kBot: Knowledge-Enabled Personalized Chatbot for Self-Management of Asthma in Pediatric Population

A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science

by

Dipesh Kadariya
B.E., Visvesvaraya Technological University, 2015

2019
WRIGHT STATE UNIVERSITY

WRIGHT STATE UNIVERSITY
GRADUATE SCHOOL

June 24, 2019

I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY Dipesh Kadariya ENTITLED kBot: Knowledge-Enabled Personalized Chatbot for Self-Management of Asthma in Pediatric Population BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Master of Science.

Amit Sheth, Ph.D.
Thesis Director

Mateen M. Rizki, Ph.D.
Chair, Department of Computer Science and Engineering

Committee on
Final Examination

Amit Sheth, Ph.D.

Krishnaprasad Thirunarayan, Ph.D.

Valerie Shalin, Ph.D.

Maninder Kalra, M.D. Ph.D.

Barry Milligan, Ph.D.
Interim Dean of the Graduate School

ABSTRACT

Kadariya, Dipesh. M.S., Department of Computer Science and Engineering, WRIGHT STATE UNIVERSITY, 2019. *kBot: Knowledge-Enabled Personalized Chatbot for Self-Management of Asthma in Pediatric Population.*

Asthma, chronic pulmonary disease, is one of the major health issues in the United States. Given its chronic nature, the demand for continuous monitoring of patients adherence to the medication care plan, assessment of their environment triggers, and management of asthma control level can be challenging in traditional clinical settings and taxing on clinical professionals. A shift from a reactive to a proactive asthma care can improve health outcomes and reduce expenses. On the technology spectrum, smart conversational systems and Internet-of-Things (IoTs) are rapidly gaining popularity in the healthcare industry. By leveraging such technological prevalence, it is feasible to design a system that is capable of monitoring asthmatic patients for a prolonged period and empowering them to manage their health better. In this thesis, we describe kBot, a knowledge-driven personalized chatbot system designed to continuously track medication adherence of pediatric asthmatic patients (age 8 to 15) and monitor relevant health and environmental data. The outcome is to help asthma patients self manage their asthma progression by generating trigger alerts and educate them with various self-management strategies. kBOT takes the form of an Android application with a frontend chat interface capable of conversing both text and voice-based conversations and a backend cloud-based server application that handles data collection, processing, and dialogue management. The domain knowledge component is pieced together from the Asthma and Allergy Foundation of America, Mayoclinic, and Verywell Health as well as our clinical collaborator. Whereas, the personalization aspect is derived from the patients history of asthma collected from the questionnaires and day-to-day conversations. The system has been evaluated by eight asthma clinicians and eight computer science researchers for chatbot quality, technology acceptance, and system usability. kBOT achieved an overall technology acceptance score of greater than 8 on an

11-point Likert scale and a mean System Usability Score (SUS) greater than 80 from both evaluation groups.

Contents

1 Introduction **1**
- 1.1 Background 1
- 1.2 Challenges 3
- 1.3 Outline of thesis 5

2 Related Work **6**
- 2.1 Chatbot Background 6
- 2.2 Chatbot in Healthcare 7

3 Implementation **10**
- 3.1 Client 11
  - 3.1.1 Technology 11
  - 3.1.2 Mode of Interaction 13
  - 3.1.3 UI/UX design 14
- 3.2 Server 15
  - 3.2.1 Technology 15
  - 3.2.2 Service layer 16
  - 3.2.3 Cloud Storage 20

4 Approaches **22**
- 4.1 Creating Better Conversations with Contextualization and Personalization . 22
  - 4.1.1 Contextualization with Knowledge Base 23
  - 4.1.2 Dialogue Processing, Context and User Intent Analysis 25
  - 4.1.3 Personalization in Response Generation 26
- 4.2 Ensuring Asthma Self-Management 28
  - 4.2.1 Monitor Patients Asthmatic Condition 28
  - 4.2.2 Encouraging Medical Adherence 30
  - 4.2.3 Alert Potential Environmental Triggers 30
  - 4.2.4 Educate Patients on Asthma Self-Management Skills 32

5 Evaluation **34**
- 5.1 Evaluation Metrics 34

5.2 Evaluation Method 36
5.3 Result 37
5.3.1 Technology Acceptance and Chatbot Quality 37
5.3.2 System Usability 39

6 Conclusion **41**

7 Future Work **42**

Bibliography **44**

List of Figures

1.1 Factors triggering asthma symptoms 1
1.2 Various IoT devices and data sources as part of kHealth system. 2

3.1 **System architecture and workflow of kBot:** The pipeline starts with the patient conversing with the front-end Android application (client) and data being propagated to the backend server that manages the dialogues. A client communicates with the server through an SSL encrypted socket layer. Patient data captured from the conversation is stored in Elasticsearch, a NoSQL database, in JSON format. A service layer in the server facilitates clients with services like notification, email, data storage, and weather reports. kBot separately stores raw conversation logs with each user in a file for human review. 10
3.2 Screenshots of kBot android client application 12
3.3 Components of kBot communication interface 14
3.4 kBot server application layering 15
3.5 visual representation of web-socket connection sequence 16
3.6 work flow diagram of kBot from reminder setup to push notification 18
3.7 Overview of elasticsearch document indexing process 20

4.1 Contextualized and Personalized Conversation 22
4.2 Use of domain knowledge to generate contextually relevant response 24
4.3 Use of rich media contents to educate patients 24
4.4 Data extraction in Dialog Flow 25
4.5 Environmental data collection based on zip codes using third party weather APIs. 31
4.6 Summarizing patients past health data 33

5.1 Mean score and standard deviation for each evaluation metric of kBot (Higher mean score is better). 38
5.2 t-test with the p-value for technology acceptance comparing responses from two distinct groups 38
5.3 kBot mean System Usability scores from clinicians and researchers 39

List of Tables

4.1 List of questions used by kBot in different time of the day to collect asthma related information from the patient. The texts in [] are replaced with the values specific to the patients. 29
4.2 Frequencies in which various outdoor data are collected 31

5.1 kBot Evaluation Metrics 35
5.2 Demographic and Technological familiarity questions 36

Acknowledgment

My journey as a graduate student at Kno.e.sis center, wright state university marked a turning point in my career. I would like to take this opportunity to acknowledge such people without whose support this journey would not have been possible.

First of all, I would like to express my sincere thanks to my advisor Prof. Amit Sheth for his support and guidance. The confidence and belief he had on me forced me to believe in myself. The ecosystem he created helped me to develop my technical as well as social skills, which I believe to be useful not only in my professional career but throughout my life.

I would like to thank the rest of my thesis committee members: Prof. T.K. Prasad, Prof. Valerie Shalin, and Dr. Maninder Kalra. The in-depth comments and discussion from Dr. Prasad helped me solve numerous research problems I faced in this thesis work. The valuable insights from Dr. Shalin as a cognitive scientist enabled me to look at this research problem from a different perspective. I got a chance to have multiple meetings and discussions with Dr. Kalra through which I could address various domain-specific challenges. My sincere thanks to my collaborator Revathy Venkatramanan for all the thoughtful conversations and insights into this work. I am grateful to my fierce friend, Vaikunth Sridharan, for his guidance and encouragement. I would also like to thank Dr. Shreyansh Bhatt for his advice in this research work and Kirill kultinov for his technical help.

I couldn't think of a graduate life without the support of my family. I am thankful to my parents for all their tireless effort and sacrifices. Their continued faith and belief encouraged me never to give up. Thanks to my wife, Sima for understanding me and being so supportive throughout this journey. Thanks to my younger sister, Diksha, for her love and blessings.

Finally, I would like to thank the funding source. This work is partially supported by National Institutes of Health (NICHD/NIH) under the Grant Number: 1R01HD087132. The content of this thesis work is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

Dedicated to

my Grandparents Bal Ram and Sita

and

my parents Ek Raj and Nirmala.

Introduction

1.1 Background

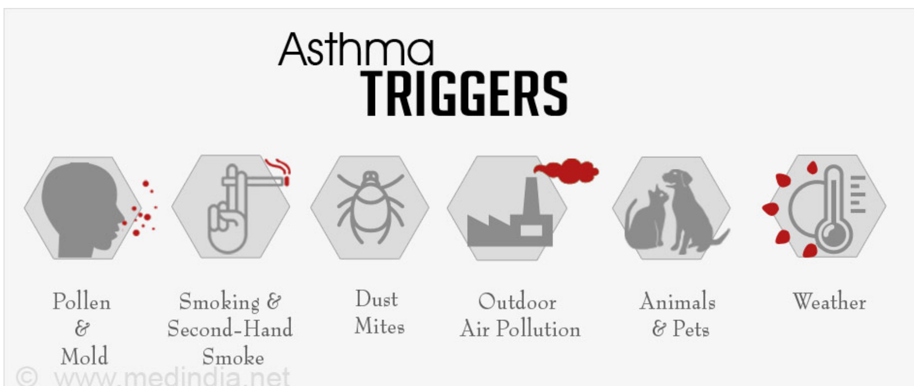


Figure 1.1: Factors triggering asthma symptoms
https://www.medindia.net/patients/patientinfo/asthma_factors.htm

Asthma is a lung inflammatory disease that has prevailed more than 26 million people in the United States, out of which 6.1 million are children [5]. It is the most chronic condition among the pediatric population[11] accounting for 13.8 million missed school days each year [4]. Though incurable, asthma can be controlled and managed by strict adherence to a medication care plan and by avoiding the triggers [1]. However, due to a lack of consistent adherence to the asthma care plan, and inadequate information about the patients environment, asthma management can be challenging [18]. These issues are further compounded by its multifactorial nature, where every patient is sensitive to different triggers, and react differently even when exposed to the same trigger [24]. This demands personalized care beyond the regular hospital setup to which the clinical professionals are limited. The advent of digital health monitoring technologies such as smart wearables and increasing adoption of mobile devices and low-cost sensors translate to an unprecedented amount of data being generated and collected from the users. With such technologies, It is now possible to monitor long-term medication adherence, exposure to environmental triggers, and asthma control level of patients in real-time[21]. By leveraging such technology prevalence, our NIH funded kHealth Asthma project involves an ongoing pilot study that is in collaboration with Dayton Childrens Hospital (DCH), approved by the DCH Institutional Review Board (IRB) with a targeted cohort size of 200 (120 deployments already consented) asthmatic children between 5 and 17 years.

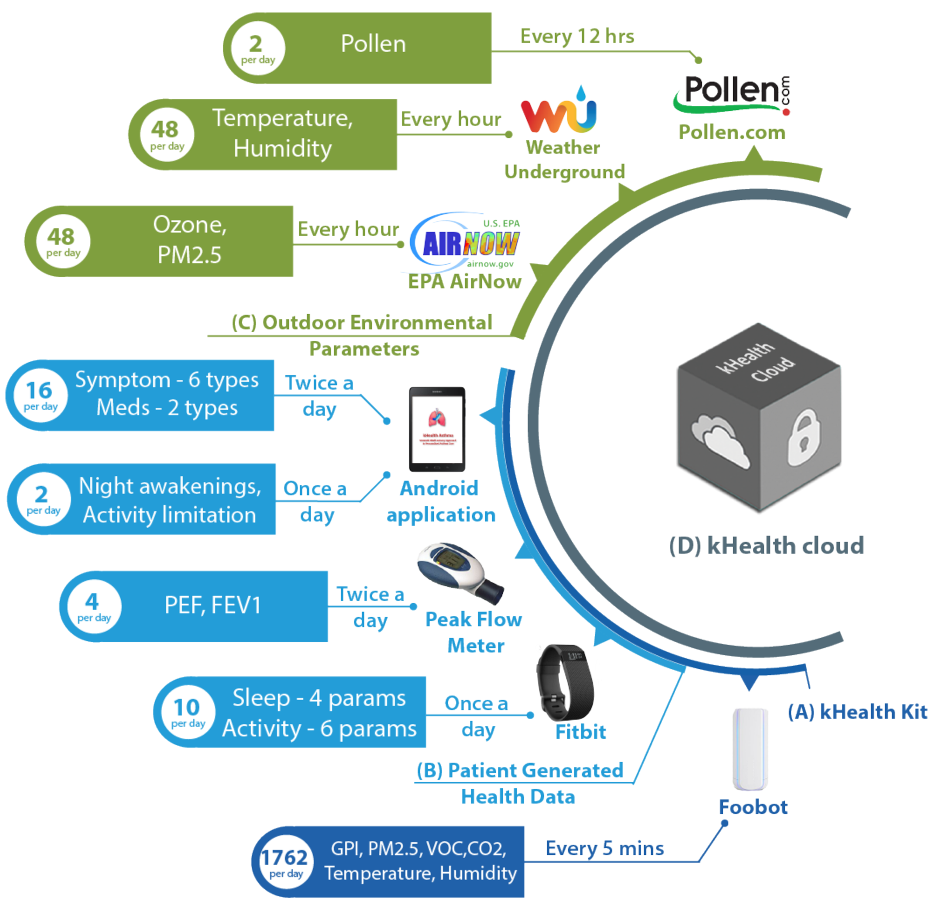


Figure 1.2: Various IoT devices and data sources as part of kHealth system.

kHealth Asthma is a digital framework that personalizes the long-term assessment and management of asthma in children [2]. It consists of a kit given to each consented patient. The kit comprises of a mobile health application with a broad range of low-cost wearable and sensors (Fitbit for sleep measurement, Foobot for indoor air quality monitoring, and peak flow meter for measuring lung function) (refer to Figure 1.2). The kit is deployed for one or three months period with each consented patient. We have achieved a compliance rate of 63% so far across 107 completed deployments. These health data signals, along with anonymized data extracted from respective Electronic Medical Records (EMRs), and publicly available outdoor environmental data are then aggregated, analyzed, and transformed into actionable information. The goal is to help clinicians make better and more timely decisions that eventually lead to an overall improved asthma-related outcome. Our findings involving clinical collaboration have revealed that continuous monitoring of asthmatic patients in their everyday life can indeed give more useful insights into their asthma health as opposed to episodic clinic visits. Patients with poor medication compliance reflected poor asthma control [14], and different patients reacted to different environmental triggers with varying intensity [26]. Our results were in concordance to existing studies which have concluded that medication nonadherence continues to be a frequent problem among asthma patients [23]. Nonadherence could be attributed to factors such as forgetfulness, laziness or carelessness, inadequate training in the inhalation techniques, and lack of understanding about the need for controller medicine [13]. Such issues, along with the assessment of environmental triggers and asthma control could benefit from a lighter-weight, more interactive, and knowledge-driven conversational approach [30].

1.2 Challenges

- Continuous monitoring of the patients asthmatic condition requires their active involvement in the process. However, due to the static user interface of current monitoring systems, poor patients compliance badly affects the quality and quantity of data collection.

- In asthma care, the effectiveness of treatment is affected not only by patient compliance but also by the inhalers usage techniques. If asthma inhalers are not used in a proper way, it has no effect on patients asthmatic condition which may lead to worsening of asthma.

- Asthma is a multifactorial disease; each patient reacts to both triggers and treatment differently. A general treatment approach such as a generic asthma care plan proves to be ineffective in such a scenario. A more personalized approach to monitor patients and their environmental factors are required.

Recent years have seen immense maturity in Artificial Intelligence (AI) research which has in part proliferated the growth of intelligent conversational systems, also known as chatbots. They are increasingly popular due to their capability of simulating human-like conversations with a user through speech, text, smart display, and multimodal communication [1]. Contrary to static applications, it can understand user intents and choices through interactions and communicate accordingly. An exciting trend is that chatbot-assisted queries are 200 times more conversational than search, and users are demanding more human-style interaction [19]. Such technology is rapidly gaining traction in the healthcare domain where professional care is limited [2]. It is evident that current long-term healthcare monitoring demands a more ubiquitous solution. Chatbots are capable of delivering a more convenient and accessible approach through cost-effective mediums. Nonetheless, they are limited in their inherent ability to contextualize, learn interactively, and provide the proper hyper-personalization needed to hold a meaningful conversation.

By leveraging such technology and considering the challenges mentioned earlier, we introduce a knowledge-enabled personalized chatbot system kBot, that is intended to re-

[1] https://bit.ly/forbes-chatbot
[2] https://bit.ly/modern-healthcare

place our use of the mobile app in the kHealth Framework. It is capable of interacting with a patient through a contextualized and personalized manner on hand-held devices (mobile phones and tablets), or as part of smart displays (e.g., Google Home Hub). It curates and contextualizes its asthma domain knowledge from different online sources such as Asthma and Allergy Foundation of America (AAFA) [3], verywell health [4], Mayo clinic [5], and webMD [6] as well as local inputs from our clinical collaborators. It then aggregates this knowledge with patients data such as symptoms and medication intake to deliver a personalized conversation experience. The first version of kBot reported here takes on a design approach that centers around addressing medication nonadherence issue in pediatric asthma management and assessing environmental triggers at an individual level. The ultimate goal is to bridge and simplify long-term real-time monitoring of asthma condition, alert on potential environmental triggers, and educate the patients on various asthma self-management skills. Our current implementation is limited to the Android ecosystem but can be easily adapted to iOS.

1.3 Outline of thesis

The rest of the document is structured as follows. We first discuss related work with some history of chatbot technology in Section 2. In Section 3 we discuss system architecture and implementation process where server client implementation of kBot is described in detail. The following Section 4, presents the various approaches used to achieve functionalities and overall goal of kBot. In Section 5, we present the preliminary evaluation results for technology acceptance and usability of kBot within domain expert and non-domain expert group. Lastly, we discuss our findings and plans for future work in Sections 6 and 7 respectively.

[3] https://www.aafa.org/asthma
[4] https://www.verywellhealth.com/asthma-4014760
[5] https://www.mayoclinic.org/
[6] https://www.webmd.com/asthma/default.htm

Related Work

2.1 Chatbot Background

Chatbots are computer programs that interact with users through natural language trying to mimic human conversation. Various terms have been used for a chatbot such as conversational agent, virtual assistant, chatterbot and dialog system. Chatbot history begins with Weizenbaum's ELIZA[28] from 1966, a chatbot system representing a mock psychotherapist. It is a rule-based system that uses simple keyword matching techniques to drive its conversation. User input (text) is inspected for matching keywords or phrases. If a keyword is found, the corresponding pre-programmed sentence from its rule-based mapping is returned as response conducting an apparently meaningful conversation e.g if input with word MOTHER is encountered, it is replied with TELL ME MORE ABOUT YOUR FAMILY. If no matching keyword is found, it uses canned responses such as "Please go on." and "Tell me more about that." that is intended to maintain the conversation flow.

PARRY [6] is another noteworthy example of an early chatbot system written by Kenneth Colby in 1972 at Stanford University. It is considered as a much more serious, and advanced form of ELIZA and sometimes referred to as ELIZA with attitude. Unlike ELIZA, PARRY tries to simulate a person with paranoid schizophrenia during an interview with the therapist. It implements a crude model of the behavior of a person with paranoid schizophrenia such as assumptions, attributions, and emotional responses. The transcripts of conversations with PARRY along with the transcripts with real patients are shown to 33 psychiatrists and asked to distinguish among two. They could identify correctly only 44% of the time. This made PARRY the first machine to pass a version of the Turing Test.

While both ELIZA and PARRY uses keyword based pre-programmed dialogs to make an illusion of meaningful conversation, Wallace introduced A.L.I.C.E (Artificial Linguistic Internet Computer Entity) [27] in 2003 that uses heuristic pattern matching approach to find patterns in user input and give corresponding output. These heuristic conversation rules are written using AIML (Artificial Intelligence Markup Language). AIML is an XML based markup language to represent dialog input/output patterns for natural language software agents. *<category>* is the basic units of AIML that represents a knowledge unit. Each category has *<pattern>* representing what user may input and *<template>* representing the corresponding output string. Many chatbots came into existence with better approaches and advanced technologies such as machine learning, enabling them to conduct more natural and human-like conversations.

Today, with the advancement in machine learning and AI techniques, we can find much-advanced chatbot systems intervening in various sectors such as business, education, e-commerce, entertainment, and healthcare. Chatbots are not limited to the text-based conversation anymore; they can produce speech synthesis and converse with users through voice. Some notable examples include IBMs WATSON[1], SIRI[2], GOOGLE ASSISTANT[3] and ALEXA[4]. These conversational agents are generic purpose agents that assist users to perform their daily activities and provide information based on user request.

2.2 Chatbot in Healthcare

Numerous chatbot applications have been developed to address issues of healthcare management such as health monitoring, medication tracking, health alerting, and managing

[1] https://www.ibm.com/watson
[2] https://www.apple.com/siri/
[3] https://assistant.google.com
[4] https://developer.amazon.com/alexa

chronic diseases. However, all of these chatbots are built to address these issues in isolation. There are chatbot technologies that encourage users to improved quality of life. Fadhil et al. [10] designed a chatbot system that uses behavior change intervention approach to achieve a healthy lifestyle. This chatbot intends to encourage adult population towards healthy eating habits to prevent weight gain. It regularly interacts with patients to collect data related to their diet, helps them to track their food habits and exercise, and provides healthy recommendations at the time of making food choices.

Your.MD [5] is an example of health assistants that provide online health counseling. Users can ask questions related to their health, any illness or any symptoms they are worried about to these chatbots. Relevant information is then provided based on user profile and the reported symptoms. In addition, they also help users to find online doctors or local specialist for their health issues.

Similarly, some chatbots focus on streamlining and simplifying the existing healthcare system. MANDY [16] is a primary care chatbot that assists healthcare staff by automating the patient intake process. It has a mobile app as frontend using which it converses with patients in hospital intake queue collecting their chief health complaints and submits it to doctors. It also provides an interface for doctors to access and analyze the patient's records. In the background, it has its analyzer engine to understand patients symptoms from the conversation text and a symptom-to-cause mapper to derive potential causes of user symptom.

Other forms of healthcare chatbots are available on various popular messaging platforms, such as Facebook messenger and Slack, and work to help patients to adhere to their regular care plan and better manage their health. FLORENCE[6] Bot is an example of a Facebook messenger bot that reminds patients to regularly take their medication or birth control pills and provides information related to their medicine. It also helps to tracks users health factors like body weights and encourages them to follow their health regimen. As

[5] https://www.your.md/
[6] https://florence.chat/

an additional feature, FLORENCE can help users to find the location of the closest doctor or pharmacy upon request. Similarly, SMOKEY[7], another healthcare chatbot in Facebook messenger bot platform, alerts patients about air pollution. It provides air quality data of the city to the users like normal weather data. Users get real-time alerts from SMOKEY which helps them to make decisions like when and how to avoid air pollution in their environment.

While contemporary chatbots focus on solving individual issues of healthcare, our holistic approach to managing chronic and multifactorial asthma seeks to address its self-management issues by addressing various aspects of patient health such as monitoring, medical adherence, environmental alert and asthma management education. kBot, as a multi-functionality personal assistant, distinguishes itself by offering a personalized approach to track patients' health and their medication intake, remind and encourage them towards medication adherence, alert them about presence of personalized asthma triggers in their environment, and collectively help them self-manage their asthma to achieve an overall improved health outcomes.

[7] https://botlist.co/bots/smokey

Implementation

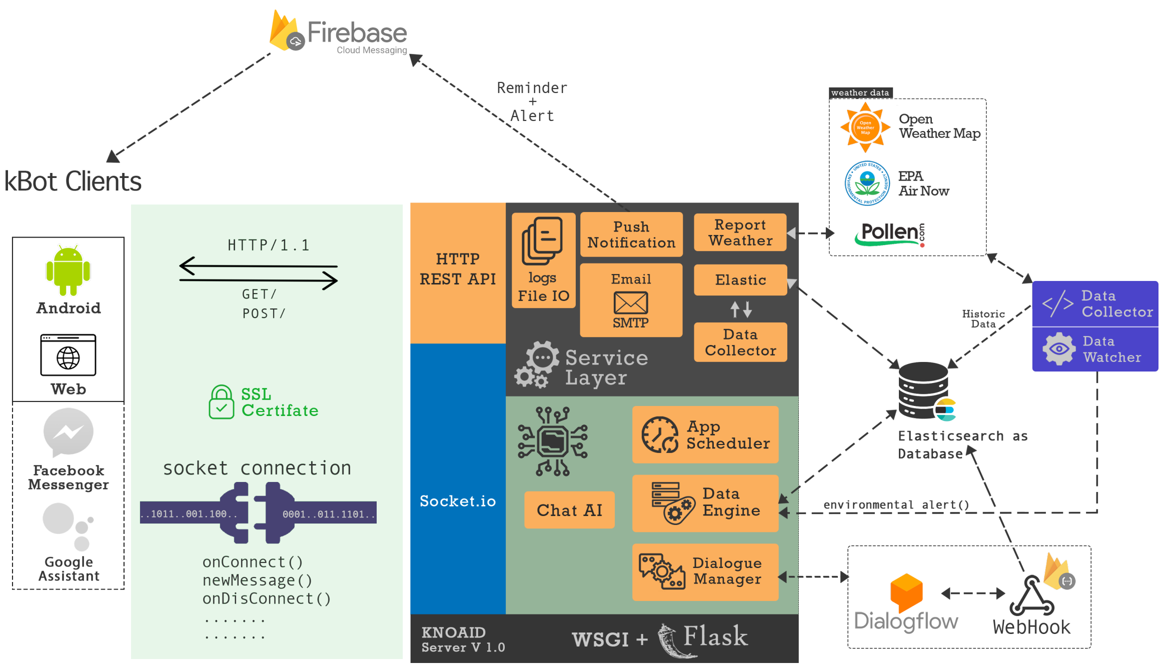


Figure 3.1: **System architecture and workflow of kBot:** The pipeline starts with the patient conversing with the front-end Android application (client) and data being propagated to the backend server that manages the dialogues. A client communicates with the server through an SSL encrypted socket layer. Patient data captured from the conversation is stored in Elasticsearch, a NoSQL database, in JSON format. A service layer in the server facilitates clients with services like notification, email, data storage, and weather reports. kBot separately stores raw conversation logs with each user in a file for human review.

kBot follows a client-server architecture (Figure 3.1) where the client is a lightweight frontend chat interface, and the backend server is a standalone web application hosted in the cloud. Users could interact with kBot through the client application in both modes of communication: text and voice. A unique CHAT ID is assigned to each user profile during the initial user profile setup which works as a primary ID to identify the user. This ID is generated in client app using the MD5 hashing algorithm that takes a string of any length as input and encodes it into 128-bit fingerprint as hash output. It is used by the client to authenticate the communication request with the server and maintain the user session.

The client communicates with patients at least twice a day and logs all the patient-specific conversation history in the server. JSON [1], a lightweight data-interchange format, is used for client-server mode of communication. The data of interest (refer to section 3.2.2) are then extracted from the conversation logs in the server. Concurrently, the server continuously monitors and collects environmental data, at different frequencies, through third-party weather Application Programming Interface (API) for the zipcodes specific to each patient (more on section 4.2.3).

3.1 Client

3.1.1 Technology

kBot clients are Google Android chat applications. We choose the Android platform for its widespread popularity and availability on a wide range of devices and operating systems. Clients are lightweight applications serving as a frontend chat interface. A client acts as an instance of kBot server that converses with patients and sends raw user inputs back to the server. All the computational and data processing tasks including the dialog generation are server-centric, and clients receive and display the finalized and polished response from the server. This data exchange between client and server takes place seamlessly in real time using the web sockets as the communication protocol.

Activities are a fundamental part of the Android application model [2]. Each activity

[1] https://www.json.org/

[2] https://developer.android.com/guide/components/activities/intro-activities

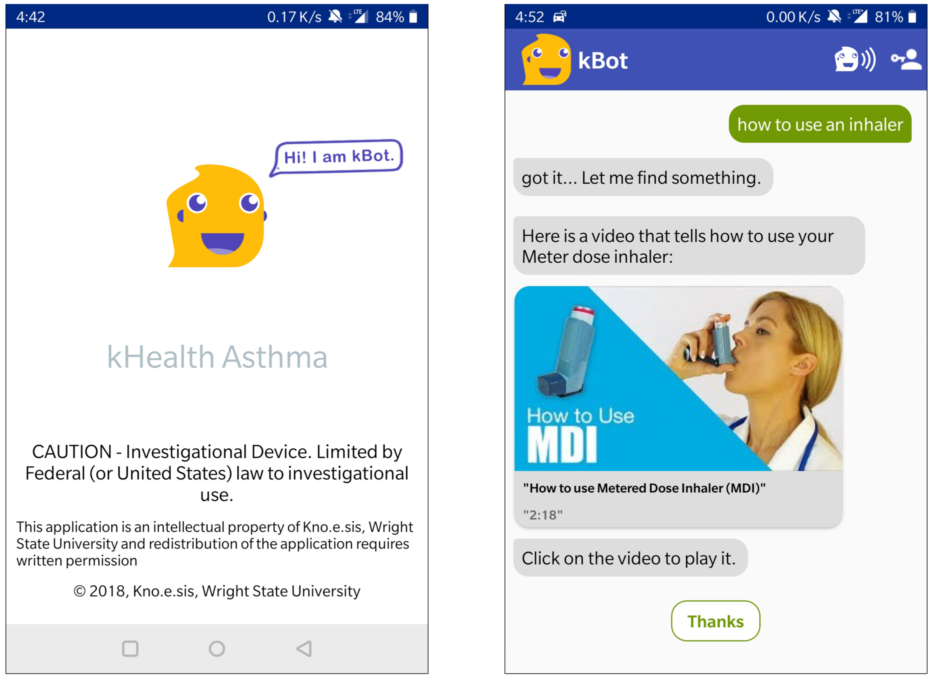


Figure 3.2: Screenshots of kBot android client application

represents a window on top of which application can draw its UI. Kbot application contains multiple such activities which collectively makes a chat application. Among all such activities, the ”chatroom” activity serves as main activity providing a chatroom interface for patients to converse with kBot. This activity supports text as well as rich media contents like images, videos, and hyperlinks. kBot uses these media contents for audiovisual communication and to disseminate asthma-related information. When active, this activity constantly checks the connectivity with kBot server. If the connection is broken, all the chat features are disabled and the user is requested to re-establish the connection in order to continue. Another activity named ”admin_session” provides an admin section (requires login credential) in the client application that allows clinicians to perform patient management activities like initialize patient profile, set up the active user, and delete the user profile. Since all the user data are stored in the server side cloud storage (refer section 3.2.3), new patients profile or any updated data are submitted to the server through HTTP POST request at the end of the activity.

3.1.2 Mode of Interaction

kBot supports both text and voice-based interaction between the user and the client. Voice is the primary mode of interaction with the kBot. Users can long tap anywhere in the chat window to record their voice. This voice input is then converted to textual data by the application using Android SpeechRecognizer service[3] prior to sending it to the server. A textbox with typing feature is also available in the bottom of the chat window as a secondary mode of input. Text input option simplifies the user input process in scenarios where the speech-to-text engine fails to understand the voice due to factors such as noise in the environment or users non-native accent.

Additionally, Kbot provides quick reply options which are a button list of possible responses allowing users to respond quickly with a single tap. These quick reply option appears with their relevant dialog and disappears as soon as they are clicked, or user replies using any mode of input. Quick replies give a hint to the user about how to reply to kBot and facilitate the flow of the conversation.

The kBot server processes only textual data and responds with the same to the clients. This textual response from the server is presented in both textual and voice form to the user. The text form of response appears in the chat window as a text bubble with the timestamp representing the time of response. For voice response, a Google Cloud Text-To-Speech (TTS) API[4] is leveraged to generate the speech output in a natural-sounding human utterance. The textual data is sent to Google Cloud TTS API as an HTTP POST request using OkHttp client[5]. A synthesized audio content is received as the response which is played as a voice response to the user. The voice-enabled conversation might not be preferable in all patients scenarios, where they might want only the textual mode of interaction. To facilitate such user need a toggle button is provided in the top right corner

[3] https://bit.ly/speechRecognizer
[4] https://cloud.google.com/text-to-speech/
[5] https://square.github.io/okhttp/

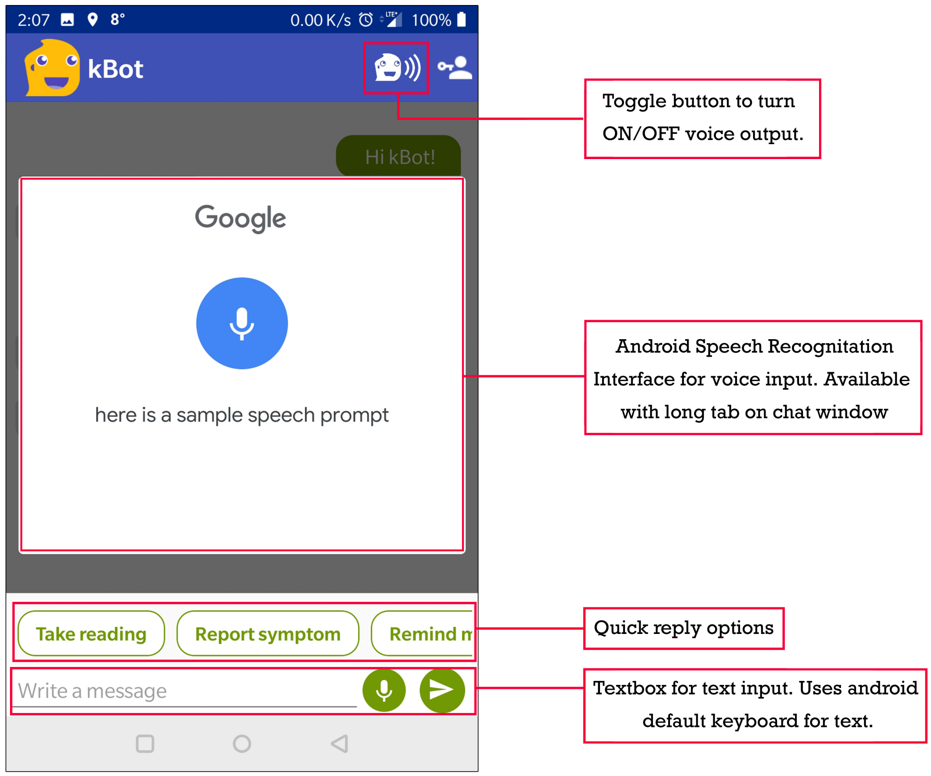


Figure 3.3: Components of kBot communication interface

of the chat window (figure 3.3) that allows users to turn on and off the voice output feature.

3.1.3 UI/UX design

Aside from its system functionality and usability, we recognize the vital role user experience plays in the success of a chatbot application. Hence, kBot user interface is designed according to the best practices laid by chatbot UI/UX guidelines[6] to deliver a rich and seamless user experience. Additionally, kBot client application is iteratively tested against standard (simulated) test case scenarios[7] to identify and eliminate any bugs or idiosyncratic interactions that may arise in real patient scenarios.

[6]https://uxofchatbots.com/
[7]https://bit.ly/appTestCase

3.2 Server

3.2.1 Technology

On the server side, kBot has a standalone Python web application instantiating and serving multiple kBot clients. Flask[8], a micro web framework, is used to build the web application. This web application is wrapped around with Eventlet server and a Web Server Gateway Interface (WSGI)[9] middleware layer. The middleware allows the kBot to be a scalable system by handling multiple client requests concurrently and addressing network overhead issues such as load balancing.

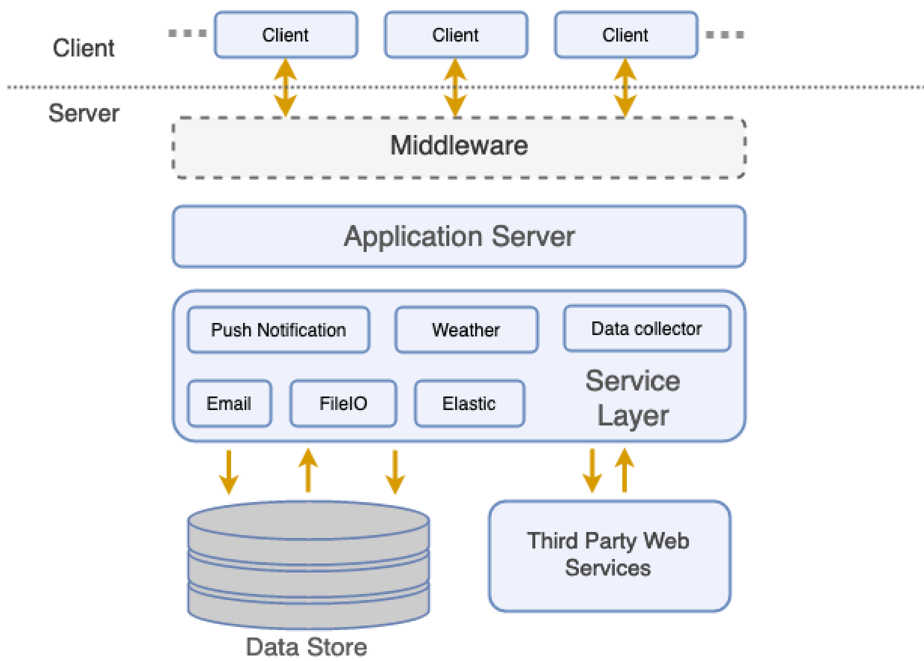


Figure 3.4: kBot server application layering

The server connects with clients through a standard web-socket which enables real-time data exchange. Web-Socket is a standard communication protocol that offers a full-duplex communication channel over a single TCP connection[10]. Once the socket con-

[8] http://flask.pocoo.org/
[9] http://eventlet.net/doc/modules/wsgi.html
[10] https://en.wikipedia.org/wiki/WebSocket

nection is established between the server and the client, it provides a persistent connection channel unless the connection is closed from one end (server or client). kBot server also offers HTTP POST or GET methods for other essential operations like Create, Read, Update, and Delete (C-R-U-D) on patient profiles, that requires a minimal connection overhead. A secure HTTPS connection is established between the server and client using SSL certificates for encrypted data exchange. The server application including the data store is hosted in a secure cloud in our Kno.e.sis private server.

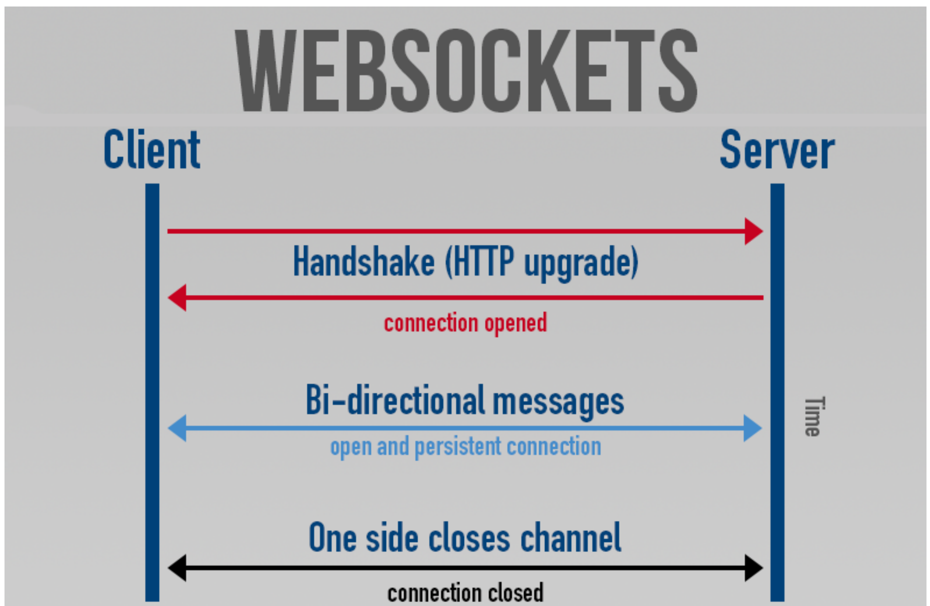


Figure 3.5: visual representation of web-socket connection sequence
https://www.pubnub.com/websockets/

3.2.2 Service layer

A service layer defined internally to the server provides services such as database operations, push notification, data collection, email alerts, weather report, and file logs. These services are defined as python modules and are callable in any part of the server by simply importing it like other standard python modules. Some of these services are discussed in detail in the following sections:

Elastic

This service is used by kBot server to connect with kBot cloud storage (discussed in detail in section 3.2.3) and handle database operations. It has a list of user-defined functions to handle various database operations such as create or delete an index, create or delete a user, get/put user-specific asthma data, get/put environmental data, and many more. It uses Elasticsearch, a python library, as a client to establish a connection with the database. This library provides a convenient and idiomatic way to write and manipulate Elasticsearch queries[11].

Push Notification

This service allows kBot server to send out notifications to the clients. It uses Firebase cloud messaging (FCM)[12], a Google platform replacing Google cloud messaging, to send notifications to the Android clients. Each client instance is registered with FCM and assigned a unique token during the initial setup. This token is stored in the user profile by the server and used every time to send a client-specific notification. FCM auto updates this token and notifies the kBot server if the client application is re-installed or reset. The notification could be broadcast (that goes to all clients at once) or specific to a particular user depending on the type of notification. Notifications are primarily of three types: Daily reading reminder, Medication reminder, and Environmental alert. Daily reading reminder are the broadcast notification that goes out to all users two times a day, one in the morning and one in the evening. This notification is pre-scheduled for a specific time and is intended to remind patients to provide their daily asthma log.

Medication reminders are notifications that go out to a specific user at a time. The purpose of this reminder is to remind users to take their daily medication on time. Users can choose a specific time when they want to be reminded of the medication through the

[11] https://pypi.org/project/elasticsearch/
[12] https://firebase.google.com/docs/cloud-messaging/

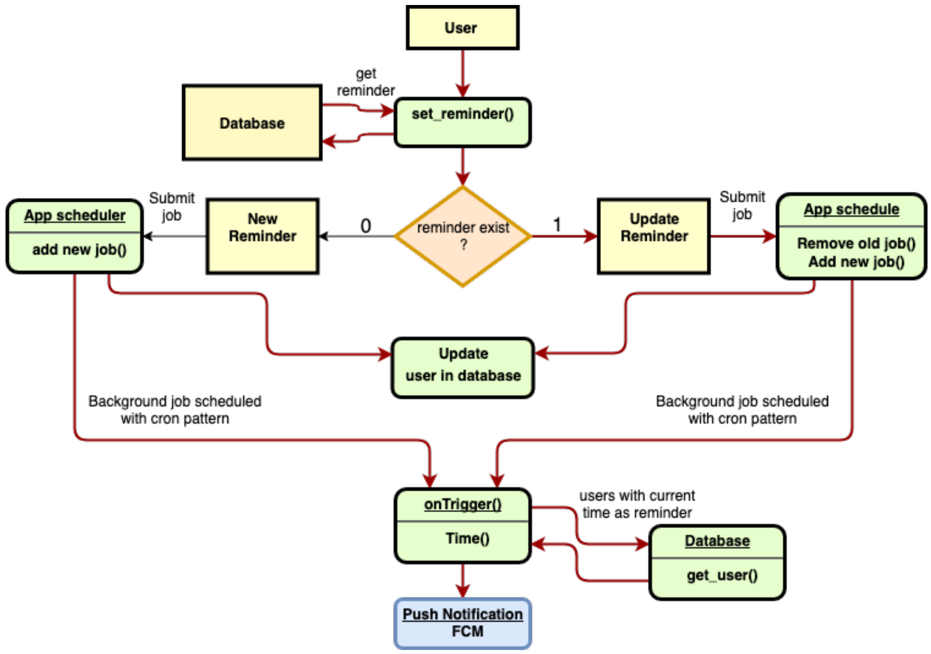


Figure 3.6: work flow diagram of kBot from reminder setup to push notification

conversation. A notification is scheduled to go out in this user chosen time using the user-specific token. This scheduling task of the notification is handled by the Advanced Python Scheduler (APScheduler)[13], a python library that lets python code to run on a later time. APScheduler provides three built-in scheduling systems(Cron-style, Interval-based and One-off delayed) out of which, Cron-based scheduling is used by kBot. Cron-based scheduling system allows to run jobs on a specific time, date and intervals e.g. *execute a job in the fifteenth minute of every hour of the day, or every 5 am and 5 pm on weekdays.*

The third type of notification is the environmental alert. This notification is pushed to the specific user as an alert of their environmental conditions. A script (not part of this service) continuously collects and monitors the environmental data of each patient. These environmental data are collected from third-party weather APIs such as open weather map[14], pollen.com[15], and EPA AirNow[16]. When specific triggers (refer section 4.2.3) in the

[13]https://apscheduler.readthedocs.io/en/latest/
[14]https://openweathermap.org/
[15]https://www.pollen.com/
[16]https://airnow.gov/

patient's environment exceeds the threshold value[17,18], the script makes an HTTP POST request to the kBot server with the trigger type, its value, and the zip code. All the patients within this zip code are then sorted out and alerted by the push notification service.

Weather

This service is used by kBot to provide weather report upon user request. A user could ask about the current weather condition thought the conversation. When a request is detected, the server makes a call to weather service which aggregates the current weather data from OpenWeatherMap[19] and returns a weather report. Along with the weather, environmental triggers are also checked for any value in the unhealthy range. If these unhealthy triggers are on the list of potential triggers (discussed in the next section) of the requesting patients, an alert is sent along with the weather report to be cautious and avoid any outdoor activity.

Data collector

The data of our interest lies within the conversation kBot has with the user. The job of this service is to capture such data of our interest and write it into the data store. This data collector service works in coordination with the dialog flow (discussed in section 4.1.2) to capture the data from the dialog. Dialog flow has predefined entities that help to tag the general concepts such as date, time, numeric value and location. Besides, A custom list of asthma entities is preconfigured in the dialog flow to identify asthma concepts such as symptoms, medication and activity limitations that helps to tag these concepts in the dialog. This tags in the dialogues are used by the data collector service to capture the data. These captured data are classified and inserted into different structured buckets based on their timestamp. These buckets represent the patient's asthma reading from the different time of the day such as "night_reading", "day_reading", and "current_reading". Once these

[17] https://www.pollen.com/help/faq
[18] http://bit.ly/aqi-basics
[19] https://openweathermap.org/

buckets are complete, they are flushed to the data store in the user-specific index using the Elastic service.

3.2.3 Cloud Storage

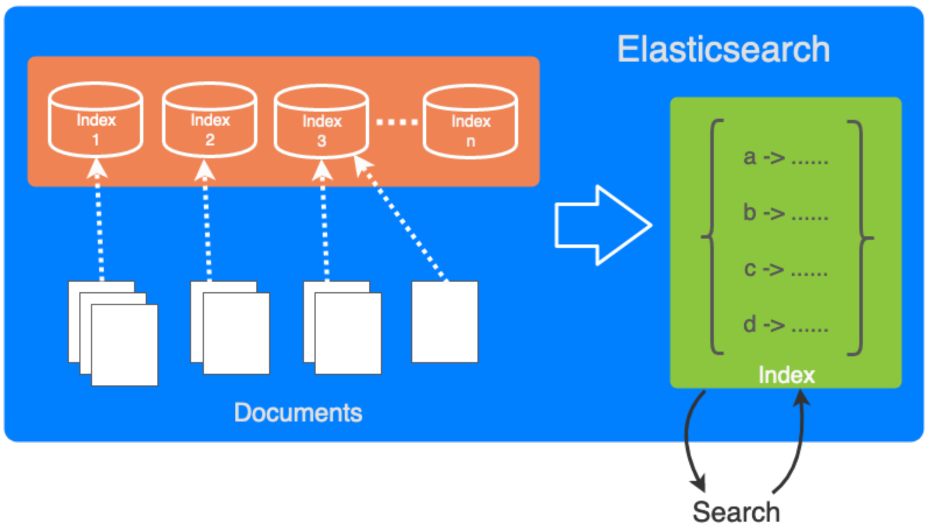


Figure 3.7: Overview of elasticsearch document indexing process

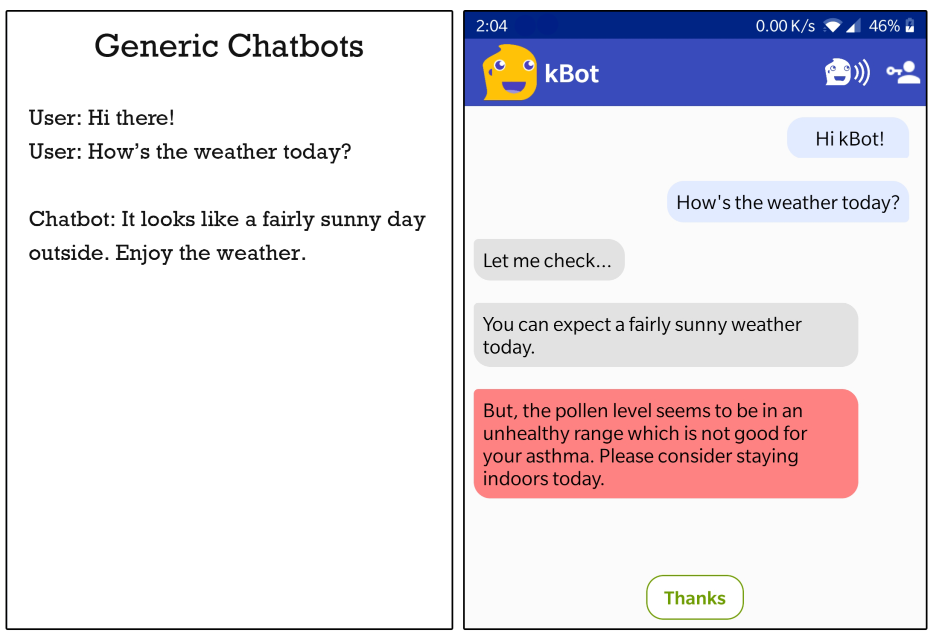
kBot has Elasticsearch[20], a search engine based on Lucene library with a NoSQL datastore, as its cloud storage. Elasticsearch provides a full-text search engine with an HTTP web interface. Contrary to traditional SQL databases, data in Elasticsearch are stored in the form of JSON documents that are individually indexed in order to facilitate fast and scalable index based search engine. This fast search capability allows kBot to use the stored data to generate dynamic and personalized responses seamlessly. Multiple indices are defined, similar to the table in RDBMS, to store different types of data such as user profile, user asthma logs, reminder schedules, notification details, and environmental data. Indices with asthma data and environmental data are static with no change in its data once written; they are only accessed. However, data in indices related to notification, reminder and user profile are updated continuously to represent states of the patient. Different states of

[20]https://www.elastic.co/products/elasticsearch

patients could be First-time patient, Returning patient, Notification pending for the patient, Schedule of the reminder, FCM token, Best PEF reading of the patient or Asthma zone of the patient.

Approaches

4.1 Creating Better Conversations with Contextualization and Personalization



(a) (b)

Figure 4.1: Contextualized and Personalized Conversation

Contextualization refers to data interpretation in terms of domain knowledge, in this case, the asthma context. It determines the data type and value, and then situates it in relation to other domain concepts, thus developing a meaningful interpretation of results. Whereas, personalization in the asthma context refers to the determination of a treatment plan based on the severity of the disease, the prevalence of triggers, and vulnerabilities based on the use of past and current health data. Together, they create better conversations that are meaningful and relevant to the patient which are essential to captivate long-term interest in kBot. For brevity, we describe an instance of kBot conversation (Figure 4.1) that demonstrates the value of contextualized and personalized knowledge in the chatbot conversation.

A conversation without contextualization and personalization provides a response to the user question like a question answering system. While in kBot, it warns about high pollen as a potential trigger (contextualization) to patients asthma in addition to answering the question (personalized response). kBot uses its past knowledge on the patient to identify pollen as a trigger, checks the pollen level in the patients environment, and warns the user if pollen is in harmful range (more on Section 4.2.3).

4.1.1 Contextualization with Knowledge Base

Asthma knowledge is manually extracted from different online sources such as Asthma and Allergy Foundation of America (AAFA)[1], Verywell health[2], Mayo clinic[3], and webMD[4] as well as inputs from our clinical pulmonologist. This information is curated to best represent the domain knowledge (context) and stored in kBot cloud server as a knowledge base in the form of NoSQL database as well as preloaded to DialogFlow as entities (more on Section 4.1.2). Patients can, therefore, ask kBot on asthma-relevant questions to learn more about asthma zones[17], symptoms, various triggers, medications (their usage and side-effects),

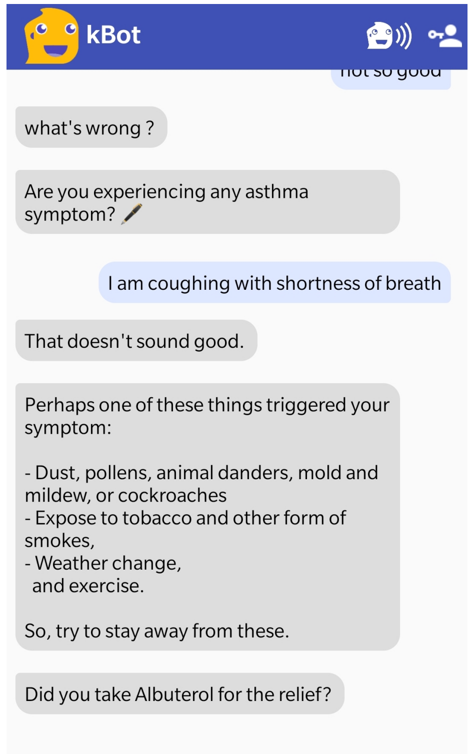


Figure 4.2: Use of domain knowledge to generate contextually relevant response

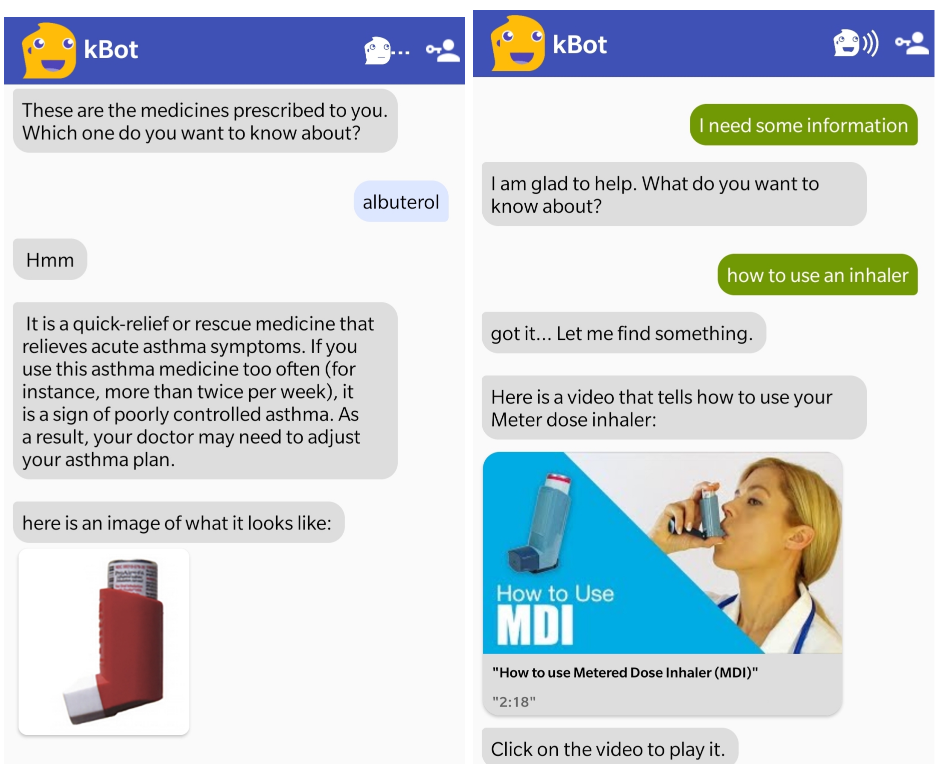


Figure 4.3: Use of rich media contents to educate patients

and self-management skills (Figure 4.2).

Apart from asthma domain knowledge, kBot uses rich media contents such as images and videos to deliver and present information more effectively (Figure 4.3). Images of different asthma medicines and inhalers are used to help patients to quickly identify the various types of medicines, and video contents are used to educate them on skills like how to use a Metered Dose Inhaler. The image contents are available from A Guide To Aerosol Delivery Devices by American Association for Respiratory Care (AARC) [9], and video contents on inhaler techniques are sourced from Use Inhalers - interactive guidance and training [20]. All the information and knowledge including the media contents are consulted and revised with our clinical collaborators to validate their authenticity and quality.

4.1.2 Dialogue Processing, Context and User Intent Analysis

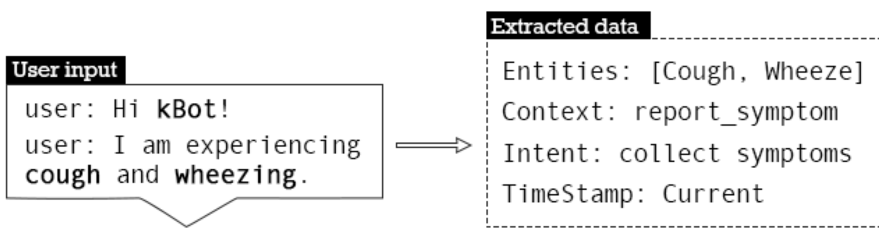


Figure 4.4: Data extraction in Dialog Flow

DialogFlow[5], a developer platform provided by Google for Natural Language Processing (NLP) and machine learning task, is leveraged for dialogue parsing and processing. A list of asthma-related concepts and vocabularies such as symptoms, medication types, and activity limitation types are preloaded into DialogFlow as the knowledge base. This allows DialogFlow to identify asthma-relevant entities correctly. For example in Figure 4.4,

[1]https://www.aafa.org/asthma
[2]https://www.verywellhealth.com/asthma-overview-4014760
[3]https://mayocl.in/2PaEBXZ
[4]https://www.webmd.com/asthma/default.htm
[5]https://dialogflow.com/

when a patient mentions ”cough” or ”wheezing”, they are captured and contextualized as *”report_symptom*, and the user intent is then represented as *collect symptoms* indicating the patient is having asthma symptoms. kBot will then use this knowledge and trigger the appropriate course of actions including but not limited to, communicating with the kBot server to retrieve the patients data required to personalize the responses (refer to Section 4.1.3) according to the current state of the context. Understanding both context and user intent are essential to maintain the state of a conversation. The dialog fulfillment task is handled by Firebase Cloud Functions linked to DialogFlow.

A shallow and dull conversation discourages users interest in conversing with kBot daily. Therefore, to improve engagement, kBot script is designed and written according to the standard UX design guidelines[6,7]. We also work in tandem with clinical collaborators and psychologist to ensure that the dialogues are encouraging asthma self-management.

4.1.3 Personalization in Response Generation

Before kBot client is provided, the patient first consents on data privacy. A user profile is then initialized based on the patient’s existing medical record. The patient data in the user profile is anonymized using a pseudonym to comply with HIPAA. This information is stored as a separate patient knowledge base and is continuously updated with data captured in patient-kBot conversations (Section 4.1.2). As the patient continues to converse with kBot, past captured data is referenced to generate a more personalized and palatable experience. Next, we describe how personalization is implemented in the context of (i) tracking medication adherence, (ii) identifying patient-specific triggers and (iii) Interpreting PEF reading.

(i) **Medication Adherence:** Once context and user intent are established, for example, when the patient reports having asthma symptoms (Figure 4.4), kBot will check for

[6] https://bit.ly/chatbotTalk
[7] https://bit.ly/chatbotDesigning

the medication history of the patient. If there is poor compliance, kBot informs the patient that his/her asthma symptoms might be a result of poor compliance with controller medicine. In another case, kBot may suggest contacting the doctor if rescue medication is used more than four times a day for two days (source: domain expert). Patient specific physician contact phone number is pre-configured during the initial patient profile setup.

(ii) **Patient-specific Triggers:** Each asthma patient reacts differently to environmental triggers. When a patient reports a symptom or asks for weather-related queries, kBot checks the patients surrounding environment for the list of triggers specific to the patient (initialized with the existing medical record) that are in the unhealthy range. These triggers in unhealthy range. are then blamed as a cause of the symptom and ranked based on its co-occurrence with the patient-reported symptoms. The higher the frequency of co-occurrence, the higher the chance of being a potential trigger. A personalized alert is then generated to the patient whenever these triggers are in an unhealthy range[8,9].

(iii) **PEF reading:** A Peak Flow meter (a device to measure lung function) is provided to patients during the initial deployment of kBot. Patients are requested to take 3 PEF readings using the Peak Flow meter and provide it to kBot in the first conversation. The best out of these three readings is recorded as the best PEF value of the patient and used as a baseline for the rest of the PEF readings. kBot request patients to log their PEF reading daily and compares it with the patients best PEF value. If the PEF reading lies with 80%-100% of best PEF, the patient's asthmatic condition is considered to be in the GREEN zone. Else if PEF reading is in the rage of 50% -79%, the asthmatic condition is in YELLOW zone. Anything below 50% is considered to be in the RED zone. If a patients asthma is in YELLOW or RED zone, kBot alerts

[8] https://www.pollen.com/help/faq
[9] http://bit.ly/aqi-basics

patients to be cautious as their asthma may worsen anytime and suggests to seek appropriate medical attention.

4.2 Ensuring Asthma Self-Management

Asthma is a chronic pulmonary disease which can have severe consequences if uncontrolled. To keep asthma well managed and under control, patients have to be enabled to self manage their asthma beyond clinical setup. Asthma self-management are strategies to help patients better manage their asthma, keep it well controlled, and live their life to the fullest [12]. kBot engage itself in the day to day life of patients through conversation and help them learn these skills allowing them to cope with their asthma. To achieve self-management in patients, kBot primarily focus on four objectives: Monitoring patients asthmatic condition, Encouraging medical adherence, Alert potential environmental triggers and Educating patients on self-management skills. These objectives collectively ensure asthma self-management. We further discuss these objectives in details:

4.2.1 Monitor Patients Asthmatic Condition

Monitoring patients asthma in their daily life gives a considerable advantage over the traditional healthcare system. Daily monitoring provides an in-depth insight into patients asthmatic health that could be used to explain the cause of asthmatic symptoms and device a personalized care plan. kBot acts as a virtual assistance conversing daily with patients through text or voice and collecting data related to their asthmatic health. A fixed set of the questionnaire designed carefully in consultation with our clinical collaborator is used by kBot in between the conversation to collect data on patients asthma. The way these questions are asked differs with the time of the day (refer table 4.1). Some of these questions are specific to the particular time of the day, e.g. questions related to nighttime awakening are asked only during the morning conversations and question-related to daily medication are asked only during the evening or night conversation.

Table 4.1: List of questions used by kBot in different time of the day to collect asthma related information from the patient. The texts in [] are replaced with the values specific to the patients.

Type	**Questions**
Current	• Are you experiencing any asthma related symptoms now? (if YES) – Did you take your prescriber [rescue medicine] for the relief? – How limited is your activity due to your symptoms?
Day	• Did you get any asthma related symptoms during the day? (if YES) – Did you use your [rescue medicine] for the relief? – How limited was your daily activity due to asthma symptoms? • Did you take your [daily- prescribed] medicine? • Please measure your lungs function using the peak flow meter provided with your kHealth kit and provide the PEF value.
Night	• Did you get any night time awakening due to asthma symptoms? (if YES) – Did you use the [quick relief inhaler] for the relief?

Note: The sentence structure and presentation of these questions may differ in actual conversation scenarios due to the dynamic nature of the conversation.

This daily monitoring of patient collects data related to patient's symptoms, rescue inhaler used, daily medication intake and their lungs functioning. A peak flow meter is provided to the patient, as part of kHealth kit[13], to measure the lungs functioning. During the daily reading session of the conversation, the patient is asked to use the peak flow meter to measure the lung functioning and reply with its PEF value.

4.2.2 Encouraging Medical Adherence

Patients are more likely to adhere to their medication if they know that someone is monitoring them [13]. kBot tracks the daily medication intake of the patients and also encourage them towards better medication adherence. Various information related to the importance of medication in asthma management is presented in between the conversation to encourage patients towards medical adherence. Besides, patients are made aware of consequences that might be incurred by missed medication, whenever a non-adherence is detected. Forgetfulness/carelessness and inadequate training in the inhalation techniques are found to be significant causes of medication non-adherence[13]. kBot addresses the first issue through behavioral interventions such as medication reminder and rewards. Patients can set a custom reminder as per their convenience and kBot reminds them to take medicine at the given time(refer section 3.2.2 ->push notification for detail). To address the issue of improper inhaler technique, kBot uses audiovisual intervention. Patients are presented with the video that step-by-step demonstrates how to use different types of inhaler. These videos are the standard contents provided by Use Inhalers - interactive guidance and training[20].

4.2.3 Alert Potential Environmental Triggers

Allergic asthma is the most common form of asthma[29]. Moreover, asthma is a multifactorial disease; hence, a personalized approach is required to identify and avoid allergens that could trigger patients asthmatic symptoms. Apart from monitoring the patients, kBot also monitors the environment of each patient continuously using their zip code. The common asthma triggers such as pollen, AQI, ozone, temperature, and humidity are the data of our interest in the patients environment. These environmental data are collected in different frequencies as per their variance over time (refer table 4.2).

Whenever a patient reports an asthma symptom, it is mapped with the environmental

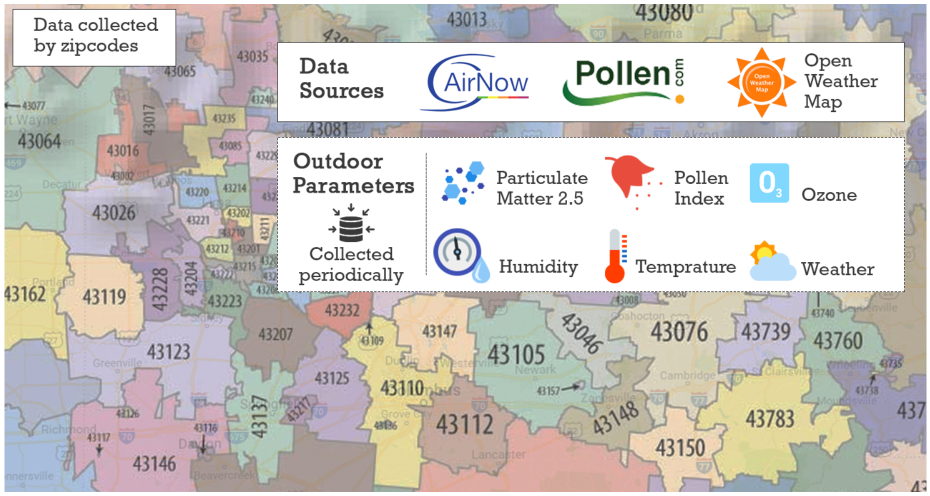


Figure 4.5: Environmental data collection based on zip codes using third party weather APIs.

Table 4.2: Frequencies in which various outdoor data are collected

Trigger type	**Frequency**
Pollen	Twice a day
AQI	Every hour
Ozone	Every hour
Temperature	Every two hours
Humidity	Every two hours

data to identify the triggers that were in an unhealthy range in the past 8 hours window. These triggers in the unhealthy range are blamed for the symptoms, and a ranked list of the potential triggers are created based on its co-occurrence score with the patient-reported symptoms. Co-occurrence score is a binary score that indicates if a particular trigger was present or absent during a time window of the symptom. Co-occurrence score of each trigger represents its frequency of being in an unhealthy range when the patient has a symptom. The higher the score, the higher the chance of being a potential trigger. Thereafter, whenever abnormal values of these triggers[10,11] are sensed in the patient's environment, kBot alerts the particular patient through its notification system. Through this information, patients could take the necessary steps to avoid the trigger or at least prepare for its effect.

[10] https://www.pollen.com/help/faq
[11] http://bit.ly/aqi-basics

4.2.4 Educate Patients on Asthma Self-Management Skills

A crucial component of asthma self-management is to educate patients with management skills. These skills are regular management strategies that teach patients how to deal with their day to day asthma problems and keep it under control. To educate the patient, kBot focuses on self-management strategies and knowledge. Strategies such as early detection of asthma symptoms, its prevention, managing asthma symptoms in their early stages and different relaxation techniques allow patients to prevent their asthma from exacerbation. These strategies are suggested to patients through conversation based on the patient's condition e.g. when they report a symptom, a relaxation technique to ease with symptoms is suggested.

Along with strategies, kBot also educates patients with information related to asthma and its management. It focuses on improving patients knowledge about asthma and bringing in a positive attitude in them towards asthma self-management. kBot has information dissemination as one of its primary functions that allow patients to request for this asthma-related information explicitly. Patients could request various information related to asthma such as symptoms, medication, various asthma zones, asthma triggers and inhaler techniques. These self-management knowledge and strategies are derived from official asthma care quick reference guide [15] and various literature related to asthma management [7] [13].

kBot also has the feature to summarize patients data using which patient could get an overview of their asthmatic health such as their symptom report, medical compliance, PEF trend, and asthma control level. This summary is provided with an intention to let patients self-evaluate their effort towards asthma self-management and encourage them to achieve better outcomes. A summary report along with a progress graph chart is presented to the patients upon request. Looking at this report, patients could self-realize their current asthma state and plan accordingly to improve it.

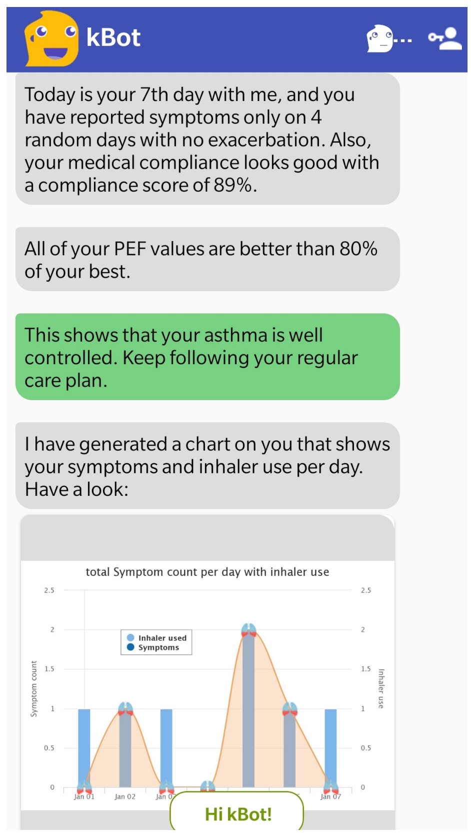


Figure 4.6: Summarizing patients past health data

Evaluation

A preliminary evaluation was conducted on kBot to assess technical viability, effectiveness, and usability. This evaluation primarily tries to measure how well the target population will accept this technology as a system for self-management of asthma. The metrics used, methods, and the results of the evaluation are discussed in the following sections.

5.1 Evaluation Metrics

The criteria of the evaluation are chatbot quality, technology acceptance, and system usability (Table5.1). Chatbot quality is further divided into three categories: naturalness, information delivery, and interpretability. Naturalness focuses on how natural were the phares and dialogues used by kBot during the conversation. Information delivery focuses on how well was the kBot able to provide asthma-related information to the patient through the conversation. Interpretability tries to measure if kBot was able to interpret the asthma-related data from user's dialog correctly. The response formats for chatbot quality and technology acceptance are 11 points Likert scale ranging from 0-10. Zero being strongly disagreed and ten being strongly agreed. These assessment criteria are designed in consultation with a cognitive psychologist.

Overall system usability of kBot was evaluated using the System Usability Scale (SUS)[3]. It is a standard 10 set questionnaire that can be used to assess the usability

Table 5.1: kBot Evaluation Metrics

Metrics		Questions
Quality of chatbot	Naturalness	• kBot uses simple and understandable vocabulary. • kBot dialogues were unambiguous. • kBot dialogues were natural.
	Information delivery	• kBot provides patients with the right information at right time. • Information provided by kBot helps an asthma patient manage their asthma better.
	Interpretability	• kBot properly understood what a patient intended to say during the conversation. • The patients will be able to express their current asthma condition and medication usage accurately through the conversation.
Technology acceptance		• The information kBot is trying to collect through the conversation adequately conveys a patients asthma condition. • I recommend this technology to monitor and manage a patients daily asthma condition. • Overall, I am very satisfied with this technology.

of a wide variety of systems. It provides a quick snapshot of how usable a system is. The response format for each question in SUS is a 5 point Likert scale ranging from 1 to 5. One being strongly disagreed and five being strongly agreed. The result of SUS is interpreted in a range of 0 to 100 as a combination of responses to all 10 questions from each participant. Research findings indicate that any system with a SUS score better than 68 would be considered above average and below 68 is below average[3].

Apart from metrics mentioned above, questions related to demographics and technology familiarity were also included in the evaluation (refer Table 5.2). These questions were asked to have an understanding of the evaluation cohort for better interpretation of the

Table 5.2: Demographic and Technological familiarity questions

Metrics	**Questions**
Demographics	• kBot uses simple and understandable vocabulary. • kBot dialogues were unambiguous. • kBot dialogues were natural.
Technology familiarity	• kBot provides patients with the right information at right time. • Information provided by kBot helps an asthma patient manage their asthma better.

evaluation result.

5.2 Evaluation Method

Qualtrics [22], an online survey tool, was used for designing and conducting the evaluation. The evaluation involved eight domain expert (clinicians from pediatric pulmonology, and allergy departments) and eight non-domain experts (computer science researchers from Kno.e.sis center). The non-domain expert group participants were provided with background information of asthma and the patient scenarios prior to their participation in the evaluation. The reason behind conducting the evaluation on two different cohorts is to measure how well technology performs within a diverse group. Each evaluator is provided with an Android device hosting the kBot client application and asked to interact with it separately using random patient scenarios. These patient scenarios are created based on clinicians experience with real patients. This study is yet to be approved by the IRB board which will allow our future studies to evaluate the clinical effectiveness of kBot in children with asthma.

Illustrative patient scenario: *Patient A is a 12-year-old male with a history of moderate persistent asthma. On a Sunday morning, he started experiencing vigorous coughing* *with wheezing and shortness of breath. He took a dose of Albuterol inhaler followed by another dose and the symptoms subsided. He reported this episode to kBot. Based on its domain knowledge, kBot suggested the patient to stay on controller therapy and contact doctor if albuterol was taken more than four times a day for two consecutive days.*

A survey form, generated using qualtrics, was presented to the evaluators at the end to assess kBot based on their recent user experience. The survey consists of two sets of questionnaires. The first set accesses the technology acceptance and quality of kBot and the second set as System Usability Scale (SUS) access the system usability of kBot. In total, 16 responses were obtained from 8 clinician and 8 researchers for each set of questionnaire. These responses are brought together and analyzed. The result of the evaluation is discussed in the following section.

5.3 Result

5.3.1 Technology Acceptance and Chatbot Quality

The evaluation responses from both clinicians and researchers for each question of all four metrics (naturalness, information delivery, interpretability, and technology acceptance) are aggregated and averaged to get per metric mean scores. kBot received a mean score greater than 8 out of 10 for each of the four metrics from clinicians. Similarly, researchers rated kBot with a mean score better than 8.4 for all the metrics. A response better than 7.5 on 11 points Likert scale is equivalent to a score better than 4 on a 5-point Likert scale [8]. The detailed score of each metric is shown in Figure 5.1.

As described earlier, this evaluation sought to measure technology acceptance. The mean score of technology acceptance obtained from both groups are above 8 out of 10. In addition, we also analyzed the significant difference of this metric within the two distinct

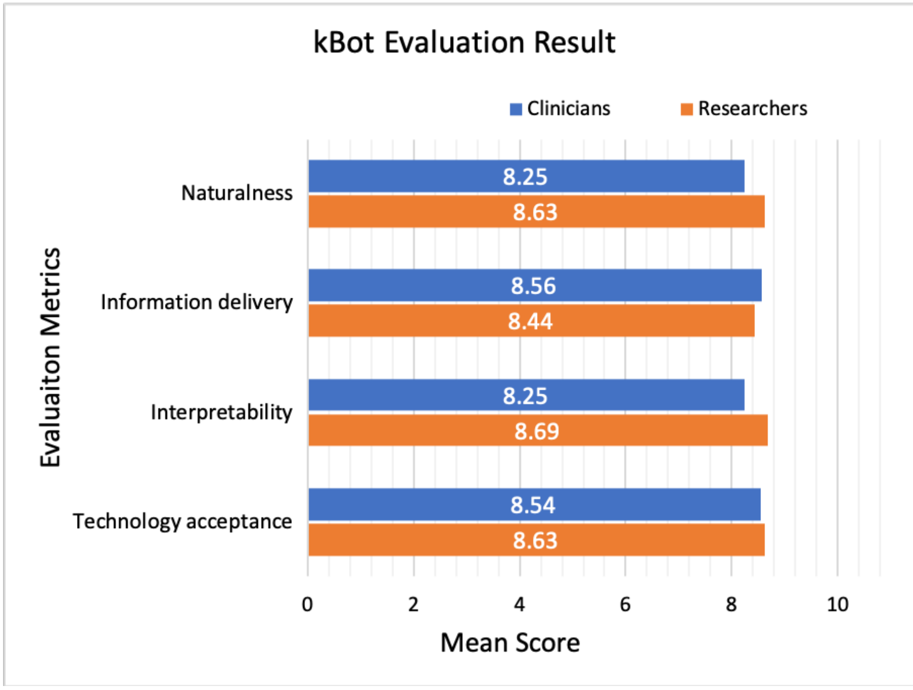
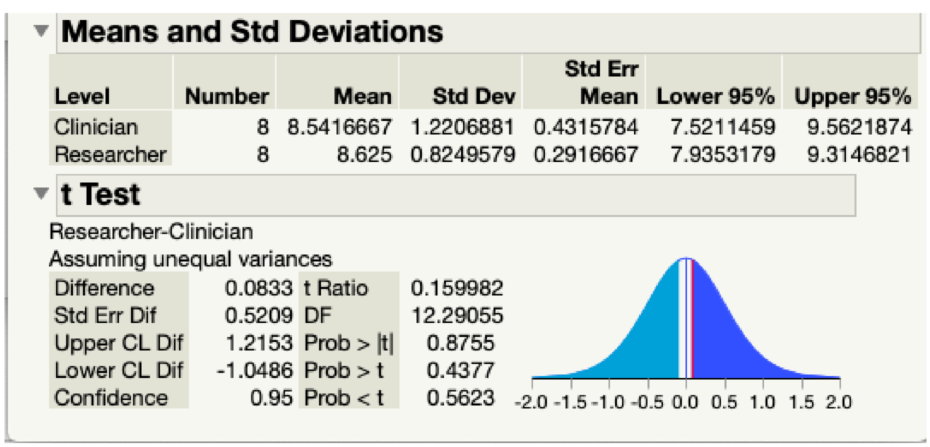


Figure 5.1: Mean score and standard deviation for each evaluation metric of kBot (Higher mean score is better).



Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean	Lower 95%	Upper 95%
Clinician	8	8.5416667	1.2206881	0.4315784	7.5211459	9.5621874
Researcher	8	8.625	0.8249579	0.2916667	7.9353179	9.3146821

t Test

Researcher-Clinician
Assuming unequal variances

Difference	0.0833	t Ratio	0.159982
Std Err Dif	0.5209	DF	12.29055
Upper CL Dif	1.2153	Prob > |t|	0.8755
Lower CL Dif	-1.0486	Prob > t	0.4377
Confidence	0.95	Prob < t	0.5623

Figure 5.2: t-test with the p-value for technology acceptance comparing responses from two distinct groups

groups using the t-test. This is performed for hypothesis testing. However, with the p-value of 0.88 (>0.05)(refer Figure 5.2), we cannot reject the null hypothesis stating that there is no significant difference between the two groups in terms of technology acceptance. Hence, we can conclude that both the group finds this technology useful for self-management of asthma.

5.3.2 System Usability

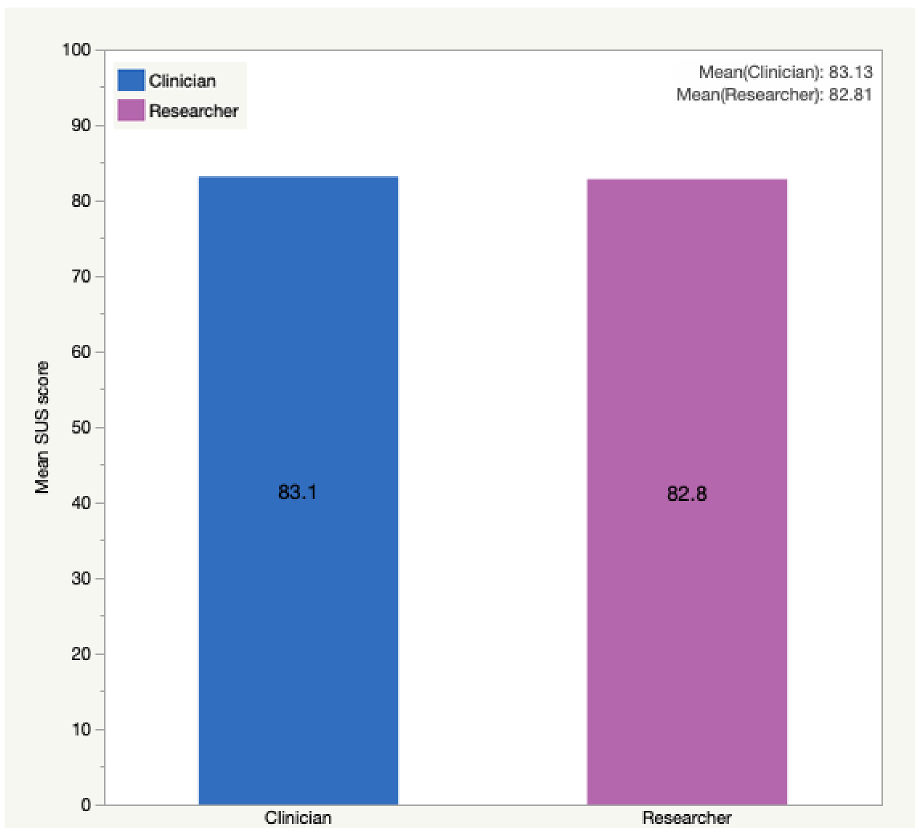


Figure 5.3: kBot mean System Usability scores from clinicians and researchers

The evaluation responses from all participants for the second set of the questionnaire (SUS) was put together and aggregated to calculate mean usability score of the kBot. At first, each participant's response was scaled and converted into a range of 0-100 for interpretation. In this new range, any score above 68 would be considered better than average, and anything else is below average[1]. This score in the range of 0-100 is its percentile ranking; not a percentage. On averaging, SUS scores of clinicians gave kBot a mean score of 83.13. Similarly, researcher rated kBot with a mean SUS score of 82.81. These SUS scores ($>$82) from clinicians and researchers rank kBot among excellent system[3].

[1]https://measuringu.com/sus/

Conclusion

With the digitization of healthcare, a massive amount of patient-relevant data is generated every day. Converting this data into meaningful and profound insights about patients health would enhance the healthcare approach. Healthcare professionals are limited by resources to monitor the patients and get insights personally. In such a scenario, technology such as chatbot can closely interact with patients and monitor them engaging personally in their everyday life. Hence, building chatbots for healthcare that collects comprehensive data related to patient and their environment is demanding. However, a generic chatbot system without domain knowledge or patients history is improbable to bring any changes into patients health. Chatbots can be far more effective by using patient history and domain knowledge to generate personalized responses. kBot, as such a system, is aware of patients history and has in-depth domain knowledge which enables it to generate a response that is more meaningful and contextually relevant to the patient.

We have successfully prototyped a chatbot system that is capable of interacting with asthma patients with in-depth context knowledge and personalization to monitor their asthma relevant data and help them self-manage their asthma. Nonetheless, kBot is not a medical diagnosis or a decision-making application. The preliminary evaluation shows great acceptance of kBot among domain and non-domain experts as a system for asthma self-management. The next step is to conduct a pilot study on a group of pediatric asthma patients.

Future Work

In this thesis work, we presented a conversational system that monitors and collects data from asthmatic patients through voice or text-based conversation. In addition, it also collects environmental data related to each patient. These data are brought together and used by the kBot to provide feedback and explain asthma events to the patient for self-appraisal and ultimately self-management of their asthma. However, there are specific scenarios where clinical insights and decision making are required beyond chatbot, e.g. A scenario, where a patient is compliant to his/her asthma care plan, but still, he/she is getting symptoms, may require a change in the treatment plan. To facilitate such need, we plan to extend this thesis work by connecting the kBot system with our existing dashboard system in the khealth framework: kDash [25]. kDash is a personalized dashboard system that integrates and visualizes different modalities of data helping clinicians to get deeper insights into patient health and make a better decision for asthma management. This extension of kBot creates a complete pipeline of data from the patients daily life to the clinician's office allowing real-time monitoring and managing of asthma.

As future work, kBot could improve upon a few things. First, asthma symptoms vary from a simple cough that subsides with use of the short-acting inhaler to shortness of breath that requires immediate medical attention. Thus, we need to classify the severity level for each symptom and handle patient-reported symptoms separately. Second, to be able to deliver a more human-like conversation, we can design a custom language model and train it on real-life patient-doctor conversation data. In addition to environmental data, we can incorporate various IoT sensors to collect data such as indoor air quality and sleep activity to better understand the patients surrounding environment for a more likely prognosis of triggers contributing to the worsening of asthma condition. Last but not least, the current kBot knowledge base can be further enriched with various asthma concepts to answer a broader and wider variety of questions.

Bibliography

[1] Center for Disease Control and Prevention-Asthma management and treatment. https://www.cdc.gov/asthma/management.html, 2018. [Online; accessed March 8-2019].

[2] Kno.e.sis- Ohio Center of Excellence in Knowledge Enabled Computing, kHealth-Asthma. http://wiki.knoesis.org/index.php/Asthma, 2018. [Online; accessed March 8-2019].

[3] Aaron Bangor, Philip Kortum, and James Miller. Determining what individual sus scores mean: Adding an adjective rating scale. *Journal of usability studies*, 4(3):114–123, 2009.

[4] CDC. Center for Disease Control and Prevention-Asthma-related Missed School Days among Children aged 517 Years. https://www.cdc.gov/asthma/asthma_stats/missing_days.htm, 2018. [Online; accessed July 20-2019].

[5] CDC. Center for Disease Control and Prevention-Most recent asthma data. https://www.cdc.gov/asthma/most_recent_data.htm, 2018. [Online; accessed March 8-2019].

[6] chatbots.org. parry. https://www.chatbots.org/chatbot/parry, 2018. [Online; accessed May 8-2019].

[7] Vivian T Colland. Learning to cope with asthma: a behavioural self-management program for children. *Patient education and counseling*, 22(3):141–152, 1993.

[8] John Dawes. Five point vs. eleven point scales: Does it make a difference to data characteristics. *Australasian Journal of Market Research*, 10(1), 2002.

[9] Shawna Strickland Douglas S. Gardenhire, Dave Burnett and Timothy R. Myers. A guide to aerosol delivery devices for respiratory therapists. *AARC: Times*, 2018.

[10] Ahmed Fadhil and Silvia Gabrielli. Addressing challenges in promoting healthy lifestyles: the al-chatbot approach. In *Proceedings of the 11th EAI International Conference on Pervasive Computing Technologies for Healthcare*, pages 261–265. ACM, 2017.

[11] David A Fedele, Andrew McConville, J Graham Thomas, Elizabeth L McQuaid, David M Janicke, Elise M Turner, Jon Moon, and Mutasim Abu-Hasan. Applying interactive mobile health to asthma care in teens (aim2act): Development and design of a randomized controlled trial. *Contemporary clinical trials*, 64:230–237, 2018.

[12] Centers for Disease Control, Prevention (CDC, et al. Asthma self-management education among youths and adults–united states, 2003. *MMWR. Morbidity and mortality weekly report*, 56(35):912, 2007.

[13] Adrian Gillissen. Patients' adherence in asthma. *Journal of physiology and pharmacology*, 58(5):205–222, 2007.

[14] Utkarshani Jaimini, Krishnaprasad Thirunarayan, Maninder Kalra, Revathy Venkataraman, Dipesh Kadariya, and Amit Sheth. How is my child's asthma? digital phenotype and actionable insights for pediatric asthma. *JMIR Pediatrics and Parenting*, 1(2):e11988, 2018.

[15] National Heart Lung and Blood Institute. Asthma care quick reference. *National Institute of Health*, 2012.

[16] Lin Ni, Chenhao Lu, Niu Liu, and Jiamou Liu. Mandy: Towards a smart primary care chatbot application. In *International Symposium on Knowledge and Systems Sciences*, pages 38–52. Springer, 2017.

[17] National Institute of Health. Asthma Action Plan. https://www.nhlbi.nih.gov/files/docs/public/lung/asthma_actplan.pdf, 2007. [Online; accessed July 20-2019].

[18] Hilary Pinnock. Supported self-management for asthma. *Breathe*, 11(2):98–109, 2015.

[19] Popular Science. Your digital assistant may have tons of new features it didn't tell you about. https://www.popsci.com/smart-assistant-update-google-home-alexa/#page-3, 2018. [Online; accessed May 8-2019].

[20] Romil Shah and Luis Velez. Effectiveness of software-based patient education on inhaler technique: A clinical study. *European Respiratory Journal*, 44(s58), 2014.

[21] Amit Sheth, Utkarshani Jaimini, and Hong Yung Yip. How will the internet of things enable augmented personalized health? *IEEE intelligent systems*, 33(1):89–97, 2018.

[22] Jonathan Snow and M Mann. Qualtrics survey software: handbook for research professionals. *Qualtrics Labs, Inc*, 2013.

[23] Kaharu Sumino and Michael D Cabana. Medication adherence in asthma patients. *Current opinion in pulmonary medicine*, 19(1):49–53, 2013.

[24] Simon F Thomsen. Genetics of asthma: an introduction for the clinician. *European clinical respiratory journal*, 2(1):24643, 2015.

[25] R. Venkataramanan, V. Sridharan, D. Kadariya, A. Sheth, K. Thirunarayan, and M. Kalra. Knowledge-enabled personalized dashboard for asthma management in children. *Annals of Allergy, Asthma Immunology*, 121(5, Supplement):S42, 2018.

[26] Revathy Venkataramanan, Krishnaprasad Thirunarayan, Utkarshani Jamini, Dipesh Kadariya, Hong Yung Yip, Maninder Kalra, and Amit Sheth. Determination of personalized asthma triggers from multimodal sensing and mobile application. *JMIR Pediatrics and Parenting*, 2019. [unpublished].

[27] Richard Wallace. The elements of aiml style. *Alice AI Foundation*, 139, 2003.

[28] Joseph Weizenbaum et al. Eliza—a computer program for the study of natural language communication between man and machine. *Communications of the ACM*, 9(1):36–45, 1966.

[29] Sally E Wenzel. Asthma: defining of the persistent adult phenotypes. *The Lancet*, 368(9537):804–813, 2006.

[30] Andrew Whittamore. Technology can revolutionise supported self-management of asthma. *Primary Care Respiratory Society UK*, 4, 2017.