Development Of A Multi-Lingual Chatbot For Physical and Mental Health Monitoring Of Children

Judith Azcarraga, Kate Justine Ermitaño, Steven Castro, Mark Adrian Escobar
TE3D House AdRIC
De La Salle University, Philippines
{judith.azcarraga, kate_justine_ermitano, steven_castro, mark_adrian_escobar}@dlsu.edu.ph

Abstract

Physical and mental health monitoring of children is important and necessary in every country. However, in developing countries like the Philippines, the general health wellness of children in several public schools are not regularly monitored due to lack of healthcare professionals and other resources. This research presents a multi-lingual healthcare chatbot that can monitor the physical and mental wellness of young children in every school. Empowered by Artificial Intelligence, the chatbot is capable of conversing in two major Philippine languages - Filipino and Bisaya as well as English. The chatbot will allow for more frequent and regular health and wellness check among children, even without the presence of a medical doctor or even a full-time school nurse and may identify children who may need specific interventions, whether psychological, medical, nutritional, or mere social-cultural support.

1 Introduction

Monitoring the health and wellness of children is one of the main challenges in a developing country like the Philippines. Schools would have been a good venue for the government to monitor the general well-being of young children. Unfortunately, not all schools have enough resources to conduct routine checks on students, let alone have at least one full-time nurse in charge of the school clinic. Still, even with yearly check-ups, some check-ups are not done in a sufficient manner. When special medical attention is needed, diagnosis becomes futile without a systemic and specific assessment.

Assuming that the problem of inaccessible healthcare still persists in schools, the proposed project will perform a routine wellness check - that is quick and efficient - on every child, beginning in the 1st and 2nd grades. Students with urgent and specialized needs will be isolated for further assessment and diagnosis, now accompanied by a nurse.

The Philippines, with a population estimated at around 104.9 million as of 2017, according to The Philippines Health System Review, has about 40% of its population consisting of minors (World Health Organization). From that percentage, 33% of them experience stunted growth under the age of 5 because of malnutrition. The Philippines is severely lacking in healthcare professionals. The Department of Health (DOH) claimed that there is a 1:1,500 doctor-to-patient ratio. With that, it can be deduced that there are approximately 110,520 doctors in the Philippines.

Based on the study headed by the National Health Institute of the University of the Philippines, an estimated 6 out of 10 Filipinos who died due to health complications and issues have not even seen a doctor (Oxford Business Group, 2012). Furthermore, poverty makes it increasingly difficult to have access to available yet affordable healthcare, causing families to set aside regular health check-ups for their children.

Monitoring children's general well-being involves not only their physical health but also their mental health. With routine checks, from food and sleep to safety and illnesses, children will be assessed from head to toe to ensure that their growth is normal. Their milestones will be checked via their height, weight, and head circumference, making sure the measurements are right for their age and sex. Moreover, these routine checks can detect signs and symptoms of possible diseases and conditions.

Technology, specifically when powered with Artificial Intelligence (AI), can be used to ease the process of assessing multiple children in one run. The Microsoft Healthcare Chatbot (Azure, n.d.), one of the pioneers of this project, is one example of AI assisting healthcare professionals in conversing with patients using natural language while also gathering and processing information that leads to a calculated diagnosis. Other healthcare chatbots also surface with different features yet similar functions. Sensely can infer diagnosis based on speech, text, image, and video data, while Infermedica can do the same but with access to online browsers and mobile phones. Buny Health recommends solutions once the questionnaire has been answered, and Babylon Health books personal health consultations with a doctor based on medical history and common health knowledge (Mesko, 2023).

In order to provide access to regular health checks in public schools, technology may be utilized in monitoring the physical and mental wellness of young children. This research presents a multi-lingual health monitoring system for public school children assisted by a healthcare chatbot that is capable of interpreting audio and text input and conversing in two major Philippine languages – Filipino and Bisaya, and in English.

2 Related Works

A chatbot that specializes in triage, which is achieved by conversing with patients to determine their condition is presented in the work of Ghosh, Bhatia, and Bhatia (2018). Once the results have been calculated, the chatbot will report to the patient if they can perform self-care, seek a general practitioner, or receive urgent care.

Another similar study is a chatbot that can converse in Bangli, with a knowledge base that can fetch and store session data and health information and multiple machine learning algorithms such as decision trees, random forest, multinomial NB, SVM, AdaBoost, and k Nearest Neighbor. With a knowledge base and machine learning, the chatbot can monitor user health data to diagnose and report potential health hazards and diseases to the user (Rahman, et al., 2019).

Other than chatbots, a recommender system may simulate a human physician in a clinical setting. Users may ask questions or suggestions that are outside the healthcare assessment, such as the clinic, disease prevention, and booking physical examinations. This system consists of HOLMes (for module communication and logic operation), IBM Watson (deep mining for text mining), NLP (to make conversations very human-like), and Spark (the computational cluster). The conversation is generated by the IBM Watson Conversation APIs and uses the dataset by the C.M.O. center to make diagnoses. Lastly, the output of the system is a histogram ranking all the possible diseases to be assessed by a physician (Amato et al, 2017).

Mental health of an individual is as equally important as the physical health. There are several mental health chatbots such as Woebot, Wysa and Flow that have been developed. Woebot is a digital therapist that utilizes cognitive behavioral therapy and comes with daily check-ins suitable for both adult and adolescent users. The chatbot uses multiple choice, with some questions being open to text input from the user (Woebot Health, 2023).

Wysa, on the other hand, makes suggestions to guide users on self-care exercises and keeps track of the user daily. However, the added features, such as consulting with human therapists have some fees and a lot of users may not be able afford for therapy (Inkster & Subramanian, 2018).

Lastly, Flow is a chatbot aimed at overall health, such as sleep, diet, exercise, and meditation, to treat symptoms of depression. Therapy is conducted via chat messages. Like Wyse and Replika, the feature for full treatment that comes with a headset has an additional cost for the whole package (Woodham, et al., 2022).

3 Design and Implementation

3.1 Data Collection and Preparation of the Dialogues

Dialogues of the chatbot are based from the Instrumental Activities of Daily Living (IADL), the Pediatric Symptom Checklist and the actual interview of nurses and psychologists with young children. Interviews are in Filipino and Bisaya languages where questions involve physical and mental wellness.

Since the interviewees are young children, consent form was sent to their parent/guardian prior to the actual interview.

Figure 1 presents the chatbot use case diagram. The system has two main users, namely, (1) children, whose health is being monitored, and (2) the adult, who is most probably the teacher supervising the children. The users interact with the system by talking to the chatbot through tablet.

The chatbot is deployed on the cloud, and is accessible via the Internet.

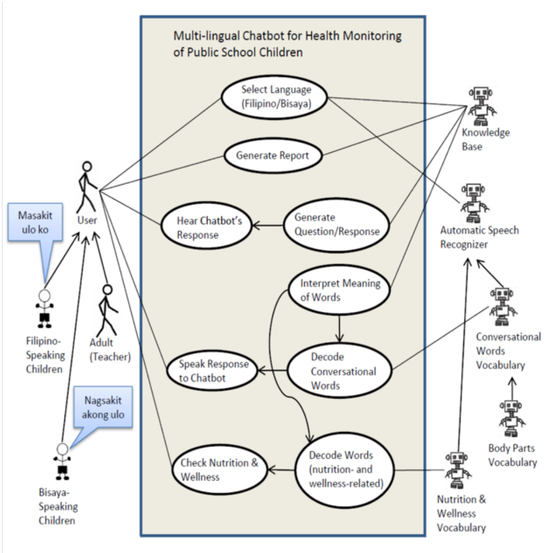

Figure 1. Chatbot Use Case Diagram

The chatbot understands Filipino, Bisaya and English. It asks questions to gather information on the child's general physical wellness, based on WHO's Global School-based Student Health Survey (GSHS, 2015). The collected information will be stored in a database for the generation of needed reports.

As part of a bigger system where input can also be the speech of a child, this paper focuses only on the discussion of the text-based chatbot were input are purely in text via Messenger or in a Web application.

3.2 Chatbot Framework

Figure 2 illustrates the architecture of the chatbot framework (Fernando, et al. 2024). As a web application, a Chatbot Web Application Server handles the communication between the users and the chatbot modules. The system is designed as a mobile application for ease of use by its target users. The conversation initiates when a user sends a message to the chat server. Subsequently, the chat server processes the message to generate a response. The Web App Server retrieves the appropriate response from the Dialogflow CX that handles the flow of the conversation. All the dialogues of the chatbot are retrieved from the Google Cloud Firestore which serves as the storage for the dialogues and all the information gathered from the user during a conversation. The Fulfillment Server, on the other hand, manages additional chatbot logic, including the storage of session data, response translation, and flagging. Communication with Google Cloud Firestore facilitates the retrieval of translated responses and session parameters essential for structuring conversation flow. Since the chatbot allows voice and text input from the user, the Automated Speech Recognition (ASR) Server is called whenever a child responds to the chatbot through speech. The ASR translates the speech to text which is then sent to the Web App Server. The Web App Server sends the text to the Dialogflow CX which processes the input, generates and displays the appropriate response in the Web App or FB messenger depending on the platform being used. Data collected in all the conversations are secured and stored in the Firestore. These are the data that Data Visualization Web Application Server use to provide an individual summary report and visualization of health information from different schools.

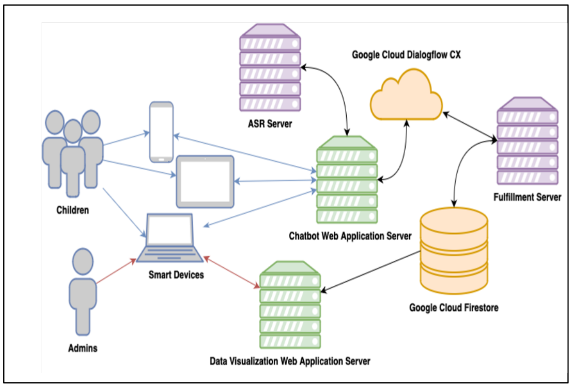

Figure 2. Architecture of the Chatbot (Fernando, et al. 2024)

3.3 Conversational Flow

Conversational flows are organised into modules or flows in DialogflowCX; each module represents a general context of the conversation. DialogFlowCX models each flow as a finite-state machine, with the pages as the states and the state handlers as the transitions. The intermediate page, after the start of the flow, sets the parameters for the communication between the chatbot and the knowledge base. In each individual module, it aims to extract certain types of information from the user. The extracted information is stored as session variables and influences the conversation's transitions between states. Concluding modules or flows triggers another intermediate page, which saves and stores session parameters in the database for future reference.

Figure 3 presents the conversation flow of the chatbot. A session is initiated with the chatbot by asking for the child's preferred language and information (username and data privacy consent). The session terminates if the child does not consent to the use of the chatbot. Otherwise, it continues to a review of body systems, which is handled by multiple specialized modules under the hood. Specialized modules transition back to the probing-menu-page when a module concludes.

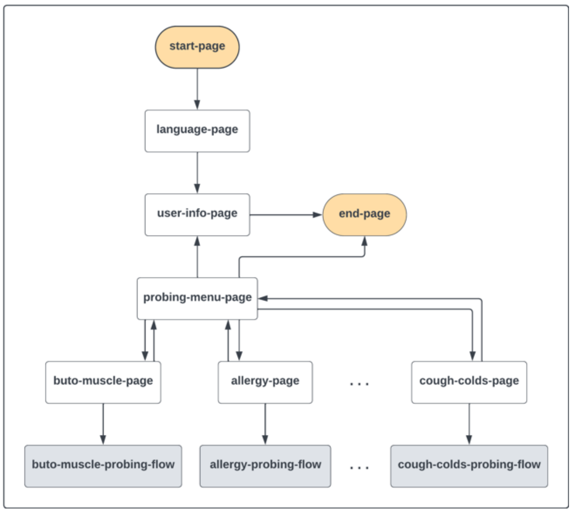

Figure 3: Conversation Flow

This allows the user to go over the other modules until they are satisfied, in which they may opt to end the session.

Figure 4 presents the conversation flow for the allergy module. The module is designed to systematically extract allergy information from pediatric subjects. Information including the duration of affliction, reported symptoms, and identifiable triggers. Transitions between pages or states changes based on the condition defined in the transitions or routes in DialogFlowCX. Introducing a more dynamic approach of questioning as the chatbot avoids redundant or extraneous follow-up responses from the chatbot. The module concludes whenever the conversation reaches the End Page, instigating the storage process of the accumulated information. The collected data is subsequently stored in the database for later utilization in the generation of comprehensive reports.

Figure 5 presents the conversation in probing for the Buto (bone) and muscles wellness. The module is devised to probe for information related to bones and muscles. The flow is structured in a loop to iterate through a list of distinct conditions. Individual conditions can share similar follow-up details such duration, degree of pain, etc. Instead of exhaustively creating new pages for each condition, pages are reused by storing the subject (condition) into a session variable. Creating an identifier during the looping process and for the record during data storage.

Figure 4: Allergy Conversation Flow

3.4 Dialogue Processing

In the dialogue processing workflow, webhooks play a pivotal role in producing dynamic responses, validating data, and triggering backend actions. A webhook is called and sent to an endpoint for almost every response the chatbot has. Its primary responsibility is to retrieve the relevant dialogues corresponding to each question, ensuring that the user receives the appropriate context. Once a question is asked, the user's input will be expected.

The chatbot emphasizes its multilingual support, accommodating English, Filipino, and Bisaya simultaneously through its entity extraction capabilities. Entity extraction plays a huge role in comprehending user inputs across different languages. Once an entity is extracted, the subsequent step involves determining its reference value. An example of an entity type with its entities and synonyms is shown in Table 1, wherein red is the entity or reference value, and some of its synonyms are blood-tinged, bloody, and pula. This makes it possible for the chatbot to understand the user's input regardless of the language.

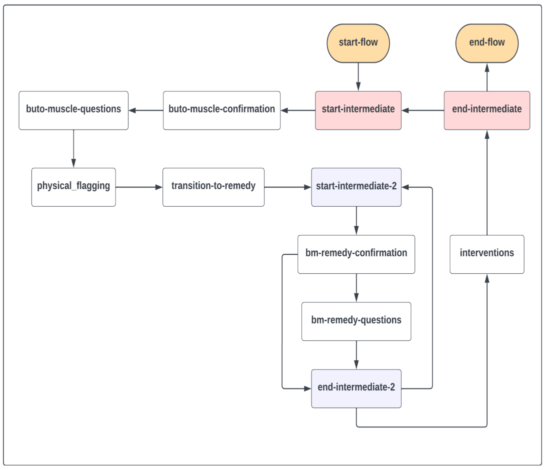

Figure 5. Probing for the Buto (bone) and Muscles.

Table 1: Lists of the corresponding synonyms for each entity name under an entity type.

Entity Type	Entity Name	Synonyms
phlegm_colors	red	red, blood-tinged, bloody, pula, dugo
phlegm_colors	white	white, whitish, puti

C: Madali ka bang mahawa o kaagad inuubo? *(do you easily get infected or get cough?)*
U: **Oo** *(yes)*
C: May kasama bang plema? *(is there phlegm?)*
U: **Meron** *(there is)*
C: Ano ang kulay ng plema? *(what is the color of your phlegm?)*
U: May halong **dugo**. *(with blood)*

Listing 1: Sample dialogue with entity extraction. *C* refers to the chatbot, while *U* refers to the user. The entities extracted in the context are underlined. In this context, the inquiry about the color of phlegm is prompted by the user's earlier acknowledgment of its presence. This ensures that the subsequent question aligns with relevant information obtained during the ongoing conversation.

3.5 Dialogue Storage

Chatbot dialogue is stored using Google Firebase, specifically Firestore. Firestore is a NoSQL database, a type of database management system that provides a mechanism for storing and retrieving data modeled in a non-tabular or non-relational manner. Dialogue is essentially a series of questions and responses, modeling it as a NoSQL document composed of field-value pairs allows for a straightforward and flexible representation compared to the table-based approach of relational databases. Firestore stores data in collections that are analogous to tables in relational databases. These collections contain a set of documents where each document is composed of field value pairs that store the actual data. Dialogues are organized by chat modules; each module has its own corresponding collection and stores a group of documents. Each document represents a type of question or response of the chatbot for the particular module, storing translated responses for each language and their corresponding quick replies. Table 2 presents how a dialogue is stored in Firestore. Table 3 illustrates a document representation of the sample dialogue in Listing 1. Health documents store the collected session variables extracted from user utterances

Responses and quick replies are fetched from the database according to the user's preferred language. Quick replies are supplementary options shown in the user interface that help guide the user on the expected answers.

3.6 Problems Encountered and Remediation

The Buto Muscle Module faced structural organization and templating issues, possibly due to a lack of testing in prior development stages. The module generally has a nested loop structure, with one loop addressing the general problem and another focusing on the remedies for each of the general problems addressed in the first loop. A crucial parameter, the current object parameter, determines the ongoing general problem in each cycle. After each general problem, it continues using the current object parameter for the list of remedies in the second loop.

Table 2: Table representation of a dialogue document stored in Firestore.

Key	Subkey	Value
qck_reply	cebuano_replies	[Iro, Iring, Uban pa]
	english_replies	[Cat, Dog, Others]
	tagalog_replies	[Pusa, Aso, Iba pa]
question_translation	cebuano_response	Sa unsa na mananap nga naay balhibo ka alerdyik?
	english_response	Which animal furs are you allergic to?
	tagalog_response	Sa anong hayop na may balahibo ka allergic?

Table 3: Document representation of the sample dialogue in Listing 1.

Field	Value
session_name	"1234567890"
module	"cough_and_cold_module"
ccf-confirmation	"meron"
cough-with-phlegm	"meron"
phlegm_color	"red"
kind	cough
updated_at	Oct 11, 2023, 12:40:14.437 PM

3.7 Problems Encountered and Remediation

The Buto Muscle Module faced structural organization and templating issues, possibly due to a lack of testing in prior development stages. The module generally has a nested loop structure, with one loop addressing the general problem and another focusing on the remedies for each of the general problems addressed in the first loop. A crucial parameter, the current object parameter, determines the ongoing general problem in each cycle. After each general problem, it continues using the current object parameter for the list of remedies in the second loop.

The primary issue was using consecutive "Change Loop" endpoint calls, where each call alters the current object parameter to move to the next loop object. Once it enters the loop for remedy, it still has the current object parameter from the general problems loop, which is overwritten after each iteration in the remedy loop. Overwriting the data results in the loss of progress from the previous iteration, leading to a repetition of the initial loop and, eventually, an infinite loop.

To address the structural organization and templating issues within the Buto Muscle Module, a restructuring of the loop logic was made to ensure that the current object parameter is appropriately managed throughout the iteration process. By controlling the flow of the loops and preserving the relevant data between iterations, the flow of the module can proceed the way it was intended to do and maintain progress across successive cycles.

3.8 Endpoints

Fulfillment in Dialogflow is deployed as a webhook and is used to perform backend logic every time it is called. This functionality enables the chatbot to deliver dynamic responses when engaging in backend logic. Within this system, Dialogflow can interact with six distinct backend endpoints specifically designed for data processing.

Among these endpoints is one that is structured to allow Dialogflow to receive custom payloads as responses. Another endpoint is tailored to focus on modifying conversational flows that utilize templating. Additionally, there exists an endpoint dedicated to storing the data in the knowledge base. Conversely, a separate endpoint serves the purpose of resetting the current session values. Lastly, there are health flagging endpoints that are split into two categories: physical and mental health; these focus on monitoring the symptoms of the user and flagging when necessary.

These endpoints play a crucial role in managing, fetching, storing, and processing the data transmitted within the system. Each endpoint serves a unique purpose tailored to enhance the functionality of the chatbot.

3.9 Language Limitations of the Chatbot

To be able to manage the responses of the user, all possible answers for each question generated by the chatbot are provided in a form of buttons. Input can also be typed in the text box. However, if the input does not match any of the expected answers, the system will continuously wait for the correct answer for it to proceed to the next question. The system's understanding of the free-form text is very limited since it will only respond if the provided answer is correct.

4 The Chatbot System

The multi-lingual chatbot is deployed as a web application and in Facebook messenger. Figures 6 - 7 present screenshots of the actual conversation in FB Messenger (prototype version) and Web App Deployment (Figure 8). Figure 6 presents the conversation about allergies. The system asks systematically the user about allergies on food (bread, seafood, etc.), medicines, dust, pollen and animal fur. If the user says yes to one of the allergens, the chatbot asks for the side effects, its duration, remedy and if it has relieved after the remedy. Same set of questions are asked if the user has allergies to other allergens as what is illustrated in Figure 4. Figure 7 presents the questions based on the Pediatric Symptom Checklist. Figure 8 presents the chatbot running as a web application. A report can be generated based on the responses of the user as shown in Figures 9-11. Figure 9 presents the visualization of allergens of all students in all schools while Figure 10 presents the allergens of students per gender. Figure 11 shows the mental health report particularly on what psychological areas need attention by a mental health professional.

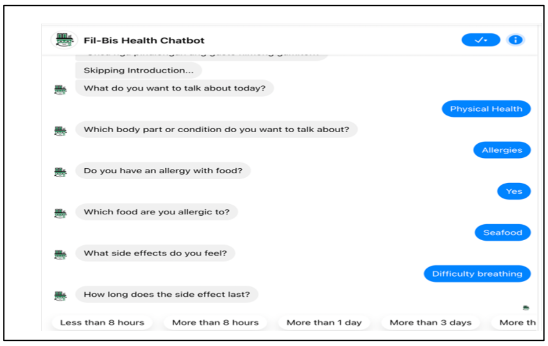

Figure 6. Conversation on Allergies

Figure 7. Mental Health Conversation in FB Messenger

Figure 8. Choice of Language conversation as a Web Application

5 Future Work

Monitoring the health and wellness of individuals ensures that their development is on a normal level, and this should begin in children as they will experience the most milestones in their growth and development. Schools monitor the children's health to ensure that they will turn out healthy in the future.

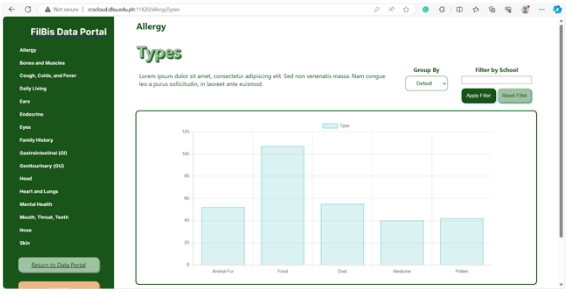

Figure 9. Report of Allergens in all Schools

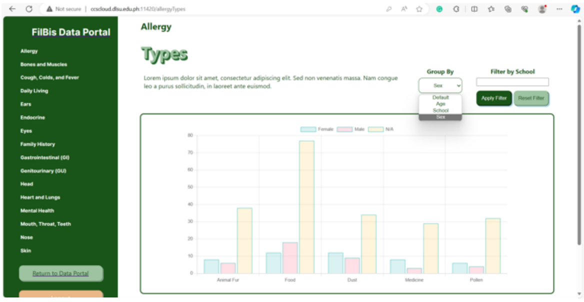

Figure 10. Report of Allergens per Gender.

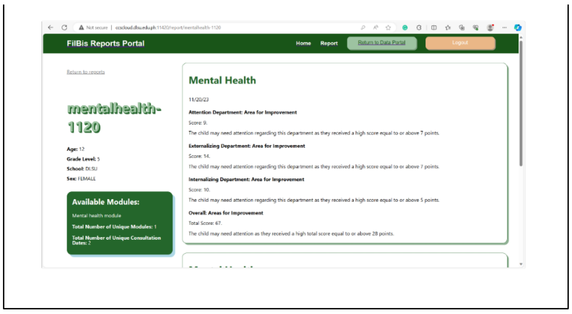

Figure 11. Mental Health Report per student.

This research presents how a multi-lingual healthcare chatbot that can monitor the physical and mental wellness of young children is designed and implemented. Empowered by Artificial Intelligence, the chatbot is capable of conversing in two major Philippine languages - Filipino and Bisaya as well as English. The chatbot will allow for more frequent and regular health and wellness check among children, even without the presence of a medical doctor or even a full-time school nurse and may identify children who may need specific interventions, whether psychological, medical, nutritional, or mere social-cultural support. This is motivated due to the fact that not all schools have the facilities to conduct routine checks on students. This project aims to utilize the technology such as chatbot that can run in mobile devices in order to address the lack of health professionals and resources in monitoring the general wellness of children. Future work includes the deployment of the system in most public schools in the Philippines.

Acknowledgment

This work was supported by the Department of Science and Technology - Philippine Council for Industry, Energy, and Emerging Technology Research and Development (DOST-PCIEERD) and the Advanced Research Institute for Informatics, Computing and Networking (AdRIC) Research Center of De La Salle University, Philippines.

References

Amato, F., Marrone, S., Moscato, V., Piantadosi, G., Picariello, A., & Sansone, C. (2017). Chatbots meet eHealth: Automatizing healthcare. *Proceedings of the Workshop on Artificial Intelligence with Application in Health co-located with the 16th International Conference of the Italian Association for Artificial Intelligence*.

Azure health bot: Microsoft Azure. Azure. (n.d.). https://azure.microsoft.com/en-us/products/bot-services/health-bot

Baheti, A., Ritter, A., & Small, K. (2020, July). Fluent response generation for conversational question answering. In *Proceedings of the 58th annual meeting of the association for computational linguistics* (pp. 191– 207). Online: Association for Computational Linguistics.

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019, June). BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 conference of the north American chapter of the association for computational linguistics: Human language technologies, volume 1* (long and short papers) (pp. 4171–4186). Minneapolis, Minnesota: Association for Computational Linguistics.

Du, X., & Cardie, C. (2018, July). Harvesting paragraph-level question- answer pairs from Wikipedia. In *Proceedings of the 56th annual meeting of the association for computational linguistics* (volume 1: Long papers) (pp. 1907–1917). Melbourne, Australia: Association for Computational Linguistics.

Fernando, J., Garcia, T. Macaraeg, K.& Azcarraga, J. (2024). Assessing the Effectiveness of FilBis: A Chatbot for Monitoring Young Children's Physical and Mental Wellness. To appear in the *Proceedings of ASIAN-CHI, 2024.*

Ghosh, S., Bhatia, S., & Bhatia, A. (2018). Quro: Facilitating user symptom check using a personalised chatbot-oriented dialogue system. *Connecting the System to Enhance the Practitioner and Consumer Experience in Healthcare,* 51-56. 10.3233/978-1-61499-890-7-51

Inkster, B., Sarda, S., & Subramanian, V. (2018). An empathy-driven, conversational artificial intelligence agent (Wysa) for digital mental well-being: real-world data evaluation mixed-methods study. *JMIR mHealth and uHealth*, 6(11), e12106.

Manning, C., Surdeanu, M., Bauer, J., Finkel, J., Bethard, S., & McClosky, D. (2014, June). The Stanford CoreNLP natural language processing toolkit. In *Proceedings of 52nd annual meeting of the association for computational linguistics: System demonstrations* (pp. 55–60). Baltimore, Mary-land: Association for Computational Linguistics.

Mesko, B. (2023, August 2). The top 10 healthcare chatbots. The Medical Futurist. https://medicalfuturist.com/top-10-health-chatbots/

Oxford Business Group. (2012). The report: The Philippines 2012 Oxford Business Group.

Papineni, K., Roukos, S., Ward, T., & Zhu, W.-J. (2002). Bleu: A method for automatic evaluation of machine translation. In *Proceedings of the 40th annual meeting on association for computational linguistics* (p. 311–318). USA: Association for Computational Linguistics.

Rahman, M.M., Amin, R., Khan Liton, M.N., & Hossain, N. (2019). Disha: An implementation of machine learning based Bangla healthcare chatbot. *2019 22nd International Conference of Computer and Information Technology (ICCIT).* 10.1109/ICCIT48885.2019.9038579

Rajpurkar, P., Jia, R., & Liang, P. (2018, July). Know what you don't know: Unanswerable questions for SQuAD. In *Proceedings of the 56th annual meeting of the association for computational linguistics* (volume 2: Short papers) (pp. 784–789). Melbourne, Australia: Association for Computational Linguistics.

See, A., Liu, P. J., & Manning, C. D. (2017, July). Get to the point: Summarization with pointer-generator networks. In *Proceedings of the 55th annual meeting of the association for computational linguistics* (volume 1: Long papers) (pp. 1073–1083). Vancouver, Canada: Association for Computational Linguistics.

The AI companion who cares. Replika. (n.d.). https://replika.ai/

Woebot Health. (2023, November 1). https://woebothealth.com/

Woodham, R., Rimmer, R., Young, A. H. and Fu, C. (2022). Adjunctive home-based transcranial direct current stimulation treatment for major depression with real-time remote supervision: An open-label, single-arm feasibility study with long term outcomes. *Journal of Psychiatric Research.* 153, pp. 197-205. https://doi.org/10.1016/j.jpsychires.2022.07.026

Yang, Z., Yang, J., & Xu, Z. L., Can. (2019, November). Low-resource response generation with template prior. In *Proceedings Of 2019 Conference On Empirical Methods In Natural Language Processing And 9th International Joint Conference On Natural Language Processing,* (p. 1866- 1897). Online: Association for Computational Linguistics.

Zhang, Y., Sun, S., Galley, M., Chen, Y.-C., Brockett, C., Gao, X., . . . Dolan, B. (2019). Dialogpt: Large-scale generative pre-training for conversational response generation. arXiv preprint arXiv:1911.00536 .

Zhu, P., Zhang, Z., Li, J., Huang, Y., & Zhao, H. (2018, August). Lingke: a fine- grained multi-turn chatbot for customer service. In *Proceedings of the 27th international conference on computational linguistics: System demonstrations* (pp. 108–112). Santa Fe, New Mexico: Association for Computational Linguistics.