Through rigorous testing, the system will be refined to meet the needs of real-world clinical environments.

6.6 Deployment & Continuous Improvement

- **Initial Deployment:** The system will first be deployed in a limited clinical setting to monitor performance and gather initial user feedback.
- **AI Model Updates:** The machine learning models will be periodically retrained using new clinical data to improve accuracy.
- **Performance Monitoring:** Continuous monitoring will be conducted to track system efficiency, user engagement, and error rates.
- **Updates & Enhancements:** The system will evolve based on user feedback, medical advancements, and regulatory updates.

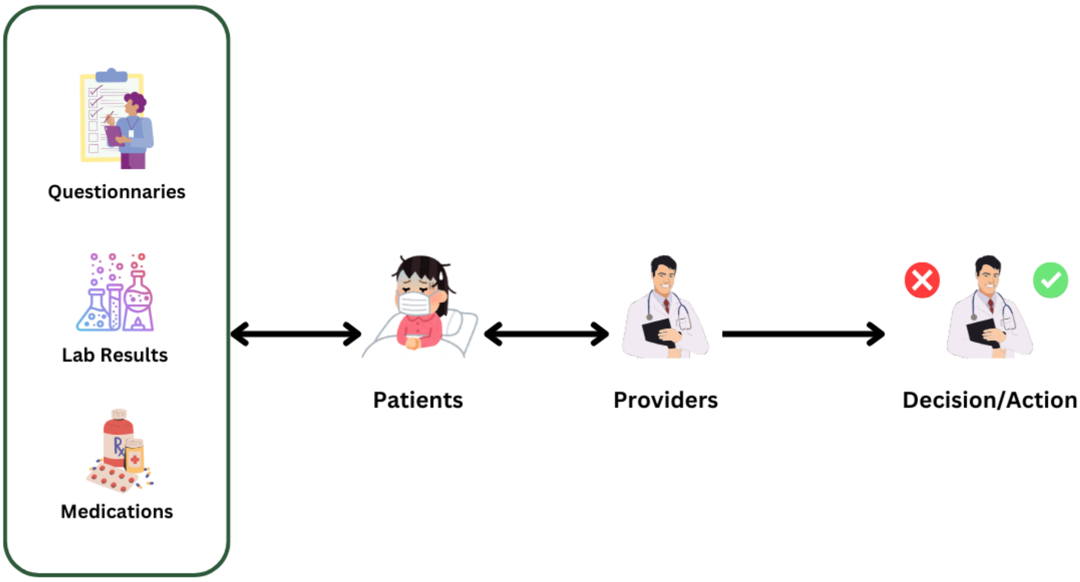

Figure 21: Doctor-Patient Interactions

7 Expected Result

The 'Smart Clinical Support: A Unique Approach to Healthcare Support in Bangladesh' is expected to significantly enhance healthcare accessibility and communication between patients and doctors through a user-friendly web and mobile platform. Key outcomes include improved medication adherence via automated reminders, reduced medication errors through drug interaction detection, and efficient appointment management. The secure centralized database will ensure patient data confidentiality. Additionally, the emergency alert system will facilitate rapid responses to critical health situations, ultimately leading to better patient outcomes and a more efficient healthcare environment in Bangladesh.

8 Conclusion

A Smart Clinical Support System can significantly improve healthcare by reducing medication errors, enhancing data sharing, and increasing access to services. By facilitating communication between doctors and patients, securely storing information, and providing medication reminders, it enhances both safety and efficiency. Technology plays a vital role in improving healthcare, especially for those in remote or underserved areas, making it easier for patients to access care and for doctors to manage it effectively. However, challenges remain, including ensuring data security, compatibility with existing platforms, and user-friendliness. Future efforts should focus on overcoming these hurdles. Overall, a well-designed Smart Clinical Support System can lead to safer, more efficient healthcare and better access for patients, ultimately improving care for everyone.

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Appendix