2025-05

Design and Early-Stage Development of a Handwritten Prescription Interpretation App for Bangladeshi Citizens

Rubyat, Afsana

IUB

Design and Early-Stage Development of a Handwritten Prescription Interpretation App for Bangladeshi Citizens

May 2025

Prepared by:

Afsana Rubyat
ID: 2121008

Bushra Rahman
ID: 2131283

Mohammad Faiyaz Uz Zaman
ID: 2130070

Department of Computer Science and Engineering
Independent University, Bangladesh

Supervised by

Ashraful Islam, PhD
Assistant Professor
Department of Computer Science and Engineering
Independent University, Bangladesh

Attestation

We are aware of the fact that plagiarism is strictly prohibited and it conflicts with our university's rules and regulations. We guarantee the authenticity of our work. We have used some copyrighted material and models of others in our project which has been properly cited following the international standards proper guidelines.

Author Name:

. . . .

Signature:

. . . .

Author Name:

. . . .

Signature:

. . . .

Author Name:

. . . .

Signature:

. . . .

Evaluation Committee

Supervision Panel

Ashraful Islam
....
Supervisor

for
Akmam ...
....
Co-supervisor / Internal Member

Examiners

Rashedur Rahman
....
Internal Examiner

Zahid
MOHAMMAD ZAHIDUL ALAM
....
External Examiner

Office Use

....
Program Coordinator

....
Head of the Department

....
Director Graduate Studies, Research and Industry Relations

....
Library

Acknowledgement

We would like to express our sincere gratitude to our respected supervisor, Dr. Ashraful Islam, Independent University, Bangladesh. His dedicated guidance, insightful suggestions, remarkable patience, and the generous investment of his valuable time played a pivotal role in the successful completion of our project. Our supervisor's expertise and mentorship greatly enhanced the quality and depth of our work, and we are truly appreciative of his unwavering support throughout our academic journey.

Additionally, our heartfelt gratitude goes to the CCDS (Center for Computational & Data Sciences) for their extraordinary help and consistent support. The collaborative and resourceful environment provided by CCDS significantly contributed to the development and execution of our project. Moreover, the encouragement and assistance have been instrumental in shaping our academic and research fields. We are grateful for the opportunities and resources extended to us during our research, which undoubtedly enriched our learning experience.

We acknowledge and appreciate the contributions of all individuals who supported us, both directly and indirectly, during this endeavor.

Abstract

In Bangladesh, handwritten prescriptions remain the conventional method of medical documentation, presenting significant challenges in accurately interpreting medication information. The diverse handwriting styles make these prescriptions difficult to read, potentially compromising patient health. This study introduces a novel solution for digitizing handwritten prescriptions using the User-Centered Design (UCD) methodology. The aim is to develop a mobile application tailored to the needs of Bangladeshi citizens, enhancing access to clear, reliable medication information, reducing errors, and promoting safer healthcare practices. The research objectives include conducting design requirements analysis, need-finding, and developing a high-fidelity prototype.

A survey involving 155 participants was conducted to gather insights on the essential features and design requirements of the app. The findings revealed common difficulties faced by participants, such as the inability to read handwritten prescriptions accurately and challenges in understanding the names and dosage instructions of the medicines. Participants highlighted the need for features like daily medication reminders, medication names, automatic prescription scanning, voice and chat-based interactions with a Relational Agent, and user guidelines for prescription scanning. The insights gathered from the survey guided the creation of a low-fidelity paper-based prototype, which was then refined into a high-fidelity digital version of the app. The development process followed a human-centered approach, starting with need-finding analysis and design requirement collection, leading to the creation of both low-fidelity paper-based and high-fidelity digital prototypes. This high-fidelity prototype with an intuitive interface, named "PresCa", incorporates crucial features such as prescription scanning, scanning guidelines, a report summary, a Relational Agent for assistance, prescription crosscheck by doctors, and the ability to configure medication reminders. These preferences directly informed the design choices and functional priorities of "PresCa". By focusing on users' needs, this app aims to empower patients with accurate medication information, reduce the risk of medication errors, and ultimately foster safer healthcare practices. This innovative solution not only addresses the challenges faced by healthcare professionals in Bangladesh but also provides a foundation for future research in healthcare digitization, promoting a more efficient and reliable system for managing prescriptions. The app achieved a mean System Usability Scale (SUS) score of 76.18.

This research study illustrates methods for extracting medication information from handwritten prescriptions utilizing a straightforward, deep learning model called TrOCR: Transformer-Based Optical Character Recognition. This pre-trained model can detect complex handwritten language accurately by integrating the Optical Character Recognition (OCR) technique with the Transformer architecture. Additionally, the integration of Machine Learning (ML) techniques in the app improves the accuracy and speed of prescription scanning, making it easier for users to access and understand their medication instructions. The OCR performance of our trained model on the test set showed a Character Error Rate (CER) of 16% and a Word Error Rate (WER) of 36%. With the integration of the Levenshtein distance-based text correction technique, the CER and WER dropped significantly to 7% and 11%, indicating an improvement in the recognition of medication information. Through these advancements, "PresCa" aims to make a significant impact on the healthcare sector in Bangladesh, facilitating better medication management and enhancing overall patient safety.

Contents

List of Tables

List of Figures

1 Introduction

1.1 Background and Motivation

1.1.1 Prescription Management in Healthcare Environments

Prescriptions are an essential aspect of healthcare and serve as the primary medium to transmit medication instructions from doctors to patients. Besides, the healthcare sector is under overwhelming pressure due to the increased number of patients, limited staff availability, and increasing administrative responsibilities. In particular, the management and interpretation of handwritten prescriptions pose a major challenge. Pharmacists and doctors must frequently understand unclear handwriting, verify medication details, and manually enter information into digital systems. A study in Bangladesh reveals, alarmingly, over 50% of these prescriptions had illegible handwriting, posing risks of misinterpretation by pharmacists [14]. Effective prescription management is a critical aspect of healthcare delivery, impacting patient safety, treatment outcomes, and healthcare costs [44].

In Bangladesh, many doctors, especially in government hospitals, still provide handwritten prescriptions. These handwritten prescriptions in Bangladesh are associated with a significant frequency of both minor and major errors of omission, emphasizing the need for prescribers to be more careful [14]. However, these prescriptions are often difficult to understand due to the diverse handwriting styles, resulting in a wrong interpretation of medication information and serious health risks [28, 33, 59]. These errors also place an unnecessary financial burden on individuals and the healthcare system. This not only slows down the workflow of the healthcare sector but also increases the risk of medication errors and adds to the cognitive burden on medical staff.

In response to this challenge, our proposed solution introduces a mobile application aimed at helping both patients and pharmacists understand prescriptions more effectively. This approach can reduce human errors in traditional medication systems by automating the extraction of prescription data through Optical Character Recognition (OCR) and Machine Learning (ML) techniques. It does not aim to diagnose or treat users, but rather to reduce workload, manual errors, and improve efficiency in medical environments. Our goal is to use technology to eliminate medication errors, repetitive tasks, and allow medical professionals to focus on what truly matters, patient care. This project follows principles from Human-Computer Interaction (HCI) and User-Centered Design (UCD), which place the user at the core of the development process. Before designing the solution, we conducted user research to understand the needs and findings of the end users. Their feedback shaped the design and functionality of the app, ensuring it meets real-world needs and seamlessly integrates into daily practice.

1.1.2 Human-Computer Interaction (HCI)

HCI plays a significant role in developing and designing digital tools to enhance user experience, especially in high-pressure domains like healthcare. HCI focuses on improving user experiences and creating intuitive systems that promote performance, usability, and satisfaction [43]. The core aim of HCI is to enhance user flexibility and offer smooth interaction through adaptive design concepts of HCI, prioritizing users to accomplish their tasks with minimal mental effort and maximum clarity [62]. A key motive of HCI is enabling people to engage smoothly with technology, encouraging them to achieve their goals without excessive cognitive demands [16]. HCI research is conducted on several core principles, including usability, UCD, feedback, and accessibility. Usability, a foundational concept, ensures that systems are both user-friendly and efficient, while UCD places the needs and limitations of users at the early stage of development [13].

In the context of our mobile application, HCI principles were applied to ensure the system was functional but also intuitive, responsive, and supportive of healthcare professionals' cognitive workflow. In prescription transcription tasks, poor interface design or complex workflows can significantly increase cognitive load and frustration. Our application was developed using UCD principles, where the needs, limitations, and expectations of users were kept at the forefront throughout the design and testing phases.

One of the most important design considerations was real-time feedback. The app offers immediate OCR results and visual cues that confirm the recognition process, allowing users to quickly validate or correct information. This aligns with HCI's emphasis on feedback mechanisms, which help reduce uncertainty and build trust between the user and the system [45]. Common HCI evaluation methods, such as usability testing and heuristic evaluation, were applied during the development lifecycle. Preliminary testing involved observing how users interacted with the app to detect issues like delays, misrecognition, or unclear navigation flows. These insights guided iterative refinements in layout, button placement, and information presentation, which ensures that users can complete tasks quickly and confidently [65].

Through quantitative and qualitative approaches, HCI systems are evaluated, emphasizing metrics such as error rates, success rates, and duration of task. Qualitative data collected from user interviews or surveys complements these metrics by providing insights into user satisfaction while recognizing ease of use. Metrics for user performance and satisfaction enable systematic evaluation and iterative modifications to fulfill optimal usability requirements [40]. Additionally, the application supports a mobile-first interface, recognizing that the target users, healthcare professionals, often work in dynamic, fast-paced environments where desktop solutions are impractical. The touch-based interaction and camera integration streamline the task of digitizing prescriptions, minimizing navigation layers, and maximizing usability. From a broader perspective, HCI in this project intersects with machine learning, providing an efficient system. This adaptive element aligns with recent trends in HCI that focus on intelligence and collaboration with healthcare fields to improve patient outcomes through efficient data management and accessible design.

1.1.3 User-Centered Design (UCD)

UCD is a vital methodology in creating digital solutions that effectively serve users to ensure user satisfaction and needs. One significant principle is user involvement, where users are included in the design process from the early stage to the last stage to provide continuous feedback [29]. Iteration, another key principle, follows multiple attempts to design, prototype, and evaluate users to improve the system [25]. UCD also highlights the context of usage, which suggests the system should be developed with a consideration of its particular context where it will be employed [29]. All of these principles guarantee that the products are extremely beneficial and designed to match customers' requirements.

The UCD methodology consists of numerous stages. At the very early stage, user research is conducted. In this phase, data is collected through interviews, surveys, and observations to understand user requirements. In the next step, the design phase takes place, where wireframes and mockups are created and reviewed by users, which leads to further refinements [17]. Designers develop working models of the system in the prototyping phase, which are tested through usability testing to get user feedback. Lastly, the system is tested on multiple iterations based on user survey results to ensure the final design is optimized for usability [66]. This allows the design team to continuously refine the application. Each cycle of design, testing, and evaluation reveals new insights, which lead to improved usability, better performance, and increased user satisfaction.

One key principle of UCD is user involvement. Throughout the development of this project, potential users were engaged to provide feedback from the early conceptual phases through to prototype testing. Their input shaped everything from interface layout to the final result [22]. Throughout development, users were not treated as mere testers but as design collaborators. Participatory design methods were employed to bring users into the creative process. Their ideas, frustrations, and expectations directly influenced the system's features and interactions.

Inclusive design is another growing focus within UCD, aiming to make systems accessible to all users, including those with disabilities or limited digital literacy. Thus, future iterations could integrate accessibility features such as voice commands, larger text displays, or multilingual support to accommodate a broader user base. Additionally, remote user testing and global feedback loops are becoming standard practice in UCD, making it easier to collect insights from distributed user groups and tailor systems for international use [18].

The UCD process adopted in this research began with qualitative user research. Observational studies were conducted to understand how healthcare professionals currently deal with handwritten prescriptions and where they encounter the most friction. This information helped define the requirements and informed the initial designs. These designs were developed into functional prototypes and tested in simulated environments. Users interacted with the application while completing realistic prescription transcription tasks, which helped the team assess usability and identify areas for improvement. This participatory approach not only ensured a higher quality user experience but also increased user trust in the final system. Our mobile application, designed to digitize handwritten prescriptions using OCR and machine learning UCD principles, was instrumental in ensuring that the app stands for the optimal needs of end users. Therefore, the application needed to be easy to use, responsive, and well-aligned with their existing workflows.

User-centered design has proven to be highly effective across industries, particularly in healthcare. Digital health tools designed with UCD principles have shown improvements in both system usability and user satisfaction [29]. In our case, the UCD approach contributed significantly to building a solution that reduces medication errors for users dealing with unclear prescriptions.

.

1.1.4 Importance of Mobile Applications in Prescription Management

Mobile applications play a crucial role in improving prescription management by enhancing medication adherence, empowering patient engagement, and streamlining healthcare workflows. These applications are increasingly recognized for their potential to significantly improve prescription management, offering numerous benefits for both patients and healthcare providers [63]. By offering medicine interaction checks and educational content, mobile apps also increase patient awareness and engagement, enabling users to get to know their treatment process [36]. A key advantage of prescriptions lies in their accessibility and seamless integration into the users' existing workflow. For professionals such as doctors and medical assistants, the ability to digitize and interpret handwritten prescriptions quickly allows for more accurate record-keeping, faster processing of patient information, and ultimately, fewer chances of miscommunication or prescription errors. Another significant benefit of using such mobile applications is the reduction of professional burnout and increased patient safety. By automating the scanning of prescriptions with illegible handwriting, healthcare workers experience fewer prescription errors. Furthermore, since the application runs on mobile platforms, it promotes flexibility without requiring additional hardware or technical infrastructure.

In the context of Bangladesh, where challenges like unequal access to healthcare and medication errors in handwritten prescriptions persist [63], mobile applications can play a crucial role in enhancing this aspect of healthcare. In contrast to traditional handwritten prescriptions, which are prone to errors of omission such as missing medicine strength (43.78%), incomplete directions for use (37.56%), and illegible handwriting (over 50%) [14].In this regard, mobile applications offer the potential for clearer and more complete prescription information. While the study on e-prescriptions focused on patient compliance, it underscores the issues with handwritten prescriptions that digital solutions aim to overcome [31]. By providing digital prescriptions and management tools, mobile apps can contribute to reducing medication errors and improving patient safety [31]. Several existing mobile healthcare applications in Bangladesh already incorporate features relevant to prescription management. These apps streamline the process of medication delivery, offer users access to medicine information and side effects, and simplify the procurement process and medication reminders, which can be vital for improving patients' health and the overall health sector [63].

By minimizing medication errors and providing fast, intelligent support through OCR and ML capabilities, mobile applications like ours play a growing role in a developing country like Bangladesh. This approach represents a practical and scalable solution in essential medical processes.

1.1.5 Machine Learning (ML) in Prescription Management

ML has increasingly become a core technology in prescription scanning and medication management systems. It is playing an increasingly significant role in enhancing various aspects of prescription management, offering solutions for improved accuracy, efficiency, and patient adherence [52]. Several mobile applications and proposed systems leverage ML to address the challenges associated with traditional prescription processes. Its ability to analyze various styles of handwriting and large-scale datasets enables one to identify accurate medicine names and dosages.

ML algorithms, including techniques like OCR powered by trained ML models and Bidirectional Recurrent Neural Networks (Bi-RNN), are used to accurately extract information from prescriptions, both digital and potentially scanned from paper [52]. Research suggests that ML can facilitate the delivery of personalized medication reminders to patients. ML algorithms can optimize the timing of medication reminders to improve adherence by analyzing user activity and medication schedules [52].

The integration of ML with mobile applications and Internet of Things (IoT) devices presents significant opportunities to enhance the safety and effectiveness of medication use [52]. Furthermore, ML can be used to detect potentially harmful prescription behaviors by analyzing a client's prescription and medication-taking behavior to identify potentially damaging patterns [55].

In many healthcare systems, illegible handwriting remains a critical issue that often leads to misinterpretation of medication names, dosage errors, and adverse drug reactions. ML, particularly through OCR, offers a promising solution by automatically extracting and digitizing handwritten medical information with high accuracy. Transformer-based OCR models have shown exceptional capabilities in recognizing complex and diverse handwriting styles. This approach not only enhances the accuracy of medication identification but also reduces the manual burden on pharmacists, supports safer drug dispensation, and lays the groundwork for intelligent prescription systems that can be integrated into mobile and healthcare platforms for real-time access and patient support.

In our proposed mobile app, ML serves a dual purpose by enhancing text recognition accuracy and reducing errors for users by minimizing manual errors in medication management. Moreover, as machine learning systems become more refined, they can enable highly personalized digital experiences and offer more efficient features.

1.2 Problem Statement

Handwritten prescriptions are still widely used across many hospitals and clinics, particularly in regions with limited access to digital infrastructure. Unfortunately, these handwritten documents often suffer from poor legibility, inconsistent formats, and misinterpretation. The continued use of handwritten prescriptions by doctors poses significant health risks to patient well-being [7]. Healthcare professionals must spend significant time reading, understanding, and transcribing these prescriptions. In a high-stakes environment like healthcare, mistakes in interpreting prescription information can lead to serious consequences, including adverse drug reactions and compromised patient safety [28, 33]. ADR (Adverse Drug Reaction) represents a critical public health challenge that leads to considerable morbidity and mortality, with 0.15% of patients losing their lives as a consequence [33]. The high patient load in healthcare facilities, combined with inexperience, mismanagement of medical staff, and limited training of pharmacists to interpret complex handwritten prescriptions, are major factors contributing to medication errors. These errors also place an unnecessary financial burden on individuals and the healthcare system. A study analyzing 900 handwritten outpatient prescriptions in Bangladesh revealed significant frequencies of errors of omission, including missing medicine strength (43.78%), incomplete directions for use (37.56%), and omitted dose and duration of therapy (16.44%) [14]. There have been 38% cases of medication errors in Bangladesh [7]. In a densely populated and rapidly evolving nation like Bangladesh, accurate medication information plays a pivotal role in ensuring effective treatment and safeguarding patients. Therefore, there is a strong need for an intelligent tool that can assist medical staff in accurately reading and digitizing prescription data. The absence of such tools, especially ones that prioritize ease of use and integrate well with existing workflows, creates a gap that our proposed solution seeks to fill.

1.3 Ethical Consideration

The home institution's Institutional Review Board (IRB) approved the user studies conducted as part of this research (Reference: 2022-SETS-05). All analyses were conducted online to ensure convenience for participants, and their participation was anonymous. Before starting the survey, the objectives of this research were clearly explained to the participants. They were required to provide informed consent before proceeding. Consent was obtained by asking participants to write their names and answer "yes" to the first question, indicating their willingness to participate in the study. Afterward, the participants were granted access to the actual surveys.

1.4 Research Gap

While several studies have explored prescription digitization using OCR and machine learning technologies [52, 55, 63], there remains a critical gap in research focused specifically on the unique challenges of handwritten prescriptions in Bangladesh. In many existing systems, OCR models are trained on structured, printed texts or standardized handwriting datasets from high-resource settings, resulting in limited applicability in low-resource environments where prescription formats vary widely and are handwritten in inconsistent, often cursive styles. Current literature lacks context-specific models or tools tailored to Bangladeshi prescriptions, which frequently mix English, Bangla, and abbreviations, making generic OCR tools unreliable in this domain. Furthermore, while prior research has emphasized the technical development of prescription scanning systems, there is a notable lack of user-centered mobile applications built with active input from patients and non-expert users—particularly those with limited health literacy. Most prescription digitization efforts have been integrated into complex hospitals with minimal attention to how patients or caregivers interpret prescription information independently. This creates a significant usability gap, especially in Bangladesh, where patients often rely on pharmacists or family members to understand their medications, increasing the risk of misunderstanding and misuse. Although the potential of OCR and ML in healthcare is well-documented, existing research tends to prioritize system accuracy over usability, accessibility, and cultural adaptability. Bangladeshi citizens face major challenges in recognizing medicine names, interpreting dosage instructions, and navigating handwritten prescriptions without professional help. However, very few systems have been designed to address these issues from the UCD perspective, which involves co-designing with the target population to ensure that the system addresses real-life barriers to access, trust, and comprehension. Additionally, interactive support systems, such as Relational Agent or conversational interfaces, are virtually absent in existing prescription recognition tools. These features, when implemented effectively, can significantly enhance understanding and engagement among users by providing voice or chat-based explanations of complex medical terms. Yet, such Artificial Intelligence (AI) assisted communication models remain underutilized in prescription-focused applications for non-clinical users. This study addresses these gaps by proposing and evaluating a mobile solution that applies UCD principles throughout the development cycle, integrates a context-aware OCR and ML pipeline, and includes an interactive Relational Agent to support users in understanding scanned prescriptions. By introducing this app to real user needs in Bangladesh, this research contributes an inclusive and practical solution to the ongoing issue of handwritten prescription misinterpretation.

1.5 Research Objectives and Research Questions

1.5.1 Research Objectives

This research aims to develop a user-centric mobile app, named 'PresCa', specifically designed to ensure smooth operation of medication management among Bangladeshi citizens and reduce medication errors and administrative workload for healthcare by digitizing handwritten prescriptions using OCR and machine learning techniques.

The key contributions of this work are:

- Identification of root causes of medication errors in the Bangladesh healthcare system.
- Development and usability evaluation of PresCa for Bangladeshi citizens to assist patients of all ages and classes by offering a personalized medication management system to improve their safety, especially in rural and semi-urban areas of Bangladesh, where handwritten prescriptions are still relevant.
- Proposing an ML-based, efficient, and automated prescription scanning method that could be integrated into the backend of a fully functional medication management app for Bangladesh citizens in future work.

1.5.2 Research Questions

This study is structured around three central research questions (RQs), each targeting a key aspect of developing a mobile application that digitizes handwritten prescriptions to support patients in Bangladesh:

1. **RQ1:** What design features and functionalities should be incorporated into a mobile application to digitize handwritten prescriptions for users in Bangladesh effectively?
    - **Rationale:** This question investigates the necessary components of the app that enhance usability, accuracy, and accessibility for end users. It focuses on understanding user preferences for features like automatic prescription scanning, reminders, clear display of medicine names and dosages, voice interaction, and report summaries, as suggested by user feedback gathered through surveys and usability testing
2. **RQ2:** What is the readiness and willingness among Bangladeshi citizens to adopt a mobile app with unique features (Relational Agent) instead of their traditional medication system?
    - **Rationale:** It aims to explore the openness of users in Bangladesh to transition from traditional, often handwritten and manual medication systems to a digital mobile application that offers intelligent support features like a Relational Agent. It is crucial to understand user readiness to determine how cultural habits, technological accessibility, and trust in AI-driven assistance influence adoption. It also helps identify potential resistance, barriers, and motivators that could impact the successful implementation of the app.
3. **RQ3:** What are the users' perceptions of the usability, effectiveness, and reliability of the proposed mobile app prototype for interpreting handwritten prescriptions?

- **Rationale:** It is essential to gather qualitative and quantitative feedback from users to assess how well the prototype addresses their needs. This includes measuring ease of use, satisfaction with OCR performance, clarity of displayed information, and overall interaction with the app's interface and features such as reminders and the Relational Agent.

These research questions guide the study's focus on building a practical, user-friendly mobile application that applies ML and OCR to support clearer interpretation of prescriptions. The goal is to reduce user confusion, promote safer medication practices, and enhance the healthcare experience for Bangladeshi citizens through a well-researched and iteratively designed digital solution.

1.6 Research Outcome

This study reveals significant insights into the design, development, and user validation of a mobile application aimed at digitizing handwritten prescriptions for Bangladeshi citizens. By applying UCD methodology, the research ensured that the app was developed based on direct input from real users, aligning its functionality and design with their actual needs and expectations.

One of the most prominent findings from the research was the clear challenge that citizens face in reading and interpreting Bangla handwritten prescriptions. Survey results from 155 participants revealed widespread difficulty in understanding medication names, dosages, and instructions due to unclear handwriting and unfamiliar medical terms. These difficulties often lead to misinterpretation or dependency on others, which introduces a high risk of medication errors and compromises patient safety. This problem strongly supports the necessity of a solution like PresCa, which offers a digital bridge between healthcare professionals and patients by presenting medication information in a clear, accessible format.

The iterative design process of the application, driven by user feedback gathered through surveys and interviews, led to the creation of both low-fidelity and high-fidelity prototypes. Early design iterations highlighted the importance of simplicity and clarity in interface design, especially given the varying levels of digital literacy among users. Participants emphasized their preference for intuitive navigation and minimal steps in completing essential tasks such as scanning a prescription or setting a reminder.

Participants' responses significantly influenced the final set of features in the high-fidelity prototype of PresCa. Among the most appreciated functionalities were the ability to scan handwritten prescriptions using OCR, receive summarized reports of the scanned data, set up daily medication reminders, and interact with a Relational Agent through both voice and text. The Relational Agent was particularly well-received as it added an extra layer of accessibility and engagement for users, especially those who might struggle with text-based interfaces. This conversational interface enhanced the user experience by offering guidance and explanations in a more natural, interactive manner. Technically, the integration of OCR and ML into the app showed promising results in extracting medication data from diverse handwriting samples. While the OCR model faced challenges in cases of extremely illegible handwriting or poor image quality, it performed effectively in many cases, especially when supported by user guidance in capturing the prescription image. These findings point to the potential of further enhancing the OCR model by expanding the training dataset and refining its recognition capabilities through continuous learning.

Another critical research outcome was the confirmation of users' readiness and openness to adopt such digital tools, even among populations that had not previously engaged with health-related mobile applications. Despite initial hesitations, especially from older users, most participants showed a willingness to use the app regularly after interacting with the prototype. The convenience of automatic reminders, access to readable prescription data, and interactive assistance from the Relational Agent created a sense of empowerment among users, encouraging them to manage their medications more independently.

The research validates the viability of a mobile solution like PresCa in improving the clarity and accessibility of prescription information in Bangladesh. The outcomes highlight how thoughtful integration of technology, guided by continuous user involvement, can address real-world problems and contribute to safer, more informed healthcare practices. The success of the prototype underscores the potential for scaling this solution to wider user groups, while also offering opportunities for future development in prescription analytics, language support, and AI-driven personalization.

1.7 Report Outline

Chapter 1 (Introduction):

This chapter presents the background and the reasons for this study, with a focus on medication management errors. It explains key ideas related to HCI, UCD, the role of mobile apps in medication management, and how ML can help in handling prescriptions. It also defines the problem statement, highlights ethical issues, identifies research gaps, and outlines the research objectives and Research Questions **(RQs)**.

Chapter 2 (Systematic Literature Review):

This chapter introduced a Systematic Literature Review (SLR) of existing research on medication management apps. It explains the review methodology, including the search strategy, criteria for including or excluding studies, the selection process, and how data were collected. The chapter also analyzes the results of the review by addressing the **SLR-specific research questions (1–5)**, which focus on the types of systems available, their features, evaluation methods, limitations, and security and privacy aspects.

Chapter 3 (Design Requirements Elicitation and Need-finding Study):

To guide the design of the PresCa app, this chapter details the need-finding study conducted. It outlines the study design, the demographics of the participants, the measures used for data analysis, and the key findings of the need-finding study. This chapter addresses **RQ1**, which is related to the essential design elements and features of the app. It additionally answers **RQ2** about the readiness and willingness of Bangladeshi citizens to adopt a mobile app solution to manage their medication. This chapter contains content from publication [51] titled, "Early-Stage Development of a Handwritten Prescription Interpretation App for Bangladeshi Citizens."

Chapter 4 (PresCa Prototype and Its Features):

Describing the design and development of the PresCa app prototype, this chapter provides the rationale for specific features and functionalities. Key components are highlighted, such as “prescription scanning”, “scanning”, “guidelines”, “report summary” , “check reminder”, and “configure medicine reminder.” This overview aims to demonstrate the app’s practical applications for medication management. This chapter contains content from publication [51] titled, “Early-Stage Development of a Handwritten Prescription Interpretation App for Bangladeshi Citizens.”

Chapter 5 (Usability Evaluation):

This chapter describes a usability evaluation of the PresCa prototype. The chapter outlines the study design, describes the characteristics of the participants, and explains the evaluation methods used for analysis, with a particular focus on the System Usability Scale (SUS) score [15]. It discusses the study findings and answers **Research Question 3 (RQ3)**, which explores users’ perceptions of the usability of the proposed system. This chapter contains content from publication [51] titled, “Early-Stage Development of a Handwritten Prescription Interpretation App for Bangladeshi Citizens.”

Chapter 6 (Medication Information Detection):

In this chapter, ML and Deep Learning (DL)-based techniques are investigated for extracting medicine information, such as medicine names and dosages, from handwritten prescriptions. Various models, such as SimpleHTR, ViLanOCR, and RNN using CTC loss function, were compared with TrOCR, and the TrOCR model outperformed the other DL-based models. The chapter evaluates the performance of these models using metrics Word Error Rate (WER) and Character Error Rate (CER). This chapter contains content from publication [67] titled, “Recognizing Medicine Names From Bangladeshi Handwritten Prescription Images Using TrOCR.”

Chapter 7 (Discussion):

This chapter summarizes the main outcomes of the research, incorporating insights from the systematic literature review, the need-finding process, the development of the prototype, and the usability testing. It reflects on the significance of these results, outlines the study’s limitations, and proposes possible areas for further investigation.

Chapter 8 (Conclusion and Future Works):

This chapter highlights the key findings of the study, with a focus on the importance of the “PresCa app” in supporting medication management for citizens in Bangladesh. It also outlines future directions for enhancing and further developing the app.

Appendix

The appendix chapter contains two separate parts:

- **Appendix A**: This section presents a complete list of all abbreviations used in the report for reference.

- **Appendix B**: This section includes a list of publications that have been produced as a result of this research.

2 Systematic Literature Review

Significant research has been done in developing apps that would make medication management easier for patients. [55] developed a multi-platform application, “panacea”. It reduces misinterpretation of prescriptions and saves time in pharmacies by integrating a web application and two Android applications. The web application enables doctors to provide medicine recommendations to patients. The doctors will provide the dosage and consumption time. The patient will have an Android application that helps them view the prescription and produce a Quick Response (QR) code based on it. The QR code will be then scanned by the pharmacist’s application. The patient’s application can also set reminders and notifications according to the prescribed time provided by the doctor.

“MedDose” [52] is a medication management app that offers a user-friendly experience that can reduce the problem of missing dosages and refilling medicines within time. It integrates ML and works together with hardware components. The app scans prescriptions using Google’s ML Kit from the users’ digital prescriptions, helps purchase medicines, sends dosage alerts, and arranges appointments with doctors. Google’s ML Kit helps to extract relevant text from the image provided by the user. The hardware component is the ‘Medikit’ Box, which has a NodeMCU and an Infrared Radiation (IR) sensor that helps the system update inventory whenever the user takes their medicine. An admin panel is also involved, which manages and observes all the activities. The user experienced a profound benefit from all these functions integrated within a single app.

“WiseMed” is an app specially made for elderly people using Thai and English [61]. It tries to solve the problem of the existing apps “Teun-Tan-Ya” and “Mr. Pillster” [1], which require users to enter their medication information by themselves and manually organize their medication timing. A web-based QR code generator is made for healthcare professionals, where they can generate a QR code by entering the medical information (medicine name, dose, number of days the patients need to consume their medicine, medicine consumption time, and frequency) required by the patients. The seniors will scan the QR code, and the app will automatically send reminders at the right times for the user to take their medicine. The system will track whether the patients are taking their medicine at the right time and make a graphical representation. The app was evaluated by 10 participants, who were asked to rate the three applications “Teun-Tan-Ya”, “Mr. Pillster”, and “WiseMed”. “WiseMed” was better in all aspects except for simplicity, whereas “Teun-Tan-Ya” performed better.

“ScanMed” is an app that aims to help patients consume the right medicine prescribed by doctors and follow the prescribed schedule for taking their medicine correctly [44]. The system consists of a web-based interface and a mobile application interface. Both interfaces are designed to be simple so that individuals with no expertise can also use them without any trouble. Healthcare providers can manage patient and medicine records and also enable them to input and update medicine, prescription details, instructions, and patient types using the web-based interface. A QR code is generated and printed on the patient’s medicine label for easy tracking and verification. The patient can scan the QR code using the camera in the mobile application interface, which acts as proof of medication interaction. After that, it displays medication information, such as dosage instructions and side effects. Finally, it provides notifications and reminders when the patient has to take their medicine.

This SLR aims to support the development of prescription extraction apps by compiling the most recent findings on the effectiveness of OCR and DL techniques in extracting medicine information from handwritten prescriptions. This review will focus on answering the RQs set specifically for this review, as mentioned in table 2.1, and will offer insights into the potential of the apps' solution to interpret handwritten prescriptions

Table 2.1: RQs for SLR and their Rationale

ID	**RQ**	**Rationale**
RQ1	What are the specific features offered by the available mobile apps that help users get assistance with medication?	Analyzing what type of features users are currently utilizing and identifying existing gaps and potential areas for feature improvement
RQ2	What are the current limitations and gaps in the literature regarding mobile apps for interpreting handwritten prescriptions and medication management	Identifying limitations and gaps in the existing literature helps highlight areas for future research and development of this kind of medication information extraction and management app.
RQ3	What are the common medication errors that are found in handwritten prescriptions, and how can they be corrected by using AI	Identifying common medication errors in handwritten prescriptions and exploring how AI can reduce this problem.
RQ4	What features and functionalities do users prioritize more in a prescription interpretation and medication management app	Understanding the different types of features and functionalities users prefer for prescription interpretation and medication management applications.
RQ5	How do patients manage prescription reading challenges currently, and the limitations of existing solutions in Bangladesh	Exploring how patients currently manage prescription reading-related challenges. Analyzing the existing solutions used for these types of problems

2.1 Method

To analyze the research papers on how mHealth apps have been developed or used to assist users in interpreting handwritten prescriptions, we conducted a systematic review according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [2] guidelines as shown in Fig. 1. A systematic search was done using Scopus, a large peer-reviewed literature database. The search was limited to studies published in English from 2005 to 2024. It provided papers from multiple authors across various databases that were screened for relevance based on our eligibility criteria.

2.1.1 Search Strategies

At first, we identified keywords that are relevant to our topic. Then we entered the resulting search string, consisting of keyword combinations using the Boolean operators

Table 2.2: Lists of Inclusion and Exclusion Criteria

Area Specification	Inclusion Criteria	Exclusion Criteria
Database	**IC1.** ScienceDirect, Springer, IEEE Xplore/Access, PubMed, Frontiers, MDPI, Wiley Online Library, SAGE, World Scientific	**EC1.** Other Journals except for Predatory Journal and journals mentioned ”Inclusion Criteria”
Journal/ Conference Type	**IC2.** Research article	**EC2.** Book Chapter, Reviewed article, etc.
Area of Interest	**IC3.** Medication Management, Prescription information extraction, Handwritten Prescription Understanding	**EC3.** Areas excluding “Inclusion Criteria”
Selected Time Period	**IC4.** 2005-2023	**EC4.** Before 2010

“AND” (must be included) and “OR” (may or may not be included). We restricted our search to the papers’ abstracts, titles, and keywords. The initial search gave us 139 papers. The string used was:

(“medication management” OR “prescription” OR “prescription extraction using DL” OR “prescription information extraction” OR “medication management using AI”) AND (“healthcare professional” OR “Pharmacist” OR “doctor”) AND (“mobile app” OR “smartphone app”).

2.1.2 Inclusion Criteria

The 120 papers were then assessed against inclusion and exclusion criteria. We got 93 articles after excluding the review paper, short paper, data paper, and abstracts. These articles were screened again manually by reading through the titles and abstracts to assess their relevance to the inclusion criteria, which reduced them to 13 papers. Studies were included if they:

- Focused on mobile or web applications for prescription interpretation and medication reminders.
- Investigated the use of DL techniques for medical information extraction.
- Were published between 2010 and 2025

2.1.3 Exclusion Criteria

The exclusion criteria that were followed to exclude a study are:

- Papers published before 2010
- Book Chapters
- Review Papers

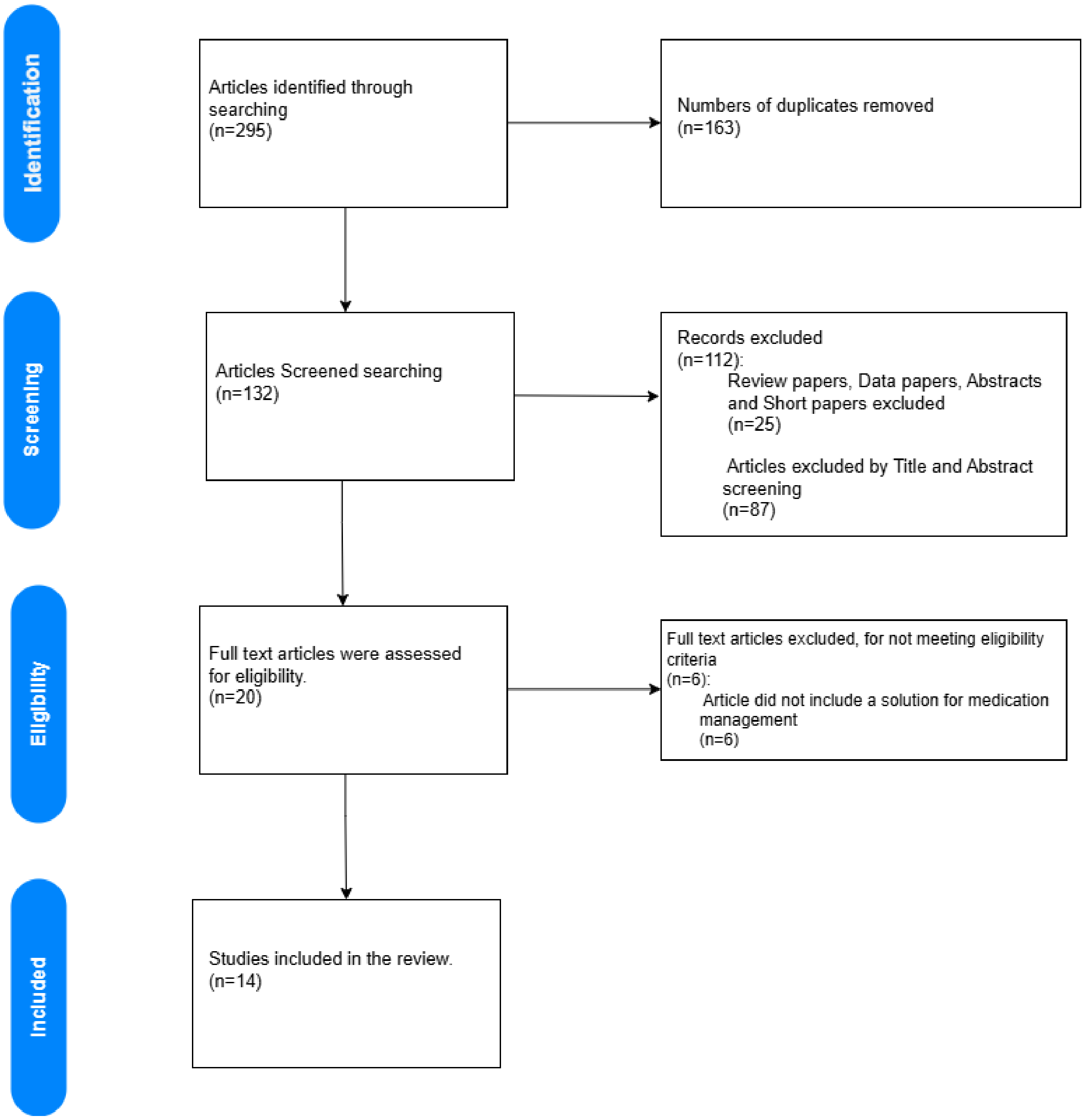


Figure 1: PRISMA flowchart for the literature search process

2.1.4 Study Selection

A total of 295 articles were initially retrieved from major databases, including IEEE Xplore, ACM Digital Library, Springer, ScienceDirect, Sage, IOP, Wiley, Oxford, Taylor & Francis, and Cell. Using an automation tool called Zotero, 163 duplicate records were identified and removed. After that, 25 articles consisting of short papers, data papers, abstracts, and review articles were excluded. These types of papers were omitted because they typically lack the depth and detailed analysis required for this study, and review articles do not align with the objectives of an SLR.

This left 107 articles for further screening. However, after reviewing titles and abstracts, 87 articles were excluded for being irrelevant. This high number of exclusions was largely due to the use of broad or common keywords in the search query, which led to many unrelated results.

The remaining 20 articles underwent a full-text review, and 6 more were excluded as they did not meet the inclusion criteria outlined in Table 2.2. In the end, 14 articles were deemed relevant and selected for the final systematic literature review.

2.1.5 Data Extraction

The following phase focused on the in-depth analysis of the remaining articles to identify relevant data based on the review topic. As shown in Fig. 4, a set of predefined categories was used to extract data in a structured manner.

Topical Association

- **Title Based:** The initial screening was performed based on article titles, articles were included if their titles indicated relevance to the study topic such as prescription management, medication errors, healthcare professionals, and mobile app management.

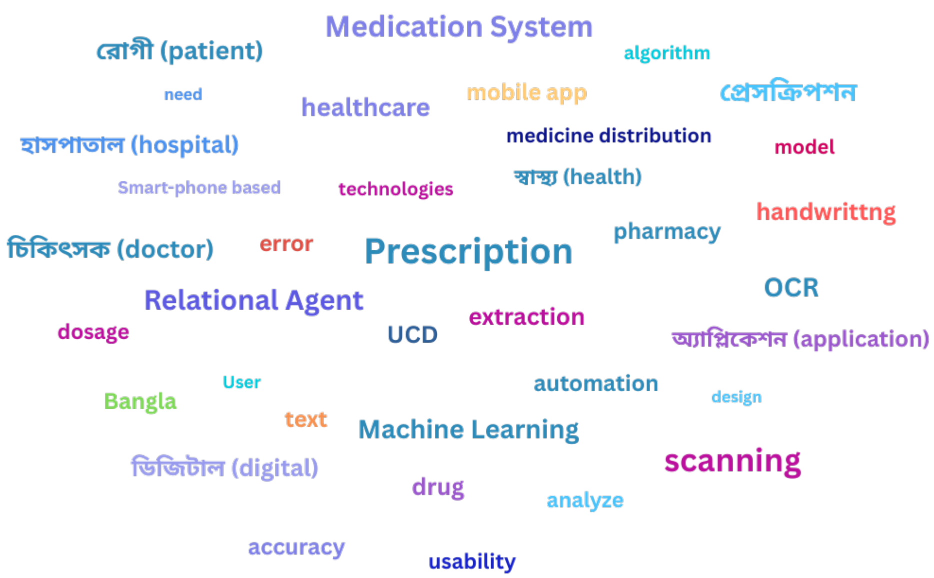


Figure 2: Word cloud based on the keywords

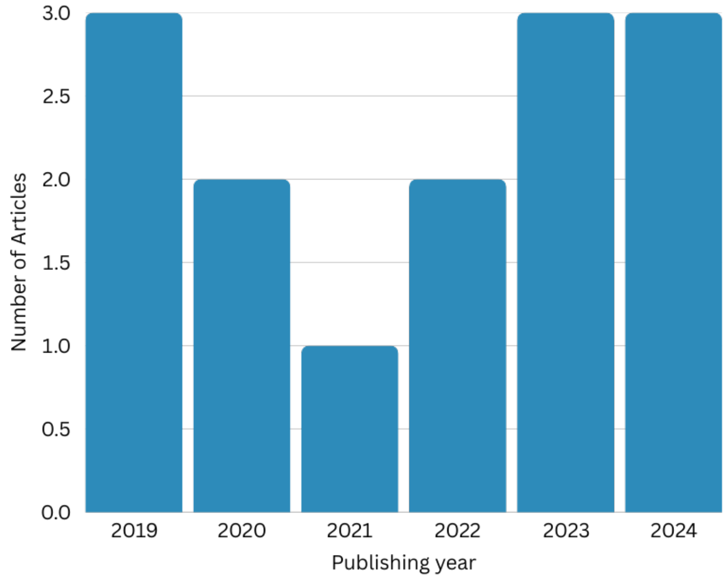


Figure 3: Number of articles published based on year

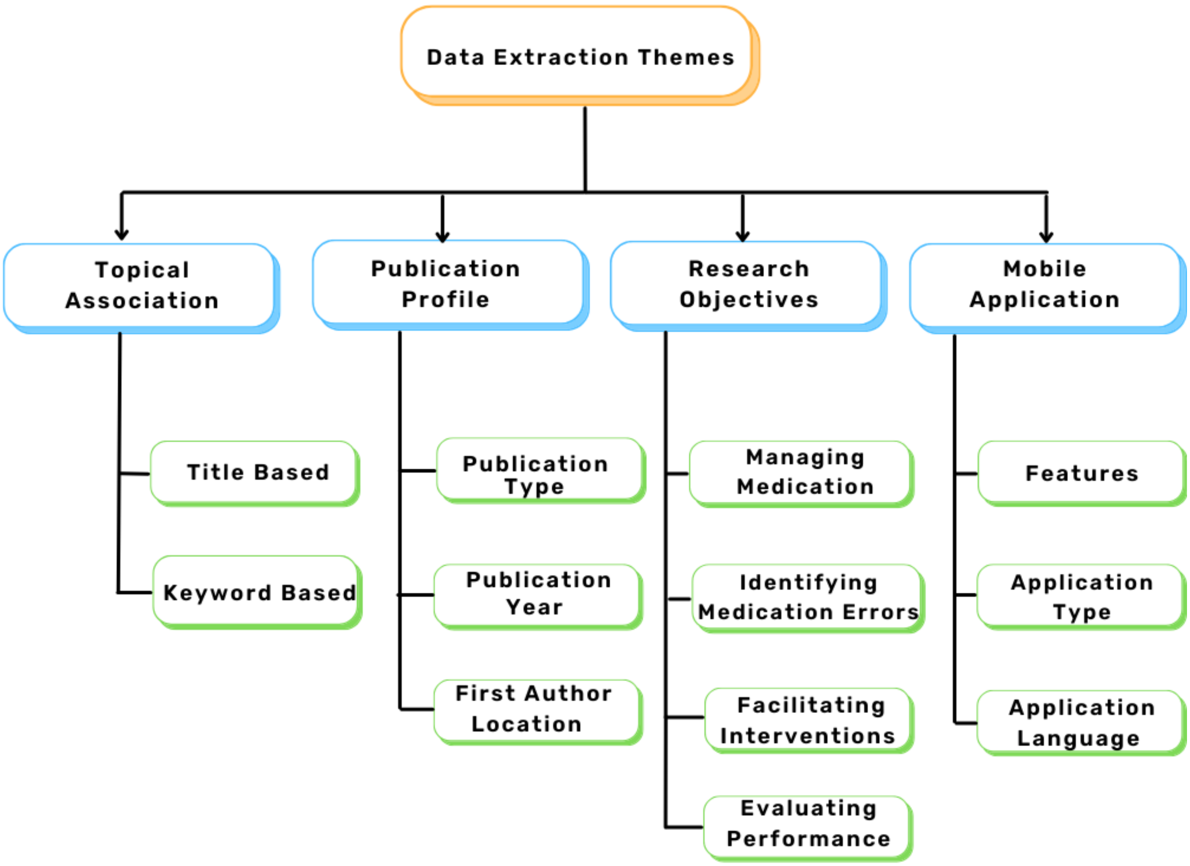


Figure 4: Data Extraction Themes

- **Keyword Based:** Papers that included keywords "medicine", "prescription scanning", "medication error". , "healthcare", "doctor", "app" were used to extract relevant data.

Publication Profile

- **Publication Type:** Research articles were classified by publication type into conference papers, journal articles, and book chapters.
- **Publication Year:** Publishing years were extracted from the selected articles for analysis.
- **First Author Location:** The locations of the first authors were extracted to identify the countries that actively contribute to research on digitizing prescription management.

Research Objectives

- **Managing Medication:** Relevant information was extracted from selected articles to assess whether the proposed solutions adequately support accurate medication management.
- **Identifying Medication errors:** In this section, the core reasons are identified to realize which stages of the medication process are the most prone to errors and what tasks are typically involved in the health care system in each article.
- **Facilitating Interventions:** Suggested interventions outlined in the selected studies to manage prescriptions are listed below. Some common interventions include digitilizing prescriptions, a reminder and notification feature to take medicine, and medicine information.
- **Evaluating Performance and Feasibility:** Different performance and feasibility assessment scales used in the selected articles are extracted in this section.

Mobile Application

- **Features:** The mobile app features suggested in the selected studies are detailed in this section.
- **Application Type:** This section identifies whether the proposed solutions in the articles consist of mobile apps or a combination of mobile and web applications
- **Application Language:** This section presents the available language options for each solution to understand the linguistic reach and intended user base

2.2 Literature Search Outcomes

The associations between the selected articles are visually represented in Fig. 2 using a word cloud, where the relative importance of keywords is indicated by font size—larger fonts denote higher frequency and thematic relevance. In this visualization, the most prominent terms include prescription, ML, scanning, OCR, healthcare, medication system, and Relational Agent. These highlight the core research themes, emphasizing the integration of advanced technologies such as OCR and ML in automating and enhancing prescription processes. Other frequently occurring keywords like mobile app, digital, usability, doctor, hospital, and error suggest a strong focus on developing user-friendly,

Table 2.3: Categorization of Limitations According to Research Articles that Self-Reported Limitations

Categories	Limitations	Research Articles
Study Design and Methodology	Lack of standardized benchmarks for evaluating prescription digitization systems, Limited datasets, especially for handwritten prescriptions, Lack of clinical trials for real-world validation, Variability in data collection methods	[56], [4], [41]
Model and Scanning Accuracy	OCR performance drops significantly on illegible or low-quality handwriting, Distinct handwriting traits, Poor accuracy in multi-language settings, ML models trained on biased or small datasets, Errors in distinguishing between similar drug names	[56], [50], [68], [5]
System Usability and Integration	Difficulty integrating with electronic health record (EHR) systems, User interfaces not optimized for healthcare settings, Lack of user feedback features, Inconsistent system performance across devices	[68], [5], [53], [44]
Outcome Measures and Evaluation	Limited validation of clinical effectiveness (e.g., reduction in prescription errors), Over-reliance on technical metrics like accuracy without user experience measures, Short-term performance metrics without longitudinal data	[4], [41], [53]
Generalizability and External Use	Prescription formats and drug names vary regionally, Models trained in one country may not generalize to another due to differences in language, format, and medical conventions	[50], [4], [41], [53]
Technical Limitations	No offline capabilities in low-connectivity areas, High latency in complex prescriptions, Errors in image pre-processing (e.g., skewed, noisy images), Lack of explainability in ML decisions	[56], [68], [5]
User and Participant Factors	Limited digital literacy among healthcare professionals, Resistance to adopting automated tools due to trust or privacy concerns, Lack of training in using AI-based systems	[50], [5], [53], [44]
Data Security and Privacy	While the systems collect sensitive health data, there's no mention of security measures like encryption or compliance with health data regulations.	[55], [52], [63]

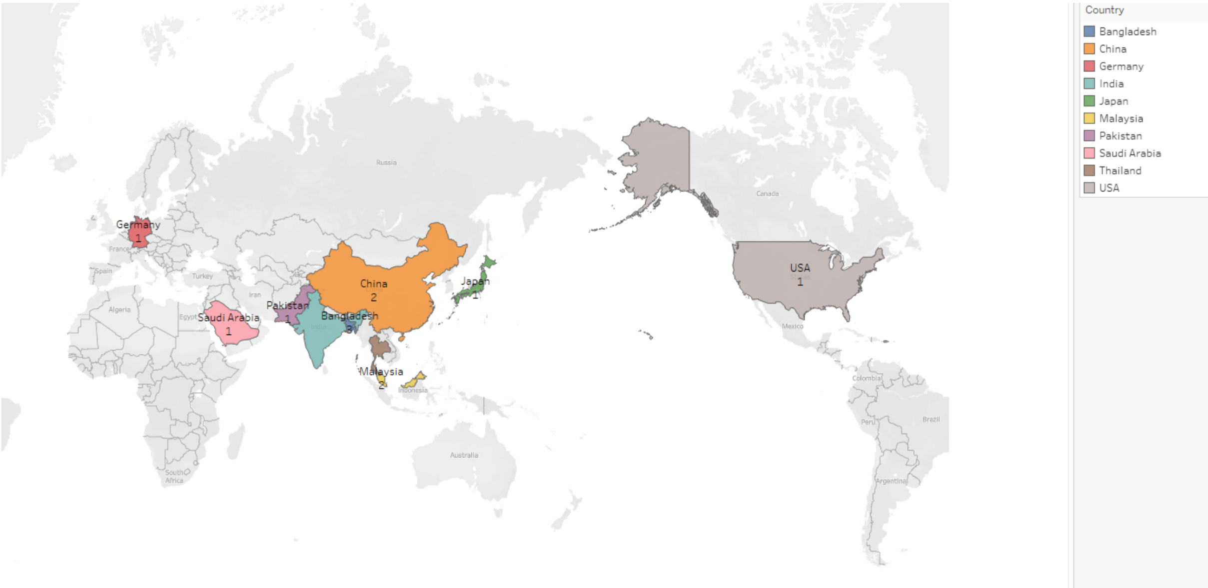


Figure 5: Global distribution of published research papers based on the country affiliation of the first author

smartphone-based systems aimed at reducing prescription-related errors and improving healthcare efficiency. The presence of multilingual terms indicates a localized or inclusive approach to system design, reflecting the consideration of diverse user groups and indicating that developing digital solutions for prescription management is a significant area of focus in the reviewed articles.

Fig. 3 illustrates the number of articles published in each year from 2019 to 2024. The overall trend of research articles about prescription management is seen to be following an increasing trend as the number of articles published continues to increase. With the same number of articles, the years 2020 and 2022 stand (n=2). The lowest number of articles published (n=1) was in 2021, while the highest number of articles published (n=3) was in 2019, 2023, and 2024. Few articles were found during the initial search period of the PRISMA method that dated as far back as 2005, however, those articles have been excluded in the screening phase due to not meeting eligibility criteria.

In Fig. 5, a world map has been demonstrated based on the affiliation of the first authors. The majority of the research (n=3, 20.00%) has been conducted in Bangladesh while researchers from Malaysia,chaina and India conducted the second highest amount of research (n = 2, 13. 33%), while the rest of the 6 articles have been conducted in Saudi Arabia, Japan, Thailand, Germany, USA and Pakistan, respectively. Based on geographic location, research effort is distributed unevenly, with a notable concentration in Asia, followed by minimal contributions from Europe and North America. This indicates a strong regional focus on health-related technological research in Asian countries, possibly due to larger population bases and emerging healthcare challenges. However, there is still a significant research gap. Many studies do not focus on certain groups of people who need the most help, such as older adults, people who are not comfortable with technology, or those living in rural areas. Future research should pay more attention to these groups to ensure that medication management apps are helpful and easy to use for everyone.

2.3 Findings

RQ1: What are the specific features offered by the available mobile apps that help users get assistance with medication?

A summary of the reviewed apps is shown in Table 2.4. Below, a selection of these apps is categorized based on their targeted areas of impact.

1. **Medication Reminders and Notifications Apps:** These apps provide reminders to users to take their medication at the prescribed times. "Panacea" and "ScanMed" explicitly mention this feature. "Daktarbhai" also aims to simplify healthcare access by offering medication reminders [44, 63, 55].

2. **Prescription Digitalization and Management:** These apps facilitate the viewing and management of prescriptions. "Panacea" allows doctors to create digital prescriptions and patients to view them through an app, generating a QR code for pharmacies. "Sebaghar" offers online prescription services for efficient medication management [55, 63].

3. **Information about Medicines:** Apps can provide essential details about the medication, including dosage, usage instructions, warnings, and potential side effects. "Oshudh Poro" retrieves relevant details of registered medicines and plays them aloud in Bengali. "ScanMed" displays information such as an image of the medicine, prescription details, medication warnings, side effects, and instructions. "WiseMed app" recovers data on the client's medicine, for example, what the medication is for, precautionary measures, and reactions [44, 61, 26].

4. **Medication Intake Tracking and Validation:** Some apps allow users to track whether they have taken their medication. "ScanMed" introduces a novel approach by requiring users to scan a QR code on the medication label as a "proof of work" to signify intake. [44].

5. **Support for Low-Literate Users:** "Oshudh Poro" is specifically designed to support low-literate rural Bangladeshi people by using image scanning and Bengali audio output of medicine details. This addresses a critical need as highlighted by the challenges faced by illiterate and low-literate people in understanding the packaging of medicines. [26].

6. **Unique Patient Identification:** "Panacea" creates a unique ID for patients and doctors, intended to be universal across consultations. This could potentially streamline the process of accessing and managing prescriptions across different healthcare providers.

   [55].

RQ2: What are the current limitations and gaps in the literature regarding mobile apps for interpreting handwritten prescriptions and medication management?

The current limitations and gaps in the literature regarding mobile apps for medication assistance are discussed below:

1. **Limited User Studies and Verification of App Design**: "Oshudh Poro" acknowledges that their prototype design assumptions lack user verification and need

user feedback. This suggests a general gap in the literature regarding thorough user studies to evaluate the usability and effectiveness of medication assistance apps, particularly for specific target populations like low-literate individuals [26].

2. **Challenges in Ensuring Actual Medication Intake**: Various apps can provide reminders and track user input, verifying actual medication consumption remains a challenge. "ScanMed" attempts to address this with QR code scanning as a proof of work, but even this doesn't guarantee ingestion. The literature could further explore and evaluate different methods for more reliable intake verification [44].

3. **Accessibility and Inclusivity**: While "Oshudh Poro" addresses low literacy, the literature may still lack comprehensive solutions for other accessibility barriers, such as for users with visual impairments or those who are not comfortable using smartphones. As "Oshudh Poro" itself notes its limitation for basic-button phone users [26]. In the paper [63], authors emphasize the need for Bangla language support, highlighting the importance of linguistic accessibility, which might be a gap in apps developed without such localization in mind. The distribution of languages used in the apps is presented in Fig. 6. English emerged as the most frequently cited language, consistent with the locations of the studies. Other languages were reported far less frequently.

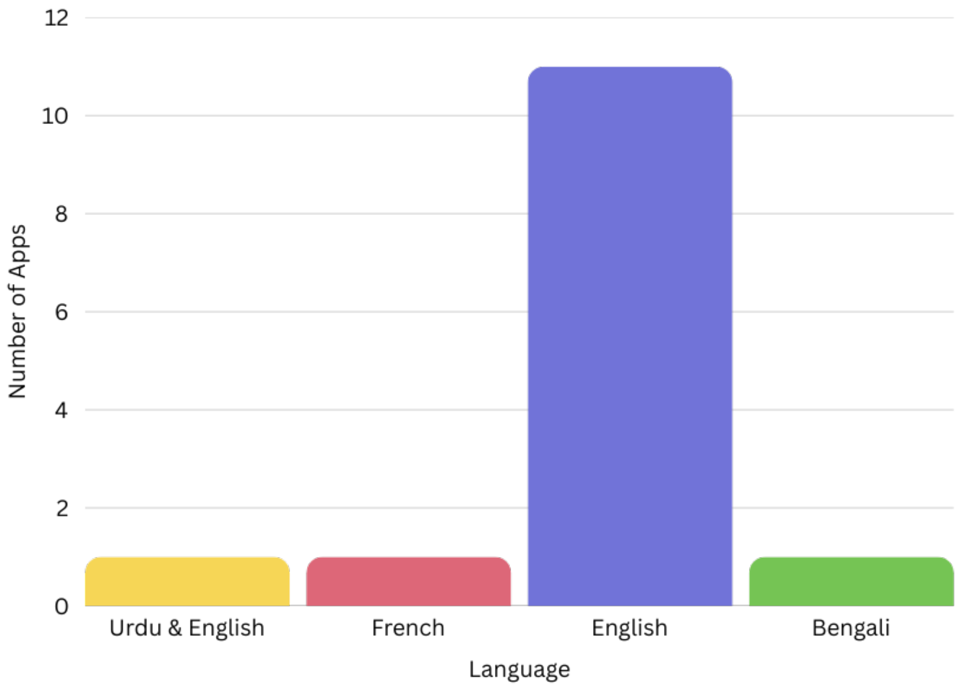


Figure 6: Language Support in Medication Apps

4. **Integration with Healthcare Professionals and Systems**: There are some gaps in the literature on how effectively these mobile apps are integrated into the broader healthcare system. While "Panacea" aims for doctor-patient connection, research on seamless integration with EHRs (Electronic Health Records) [55]. But

pharmacy systems and healthcare provider workflows may be limited in the system. The role of healthcare professionals in recommending, monitoring, and using data from these apps needs further exploration. .

5. **Focus on Error Prevention at the Prescribing Stage**: While some apps aim to manage existing prescriptions, the literature could further investigate how mobile technology can actively prevent prescribing errors in the first place. Two papers [60, 14] highlighted the prevalence of errors such as illegible handwriting, missing information, and lack of generic prescribing and suggested a need for digital prescribing solutions to be more widely adopted and studied for their impact on error reduction.

6. **Data Privacy and Security**: As medication assistance apps handle personal health information, the literature needs to robustly address data privacy and security concerns. It is vital to safeguard the confidentiality and integrity of user data. This study [63] mentions the significance of data security of these health-related apps.

RQ3: What are the common medication errors that are found in handwritten prescriptions, and how can they be corrected by using AI?

(i) *Illegibility and Misinterpretation of Drug Names:*

- Handwritten prescriptions often suffer from poor handwriting, making medicine names very hard to read. This can lead to the wrong medication. The most common cause of medication errors is illegibility of drug names [6].
- AI-based solutions like OCR tools have shown high accuracy in extracting text from handwritten prescriptions. These tools help to digitize prescriptions and reduce errors

(ii) *Dosage and Frequency Errors:*

- Another common issue is confusion over dosage instructions, especially if units like milli-gram (mg) and milli-liter (ml) are missing or wrongly written. AI models trained on a large dataset can find out the missing or wrongly written dosages.
- AI models that use Natural Language Processing (NLP) [54] can compare the prescription with known medical guidelines and give an alert when there is any error is found.

RQ4: What features and functionalities do users prioritize more in a prescription interpretation and medication management app

From different studies related to mobile health (mHealth) and medication management solutions, many different features and functionalities have been considered as primary concerns for the users. Some of them are discussed below:

(i) Most noteworthy studies mentioned that the users gave emphasis on medication reminders. Some of them are smart reminder systems with alarms, phone calls, and LED indicators [48]. These functionalities are of high value, especially among elderly users who are suffering from dementia or memory loss due to old age. Similarly, in [32] and [52], timely reminders for medication intake are given top priority. Survey data from [32] shows that 17% of the users expressed that they forget to take medications on time.

(ii) Article [9] and [52] stated that complex and illegible handwritten prescriptions are one of the barriers to proper medication adherence, especially when there is a low literacy rate. For correct medicine intake by the patients, features and functionalities like OCR-based prescription scanning and extraction are considered significant [31, 52]. It is also mentioned in the article [10] that additional information with medicine names, such as dosage information, side effect warnings, and brand name clarifications, is wanted [9].

(iii) Some additional features like an appointment system, emergency calling, and doctor selection tools were mentioned in [32] and [30].

(iv) In paper [52], it is mentioned that testing of user interfaces shows better satisfaction with the system. Furthermore, articles [48] and [3] put emphasis on personalized interfaces for elderly people or people with less technical skills.

RQ5: What are the current challenges and limitations in prescription interpretation and medication management systems?

(i) In article [48] and [52] it‘s mentioned that one of the challenges faced by elderly people is forgetfulness, with non-adherence rates ranging from 40% to 75%. Additional health risks include manual errors, incorrect timing of medication intake, and confusion due to weak memory. The existing systems don’t usually have intelligent tracking or verification mechanisms.

(ii) According to article [48], illiteracy is one of the barriers to prescription management, especially in rural areas where handwritten prescriptions are still prevalent. Patients in those areas are unable to understand medicine names, dosages, and consumption instructions. Research study [9] also discusses issues with prescription clarity, and states that 64.32% of the prescriptions are not complete, and handwritten ones are complicated to understand. The mentioned problems directly affect the patient’s health, safety, and compliance.

Table 2.4: A summary of the applications on prescription information extraction and medication management.

Purposes	Application Name	Brief Description	Features	Platform	User	Reference
Help patients track and prove medication intake	Oshudh Poro	A mobile app designed to help users interpret handwritten prescriptions in Bengali using OCR and AI.	**1.** Camera input for handwritten prescription capture, **2.** OCR and Transformer-based text extraction **3.** Dosage and schedule detection **4.** Audio playback for medicine instructions **5.** Daily medicine tracking and progress monitor **6.** Reminder and notification system	Android	Elderly and low literate users	[27]
	ScanMed	A mobile application that uses QR code scanning on medication labels to verify intake. Offers reminders, dosage info, instructions, and warnings through a user-friendly Android app, along with a web-based interface for healthcare centers.	**1.** QR code-based proof of medication intake, **2.** Reminder system with alarms, **3.** Side effects and usage instructions, **4.** Side effects and usage instructions **5.** Audio and visual guide	Android	Patients and Healthcare personnel	[44]
	MedDose	Provides an all-in-one mobile app integrated with a hardware component (Medikit Box) to support medicine intake tracking using ML-based prescription recognition and inventory monitoring.	**1.** Prescription scanning using Google ML Kit, **2.** Doctor appointment booking, **3.** Automated alerts and reminders, **4.** Real time inventory management, **5.** Admin dashboard for tracking, **6.** ML-based OCR for dosage detection	Android	Patients	[52]
	Panacea	Includes a web portal for doctors, a mobile app for patients to manage prescriptions and reminders, and a pharmacist app to read prescription QR codes	**1.** QR code generation for prescriptions, **2.** Web portal for doctors to input prescriptions, **3.** Reminders, **4.** Notifications,	Web and Android	Patients, Doctors, Pharmacists	[55]
	Med Alert	Provides a GSM-enabled medicine reminder box designed for elderly users, which not only sets reminders by alarm and phone calls but also monitors vital signs and environmental parameters	**1.** Alerts if medicine not taken, **2.** Monitors heart rate (BPM), **3.** WiFi-based app control, **4.** switch to detect if medicine chamber is opened, **5.** Real time clock and remainder system **1.** Alerts if medicine not taken, **2.** Monitors heart rate (BPM), **3.** WiFi-based app control, **4.** switch to detect if medicine chamber is opened.	Android	Hospitals and elderly people	[49]

Table 2.5: Key purposes of the reviewed articles.

Purposes	Brief Description	Reference	Frequency
To improve medication adherence	It represents a smart medicine reminder kit that provides health monitoring features (heartbeat, temperature, oxygen) and phone calls developed specifically for older people	[48]	5
	Introduced to address medication noncompliance include an all-in-one medication management system with prescription scanning, medication alerts, and automated inventory control.	[52]	
	Describes an application system for low-literate Bangladeshi users that scans medicine packaging and converts information to Bengali audio to manage their medicines effectively.	[26]	
	Outlines an application that offers features such as pill reminders and digitalized prescriptions using PHP and Android that create unique IDs for patients and doctors, and include reminder notifications	[55]	
	This article demonstrates a mobile medication adherence solution that tracks, reminds, informs, and alerts users about medicine refills using QR code scanning as verification of medicine consumption of patients.	[44]	
To digitalize healthcare services	It focuses on a smartphone application that delivers hospital information, cabin booking, doctor location, emergency services, and health utilities such as a Body Mass Index (MI) calculator for Bangladesh's healthcare system.	[32]	3
	This article describes a smartphone-based health care system that includes online appointment scheduling, cabin reservation, prescription, and illness information alerts.	[30]	
	This research examines societal effects, advantages, and e-healthcare implementation hurdles of healthcare applications in Bangladesh.	[63]	
To analyze and reduce prescription errors	This study discussed how doctors in Bangladesh write the prescriptions. It is found that most prescriptions contain antibiotics, use generic drug names, and don't write the important patient details.	[9]	4

To analyze and reduce prescription errors	It explored prescription mistakes occurring at big hospitals in Bangladesh and revealed that on average, there were about 3.85 mistakes in each prescription. Some mistakes mentioned in the article are missing information and illegible handwriting	[21]	
	Studies prescribing patterns and antibiotic use among outpatients in Bangladesh, finding incomplete prescription information and indiscriminate use of antimicrobials	[60]	
	In this study, they investigated handwritten prescriptions and found many significant errors, like missing information, not mentioning the drug dosage, and how to use a particular medicine.	[14]	
To support healthcare access for underserved populations	In this article a mobile application is designed to assist people with low literacy in rural areas of Bangladesh to manage their medications just by scanning the packaging of the medicine and giving audio information.	[34]	1

3 Design Requirements Elicitation and Needfinding Study

Fig. 7 shows the methodology followed in this research work, following the UCD technique [39]. The first step of our work starts with a background study to gather fundamental knowledge regarding the present issues related to complicated Bangla handwritten prescriptions. Afterwards, a questionnaire was developed and conducted via Google Forms. A total of 155 participants' insights were recorded for the user-specific data and design requirements of the app. The respondents also provided their suggestions and concerns that were not identified during the background study stage. The answers were later converted to visual charts and graphs for better understanding of the patterns and trends in user choices. This helped us to understand the concerns more effortlessly, making sure that the important comments were focused on in the next stages of design. In the following phase, the design recommendations were reviewed and integrated with our high-fidelity app prototype. This prototype was designed using Figma (https://www.figma.com/), a design tool that allowed team collaboration and realistic app screens. This high-fidelity prototype is highly detailed and designed in such a way that it resembles the final product. It allows the user to navigate through different screens in the app and gain experience with the app features. Once we had completed designing the high-fidelity prototype, it went through usability testing. SUS scale was utilized to understand how user-friendly and efficient our prototype is. SUS is a popular tool for measuring usability by letting the participants use and rate the prototype based on their experience. This scale involves 10 questions that help to determine whether the app is user-friendly or not. Following this structured method, we verified that the app was both handy and user-friendly, adhering to the target audiences' needs and expectations from the system.

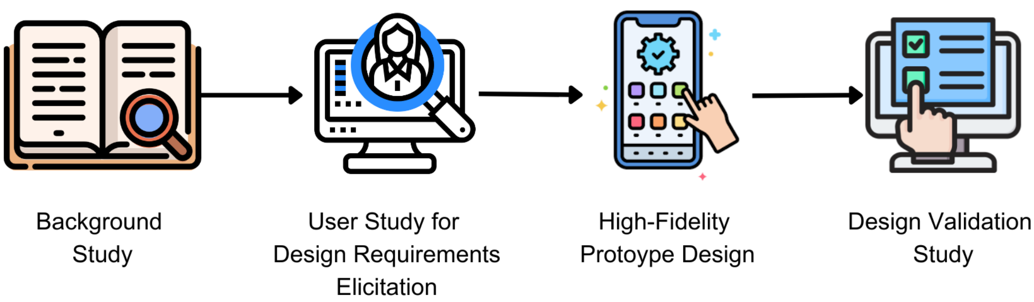


Figure 7: Flowchart describing the process of the conceptual framework for "PresCa" app

3.1 Study Design

Before designing the high-fidelity prototype, we conducted a user survey through Google Forms, which remained open for 3 weeks, from September 9th to September 30th, 2024. This survey focused on collecting data on different features of the app. Based on their feedback, we were able to design a prototype that aligns with the users' needs and preferences.

The survey was divided into different sections to guarantee a balanced understanding of user expectations. The first section of the survey focused on obtaining voluntary consent from the participants and a brief description of the research and its objectives. Through this, the respondents understood the objective of the study and how important their feedback is to developing the app.

After obtaining consent from the participants, the survey started with demographic questions like age, gender, and current employment status to understand the characteristics and behaviors of the participants. It will also be useful in designing the app to be more user-centric based on the background of the participants. For example, based on the different age groups we could select the best font sizes, color contrasts, and navigation style to improve the usability for all users, including elderly individuals. In the same way, employment status could be useful in understanding how frequently the users might use the app based on their daily routines.

In the next section, we asked the participants about the challenges they face in handling their prescriptions. This included questions regarding challenges in remembering medicine intake time and any problems faced while using mobile health apps. Figuring out these difficulties was important for developing the prototype based on their real-life problems and providing effective solutions. Additionally, through the survey, we collected information on how familiar the participants were with mobile apps and their preferred app features for the prototype. They were asked about their experience with apps, how much they are comfortable navigating, and any particular feature they wanted to see in the prescription management app. These data helped us design the prototype intuitively and based on the users' technical expertise.

A major area of focus of the survey was to determine interest in a Bangla-speaking Relational Agent within the app. They were asked if a virtual assistant could provide medication reminders, answer users' questions, and offer companionship in Bangla. The survey answers were analyzed to find patterns and trends, which were then used to design the high-fidelity prototype. The survey questions are shown in the Table. 3.1. This planned approach made sure that the app would be designed based on strong user-centric principles and address the needs of the target audience.

Table 3.1: Needfinding Survey Questionnaires

Prescription Reading	
Q1	Do you have any difficulties in reading prescriptions?
Q2	How do you currently read and interpret your prescriptions?
Challenges in Medication Management	
Q3	Can you describe any challenges you face with managing your medication currently?
Q4	How often do you forget to take your medications on time?
Technology and Medication Management	
Q5	Do you currently use any health-related mobile apps?
Q6	Do you have any concerns about using a mobile app for managing your medications?
Q7	How important is it for you to have reminders for your medications?
App Features and Preferences	
Q8	Which features would you prioritize in a prescription scanner and reminder app?
Q9	How would you like the scanning screen to be set up?
Q10	How likely are you to use an app that scans prescriptions and offers assistance from a Bangla-speaking virtual companion (Relational Agent)?

3.2 Participants

3.2.1 Age and Gender Distribution

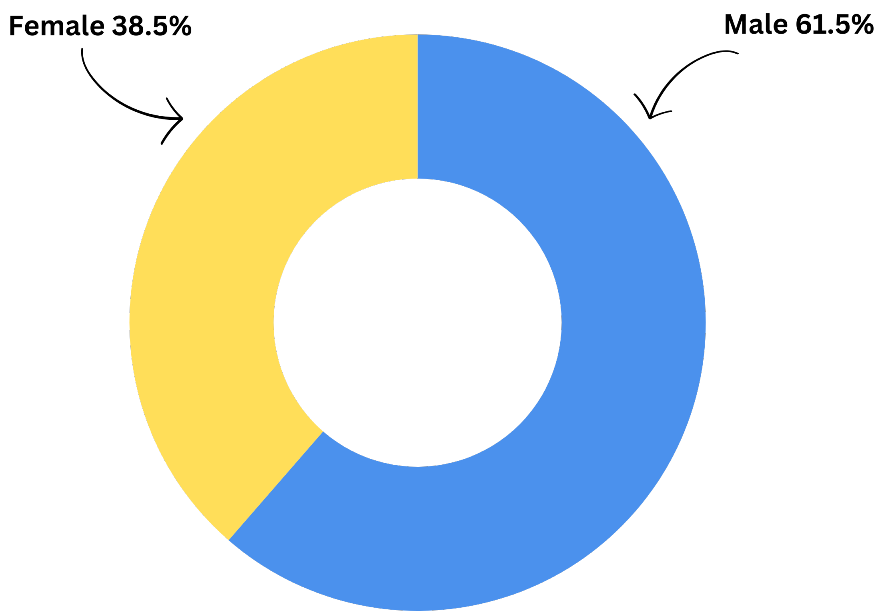


Figure 8: Participants Gender Distribution

A total of 155 responses were collected in the Google survey. The first section focused on the demographics of potential app users. The gender distribution showed in Fig. 8 that 61.5% (n = 95) of the respondents were male, and the remaining 38.5% were female. The largest age group among the respondents was 18 to 24 years, representing 61.3% (n = 95) of the total participants. This tells us that most of the users are young adults, as shown in 9, who could be familiar with mobile applications for healthcare management. The second largest age group was 25 to 30 years, making up 21.9% (n = 34) of the respondents. This group represents working professionals who may have different app functionality demands, like scheduling medications around their work hours. Surprisingly, 9% (n = 14) of the respondents were aged above 50 years or older. This demographic is very important, as the elderly require more assistance in managing their prescriptions. The smallest age group was 31 to 49 years old, comprising 7.7% (n=12).

The average age of all the respondents is 23.35 years with a standard deviation (SD) of 5.6 years. Low SD means that the age range was centered around young adults, with very little variation among age groups.

3.2.2 Employment Status

The employment status of the respondents was also determined, showing that the majority of respondents, 62.6% (n=97), were students demonstrated in Fig. 10. Since students have busy schedules, this app would be useful for them to schedule their medication time. The remaining 37.4% (n = 58) participants work in different fields, including healthcare and medicine, education, law, government service, domestic service, etc.

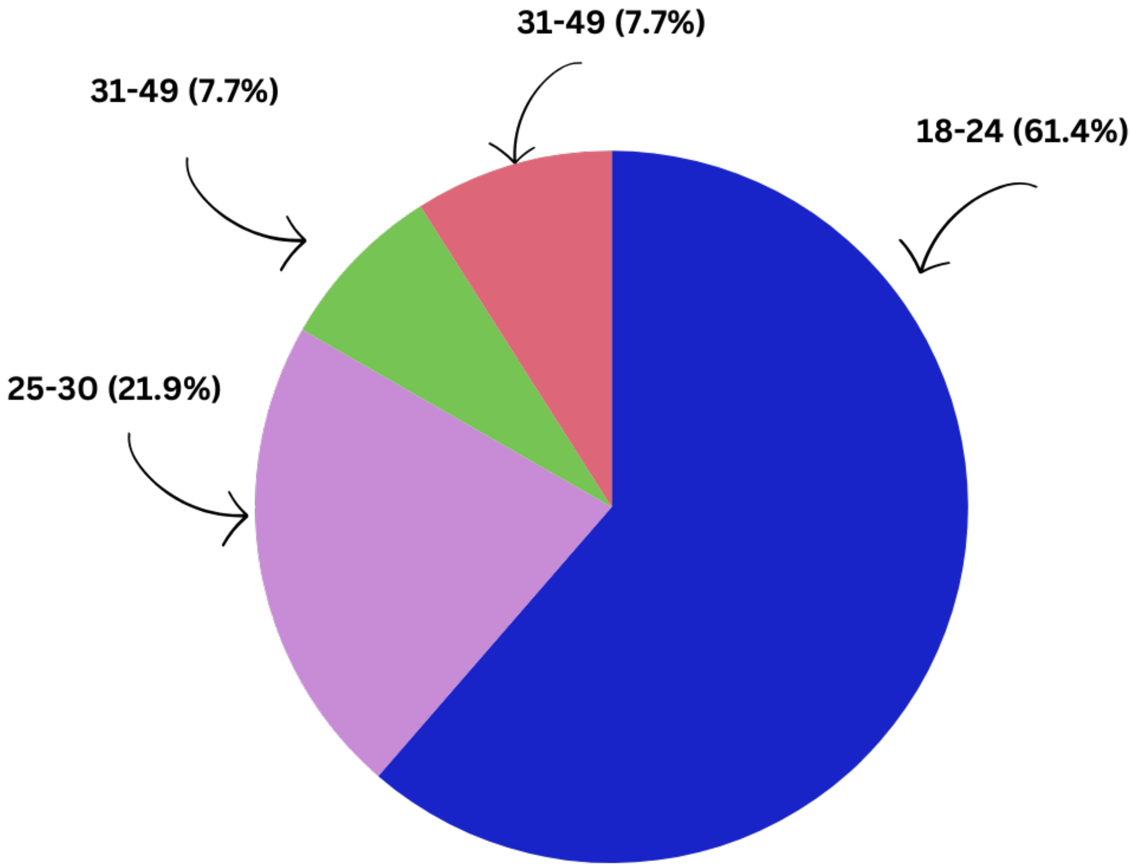


Figure 9: Age Distribution of participants

3.3 Measures and Data Analysis

In our study, we followed a mixed-method approach where participants were provided with both quantitative and qualitative data. This approach is much more preferred to understand the users' needs, experiences, and expectations regarding the app. To collect various kinds of data, a combination of multiple-choice questions, open-ended questions, and yes/no questions was used.

To understand the quantitative data, we used descriptive statistics to evaluate the responses to closed-ended questions. This aided us in knowing the patterns and trends related to user preferences, their management habits, and the acceptance of technology. We got meaningful insights from the challenges faced by the users by summarizing the pieces of information by percentages, averages, and distributions. These data were further pictured by using graphs and charts. This made it easier to understand the important factors, like the age-wise distribution of medication management difficulties.

To understand the qualitative data, we utilized thematic analysis. Through thematic analysis, we got to find out the common themes, views, and trends in the open-ended responses. This analysis also helped us to gain a deeper knowledge of the personal experiences and concerns of users. Similarly, descriptive statistics were used to identify the trends and patterns from closed-ended questions. For instance, we can find out the most common challenges faced by users while managing their prescriptions.

By pairing these two methods, we were successful in understanding the challenges faced by the users. The results from both data types helped us to design the app, ensuring it completely solves the users' needs.

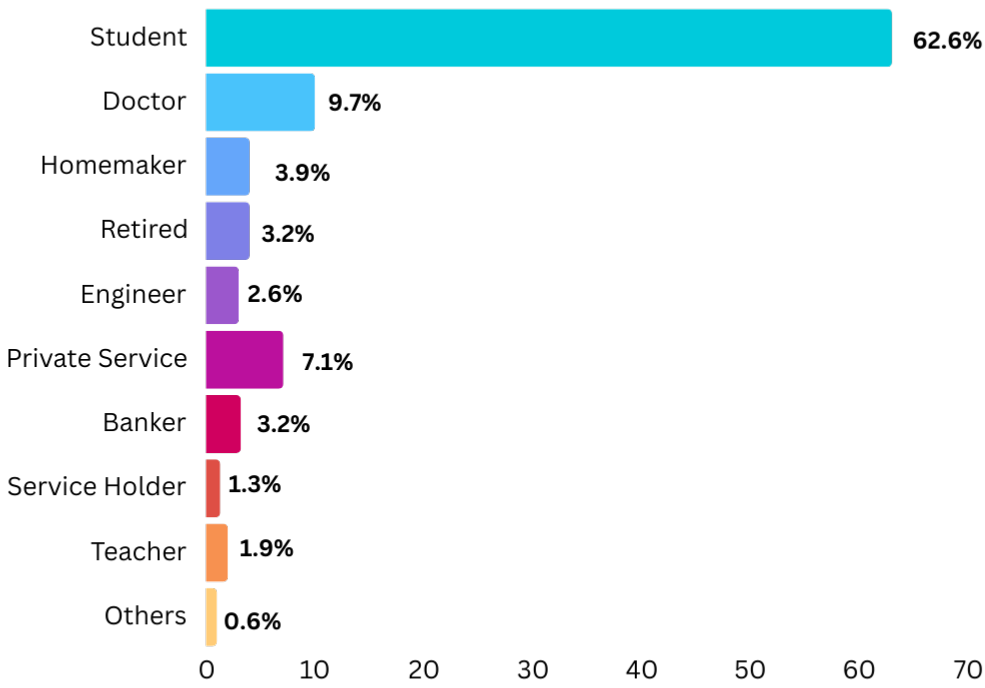


Figure 10: Participants Employment Status

3.4 Findings

3.4.1 Challenges in Prescription Management

From our research study, we found that the majority of the participants, 76.8% (n = 119), felt that reading handwritten prescriptions by themselves is difficult and often leads to confusion and error in interpreting medication names, dosages, and instructions demonstrated in figure 15. This reveals that it is necessary for a mobile application that accurately show medicine names from handwritten prescriptions. Figure 13 shows how likely they struggle to consume medications on time. Figure 12 shows how important it is to have a reminder feature in the app so that they can overcome this challenge.

Moreover, 80.6% (n = 125) of the respondents answered that they don't use any kind of mobile health app, as shown in Fig. 14. This suggests that the majority of participants might face difficulties with the existing apps. The participants expressed that the main challenges they faced while managing their medications included forgetting to take medications on time and problems in understanding dosage instructions. To solve these issues, the app will introduce a notification system and in-app reminders to assist the users.

3.4.2 Integration of a Relational Agent and Key Features

One prominent feature proposed to be integrated into the app is the Relational Agent. A Relational Agent is a conversational type of agent that can build, maintain long-term social-emotional relationships with users over time and provides human-like interaction experiences. It is a software program that is different from traditional chatbots, as it actively utilizes social, emotional, and relational cues such as remembering personal details, showing empathy, and making small talk with the user to gain trust. It can use rela-

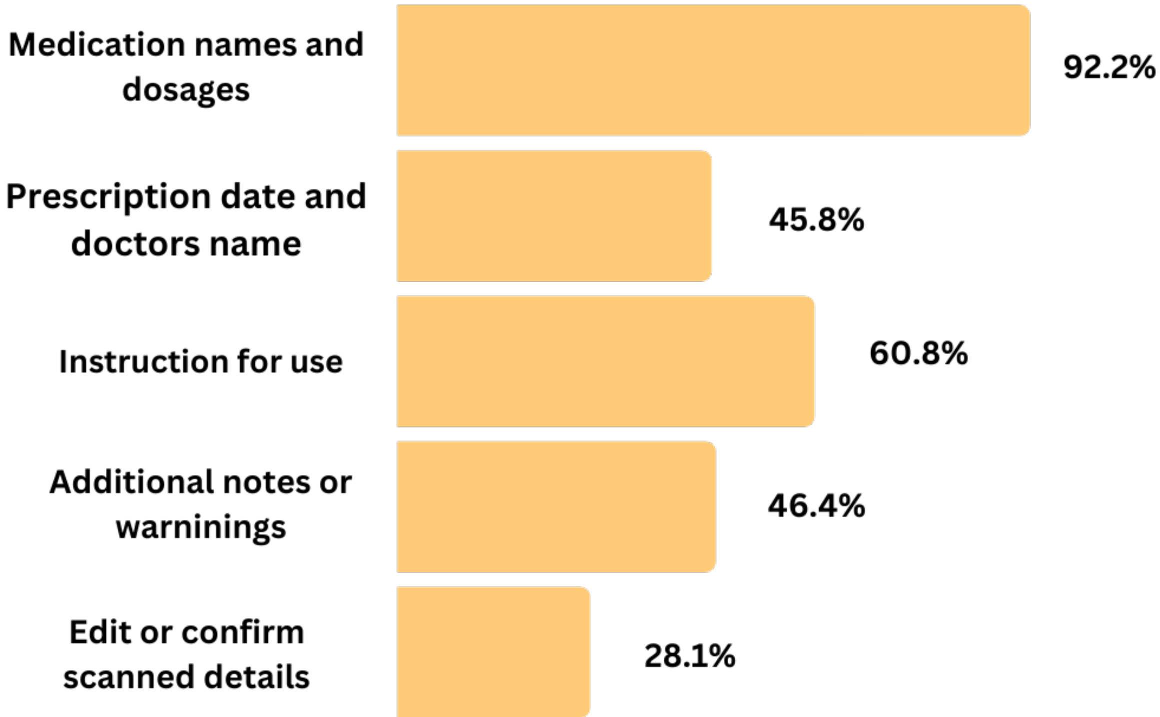


Figure 11: Most preferred information displayed from scanned prescriptions

tional strategies like small talk, expressing empathy, praising achievements, and making context-aware conversations [11].

With this agent, the users would communicate with it in Bangla. The Relational Agent will aid the users by reminding them of medication time and assist by answering any queries regarding their medications and ongoing connection with the user. The Relational Agent would provide usage, dosage, and side-effect info. To make the app more available to a larger population, users expressed a strong preference for text chat and voice command interaction methods.

92.2% ($n = 141$) of respondents expressed that medicine names should be visible after scanning the handwritten prescriptions shown in Fig. 11. In addition to this, they also needed a step-by-step prescription scanning guidelines feature to help them capture prescriptions, ensuring accurate extraction of medicine information.

3.4.3 Usability and User Interface Preferences

One thing that the participants were concerned about was whether the app would be easy to use. So the main emphasis should be on a user-friendly interface. So to improve usability, the app will have features like setting reminders, prescription scanning, and overall prescription reports. They also highlighted the need for a sidebar to navigate through the app more easily. These findings helped us to conclude that the app needs to be not only effective but also very simple to use so that users can manage their prescriptions without any hassle.

As shown in Figure 16, 41.6% of the users expressed the willingness to use a mobile app that can interpret medicine names from handwritten prescriptions. Moreover, Fig.

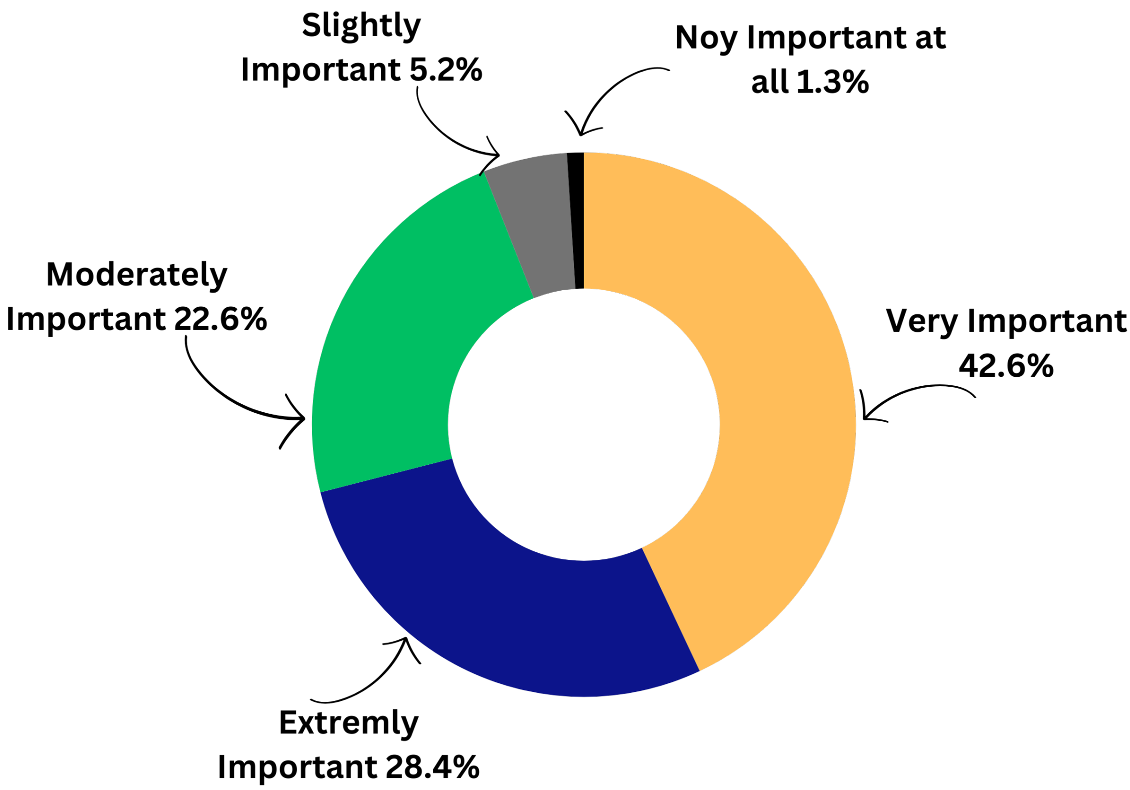


Figure 12: Importance of reminders for medication

17 depicts the preferred features identified for such an app.

3.4.4 RQ1: What design features and functionalities should be incorporated into a mobile application to effectively digitize handwritten prescriptions for users in Bangladesh?

To understand the usability needs and medication management difficulties of users in Bangladesh, the survey results showed the necessity of integrating user-centric features and functionalities into the app. For people with very limited knowledge of technology and health-related apps, their main issue was the ease of use. Therefore, the conclusion was reached that a simple and intuitive interface is a must for the app's success. Some commonly suggested features by the users are prescription scanning, customized reminder input, and overall prescription reports. These are the identified core features essential to digitizing handwritten Bangla prescriptions efficiently.

The survey results showed that 76.8% (n = 119) of participants face difficulties in reading handwritten prescriptions, which most of the time leads to wrong interpretation of medicine names. So to avoid such incidents, the app will be integrated with an OCR model optimized for Bangla script, making sure that it accurately extracts medicine names. 92.2% users voted that medication names should be displayed after scanning the prescription, which is one of the most prioritized features. Another noteworthy feature is the step-by-step guided scanning interface, which allows users to capture a clear image of the prescription.

One of our proposed features is a Bangla-speaking Relational Agent, with which users

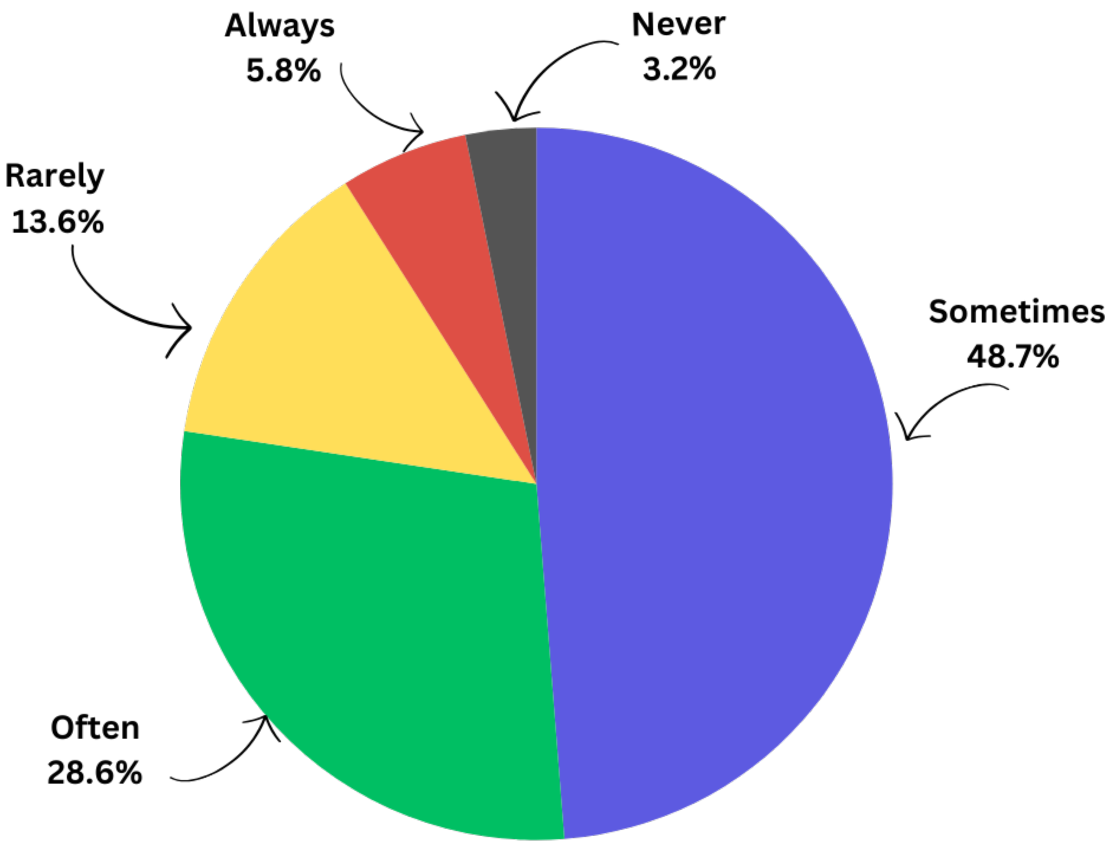


Figure 13: How likely users struggle to consume medications on time

can communicate, provide medication reminders, and answer queries. Through this, the users can mitigate forgetfulness, one of the challenges in medication management. So, it caters to both functional and emotional support for users. The agent would be able to interact with the user through text and voice commands, coupled with the notification system. Moreover, the app would be able to meet the needs of a diverse age group, notably young adults (61.3%, n = 95) and the elderly (9%, n = 14) by avoiding complex workflows that could frustrate first-time users. By integrating an OCR model, personalized interaction, and simplified navigation, the app can remove the gap between handwritten prescriptions and trustworthy digital healthcare management in Bangladesh.

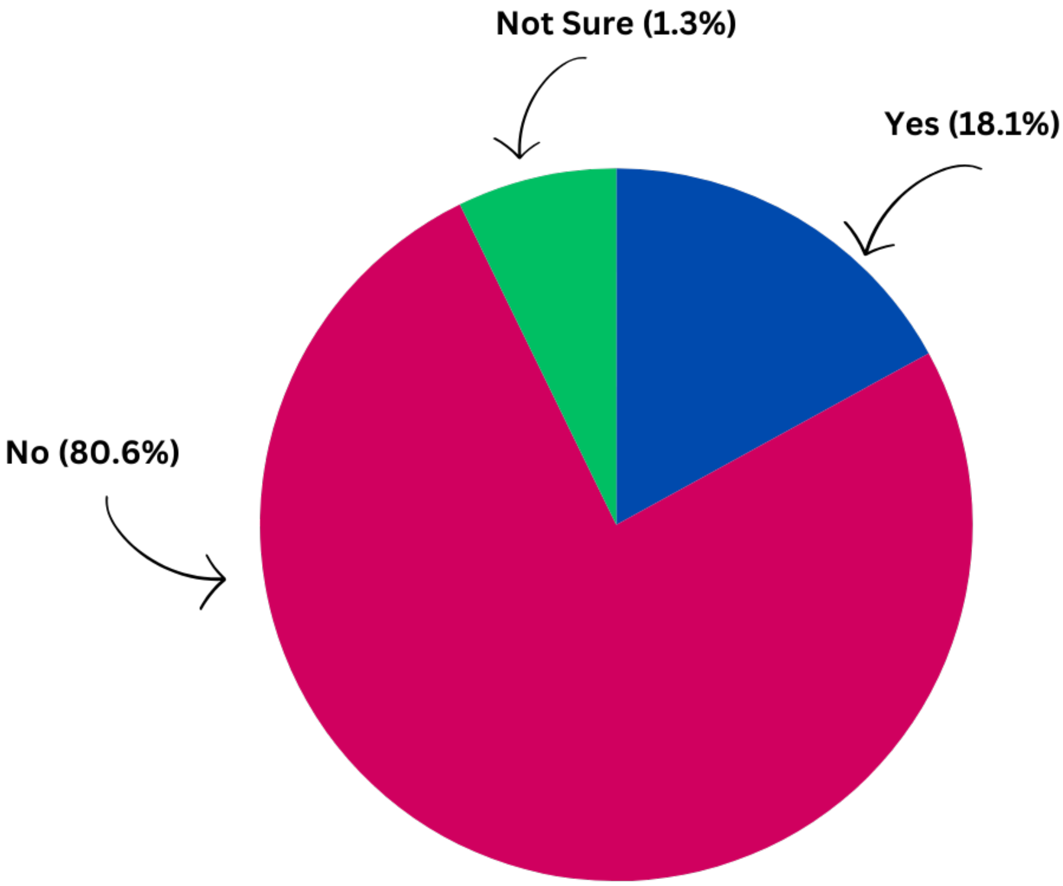


Figure 14: Use of health-related mobile app

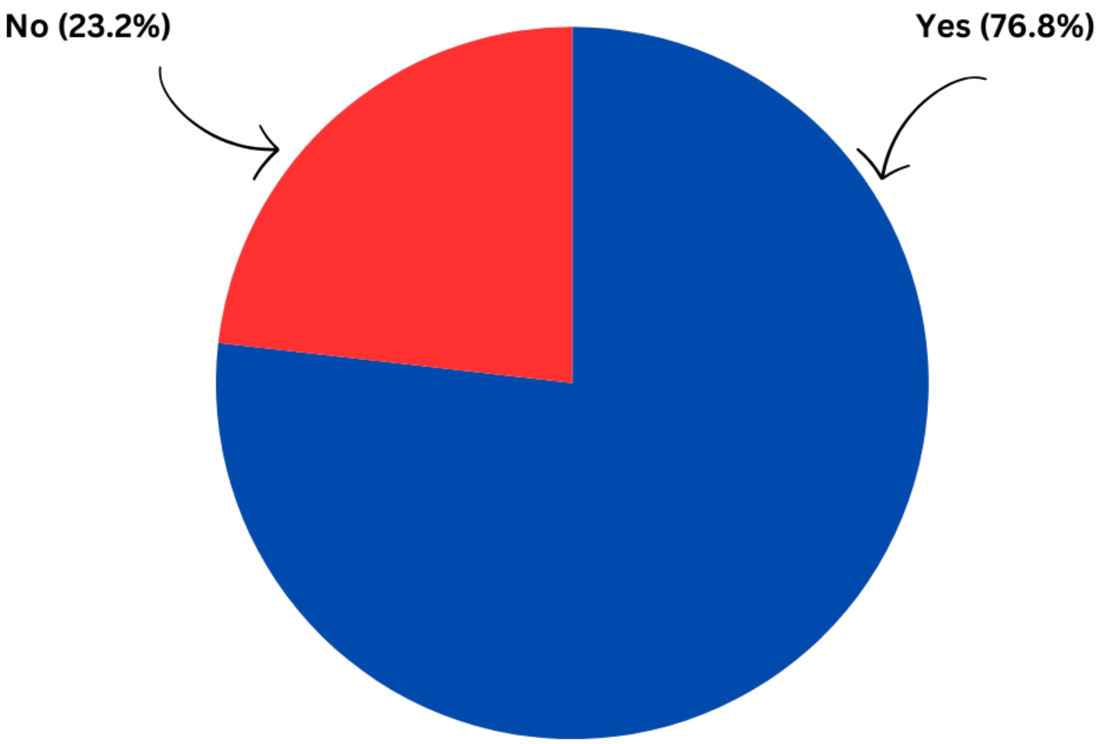


Figure 15: Challenges faced by users while managing their medications

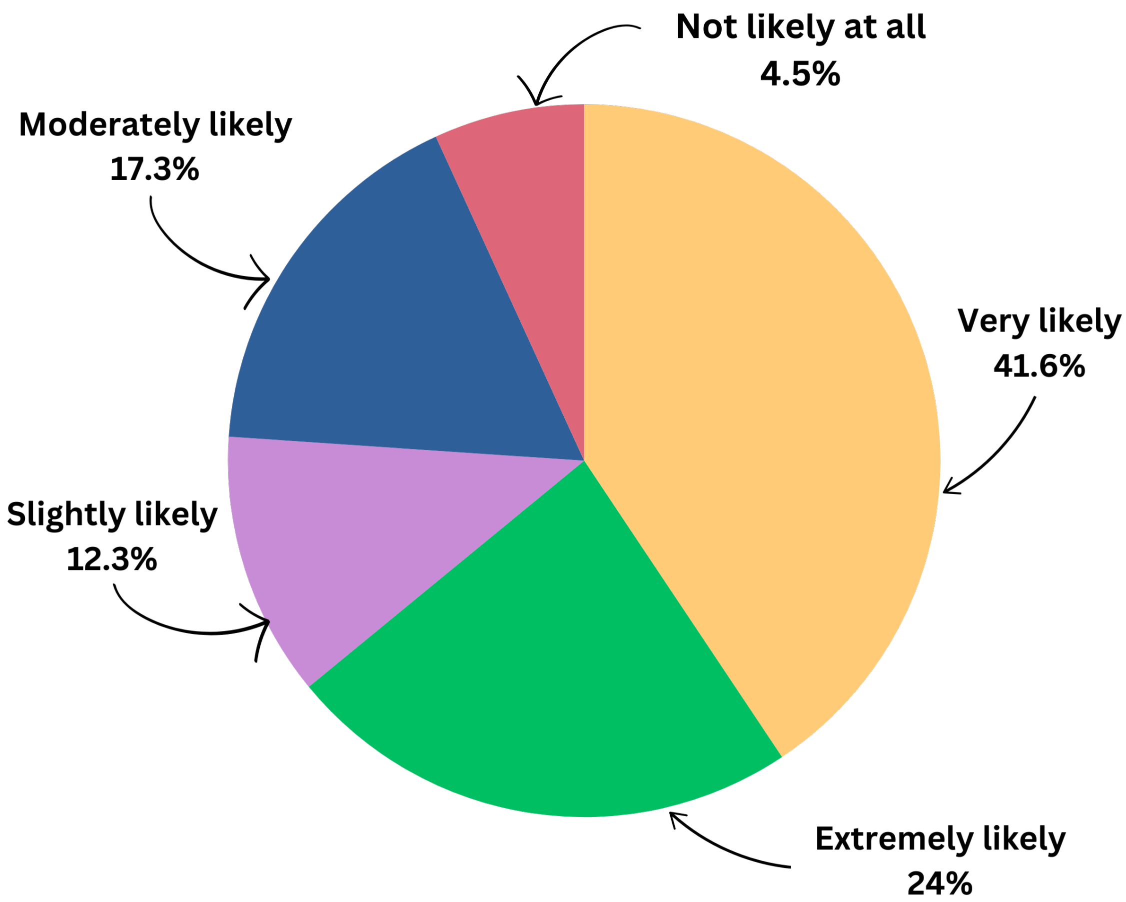


Figure 16: Willingness to use an app that interprets prescription

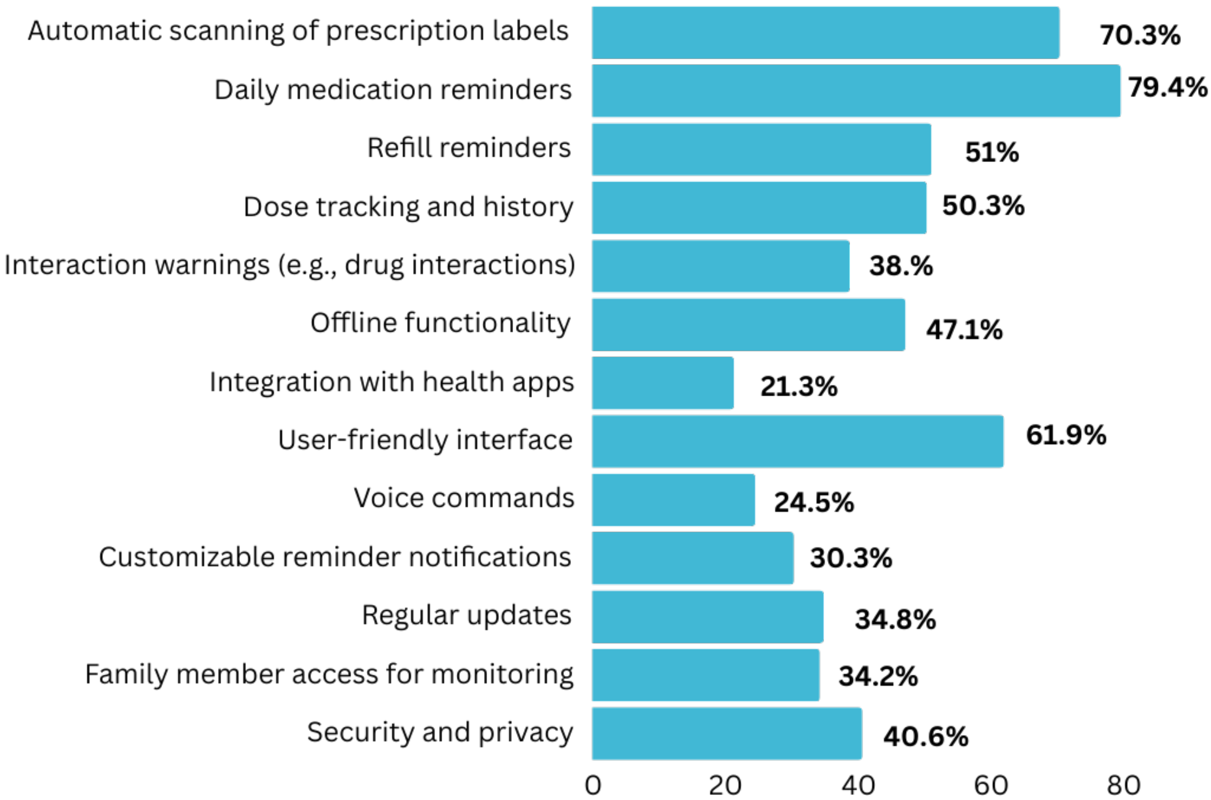


Figure 17: Preferred features for the prescription scanner and reminder app

4 PresCa Prototype and Its Features

4.1 Prototype Design and Development

Before designing the prototype, a thorough background study was conducted to identify the key features that will be integrated into our mobile app. This was supported by the survey data collected via Google Forms (https://docs.google.com/forms), which provided valuable insights into the needs and preferences of potential users. Ease of use, accessibility, and low-tech friendliness are prioritized in our development process. After identifying the key features, we proceeded with the conceptualization phase, where the app's flow, basic layout, and thematic structure were carefully planned.

To bring these ideas to life, we utilized Figma. It helped us to make a high-fidelity prototype of the app that we designed. The high-fidelity prototype helps users navigate the app and experience its features firsthand. The main reason for preferring Figma over other tools is that it has a collaborative environment and helps to understand how the user will interact with the app. The design prioritized an easy-to-use experience, where the key features will be easily accessible and simple to navigate.

The main concept of the prototype involves the conversion of handwritten prescriptions into a clear, readable digital format. The users can scan the prescription through the camera integrated into the app, which extracts the medicine name, dosage, and medicine consumption time. The users can also get assistance from the Relational Agent for any medical queries. The risk of misinterpretation can also be reduced by verifying it with the doctor.

The prototype, "PresCa", comprises several core modules such as medicine consumption progress, Relational Agent, Camera, Reminders and doctor's verification. Each of these modules is designed to enhance the user's experience and provide the right and readable medication information to the patients.

These features, along with the intuitive navigation provided through the home screen, are crucial for ensuring the app is user-friendly. As illustrated in Fig. 18, the app's home screen provides a clean and organized interface, making navigation straightforward for all users.

4.2 Available Feature Categories

4.2.1 Medicine Consumption Progress

This feature helps the user to track their medicine consumption progress. By monitoring their progress over time, the users can easily deduce their medical consumption intake. Users can also check how much impact this app has on their medicine routine. They can also use this to see how much effect this app had on their consumption rate. For example, the users can see and compare their progress for each month. If the progress improves from the last month, it ensures that the app is useful to them, but if the progress declines,

Figure 18: Home Screen

Figure 19: Checking Progress of Medicine Consumption

then they can be more cautious and try to take medicines on time. Because of this feature, it makes managing medication easier for the users.

In Fig. 19, users can see a donut chart representing the progress of their medicine consumption. The users can track their monthly progress by selecting particular dates from the integrated calendar in the app. This enables users to monitor their progress over time and ensures they stay on track with their medicine consumption.

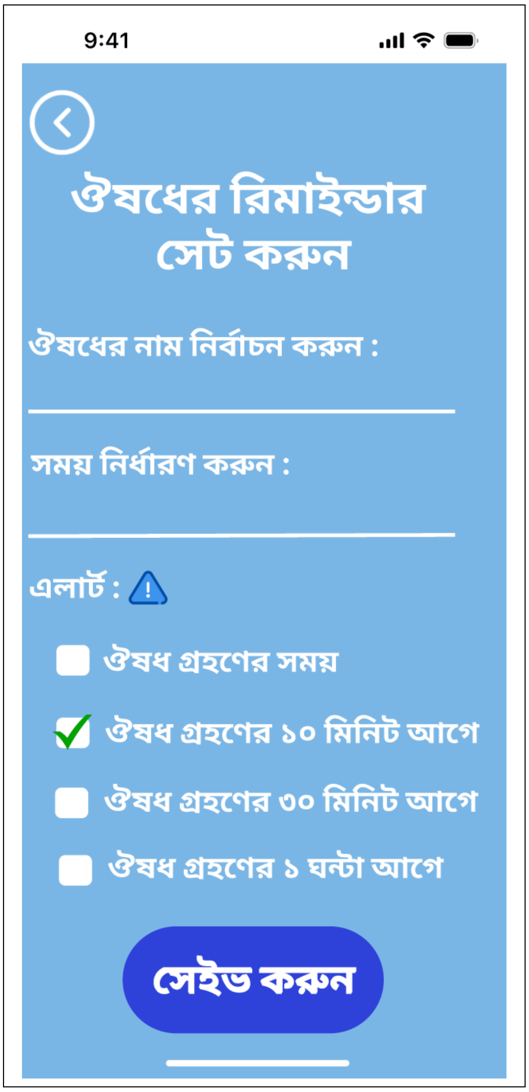


Figure 20: Notifications Settings

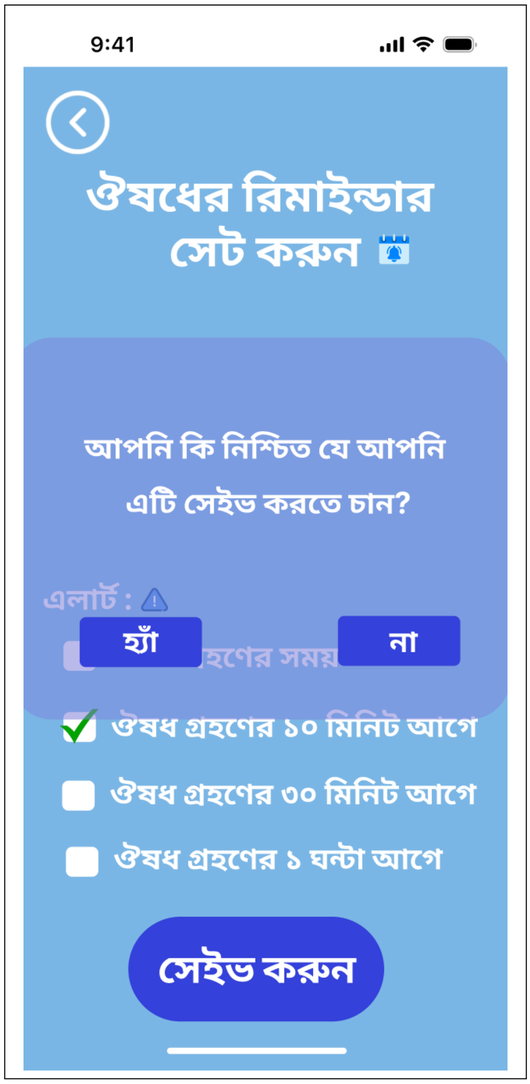


Figure 21: Confirmation

4.2.2 Reminder Settings

This feature offers the ability to create personalized alerts or reminders for taking medicine, supporting the users to take medicine on time with the correct dosage, which in turn will be beneficial for them to treat their illness effectively. Through an intuitive interface, users can easily manage their notifications, ensuring they don't miss out on a medication dose.

The 'Notification Settings' screen, shown in Fig. 20, enables users to fully customize their reminder system. The users can add new reminders, stating the medicine name and the exact time for the consumption of the medicine. Additionally, the settings provide options for users to set notifications a certain number of minutes before the assigned task, allowing flexibility to meet their individual needs.

The 'Confirmation screen', displayed in Fig. 21, presents a confirmation box after clicking "Save". This is important because if users notice an error while setting the reminder in the 'Notification Settings', they can modify their settings by clicking "No" or finalize their choices by clicking "Yes".

4.2.3 Relational Agent

The 'Relational Agent' feature stands out as one of the most innovative components of this prototype app. It evolves around a chatbox and voice command interface designed specifically to support the users in providing information on the medicine that the users want to know. The virtual assistant provides the user with a safe space to express their concerns or seek guidance about any health-related topics. The virtual assistant acts more as an always-available companion, which might help users feel more at ease and less stressed.

In Fig. 23, the users can make a query by texting with the 'Relation Agent', while in Fig. 24, the users can utilize the audio option by holding down the microphone symbol and speaking into it. This makes the 'Relational Agent' more dynamic, as it supports both text and audio input for the convenience of users.

In addition to medication management, the Relational Agent offers personalized guidance on which medicine to take and which medicine has what kind of side effects. It can also encourage users to engage in physical activities and provide tips to improve their mental health, benefiting users both mentally and physically. Whether it's a suggestion to take a walk or engage in a quick meditation session, the agent provides practical tips that users can integrate into their daily lives.

4.2.4 Camera

The 'Camera' feature plays one of the most crucial roles in simplifying prescription reading. This feature allows the user to take a picture of the handwritten prescriptions, which are then processed using Transformer-based Optical Character Recognition (TrOCR) to extract and show the medicine information, such as dosage, medicine name, and consumption time.

In Fig. 25, the camera interface is shown. Users can take a picture of the prescription by pressing the circular shutter button in the center. Users can also upload the scanned picture using previously scanned prescription photos from their gallery.

The built-in guideline or guidance system is designed to assist users in capturing clear and accurate prescription images. This can also help people who are new to technology or have never used an app before. In Fig. **??**, the system instructs the user to hold the phone steady to ensure a clear picture of the prescription. Then, in Fig. **??**, it guides the user to press the circular shutter button to successfully take a picture of the prescription.

A clear picture of the prescription is very crucial, as it allows the app to provide more accurate medicine information. If the image is hazy or unclear, the app will not be able to extract and show the correct information. So the camera and the guidance system are very important for the users to click a clear picture of the prescription.

Figure 22: Relational Agent

Figure 23: Text-Enabled Chatbox

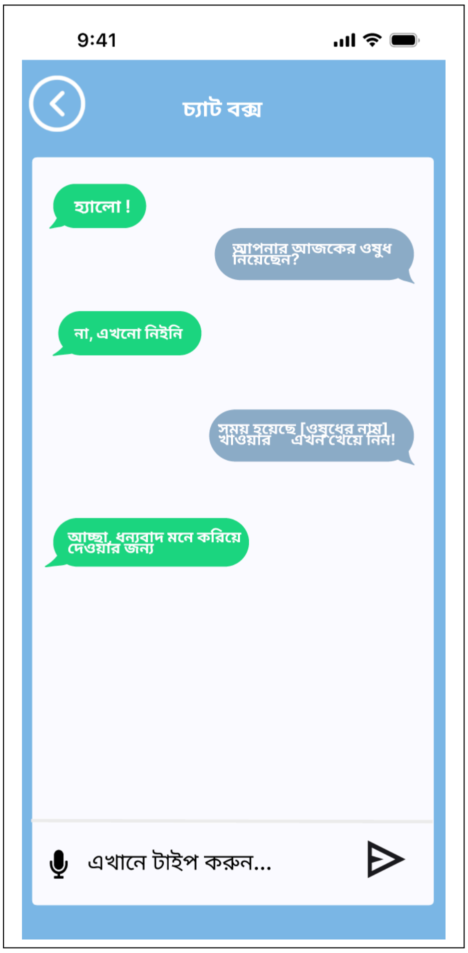


Figure 24: Audio-Enabled Chatbox

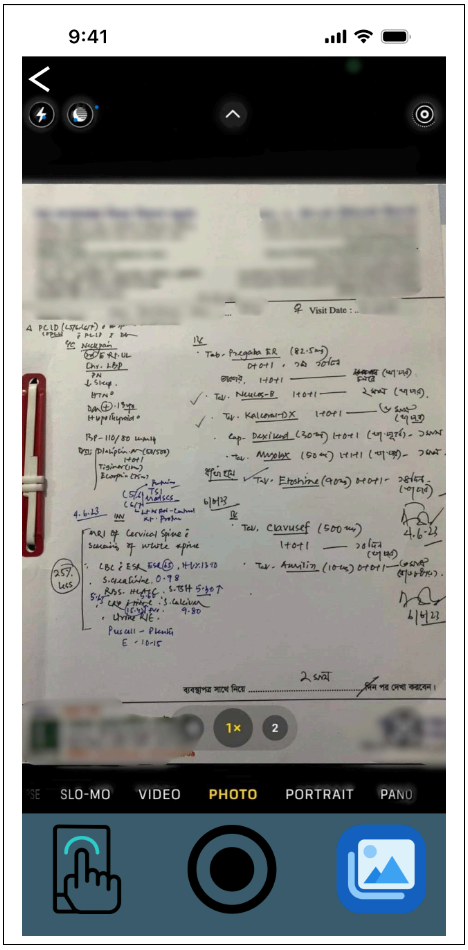


Figure 25: Camera interface for taking a prescription photo

(i) (ii)

Figure 26: Guideline for taking a clear prescription image. (i) Instructs the user to keep the phone steady for a clear photo; (ii) Guides the user to align the prescription within the frame before capturing.

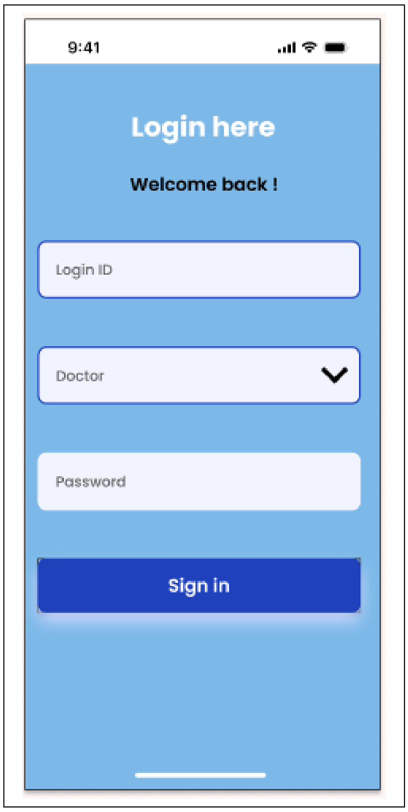


Figure 27: Doctor Login

4.2.5 Doctors' Verification

This feature helps the medical information to be verified by the doctor, which in turn will decrease the chance of any error. The doctors have the right to edit the medical information after receiving the medical information from the users, which provides an extra layer of accuracy. This feature provides users with greater confidence, as their medical information is also reviewed by doctors.

Upon successful authentication using their credentials, as illustrated in Fig. 27, doctors are redirected to the dashboard interface, Fig. 30. This dashboard presents a list of uploaded prescriptions awaiting verification, enabling doctors to selectively review and verify the prescriptions of their choice.

In Fig. 28, the doctors can see the medical information of patients. If the information is correct, then the doctor can approve it. However, if there is anything wrong or requires changes, the doctor can select the edit button. After selecting the edit button, the doctor is introduced to the edit interface as shown in Fig. 29. The doctor can provide the necessary change in the text box and text fields provided in the interface.

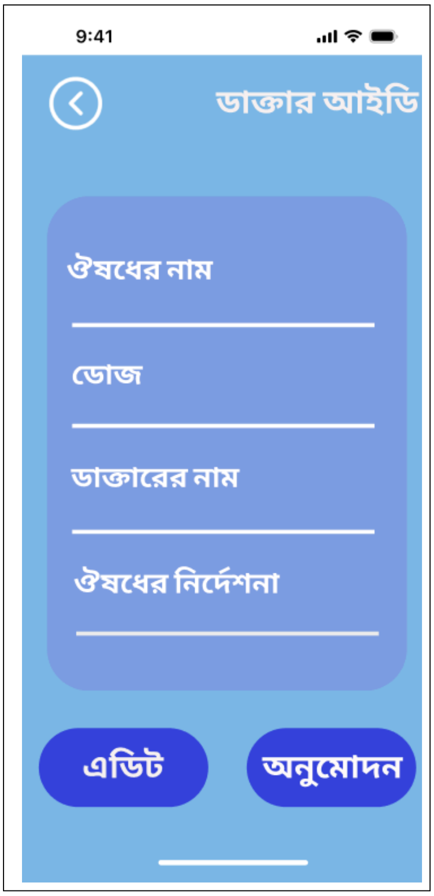


Figure 28: Doctor's interface for editing or accepting the prescription

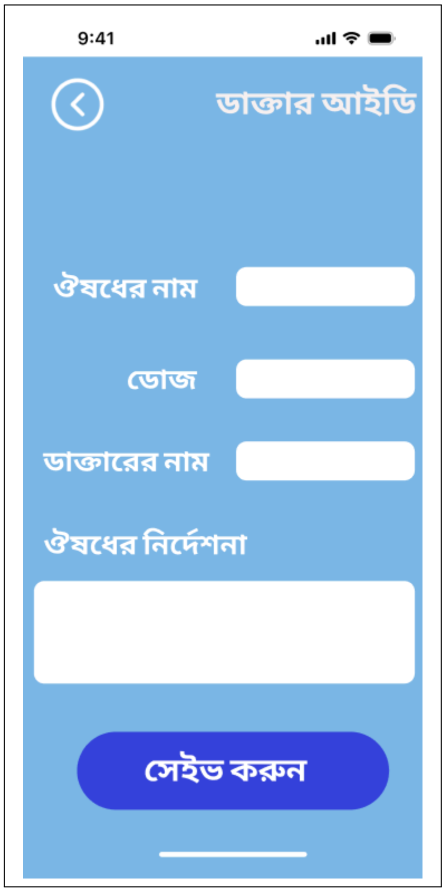


Figure 29: Edit interface

Figure 30: Doctor's Dashboard

5 Usability Evaluation

We conducted an evaluation of our “PresCa” prototype to gather quantitative information from the participants. It focuses on evaluating the app and whether it is efficient and can be used to manage medication. The study also evaluates how the app can be used for medication name extraction, setting reminders, and tracking their intake on a regular basis. Through this evaluation, it can be ensured that the app’s features and overall quality meet the users needs.

Another important aspect of this evaluation is to measure whether the users are willing to use the app’s features, analyzing if they find the app trustworthy and beneficial enough to include in their daily lives. The ultimate goal of this evaluation is to refine the “PresCa” app so that it finally becomes an effective and user-friendly tool to manage medication.

5.1 Study Design

To evaluate our prototype “PresCa”, we conducted a cross-sectional survey to obtain structured feedback. We mainly provided 10 quantitative questions which took around 10 to 15 minutes to answer. We provided the app’s Figma link in the Google survey so that they can get a better idea of how the features are going to work. Their participation was completely anonymous, ensuring their privacy and data security. Before starting with the survey we provided them with a short description of our system. Following this, they assessed the app’s usability using the SUS [15] questionnaire. This method helped us to restructure the prototype for greater output from the system.

Initially, the participants were asked some demographic questions such as age, gender, and profession to analyze how different groups of users interacted with the prototype. After that, the participants were asked about their most preferred feature of the app and their willingness to use the app. They were also asked whether they would recommend this app to others (responses were collected using ‘yes’, ‘no’, and ‘maybe’ options). These questions helped us to understand how likely the app is to be adopted and used by the users. The study took place over two weeks in December 2024, allowing participants to take part at their convenience and ensuring a flexible approach to data collection.

5.2 Participants

To get an extensive range of opinions regarding the prototype, we shared the survey among diverse participants on social media platforms, including different mailing lists. Since the survey questionnaires were both in Bangla and English, the participants didn’t require any English proficiency, and even elders could easily participate in it. Confidentiality was ensured by not taking any personal information, such as names, phone numbers, or email addresses. Additionally, we made sure the participation in the survey was voluntary. At last, the participants were able to interact with all the features available on the prototype to get a better idea of the system.

After the survey, we received in total 17 (35.3% or n = 6 females and 64.7% or n = 11 males) responses from participants between 18-50 years and beyond; with a mean value of 26.5 (SD 5.21) years (n = 13, 18-24 years; n = 3, 25-34 years; n = 1, 31-49 years). Regarding the participants' employment status, most of them were students (64.7%, n = 11), followed by doctors (11.8%, n = 2). The rest of the participants comprised a total 5.9%, included a lawyer, a teacher, a private service employee, and an engineer. This wide range of people from different professions will help us get useful feedback regarding the prototype.

5.3 Measures and Data Analysis

To evaluate the usability of "PresCa", we utilized a tool called SUS, which is a popular and common tool to evaluate any kind of application. The SUS scale has gained popularity and widespread acceptance in HCI due to its simplicity, reliability, and effectiveness in generating quick results that will assist in understanding the overall user experience. Some of the reports show that almost 43% of usability studies use this tool, which shows how common and important this tool is [15].

SUS consists of a short and carefully designed 10-item questionnaire, where each question conveys a specific aspect of the respondents' interaction with the prototype. SUS items are arranged in such a way that it capture both the positive and negative statements. The main idea behind this arrangement is to reduce biases and get more accurate responses. Using a five-point Likert scale, the participants are asked to rate each of the 10 questions based on their level of agreement. This five-point Likert scale ranges from "Strongly Disagree" to "Strongly Agree", which lets the users state their varying satisfaction or dissatisfaction with the prototype in a structured way.

After all 10 questions are answered, the final SUS score is calculated using a unique scoring system. For the positive questions (even-numbered ones), one is subtracted from the given score, and for the negative questions (odd-numbered ones), five is subtracted. Finally, all the scores are added and multiplied with 2.5 to achieve the final SUS score, which remains in the range of 0 to 100. To understand what the score means, the SUS score is mapped to a grade. These grades range from A to F, with a corresponding adjective rating like, "Excellent," "Good," "OK," "Poor," and "Awful". For instance, a score between 85-100 is graded as A and labeled as "Excellent" reflecting the usability. This unique way of converting numbers to qualitative indicators makes it available to people with less technical skills.

Overall, SUS provided a well-structured and organized way to assess the "PresCa" prototype. By carefully analyzing the answers from the respondents, we were able to come to a meaningful conclusion regarding the app's usefulness, its ease of navigation, and how effective its features are. By analyzing the results from the usability evaluation, we were able to understand how well the system performed and whether the users benefited from the system in real-world situations. This evaluation step is crucial for our design choices during the prototype stage and offers us ideas regarding any future improvements for the application.

5.4 Findings

5.4.1 SUS Score (RQ3: What are the users' perceptions of the usability, effectiveness, and reliability of the proposed mobile app prototype for interpreting handwritten prescriptions?)

To assess users' views and opinions on our developed high-fidelity prototype, PresCa, we utilized the SUS scale based on the participants' responses. The achieved SUS score of the system was 76.8, which is higher than the marginal acceptability threshold of 68. This indicates that the system is in the "Good" range and positive perception of usability among users according to standardized SUS criteria. The median score of 75 suggests that half of the participants rated the system above average, adhering to a positive impression. The SD of 15.31 indicates that there is very little difference in responses, meaning that most of the respondents had a positive experience with the prototype. Regardless of this, the adjective rating for the mean SUS score (76.18) is considered "Good", which is considered a usability grade of "B", suggesting that the system is beyond average, appropriate, and useful.

These results show that the users found the prototype can achieve the primary goals, that is, interpret illegible handwritten prescriptions and manage their prescriptions easily. It also indicates that the users trust the app's functionalities and can be counted on to manage their medications. Table 5.1 shows the average SUS score for each of the 10 questions used to evaluate the prototype. This helps us to understand which part of the prototype is preferred and which requires improvement. Fig. 31 shows where the participants agreed and disagreed for each question on a 5-point scale.

After the exploration of each SUS question, it is revealed that one advantage of the prototype is, users' confidence in the interface, as known through a high average score of 7.94 in Question 10 ("I felt confident using the app"). This favorable review tells us that the users feel comfortable and trust the core functions of the prototype and its prescription management capability. In the same way, Question 4 ("I think the app would help me manage prescriptions efficiently") suggests user confidence in the app's potential success in prescription management. The above results indicate the successful implementation of the important ideas of prescription digitization and interpretation.

Through usability evaluation, we also learned about some areas that require improvement. Question 3 ("I thought the app was inconsistent") resulted in disagreement from 36% of respondents, which might be relevant to accurate handwriting recognition. Also, Question 6 ("I found the app unnecessarily complex") got the lowest average score (6.68), proving some of the respondents had difficulty with feature accessibility. These challenges mainly originated from the difficulty of reading prescriptions and understanding medical jargon. This implies that the app needs to address error-handling mechanisms and guide users through the process.

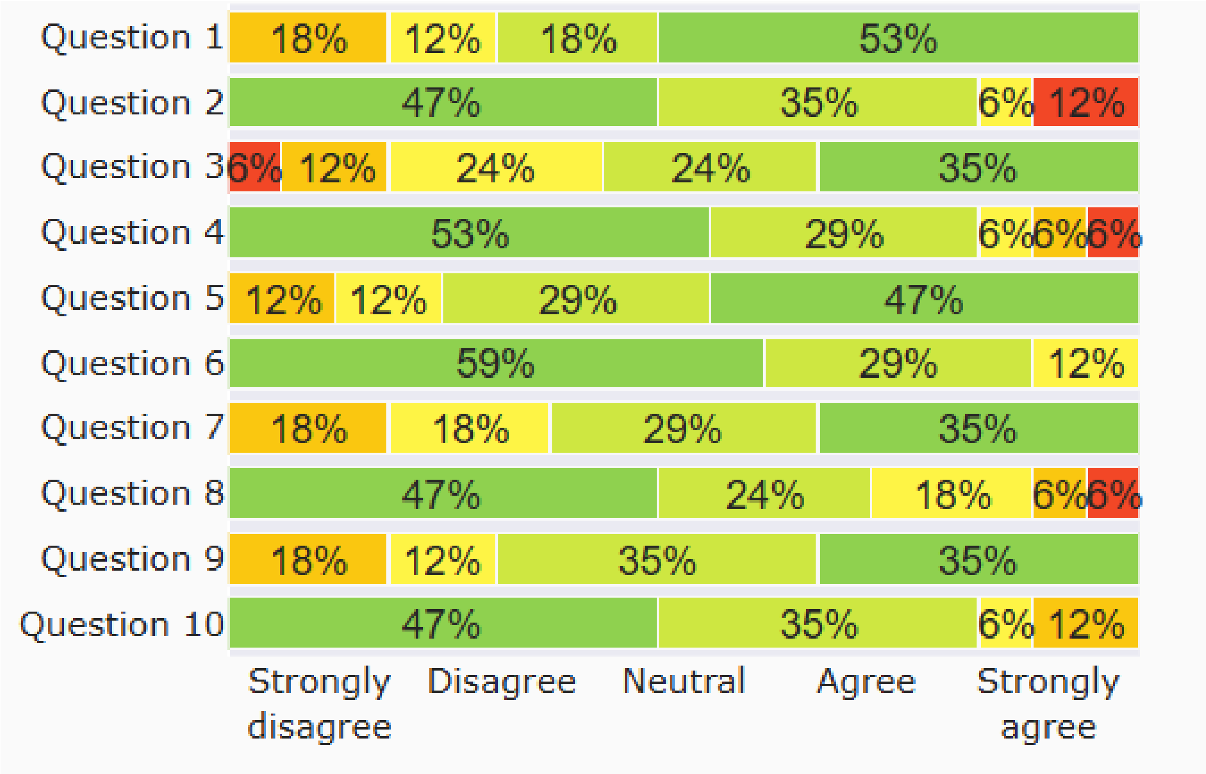


Figure 31: Participant voting on 5-point Likert scales for individual SUS items (Generated using [15])

Table 5.1: Average SUS Scores

Sl	SUS Item	Mean Score (SD)
1	I think that I would like to use this app frequently	4.05 (0.85)
2	I found the app unnecessarily complex	1.94 (0.75)
3	I thought the app was easy to use	3.70 (0.88)
4	I think that I would need the support of a technical person to be able to use this app	1.82 (0.80)
5	I found the various functions in this app were well integrated	4.11 (0.90)
6	I thought there was too much inconsistency in this app	1.52 (0.70)
7	I would imagine that most people would learn to use this app very quickly	3.82 (0.82)
8	I found the app very awkward to use	2.00 (0.78)
9	I felt very confident using the app	3.88 (0.85)
10	I needed to learn a lot before I could get going with this app	1.82 (0.80)
	Overall Mean SUS Score	**76.18 (15.31)**

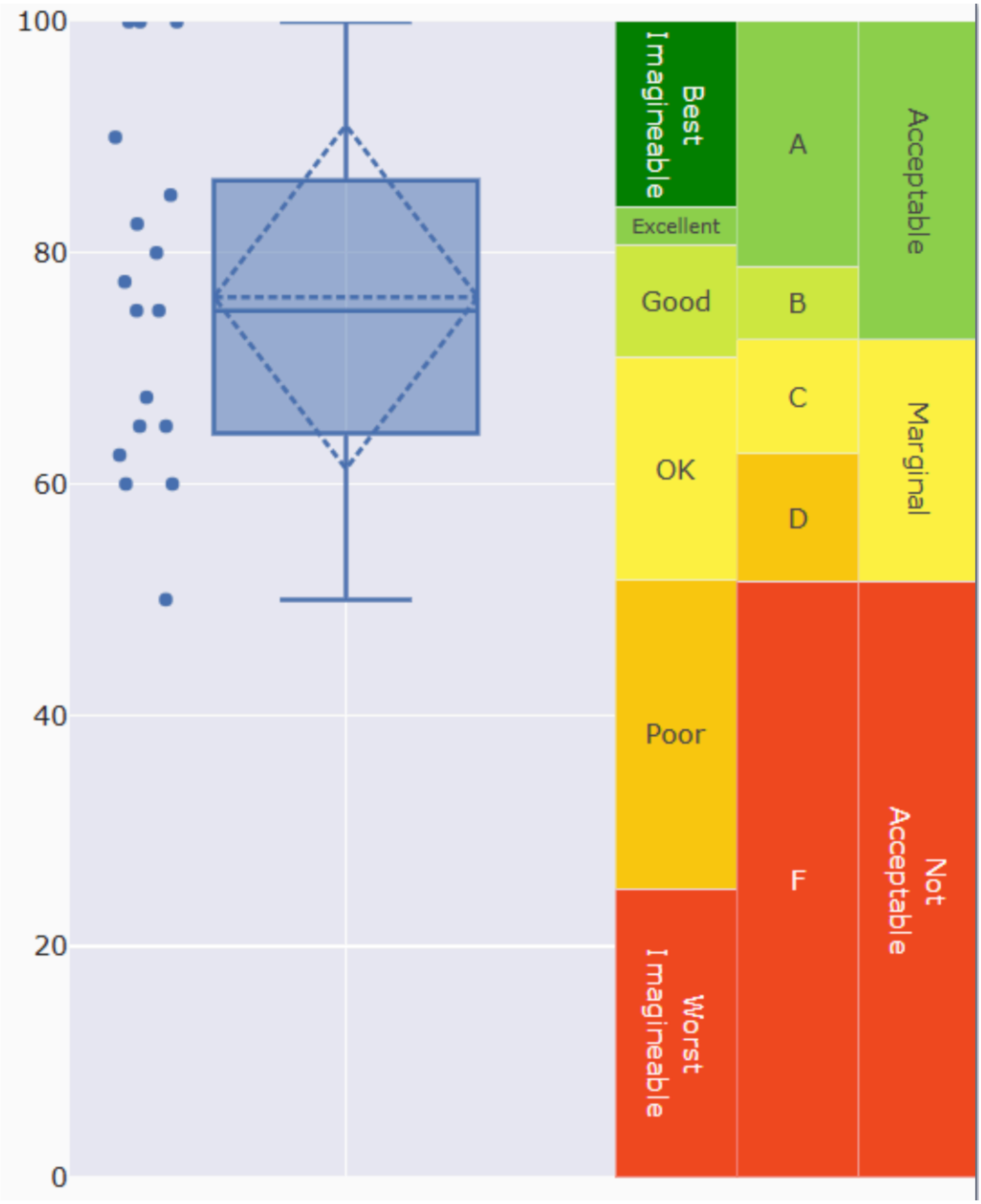


Figure 32: SUS study score (Generated using [15])

5.4.2 Overview of SUS Analysis and Key Findings

Through the SUS Analysis Toolkit, we evaluated our system to determine how easy it was based on the responses we collected from the survey. The Fig. 32 shows the graphical representation of the SUS study score and ratings of our system. Our system received a 'B' ("Good") grade on the usability scale, which means the prototype is "Acceptable". The median score is 75, and the standard deviation is 15.31, which means that responses vary moderately. The system's overall SUS score is 76.18, which is higher than the standard of 68. Some of the questions received great scores, like 7.94 for Question no 10, meaning users found that component good. Whereas some questions, like Question no 6 with a score of 6.68, indicate these are the areas where the respondents faced challenges. By improving our system, we can reach an "Excellent" rating.

5.4.3 Per-Question Analysis and Areas for Improvement

Fig. 31, a stacked bar chart, which is a detailed breakdown of the user responses to each survey question. Each survey response is studied based on five groups: Strongly Disagree, Disagree, Neutral, Agree, and Strongly Agree. Most of the responses were between Strongly Agree and Agree, which implies that the users had a positive experience with the prototype. But some of them got mixed results. For instance, in Question no 3, 36% of users strongly disagreed with the lowest score, which tells us that there is room for improvement. On the other hand, Questions 4 and 10 received the highest score, meaning that users found those aspects helpful and best among the others.

5.4.4 Popularity of Features

The two most voted features from the "PresCa" prototype are "Prescription Scanning" and "Text and Voice Interaction with Relational Agent" with 70.6% votes. The second two most favored features with votes of 64.7% are "Guidelines for prescription scanning" and "Showing prescribed medicines after scanning". "Checking for reminders" is the least voted feature with 47.1% votes.

94.1% voted that they were willing to use the app to scan their prescriptions and would recommend others to do the same. Only 5.9% were unwilling to use and recommend the system.

6 Medication Information Detection

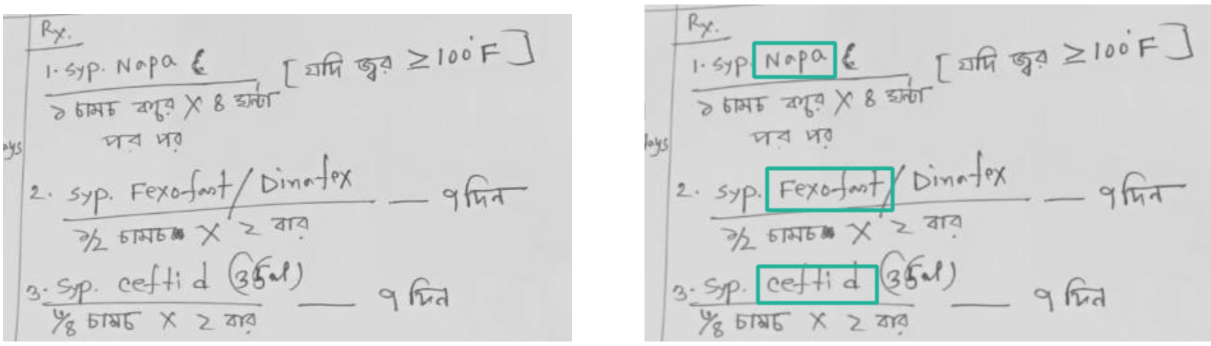
This chapter explores ML and DL-based approaches for extracting medicine information from handwritten prescriptions. Various models, such as SimpleHTR, ViLanOCR, and Recurrent Neural Network (RNN) using the Connectionist temporal classification (CTC) loss function were compared with TrOCR. The TrOCR consistently outperformed the other DL-based approaches with a CER of 7% and a WER of 11%. Data pre-processing and post-processing were used to achieve more accuracy.

These findings pave the way for developing a DL-based and efficient method of digitizing handwritten prescriptions that could be integrated into the backend of a fully functional medication management and prescription extraction app.

6.1 Background and Related Works

Significant research has been accomplished on extracting and classifying medical data from unstructured handwritten prescriptions using machine learning and deep learning techniques. In [12], the authors conducted a study of medical image segmentation and highlighted the popularity of the Otsu method, a non-parametric approach widely used in medical image segmentation. The primary objective of their research is to extract and characterize anatomical structures based on input features or expert knowledge. However, they note that the Otsu method involves time-consuming computations, which represent a challenge in real-time applications.

In [46], the researchers discussed the challenges of recognizing handwritten names of cities and text, focusing on the Russian and Kazakh languages. The Russian and Kazakh languages are complicated to understand. They used two datasets on four deep learning models consisting of deep CNN models, Simple Handwritten Text Recognition model (SimpleHTR), Bluche, and Puigcerver. The datasets consist of 21,000 images containing handwritten Cyrillic words for city names and the Handwritten Kazakh and Russian (HKR) Database. In their study, the authors compared SimpleHTR with Bluche and Puigcerver models using the HKR dataset, dividing into two different test sets: TEST1 (words that do not exist in the training and validation datasets) and TEST2 (contained words existing in the training but written in different handwriting styles). Bluche outperformed SimpleHTR in TEST1, in terms of lower CER compared to SimpleHTR, shown in Table 6.3. However, both models performed better than Puigcerver. In TEST2, SimpleHTR performed the best, exceeding both the Bluche and Puigcerver models. In [38], the authors represented a study on implementing handwritten text recognition for the Azerbaijani language using ML models, LeNet-5 CNN in the beginning, and later by SimpleHTR. The goal of this study is to evaluate the performance of two machine learning models on the Azerbaijani language, which is challenging for handwritten recognition. Applying various preprocessing techniques, they experimented on a dataset of the Azerbaijani language of 15,005 words with 4,614 unique words. The SimpleHTR model achieved 79.2% accuracy and performed significantly better on a small-scale dataset, shown in Table 6.3.



(a) (b)

Figure 33: Sample prescription image before and after applying annotation. (a) Before annotation; (b) After annotation

However, they highlighted that the experimental results are promising yet inadequate as a final product.

In [57] work, they utilized the RNN model using the CTC loss function, and their study proposes a more efficient method called Word Beam Search (WBS) decoding. WBS limits recognized words that can be found in the dictionary, while word boundaries of any non-word character strings (like numbers or punctuation marks) were allowed. The algorithm was also validated with data sets such as IAM and Bentham HTR, and it emerged as equally accurate and faster than the other decoding algorithms. In the experiments, WBS decoding achieved a remarkable result depending on the dataset and language model used, shown in Table 6.3.

Visual Language Based OCR (ViLanOCR) [19], a two-language OCR system to digitize Urdu and English text, highlighting the challenges of low-resource languages. This study adds value to OCR technology for languages with few resources, showing promising results for real-world use and revealing strong performance in two-language tasks such as turning handwritten medical prescriptions into digital form. It obtained excellent results on NUST-UHWR, PUCIT-OHUL, UPTI, and Medical-SYN datasets, demonstrated in Table 6.3. Another study in [23] represented a system for detecting, localizing, and segmenting text in images to enhance OCR. It solves the problem of complex background and unclear text together (text extraction using connected component analysis with a texture-based method). The proposed system demonstrated a robust performance.

The dataset used in this study has 893 images of prescriptions [64]. The dataset includes a wide variety of classes, which cover numerous objects and categories. The authors of the dataset annotated the names of the medicines in each prescription. Each image covered the full page of the prescription, whereas the annotated part mainly covered the medicine names. The primary format of the images was JPG, with a width and height of each image being 640x640 pixels. The author of the dataset provided the images in three different folders: train, test, and valid. Each folder also contains a CSV file named annotation. This annotation file has multiple columns: file height, name, class name, width, and coordinates. A sample of the prescription in the dataset is shown in Fig. 33, which demonstrates the picture of before and after applying the annotation. The annotations are in multiple formats, which helps them to be compatible with different machine learning frameworks

6.1.1 Data Pre-processing

From the original images, we cropped the area containing the medicine name. This process ultimately resulted in a total of 4,038 individual images of medicine names extracted from the 893 original set of images. The original image had a resolution of 640x640 pixels, which ensured a consistent quality across the overall dataset. After cropping the images to extract medicine names, each cropped image had an approximate average 4:1 width-to-height ratio, with an approximate resolution of 128x32 pixels. We did not apply any image processing or augmentation techniques to enhance the quality of the images, maintaining them in their original form. Next, we divided the cropped images into training, test, and validation sets using a ratio of 70:20:10.

6.1.2 Model Development

In this section, the selection and development of Transformer-based Optical Character Recognition model is presented, which was applied to extract the medicine information from the picture provided by the user. The model, TrOCR, is featured by its capacity to capture intricate patterns within the data [37].

The research used TrOCR, a DL model that can be used to extract textual information from images. The model uses a Transformer architecture to perform OCR tasks by combining a Vision Transformer (ViT)-based encoder and a transformer-based decoder. Before the prescription image is fed into TrOCR, image pre-processing like grayscale conversion, noise reduction and resizing, and normalization is performed. These patches act as tokens, and each of these patches consists of a small portion of the image, which may include a character, word, or symbol. The patches are then flattened into vectors and fed via an embedding layer. Each patch that consists of the raw pixel values is then transformed into numerical representations. To interpret text in a correct sequence, positional encoding is used to retain spatial relationships. The encoder uses a self-attention technique for better comprehension of the connections or similarities between different patches. The text generation happens at the transformer decoder part. The decoder generates one token at a time. The decoder uses multi-head self-attention to focus on the important portions of the image for every generated text. This helps the model to compare the generated word with the input image.

6.1.3 Data Post-processing

For the post-processing part, we have used Levenshtein distance, also known as edit distance. It is mainly used for text correction. It is an algorithm that measures the distance between two words by calculating the minimum number of character edits that are needed to make both words the same [8]. The edit consists of three operations: insertion, deletion, and substitution.

$$D(i,j) = \begin{cases} \max(i,j) & \text{if } \min(i,j) = 0, \\ \min \begin{cases} D(i-1,j)+1, \\ D(i,j-1)+1, \\ D(i-1,j-1)+1_{(a_i \neq b_j)} \end{cases} & \text{otherwise} \end{cases} \tag{6.1}$$

Equation 6.1 is used to give us the Levenshtein distance between two strings a and b. The i and j represent the positions in the strings. If either i or j is zero, this would mean that one string is empty, otherwise, it would have to insert or delete all of the other string's characters to match both the words. Hence, if min(i , j) = 0, then max(i

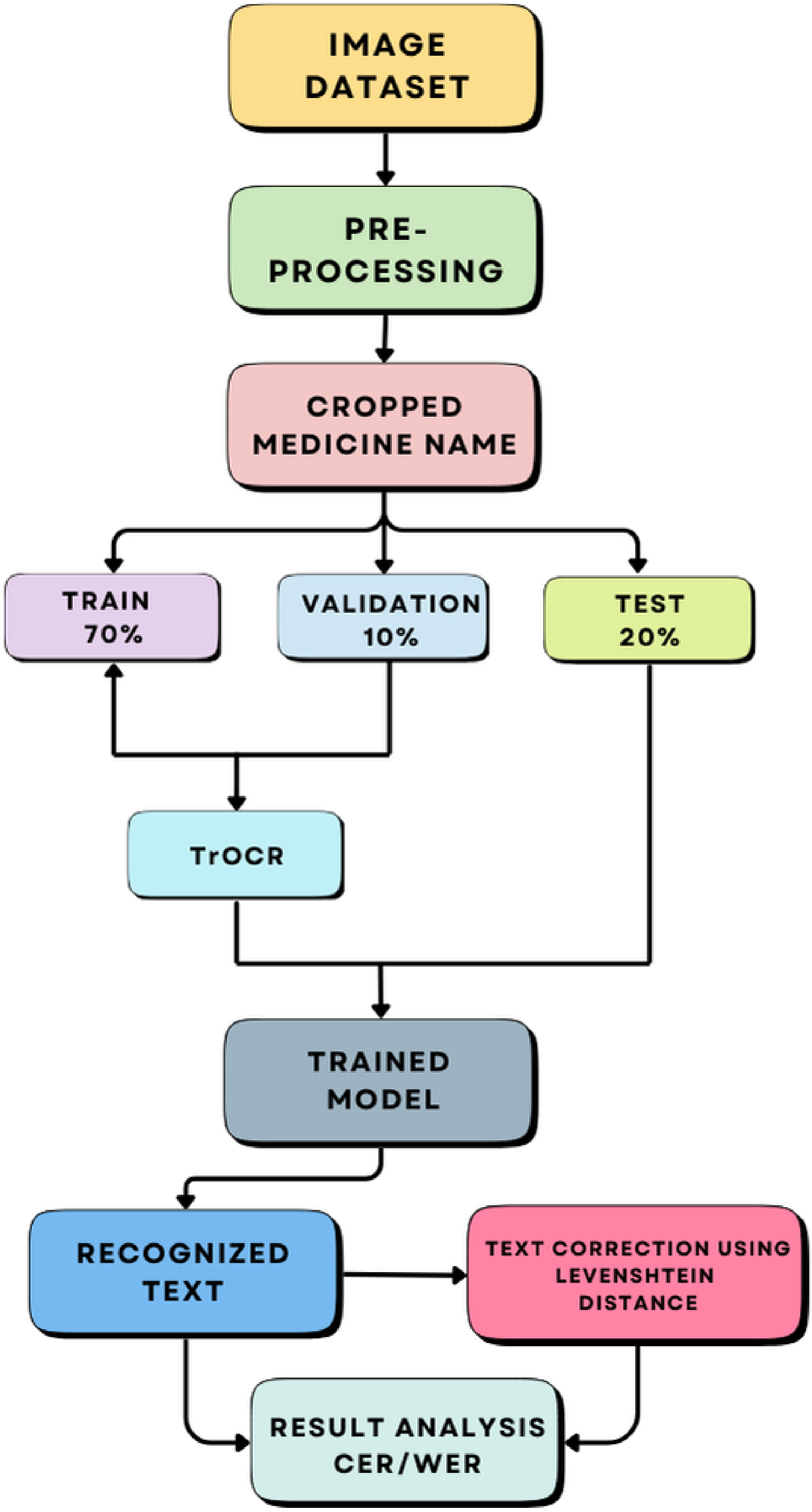


Figure 34: Overview of the methodology employed in this study.

, j) is used. If both strings are not empty, then it would go through the three possible operations, where the cost is increased by one for each operation that takes place. In the substitution operation, we check whether the last a_i and b_j are the same or not. If they are different, we use the substitution operation, and the cost increases by one. After that, it chooses the minimum value of these three operations, which helps to get the optimum sequence of edits at every step.

6.1.4 Evaluation Metrics

For evaluating the performance of the handwritten text recognition task, we used two techniques: Character Error Recognition (CER) and Word Error Recognition (WER). These help to understand the dissimilarities in texts.

Character Error Recognition (CER)

The CER is calculated by comparing the predicted text to the ground truth or actual text. Here, the actual text refers to the medicine names provided by the dataset authors, and the comparison is performed on a character-by-character basis [42]. This metric measures the number of changes needed to transform the predicted text into the correct label, which includes insertions (I), deletions (D), and substitutions (S) of individual characters. The equation for calculating CER is shown in Equation 6.2. A lower CER indicates that the model has effectively learned to understand handwriting.

$$\text{CER} = \frac{S + D + I}{N} \tag{6.2}$$

- S = Number of substitutions
- D = Number of deletions
- I = Number of insertions
- N = Total number of characters/words in the ground truth for CER.

Word Error Recognition (WER)

The WER evaluates the model's accuracy on a word-by-word basis. It calculates the ratio of word-level errors (also including operations such as insertions, deletions, and substitutions) to the total number of words in the ground truth or actual text [35]. The details for calculating WER are provided in Equation 6.3. A lower WER indicates that the model has effectively learned to understand handwriting.

$$\text{WER} = \frac{S + D + I}{N} \tag{6.3}$$

- S = Number of substitutions
- D = Number of deletions
- I = Number of insertions
- N = Total number of characters/words in the ground truth for WER.

6.1.5 Experimental Setup

For the experiment, the following hardware setup was used: CPU: Intel Core i7 @4.2GHz, Primary Memory/RAM: 64GB, Graphics Card: Nvidia RTX 4060Ti, Secondary Memory/Storage: 1TB Solid. State Drive. This hardware configuration provided sufficient computational resources to execute the necessary data analysis, model training, and evaluation tasks. In addition to the hardware setup, a suite of software programs and Python packages was used. These include: Python programming language, Spyder in Anaconda Navigator, TensorFlow, Numpy, Seaborn, KERAS, and Scikit Learn.

6.2 Experimental Results and Analysis

6.2.1 Results Analysis

In our experiment, the TrOCR model has been trained for a total of 20 epochs. Epoch means one complete cycle through the entire training dataset. Since we trained the dataset for 20 epochs, it means that the model went through 20 cycles to learn how to recognize handwritten text. A separate validation dataset was used to observe the model's performance. Instead of just being used for training, the validation set also helps us to understand how well the model generalizes to performance on unseen data. Because if we set importance only on the training set, the model might become too "overfitted". It means that the model might perform well on the training dataset but not on the new dataset.

So to avoid such a situation, we assess the model's accuracy after each epoch by calculating the CER on the validation set. CER is a common metric used to determine how many characters are wrongly interpreted. We kept the model version that had a lower CER in previous epochs. This ensures that the best version of the model is saved during the training process.

Now that the model was saved during the previous epoch with less CER, we use it to calculate the performance on the test set. The test set is a kind of set that is a completely separate and new set for the model that the model has never been explored before. This aids us in understanding how well the model will perform in real-world scenarios where the model will encounter different new datasets. Similarly, for this training set, we calculated CER and WER. The achieved CER is 16% and WER is 36%, meaning that there might still be some inaccuracy in recognizing characters.

To overcome these remaining errors, we further deploy the Levenshtein Distance technique to increase the model's accuracy. To convert the output of the model into a valid medicine name, the Levenshtein Distance technique compares the identified text output with the actual correct medicine names and tries to fix the mistakes by reducing the number of changes (insertions, deletions, or substitutions). If we say this in simpler words, this method assists the model's predictions by fixing small spelling mistakes, as handwritten texts contain errors and are not easy to understand.

Table 6.1: Performance of TrOCR Model on Test Set, Before and After Applying Levenshtein Distance Based Correction

Metric	**Before Correction**	**After Correction**
Character Error Rate (CER)	16%	7%
Word Error Rate (WER)	36%	11%

Since by using the Levenshtein Distance technique, some of the spelling mistakes and errors are fixed, CER and WER are calculated again using corrected outputs and comparing them with the ground truth (the actual correct labels). CER and WER dropped to 7% and 11%, which is a significant drop from the previous values. Levenshtein Distance techniques incorporated with the model were able to refine the model's predictions. Overall, we could conclude that TrOCR is a powerful model that can extract accurate outputs from handwritten texts with additional correction techniques. A more detailed summary of the result is given in the Table 6.1.

6.2.2 Training Validation

The performance of the TrOCR model increased progressively over time across 20 training epochs shown in Table 6.2. On the validation set, this model with a 4.5187 high train CER and a very high validation CER rate of 0.9862, showed exceeding results during the training period. At the beginning of training, the model was struggling to recognize characters from the handwritten text. By the time of the training, the model understands the pattern of the dataset. The train CER dropped to 1.4793, and the validation CER fell to 0.3908 by the fifth epoch, which showed a rapid and significant improvement in the early stage of the training phase.

During the next few epochs, the model showed improved results, which are shown in Fig. 35. The train CER decreases to 0.469, and the validation CER drops significantly to 0.1273 in the tenth epoch. This result shows that the model's performance is rapidly improving even on new and unrevealed data. The model was tested using the validation set after every epoch. When the CER result is improving, the result data is saved. Utilizing this technique helped the model to be more accurate at recognizing characters and also avoid overfitting.

On the validation set, the validation CER progressed minimally after the thirteenth epoch. The CER remained steady around 0.11, with only slight variations between epoch 13 and epoch 20. Between epochs 13 and 20, the train CER decreases from 0.3615 to 0.1765. On the other hand, the validation CER remained mostly unchanged. This shows that more training of the model will not bring significant change, as it has reached its learning capacity given the available data.

The training phase concluded successfully. In the early stage, the train CER and validation CER dropped rapidly, indicating that the model was quickly learning patterns from the data. For further testing, the most accurate and well-performed version of the model with the lowest validation CER on the validation set (approximately 0.11) was saved for final validation.

Table 6.2: Training and Validation CER across 20 Epochs

Epochs	**Train CER**	**Valid CER**
1	4.5187	0.9862
2	3.3369	0.8050
3	2.3345	0.6315
4	1.8466	0.5029
5	1.4793	0.3908
6	1.1409	0.3054
7	0.7838	0.2362
8	0.6478	0.1871
9	0.5992	0.1504
10	0.4690	0.1273
11	0.4596	0.1160
12	0.3854	0.1135
13	0.3615	0.1100
14	0.3064	0.1102
15	0.2820	0.1101
16	0.2367	0.1101
17	0.1982	0.1102
18	0.1826	0.1101
19	0.1783	0.1101
20	0.1765	0.1102

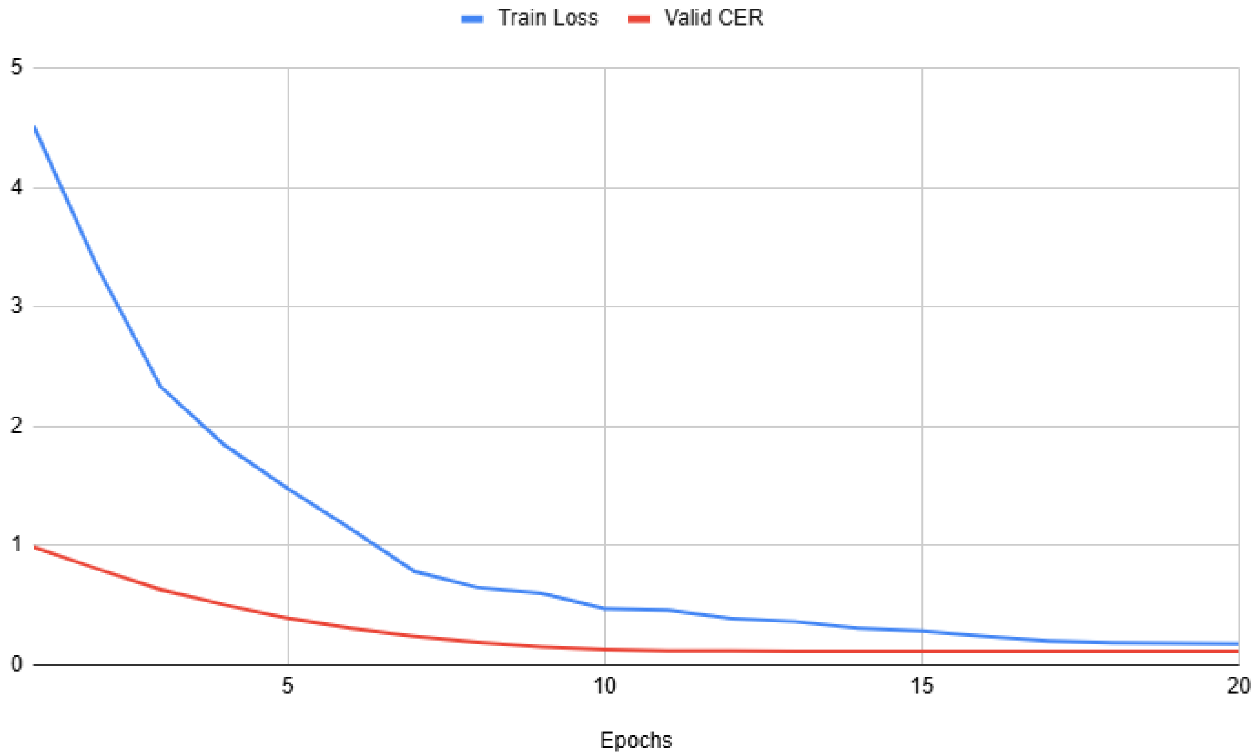


Figure 35: Train and valid CER over 20 epochs

6.2.3 Threats to Validity

A few validity threats in this study need to be acknowledged. One of the major obstacles was the size of the dataset used in this research. The dataset consisted of a total of 893 handwritten prescription images, which had 4,038 medicine names in them. Which is very little considering how diverse and different doctors' handwriting can be in real life. Handwriting style depends on person to person, everyone has a unique style of their own. To train a powerful model like TrOCR, the model should be trained on a dataset containing many different writing styles. Since the model has been trained on a small dataset, there's a chance that the model might find it difficult to read handwriting styles it has not seen before. It implies that the model might not generalize well when exposed to unfamiliar writing styles, which can affect the performance of the model.

Another noteworthy limitation is that we employed only one OCR model, TrOCR, in this study. TrOCR is indeed a strong model and showed promising results in our study, incorporated with the correction technique. But solely utilizing one model to extract medicine names is preventing other models that might perform better with Bangla handwriting styles. We have limited our scope of judging the strengths and weaknesses by not comparing TrOCR with other OCR models or any other text extraction models. So we can not entirely state that TrOCR is the best choice for Bangla handwritten prescriptions.

Finally, we incorporated Levenshtein Distance, which is one correction method among many. It helped us to improve the model's accuracy. There might be other correction strategies that could give more accuracy when incorporated with TrOCR. By not exploring other post-processing techniques, we might have missed out on other ways to increase the model's accuracy.

6.3 Comparison to Prior Works

A comparative analysis is shown in Table 6.3 of the proposed methodology against other studies mentioned in the Background and Related Works section (Section I). Key comparisons include the domain of the problem statement, which encompasses the prescription analysis and medication management addressed in the study, and the best performance achieved by our proposed methodology.

Our study achieved the lowest error rate of CER 7%, which is better than the result achieved in other studies, and approximately. The TrOCR method used in this study performed significantly better, achieving a WER score of 11%.

Table 6.3: Comparative Analysis of Our Proposed Methodology Against Related Prior Work

Paper	Algorithms Used	CER	WER
[24]	Text Detection and Localization (TDL) + Character Segmentation and Binarization (CSB) + OCR	77.71%	55.8%
[58]	WBS Decoding	8.25%	23.67%
[28]	SimpleHTR	5.3%	N/A
[47]	SimpleHTR (HKR dataset)	TEST1=20.13%, TEST2=1.55%	TEST1=58.97%, TEST2=11.09%
[20]	ViLanOCR	1.1%, 5.22%, 6.3%, and 6.77% (On different Datasets)	N/A
Our proposed methodology	**TrOCR**	**7%**	**11%**

7 Discussion

7.1 Systematic Literature Review

To develop and assess systems for medication management or prescription information extraction, the SLR identified and examined 14 recent studies. The findings imply that these apps present a viable and convenient approach to managing medications effectively. The review includes a comprehensive summary of the applications aimed at managing medications, highlighting various platforms and key features. The apps' wide range of features did assist in managing medication. The main objectives of the reviewed apps included managing medication, reducing prescription interpretation errors, and assist users for any kind of medication help.

Most of the RQs have been thoroughly addressed in the review. It gives a clear landscape of existing medication management apps, including their features (RQ1 and RQ4 for SLR). The gaps or current limitations in the literature (RQ2). The common errors that the users do while interpreting handwritten prescriptions (RQ3). Understanding how users deal with prescription reading challenges in the context of Bangladesh (RQ5).

Although this review highlights a growing interest in using medication management tools or handwritten prescription extraction systems to support users in reading the medicine information, there aren't enough studies where there has been a Relational Agent to assist the users. Also, none of the works were done for handwritten prescriptions in Bangla.

7.2 Survey Results and App Development

A survey was conducted via Google Forms, which included a total of 155 participants, where the respondents' insights were recorded for the features and design requirements of the app. Participants also provided their suggestions and concerns about a mobile app for new features or design improvements that had not been previously identified in the background study. Google Forms was used to represent the survey data in charts and graphs, helping to visualize and interpret the results more clearly. In the next phase, the design suggestions from the users were implemented to create a high-fidelity prototype using Figma. The high-fidelity prototype helps the users navigate through the app and experience its features firsthand. The main reason for preferring Figma over other tools is that it has a collaborative environment and helps to understand how the user will interact with the app.

Participants' responses highlighted the importance of features like the Relational Agent with voice command and chatbox, notification, and reminder system. The UI was also designed based on the survey results, which were then integrated into the app.

The prototype also successfully addressed the key research questions. It identified major features and functionalities that should be incorporated into an application (RQ1).

Additionally, the app's evaluation, including user feedback, provided insights into the willingness of users to adopt such a solution (RQ2).

7.3 User-Centered Design Approach

The "PresCa" app was developed to closely align with the needs of the target users through the implementation of the UCD methodology, which is a foundational strength of this study. This whole process involved participants from different backgrounds in every stage, ranging from the needs analysis survey to the development of the prototype and the evaluation of usability. One of the findings of the study is that most of the Bangladeshi citizens find it difficult to properly decipher handwritten prescriptions, and this factor influenced the app's design. This approach helped gain valuable insights from the participants of the study, and therefore important features such as Bangla language support, a medication reminder system, and a voice/text-based Relational Agent, all of which were found to be user needs, were prioritized. The interaction with the developed high-fidelity prototype assisted users in understanding how the app would be, and based on their feedback, improvements were made and make the app more relevant and easier to use. This user-centric process, led by users, ensures that the problems of mismanagement of medication and the poor accessibility of healthcare are addressed, as these are major concerns in rural and semi-urban regions where doctors are still giving out handwritten prescriptions to their patients.

7.4 Limitations

While this study successfully developed a functional prototype of the "PresCa" mobile application, certain limitations remain. The limitations of this study are as follows:

- One of the primary challenges was the OCR model's limited accuracy when interpreting diverse handwriting styles commonly found in Bangladeshi prescriptions. Although the system performed well with moderately clear text, it struggled with illegible or stylized handwriting. Despite the integration of a Doctor Verification feature to allow for manual correction, the need for human intervention in such cases suggests a requirement for further improvement of the OCR pipeline through training on a larger, more varied dataset.

- Another limitation involves the evaluation context. User testing was conducted in controlled, simulated environments rather than during extended real-world use. As such, the findings do not fully reflect how the app performs in everyday healthcare scenarios, such as in low-light conditions, rushed environments, or among users with limited digital experience. Real-time deployment and long-term usage studies are needed to assess how the app integrates into users' daily routines and its sustained effectiveness over time.

- It is important to consider the age of the handwriting when capturing prescription images. A freshly written note and one that has aged over time can differ in clarity and appearance, which may affect the model's performance

- We should take the doctor's age into account, as it can influence handwriting quality. Older doctors may have less legible handwriting, while younger doctors are more likely to produce clearer and sharper writing.

7.5 Additional Features

To enhance PresCa's utility, several additional features could be introduced in future iterations. While the current system allows doctors to verify and edit prescription data, expanding this to include shared access for caregivers or pharmacists would support collaborative use and ensure greater accuracy in medication tracking. Enhancing the Relational Agent is also a key opportunity. Currently, it offers basic, guided interactions. Expanding it to support more natural, conversational dialogue using AI would improve accessibility, especially for users with low literacy or limited medical knowledge. Another useful addition would be a prescription history dashboard, enabling users to review past prescriptions, dosage changes, and medication summaries. This would improve adherence, continuity of care, and make health records easily accessible during medical consultations

7.6 Impact on Literature

The methodological approach has significantly influenced recent literature in the fields of healthcare technology and ML. Researchers have increasingly explored how mobile apps can support users in managing their medications by offering practical and real-time assistance. The literature reflects a growing emphasis on medication reminders, dosage tracking, and digital logs to improve adherence and reduce manual errors. Recent studies have highlighted the integration of OCR and ML in mobile apps to enable accurate extraction of handwritten or printed prescriptions. This has opened new avenues for automating prescription processing, minimizing human error, and supporting healthcare professionals in the healthcare sector. As a result, there is an increasing interest in designing intelligent systems that store and remind users about medication schedules and also offer unique features to understand and adapt to individual needs.

7.7 How Chapter 6 can contribute to the main idea

- With the integration of the DL model TrOCR, our developed high-fidelity prototype would be able to automatically scan Bangla handwritten prescriptions. This will reduce the burden of manually reading complicated prescriptions, especially for elderly people and people with low literacy.
- The OCR model deployed can extract medicine names from complicated Bangla handwritten prescriptions with high accuracy (CER dropped to 7% after Levenshtein distance). This will help users to get the correct medicine information without manually reading prescriptions, which solves one of the major challenges found in the need-finding study.
- Wrong interpretation of medication names could lead to major health risks, especially for elderly people. The DL model integrated with the PresCa app would provide a platform to reduce this risk. This addresses one of the key ideas in HCI, which is to make the system safer and easier to use. With the medicine information extracted utilizing the OCR model, the app can send medicine reminders set by the users, alerts, and get assistance from the Relational Agent regarding any concerns.

8 Conclusion and Future Works

8.1 Conclusion

This study demonstrates the potential of using a mobile application, "PresCa", to reduce errors and improve access to reliable medication information by digitizing handwritten prescriptions for Bangladeshi citizens. This critical issue of misinterpretation of medication information is caused by illegible and complex handwritten prescriptions. Prescriptions can often be misread by pharmacies in busy settings, posing possible threats to patients' health. By applying the UCD approach, the app addresses the challenges of unclear handwritten prescriptions, ensuring better safety and healthcare practices. Features like prescription scanning, medication reminders, and a Relational Agent create a more interactive and accessible user experience. A precise and reliable solution for the retrieval of medication information is introduced in this research by utilizing the TrOCR model. The error rate decreased more due to the utilization of the Levenshtein Distance technique, which indicates OCR is performing significantly better. This approach may reduce the pressure on the healthcare system overall while bringing in improved technologies to address common problems related to prescription. The app particularly benefits rural and semi-urban areas, where reliance on handwritten prescriptions remains high. This research highlights the importance of modernizing healthcare solutions to improve patient health management systems and reduce risks associated with medication errors.

8.2 Future Plan

Demonstration of the prototype evaluation was beneficial for the users, but usability improvements are still needed. There is room for future work that includes

- Developing a cross-platform app that will operate on various devices and operating systems. This will make the app more accessible to a broader range of users and benefit a diverse group.
- Generate a Bangla handwritten prescription dataset that would help TrOCR to understand the textual format and structural patterns found in Bangladeshi medical prescriptions.
- Integrate a feature that can understand the layout of a prescription. This means the app will be able to tell which part has the patient's name, the doctor's notes, and which part lists the medicines, which will help the app to read and extract information more precisely.
- Conduct a larger survey with more people from different backgrounds. This will help the app to be more user-friendly.

- Integrate TrOCR into the backend of the fully functional app for extracting handwritten prescription text, and incorporate a structured large medicine database containing brand names, generic names, dosages, and commonly used medications in Bangladesh for accurate identification and mapping of extracted drug information.

A Appendix

A.1 Appendix A: Abbreviations

1. **ADR:** Adverse Drug Reaction
2. **mHealth:** Mobile Health
3. **DL:** Deep Learning
4. **SUS:** System Usability Scale
5. **ML:** Machine Learning
6. **TrOCR:** Transformer-based Optical Recognition
7. **SimpleHTR:** Simple Handwritten Text Recognition
8. **ViLanOCR:** Visual Language Based OCR
9. **RNN:** Recurrent Neural Network
10. **AI:** Artificial Intelligence
11. **HCI:** Human-Computer Interaction
12. **UCD:** User-Centered Design
13. **AR:** Augmented Reality
14. **VR:** Virtual Reality
15. **EHR:** Electronic Health Record
16. **SMS:** Short Message Service
17. **IRB:** Institutional Review Board
18. **RQ:** Research Question
19. **SLR:** Systematic Literature Review
20. **PRISMA:** Preferred Reporting Items for Systematic Reviews and Meta-Analyses
21. **PDF:** Portable Document Format
22. **SD:** Standard Deviation
23. **CNN:** Convolutional Neural Network

24. **WER:** Word Error Rate
25. **CER:** Character Error Rate
26. **MCC:** Matthews Correlation Coefficient
27. **OCR:** Optical Character Recognition
28. **WBS:** Word Beam Search
29. **RA:** Relational Agent
30. **QR:** Quick Response
31. **IR:** Infrared Radiation

A.2 Appendix B: List of Key Publications from this Work

1. M. F. U.Zaman, B.Rahman, A.Rubyat, N.Halder, A.Mahmud, A.Islam, and M.A Amin. "Recognizing Medicine Names From Bangladeshi Hand- written Prescription Images using TrOCR", presented at the 7th Asia Conference on Cognitive Engineering and Intelligent Interaction (CEII) (2024).
2. B.Rahman, A.Rubyat, M. F. U.Zaman, N.Halder, A.Mahmud, A.Islam, and M.A Amin. "Early-Stage Development of a Handwritten Prescription Interpreta tion App for Bangladeshi Citizens", presented at the International Conference on Human-Computer Interaction (HCII) (2025), Springer.

Bibliography

[1] Mr. pillster - pills reminder and medication tracker.

[2] Preferred reporting items for systematic reviews and meta-analyses: The prisma statement. *Annals of Internal Medicine 151*, 4 (2009), 264–269. PMID: 19622511.

[3] Ahmed, T., Lucas, H., Khan, A. S., Islam, R., Bhuiya, A., and Iqbal, M. ehealth and mhealth initiatives in bangladesh: a scoping study. *BMC health services research 14* (2014), 1–9.

[4] Al-Amin, M., Islam, M., Hasan, M., Ahmed, M., and Rahman, M. Machine learning in medication prescription: A systematic review. *Journal of Biomedical Informatics 139* (2023), 104312.

[5] Al-Amin, M., Islam, M., Hasan, M., Ahmed, M., and Rahman, M. Pharmaceutical decision support system using machine learning to analyze and limit drug-related problems in hospitals. *Journal of Biomedical Informatics 139* (2023), 104312.

[6] Aldhwaihi K, Umaru N, P. C. S. F. A systematic review of the nature of dispensing errors in hospital pharmacies. *Integrated Pharmacy Research and Practice 5*, 1-10 (2016).

[7] Banu, M. A., Mondal, R., and Begum, T. Factors influencing medication errors among nurses at a tertiary level hospital in bangladesh. *Asian Journal of Medical and Biological Research 10*, 4 (2024), 131–140.

[8] Beernaerts, J., Debever, E., Lenoir, M., De Baets, B., and Van de Weghe, N. A method based on the levenshtein distance metric for the comparison of multiple movement patterns described by matrix sequences of different length. *Expert Systems with Applications 115* (2019), 373–385.

[9] Begum, F., Uddin, M. R., Islam, M. S. U., Sarker, M. N., Barman, R. C., and Ali, M. Y. Evaluation of prescribing pattern of the private practitioners in bangladesh. *Faridpur Medical College Journal 7*, 2 (2012), 51–53.

[10] Begum, F., U. M. R. I. M. M. S. U. S. M. N. B. R. C. . A. M. Y. Evaluation of prescribing pattern of the private practitioners in bangladesh.

[11] Bickmore, T., and Cassell, J. Relational agents: a model and implementation of building user trust. In *Proceedings of the SIGCHI conference on Human factors in computing systems* (2001), pp. 396–403.

[12] Bindu, H., and Prasad, K. An efficient medical image segmentation using conventional otsu method. *International Journal of Advanced Science and Technology 38* (2012), 67–74.

[13] Bishop, J. Increasing participation in online communities: A framework for human–computer interaction. *Computers in Human Behavior 23*, 4 (2007), 1881–1893.

[14] Biswas, M., Roy, D. N., Islam, M., Parvez, G., Rahman, M., Tajmim, A., Ferdiousi, N., Ali, M., and Nasim, S. Prevalence and nature of handwritten outpatients prescription errors in bangladesh. *Int J Pharm Pharm Sci 6*, 5 (2014), 126–130.

[15] Blattgerste, J., Behrends, J., and Pfeiffer, T. A web-based analysis toolkit for the system usability scale. Association for Computing Machinery, p. 237–246.

[16] Brandtner, P., Auinger, A., and Helfert, M. Principles of human computer interaction in crowdsourcing to foster motivation in the context of open innovation. In *HCI in Business* (Cham, 2014), F. F.-H. Nah, Ed., Springer International Publishing, pp. 585–596.

[17] Brhel, M., Meth, H., Maedche, A., and Werder, K. Exploring principles of user-centered agile software development: A literature review. *Information and Software Technology 61* (05 2015).

[18] Bu, L., Chen, C.-H., Ng, K. K., Zheng, P., Dong, G., and Liu, H. A user-centric design approach for smart product-service systems using virtual reality: A case study. *Journal of Cleaner Production 280* (2021), 124413.

[19] Cheema, M. D. A., Shaiq, M. D., Mirza, F., Kamal, A., and Naeem, M. A. Adapting multilingual vision language transformers for low-resource urdu optical character recognition (ocr). *PeerJ Computer Science 10* (2024), e1964.
[20] Cheema, M. D. A., Shaiq, M. D., Mirza, F., Kamal, A., and Naeem, M. A. Adapting multilingual vision language transformers for low-resource urdu optical character recognition (ocr). *PeerJ Computer Science 10* (2024), e1964.
[21] Datta, S. K., Paul, T. R., Monwar, M., Khatun, A., Islam, M. R., Ali, M. A., Barman, R. K., Rahman, B. M., and Wahed, M. I. I. Patterns of prescription and antibiotic use among outpatients in a tertiary care teaching hospital of bangladesh. *Int J Pharm Pharm Sci 8*, 11 (2016), 54.

[22] Eshet, E., and Bouwman, H. Context of Use: The Final Frontier in the Practice of User-Centered Design? *Interacting with Computers 29*, 3 (10 2016), 368–390.

[23] Gllavata, J., Ewerth, R., and Freisleben, B. A text detection, localization and segmentation system for ocr in images. *IEEE Sixth International Symposium on Multimedia Software Engineering* (2004), 310–317.
[24] Gllavata, J., Ewerth, R., and Freisleben, B. A text detection, localization and segmentation system for ocr in images. *IEEE Sixth International Symposium on Multimedia Software Engineering* (2004), 310–317.
[25] Göransson, B., Gulliksen, J., and Boivie, I. The usability design process – integrating user-centered systems design in the software development process. *Software Process: Improvement and Practice 8*, 2 (2003), 111–131.

[26] Hasan, S., Alam, S. R., Sultana, S., and Ahmed, S. I. 'oshudh poro': A mobile-phone application to support low-literate rural bangladeshi people's personal medication management [poster]. In *Proceedings of the 4th ACM SIGCAS Conference on Computing and Sustainable Societies* (2021), pp. 457–461.

[27] Hasan, Shaid, S. R. A. S. S., and Ahmed, S. I. 'oshudh poro': A mobile-phone application to support low-literate rural bangladeshi people's personal medication management [poster]. *4th ACM SIGCAS Conference on Computing and Sustainable Societies* (2021), 457–461.

[28] Hassan, E., Tarek, H., Hazem, M., Bahnacy, S., Shaheen, L., and Elashmwai, W. H. Medical prescription recognition using machine learning. *2021 IEEE 11th Annual Computing and Communication Workshop and Conference (CCWC)* (2021), 0973–0979.

[29] Horsky, J., and Ramelson, H. Z. Development of a cognitive framework of patient record summary review in the formative phase of user-centered design. *Journal of Biomedical Informatics 64* (2016), 147–157.

[30] Hossain, M. K., Imteaj, A., Shakib, K. H., and Zaman, S. An approach to digitalize the health care system of bangladesh using smartphone. *SISFORMA 8*, 2 (2021), 80–88.

[31] Hossain, N., Sampa, M. B., Yokota, F., Fukuda, A., and Ahmed, A. Factors affecting rural patients' primary compliance with e-prescription: A developing country perspective. *Telemedicine and e-Health 25*, 5 (2019), 391–398.

[32] Imteaj, A., and Hossain, M. K. A smartphone based application to improve the health care system of bangladesh. In *2016 International Conference on Medical Engineering, Health Informatics and Technology (MediTec)* (2016), IEEE, pp. 1–6.

[33] Jouffroy, J., Feldman, S. F., Lerner, I., Rance, B., Neuraz, A., and Burgun, A. Medext: combining expert knowledge and deep learning for medication extraction from french clinical texts. *Published online January 23* (2020).

[34] Karim, M. M., Islam, M. N., Priyoti, A. T., Ruheen, W., Jahan, N., Pritu, P. L., Dewan, T., and Duti, Z. T. Mobile health applications in bangladesh: A state-of-the-art. In *2016 3rd International Conference on Electrical Engineering and Information Communication Technology (ICEEICT)* (2016), IEEE, pp. 1–5.

[35] Klakow, D., and Peters, J. Testing the correlation of word error rate and perplexity. *Speech Communication 38*, 1-2 (2002), 19–28.

[36] Kumar, D., Arya, M., and Agarwal, S. Mobile apps for medication management: Review and analysis. *Journal of Medical Internet Research 21*, 9 (2019), e12505.

[37] Li, M., Lv, T., Chen, J., Cui, L., Lu, Y., Florencio, D., Zhang, C., Li, Z., and Wei, F. Trocr: Transformer-based optical character recognition with pre-trained models. *Proceedings of the AAAI Conference on Artificial Intelligence 37*, 11 (2023), 13094–13102.

[38] Mammadov, A. Offline handwritten text recognition for azerbaijani language.

[39] Mao, J.-Y., Vredenburg, K., Smith, P. W., and Carey, T. The state of user-centered design practice. *Communications of the ACM 48*, 3 (2005), 105–109.

[40] Mekler, E. D., and Hornbæk, K. A framework for the experience of meaning in human-computer interaction. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (New York, NY, USA, 2019), CHI '19, Association for Computing Machinery, p. 1–15.

[41] Miotto, R., Wang, F., Wang, S., Jiang, X., and Dudley, J. Deep learning for healthcare: Review, opportunities and challenges. *Briefings in Bioinformatics 19*, 6 (2018), 1236–1246.

[42] NithyaKalyani, A., and Jothilakshmi, S. Speech summarization for tamil language. Elsevier, 2019, pp. 113–138.

[43] Nobarany, S., Booth, K. S., and Hsieh, G. What motivates people to review articles? the case of the human-computer interaction community. *Journal of the Association for Information Science and Technology 67*, 6 (2016), 1358–1371.

[44] Nor, R. M., Mohamadali, N. A., Azmi, K., Marzuki, A., Nor, L. M., and Yusof, M. Scanmed: A mobile medicine adherence application with intake validation using qr code. In *2016 6th International Conference on Information and Communication Technology for The Muslim World (ICT4M)* (2016), IEEE, pp. 112–117.

[45] Norman, D. A., and Draper, S. W. *User Centered System Design: New Perspectives on Human-Computer Interaction.* CRC Press, Hillsdale, NJ, 1986.

[46] Nurseitov, D., Bostanbekov, K., Kanatov, M., Alimova, A., Abdallah, A., and Abdimanap, G. Classification of handwritten names of cities and handwritten text recognition using various deep learning models. *arXiv preprint arXiv:2102.04816* (2021).

[47] Nurseitov, D., Bostanbekov, K., Kanatov, M., Alimova, A., Abdallah, A., and Abdimanap, G. Classification of handwritten names of cities and handwritten text recognition using various deep learning models. *arXiv preprint arXiv:2102.04816* (2021).

[48] Paul, L. C., Ahmed, S. S., Rani, T., Haque, M. A., Roy, T. K., Hossain, M. N., and Hossain, M. A. A smart medicine reminder kit with mobile phone calls and some health monitoring features for senior citizens. *Heliyon 10*, 4 (2024).

[49] Paul, L. C., Ahmed, S. S., Rani, T., Haque, M. A., Roy, T. K., Hossain, M. N., and Hossain, M. A. A smart medicine reminder kit with mobile phone calls and some health monitoring features for senior citizens. *Heliyon 10*, 4 (2024), e26308.

[50] Pavithiran, G., Padmanabhan, S., Divya, N., Aswathy, V., Jerusha, I., and Chandar, B. Doctors' handwritten prescription recognition system in multi-language using deep learning. *arXiv preprint arXiv:2210.11666* (2022).

[51] Rahman, B., Rubyat, A., Zaman, M. F. U., Halder, N., Islam, A., and Amin, M. A. Early-stage development of a handwritten prescription interpretation app for bangladeshi citizens. In *Proceedings of the International Conference on Human-Computer Interaction (HCII)* (2025), Springer.

[52] Rahman, M. M., Pranto, S. S. S., Subonty, O. M., and Rahman, M. A. Meddose-a medication management app.

[53] Rajkomar, A., Dean, J., and Kohane, I. Machine learning in medicine. *New England Journal of Medicine 380*, 14 (2019), 1347–1358.

[54] Rajkomar A, Oren E, C. K. e. a. Scalable and accurate deep learning with electronic health records. *npj Digital Med 1*, 1 (2018).

[55] SajuP, J. P., and MangalakadanP, D. K. Pill reminder and prescription digitalization application using php and android. *IJISET-International Journal of Innovative Science, Engineering & Technology 7*, 7 (2020).

[56] Samson, S., Tejaswini, C., Rishikesh, G., Ramu, M., and Ramesh, T. Analysis of scanned medical prescription using machine learning. *International Journal of Innovative Science and Research Technology 9*, 1 (2024), 399–404.

[57] Scheidl, H., Fiel, S., and Sablatnig, R. Word beam search: A connectionist temporal classification decoding algorithm, 2018.

[58] Scheidl, H., Fiel, S., and Sablatnig, R. Word beam search: A connectionist temporal classification decoding algorithm, 2018.

[59] Sultana, F., Rahman, A., Paul, T. R., Sarwar, M. S., Islam, M. A. U., and Rashid, M. Prescribing pattern and prescription errors: a study at a tertiary care hospital of bangladesh. *Bangladesh pharmaceutical journal 18*, 1 (2015), 20–24.

[60] Sultana, F., Rahman, A., Paul, T. R., Sarwar, M. S., Islam, M. A. U., and Rashid, M. Prescribing pattern and prescription errors: a study at a tertiary care hospital of bangladesh. *Bangladesh pharmaceutical journal 18*, 1 (2015), 20–24.

[61] Suwanthara, J., Noinongyao, A., and Vittayakorn, S. Wisemed: Medication reminder for seniors. In *2019 23rd International computer science and engineering conference (ICSEC)* (2019), IEEE, pp. 409–414.

[62] Szalma, J. L. On the application of motivation theory to human factors/ergonomics: Motivational design principles for human–technology interaction. *Human Factors 56*, 8 (2014), 1453–1471. PMID: 25509824.

[63] Tasnim, J., Forhad, S., Nova, S. M., Hasan, K. K., Islam, S. N., Hassan, S. B., Noor, M. A., and Siddique, A. H. Mobile applications in electronic-healthcare: A case study for bangladesh. In *International Conference on Data Science and Network Engineering* (2024), Springer, pp. 339–351.

[64] University, D. I. Merged dataset. `https://universe.roboflow.com/daffodil-international-university-s5vpr/merged-voyoh`, may 2023. visited on 2024-09-30.

[65] Waddell, T. F., Zhang, B., and Sundar, S. S. *Human–Computer Interaction*. John Wiley Sons, Ltd, 2015, pp. 1–9.

[66] Wilson, C. Chapter 5 - pluralistic usability walkthrough. In *User Interface Inspection Methods*, C. Wilson, Ed. Morgan Kaufmann, Boston, 2014, pp. 81–97.

[67] Zaman, M. F. U., Rahman, B., Rubyat, A., Halder, N., Mahmud, A., Islam, A., and Amin, M. A. Recognizing medicine names from bangladeshi handwritten prescription images using trocr. In *Proceedings of the 7th Asia Conference on Cognitive Engineering and Intelligent Interaction (CEII)* (2024).

[68] Zhang, Y., Wang, L., Chen, H., Li, J., and Liu, X. Performance evaluation of a prescription medication image classification model. *Journal of Medical Internet Research 23*, 7 (2021), e26993.