Remote Patient Monitoring Systems based on Conversational Agents for Health Data Collection

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Keywords: Healthcare, Chatbot, Conversational Agents, Cardio-thoracic Surgery, Hypocoagulability, Telemonitorization, Patient-reported Outcomes.

Abstract: The pursue of digital health has been increasing in the past years and the COVID-19 pandemic promoted it further. Remote monitoring health care allows patients to report health outcomes and receive a proper follow-up from home and personalized health care by preventing unnecessary trips to hospitals. The design, development and use of two rule-based chatbots for data collection and guidance providing in two health telemonitoring contexts, post-cardiothoracic surgery for derived-complications control and patients with hypocoagulation, is described in this paper. The designed chatbots have the goal of being simple, modular and human guided. The first chatbot was used to collect photos from the surgical wound and the second was used to collect the INR value (from a coagulometer) and six related questions, following a measurement plan. In both use cases the clinical team could analyze the collected data and interact with patients using a web application. This chatbot may contribute to the increase of the safety perception of the patient and their engagement with their health status. The inclusion of the clinical team in the development was key to identify the requirements and to improve the user experience.

1 INTRODUCTION

The pursue of digital health increased during the past years and the COVID-19 pandemic promoted it further. Preventing unnecessary trips to hospitals by constantly monitoring patients through Internet of Things (IoT) devices, mobile apps, or simply through messages shows promising results. Severe acute respiratory syndrome corona-virus 2 (SARS-CoV-2) is a highly contagious corona-virus which has put at risk human health since 2019. Due to its high contagious rate and severity, it spread all over the world and caused difficult prognosis or even death to elderly individuals and individuals with non-communicable diseases (NCDs) (Pécout et al., 2021). NCDs are long-term and in some cases life-long pathologies and include cardiovascular diseases, cancer, chronic respiratory diseases, diabetes and neurological disorders. Patients living with NCDs require constant care to delay disease progression. This leads to both health and economic consequences due to the growing age of the worldwide population (Vandenberghe and Albrecht, 2020). During the pandemics, patients have been avoiding hospitals to prevent contagion which might lead to an increased disease severity and higher costs to the healthcare system (Kardas et al., 2021).

Remote monitoring healthcare allows patients to receive a proper follow-up from home and personalized health care, which has been revealed especially important since the Covid-19 outbreak (Mantena and Keshavjee, 2021). In the healthcare context, IoT-enabled devices can be defined as any device, including computers, mobile phones, and wearable sensors that may allow data collection, transfer and storage. These devices can be used to monitor patients' symptoms in real time (Mamdiwar et al., 2021). Point-of-care (POC) testing devices are particularly useful during telemonitorization because relevant parameters can be measured and reported from home. In the case of people on long-term oral anticoagulation,

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Dias, P., Cardoso, M., Guede-Fernandez, F., Martins, A. and Londral, A.
Remote Patient Monitoring Systems based on Conversational Agents for Health Data Collection.
DOI: 10.5220/0011011000003123
In *Proceedings of the 15th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2022) - Volume 5: HEALTHINF*, pages 812-820
ISBN: 978-989-758-552-4; ISSN: 2184-4305

these tests can be used to measure the international normalized ratio (INR) and adjust accordingly the medication dose (Heneghan et al., 2016).

Conversational agents (CAs) are software tools that mimic a human-like entity during a conversation using, text, voice, images or a mixture of all (Laranjo et al., 2018). CAs are usually deployed on messaging apps, websites or mobile-phone applications, as well as multimodal platforms. They have been used in a wide range of domains such as customer service, technical support, marketing, education and healthcare. Several authors have demonstrated that humans tend to attribute human-like attributes to non-human agents. Due to this trait about human-machine interaction, CAs are perceived as social interaction partners, capable of establishing a meaningful relationship (Bickmore and Cassell, 2001; Epley et al., 2007). Therefore, a CA can be perceived by the patient as a health counselor that is available to provide continuous guidance. This continued support can be given by providing reminders or information about medication or treatment plan, assisting on self-monitoring tasks, or by interacting with healthcare professionals reporting the results of monitorization.

POC testing alone can be used to do self-monitoring and self-management. In this case, the patient is responsible for managing her/his treatment plan and does not have a proper feedback about her/his recovery. IoT have changed this paradigm by allowing healthcare professionals to monitor in real-time the state of the patient and intervene if there is an abnormality, which increases patient's safety. A CA interacts directly with the patient and can be used to increase the patient's literacy, help managing medication doses and treatment based on the patient's measurements and prognosis. A system that integrates all of these technologies might promote patient's self-care.

The aim of the present study is to demonstrate the applicability of ruled-based chatbots on two different clinical follow-up services: post-cardiothoracic surgery and patients with hypocoagulation. In both cases, a telemonitoring system capable of collecting and reporting data and provide support to the patient was developed. The principles followed to design both chatbots as well as the technology used to develop them are described in Section 3. The application, data collection procedure, implementation and results for each chatbot are further explained in Section 4.2 and 4.3. In Section 6, conclusions and future work are presented.

2 STATE OF THE ART

In 1966, the first rule-based chatbot was developed by Joseph Weizenbaum at MIT Intelligence laboratory and it was named ELIZA. ELIZA was designed to mimic a patient-centered Rogerian psychotherapist and answer based on the identification of keywords in a sentence using pattern matching (Weizenbaum, 1966). In 1972, PARRY was developed by psychiatrist Kenneth Colby to simulate the behavior of a patient with schizophrenia (Colby et al., 1971). Psyxpert was an expert on disease diagnosis developed in 1987 and used to aid psychiatrists in diagnosing psychotic disorders (Overby, 1987). SESAM-DIABETE was developed in 1989 to be an interactive educational expert and provide support to insulin-requiring diabetic patients by giving personalised guidance and therapeutic support (Levy et al., 1989). In 1995, ALICE (Artificial Linguistic Internet Computer Entity) was the first computer program to use Natural Language Process (NLP) to interpret user input (Wallace, 2009).

Nowadays, CAs can be delivered using smartphone, web or computer-based apps (Chaix et al., 2019; Denecke et al., 2018; Kamita et al., 2019), smartphone embedded software (Griol and Callejas, 2016) or any other messaging app, such as Telegram or Facebook Messenger (van Heerden et al., 2017; Fitzpatrick et al., 2017; Casas et al., 2018). It was shown that the use of apps that need to be regularly updated leads to high dropout rates and non-usage (Lee et al., 2018). Messaging applications are the preferable mean to convey a conversation since most of the population is used to use them in the daily life (Tudor Car et al., 2020).

In healthcare, CAs have been used as a mean of conveying information between healthcare providers and patients. CAs have been applied to many health care sectors such as mental health (Vaidyam et al., 2019; Luo et al., 2021), physical activity (Schachner et al., 2020), HIV prevention (Marcus et al., 2020), oncology (Abd-Alrazaq et al., 2021), nutritional disorders (Pereira and Díaz, 2019), neurological disorders (Pereira and Díaz, 2019) and chronic diseases (Schachner et al., 2020; Bérubé et al., 2021).

Personal patient data and data collected during a conversation that might change the patient behavior can be used to customize the output messages and improve the user experience (Abashev et al., 2017). Additionally, in cases where the CA has medical knowledge provided by a secure source, such as medical databases, helpful context can be automatically generated through the CA which is particularly relevant for educational chatbots (Bickmore et al., 2016). An example of educational chatbot is the electronic medication management assistant (eMMA). eMMA was developed to empower patients by giving them the maximum information about their treatment. Reminders, interactive medication plans with information about each medicine and food interaction data are provided to the user (Tschanz et al., 2018).

Human-like communicative behaviors that can have positive effects on this therapeutic relationship have been largely studied (Van Pinxteren et al., 2020). Potts et al. (2021) studied the preferred human-like characteristics that would be desired for a chatbot to help support a mental health service. They found that the desired chatbot would have a positive outlook, accessible for any person and be able to support while recalling previous conversations (Potts et al., 2021). During the interaction, CAs must endure a relationship with the user. Moore et al. (2017) mentioned that it is important to ensure that the user is engaged: (1) the dialogue is tailored to match the user's level of understanding, (2) interactions are simple and synthetic and (3) rephrasing when the user does not understand the message (Moore et al., 2017).

NCDs are hard to manage for patients recently diagnosed, who need to learn how to adapt their lives and to this new normality. CAs were identified as important factors in mitigating knowledge gaps and as supportive agents since a closer relationship between the patient and the healthcare provider might be endorsed and, additionally, might be used as a mean to increase literacy and signalling high-risk situations by monitoring vital parameters (Heneghan et al., 2016; Guhl et al., 2020; Echeazarra et al., 2021; Bian et al., 2020; de Pennington et al., 2021).

Long-term oral anti-coagulation monitorization has been used to estimate the dosage of anticoagulant given the international normalized ratio (INR) test. At first, the patient would need to provide to her/his healthcare provider the INR and accordingly to its value the doctor or nurse would be responsible for choosing the right anti-coagulation dose. Self-management would be required to trained patients. In this case, given the INR test, they would be responsible for interpreting the results and adjusting the medication (Heneghan et al., 2016). This was particularly relevant on increasing medication adherence.

In 2020, a randomized controlled trial (RCT) aimed on increasing the adherence to medication by sending reminders and the quality of life of patients with atrial fibrillation. An embodied CA was used to improve communication, prevent hospital readmission, and educate patients. This study revealed improvements in patient's quality of life, daily activity and a self-reported adherence to anticoagulation therapy (Guhl et al., 2020).

A RCT using a Telegram based chatbot assistant, TensionBot, was performed to monitor patients with high blood pressure (BP). Its main functionalities are sending reminders to patients to ensure that BP is measured, storing measurements and letting data available to healthcare professional and, giving additional support about how to measure BP (Echeazarra et al., 2021). This study revealed that patients using this CA were able to improve their ability to properly measure BP and diminish the paperwork for healthcare providers (Echeazarra et al., 2021).

A postoperative follow-up system of orthopedic patients was performed in an exploratory quantitative and qualitative study in 2020. This system was based on a CA that would perform a series of questions through a cellphone call based on a template given by the medical staff and patient's personal data. Patient's responses would be processed using speech recognition and spoken language understanding techniques. This dialogue was about patient's satisfaction regarding the hospital service, health education and wound recovery. Doctors and nurses would have access to the feedback report and be able to intervene when needed. They found that AI-assisted follow-up could replace traditional follow-up (Bian et al., 2020).

In 2021, a proposal project that aimed to evaluate the effectiveness, usability, and acceptability of a CA named Dora. This conversation model would integrate speech recognition and generation to perform telephone follow-up by asking questions regarding patient's recovery (de Pennington et al., 2021).

3 DESIGN OF CHATBOT

The designed chatbot can be categorized as a rule-based task-oriented chatbot which has the goal of being clear, modular and human guided. Safi et al. (2020) identified four stages that should be considered during CA design to facilitate user engagement: text understanding, dialog management, data management and text generation (Safi et al., 2020). The design of the proposed chatbot has considered the aforementioned four stages:

- Text understanding: it refers to the process of figuring out what is the meaning or intention of the user's input. This process can be done by using pattern matching (keyword or string matching) or intelligent models using NLP or Machine Learning (ML) models (Safi et al., 2020). Some studies revealed the embryonic stage of NLP models in healthcare due to their lack of consistent methodology and evaluation methods (Schachner et al., 2020). The proposed chatbot is used for telemonitoring purposes and vital signs gathering, thus it exists in a structured and organized context which opposes to conversational agents that work directly with free-text.

- Dialog management: it is the process of establishing a link between user's input and the CAs response. This can be handled using finite, frame or agent-based dialogue system. A finite-based dialogue is a state transition network that can be defined by a sequence of pre-determined interactions between the user and the CA. In this case, user's dialogue is limited to a set of options and the dialog flow is fixed. A frame-based dialogue is characterized by a dialog flow determined by the content of the user's input and the CAs data. The answer given by the user will be used to fill the missing data from the task. Agent-based dialogue is defined as a dynamic dialogue between two agents that have enough intelligence to pursue a conversation based on reasoning and the sequence of arguments discussed during the dialogue (McTear et al., 2016; Safi et al., 2020). In this study, a finite-state dialogue machine was developed to increase the simplicity of the interaction with the user while offering the necessary modularity to give support during the follow-up.
- Data management: the proposed CA was designed to collect patient's data to generate a daily report to the healthcare professional for further analysis. Additionally, health-related information is led available to users, in order to improve their health literacy.
- Text generation: it is responsible for answering the user. This answer can be fixed or generated in case the output is built on top of intelligent models that use NLP or DL (Safi et al., 2020). Systems that give fixed responses can be tedious and frustrating to the user due to their inflexibility (Williams et al., 2018; Irfan et al., 2020). Intelligent agent might increase user engagement (Schumaker et al., 2007), the lack of robust evaluation methods together with the black box effect related to machine learning models (Tudor Car et al., 2020) might result in adverse consequences to the patient (Laranjo et al., 2018). Therefore, the text generation of the proposed chatbot is based on pre-defined and fixed text.

That being said, following the proposed design we implemented two distinct chatbots for two use cases using Django, a Python-based framework as their backbone and Twilio as the cloud communication platform to send and receive text messages through Short Message Service (SMS) and WhatsApp messages. What is more, to handle data management we leverage the open-source database management system PostgreSQL. Finally, to host both of our applications we use the platform as a service (PaaS) Heroku.

4 APPLICATIONS

In this section we will describe two applications developed under a multidisciplinar team of healthcare professionals, engineers and linguists: CardioFollow and HemoControlBot. These applications aimed at improving the follow-up of post-surgery (CardioFollow) and patients with hypocoagulation (HemoControlBot) by giving them support and additional information. Both use cases had the objective of collecting patient reported outcomes measures (PROM) and to display this data on a web application to the pertinent clinical staff (doctors and nurses), following the human computer interaction principles. The chatbot and the web application were developed in a co-creation environment, meaning that the members of the clinical staff had a pivotal role in their design and improvement. The target population for both use cases were patients that were recovering from a cardiothoracic surgery. What is more, the chatbots implemented for the introduced use cases leverage either SMS or Whatsapp. In this section, we define the common web application that sustained both use cases, specifying the details of each use case. Afterwards we explain the functionality of each developed chatbot.

4.1 Clinical Team's Web Application

The web application is the bridge that connects patients with the clinical team. Whilst patients interact through the chatbot, the clinical staff monitors the patients' health closely through the developed application. The application goal is to show patients data through different formats and layouts which were designed side by side with the clinical team - through icons, tables and interactive graphics. The use of icons allow a quick understanding of a patient's health status, namely changing colors according to specific events - a sudden alteration in any collected measure or value outside of a specified range. The graphics were used to display the data overtime, giving the clinical team the ability to compare the last reported value with the previous ones.

A screenshot of the web application is depicted in Fig. 1. This figure provides information regarding all patients and offers an overview of their health status with the goal of being easily readable to the clinical team: all measurements are identified with a specific icon and their values are displayed in the same rectangle. When the values outbound the predefined healthy range, the color will change to properly identify the high-risk situations. Thus, allowing the clinical team to prioritize the patients according to the number of alerts.

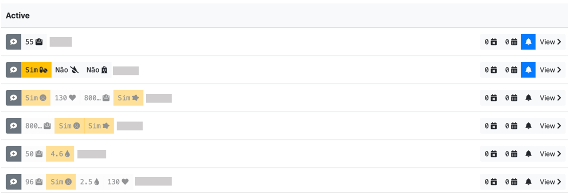

Figure 1: List of telemonitored patients with the respective outcomes and alerts. Measure that are outside of the normal range are represented with the color yellow. The names of the participants were hidden with a grey box.

Furthermore, the web application also has direct access to the dialogues within the chatbot which can be used for the clinical team to communicate directly to the patient, through the developed web application.

4.2 CardioFollow

This chatbot was used in a pilot that consisted of the telemonitoring of patients that underwent cardiothoracic surgery. Complications during surgery or hospitalization are common (Crawford et al., 2017), but risk also extends to the postoperative period, leading to hospital readmission of around 15-20% of patients during the first month and 30% in the first year (Efthymiou and O'Regan, 2011; McElroy et al., 2016; Khoury et al., 2020). This pilot had the participation of 35 patients so far, as depicted in Table 1. These patients, after the hospital discharge, were telemonitored for 1 month.

Table 1: Overview of both use cases. TD - Telemonitoring Duration; PTP - Previously Telemonitored Patients; PTF - Patients to be Telemonitored in the Future.

Use Case	TD	PTP	PCT	PTF
CardioFollow	1 month	35	0	150
HemoControlBot	6 months	0	1	29

During this period, the patients had a daily routine where they would report their blood pressure, weight, number of steps, heart rate and answer six questions, using IoT devices connected to a mobile application (Lopes et al., 2019). Whereas, the developed chatbot was used to collect daily photos of the patients' surgical wounds. That being said, we needed only a subset of the design defined above. Namely, dialog management, text generation and data management. More specifically, when the patient sends the photo of his/her surgical wound, the chatbot needs to be able to understand it, respond with clinically approved messages, and store the picture for further analysis by the clinical team. The chatbot text generation feature can be divided into two parts. The first part consists of an appreciation message that was used to engage the patient and to create some kind of empathy with him/her. The second part consists of a set of day-dependent literacy messages used to provide guidance during the patient's recovery/telemonitoring. This message calendar was developed with the clinical team based on leaflets that were given to patients after hospital discharge. The message was sent right after the photo was sent because it is at that moment that the patient has his/her attention focused on the smartphone.

This specific use case is going to be expanded to more 150 patients, as depicted in Table 1 and evaluated throughout a larger span of time where more improvements resulting from the clinical staff requirements will be developed.

4.3 HemoControlBot

This use case albeit developed in a similar context that Cardiofollow, was targeted specifically to assess hypocoagulation, through the International Normalized Ratio (INR) and additional health outcomes, through multiple-choice questions with the goal of evaluating if the use of a coagulometer allowed the patient a longer and better stay in the therapeutic range, when compared to standard clinical follow-up. That being said, the entirety of the interaction of the patient occurs through the chatbot, which is responsible for delivering the multi-step questionnaires, validating and storing the data. The patients are given a coagulometer (used to measure the INR), the chatbot's phone number and a code representing a measurement plan defined by the clinical staff. A measurement plan is a set of measures with a certain periodicity. In this specific use case the periodicity is set to 7 days and consists of 7 items: INR value and 6 questions, related to medication, bruise, bleeding, feces, nausea and trips to the hospital/health center. This chatbot is currently being tested with one patient and 29 more will enter the program, as depicted in Table 1. Each patient will report his/her outcomes to the chatbot for 6 months.

The chatbot implemented for this use case used all the four features defined in Section 3. Namely, in order for the patient to register into the chatbot we make use of the four features since we offer a self-enroll approach. That being said, the interaction is triggered by a patient's message saying "hello". The chatbot initiates the enrollment process requesting the measurement plan code, name, birth date and gender, step by step. Thus, the chatbot needs to understand, store, manage and validate the entirety of the interaction. Furthermore, the chatbot validates the user input accepting only valid answers, that are measurement dependent and in turn are defined by regular expressions. Moreover, by leveraging the dialog management and text generation capabilities of the chatbot, we display the expected input format and give proper feedback if the input does not match with the expected format. Furthermore, if the measurement is a question, we showcase the possible answers to the user. All the answers are preceded with a number that allows the user to answer with the respective number. This way, the answering process is faster and easier to the patient. In addition, due to the data management capability, we can store all the measures and user-defined thresholds for each measurement, which then permits the chatbot to send an alert (for the patient and the clinical staff) whenever any measure goes outside of the expected ranges, defined by the clinical team. Finally, with the goal of allowing the patient to validate his/her answers, the chatbot always asks for confirmation before storing the reported outcomes. If the patient does not validate the answers, the chatbot resets to the beginning of the measurement plan. The flow behind this chatbot is depicted in Fig.2.

An example of a conversation between a patient and the chatbot is depicted in Fig. 3. The green speech bubbles represent the patient and the black speech bubbles represent the chatbot.

In this use case, the requirements were translated into new features to the web application. Namely, manage measurement plans specific for a given service, in this case there is only the cardiothoracic service. Nevertheless, multiple services from multiple hospitals could use the developed software/solution/application. A measurement plan is used within two contexts: periodic reporting as noted previously, and on-demand reporting, which is triggered by the clinical staff. Thus, our web application was extended to be able to create and manage measurement plans, as well as their periodicity and allowing the clinical staff to request specific measures if desired. Intuitively, we offer a easy to use interface for the clinical staff to manage all the features described above.

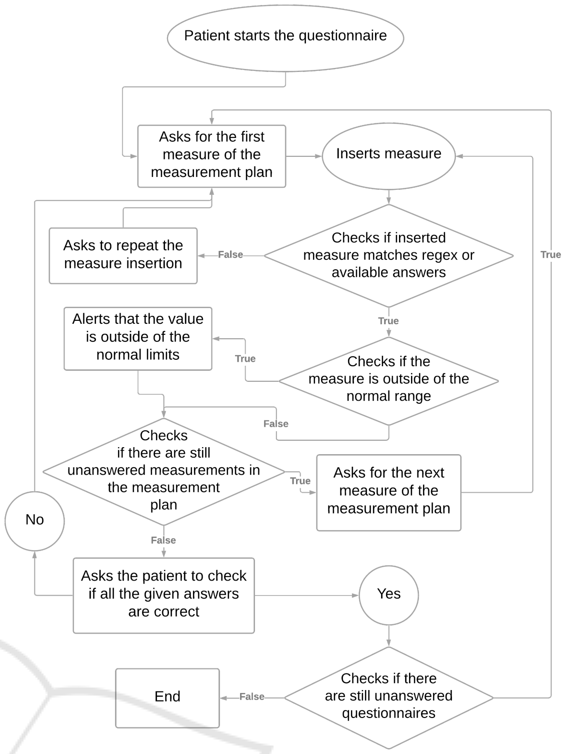

Figure 2: Measure collection flow. The circle represents the patient, the diamond represents the finite state machine and the rectangle represents the chatbot.

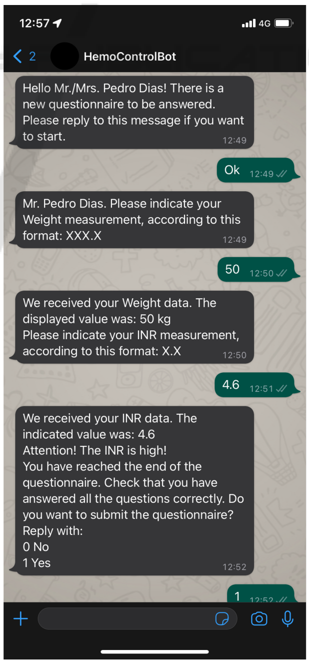

Figure 3: Example of a conversation between a patient and the chabot.

5 DISCUSSION

As it is mentioned in subsections 4.2 and 4.3, two CAs were developed to provide support to patients after discharge from the hospital. The information delivered to the patient was defined after several meetings with the clinical team and it contains guidelines to improve recovery. These chatbots are specially important due to the huge amount of information provided to the patient after diagnosis, which usually lets the patient overwhelmed and might be difficult to remember when away from the hospital. Thus, with these solutions we aim at providing health literacy, solve the issue regarding the lack of understanding of medications regimens, monitor vital signs while targeting high-risk situations, and equip the clinical team with an easy to use web application to communicate and understand the patient's recovery.

The CAs design aimed at the development of a system adapted to most patients. Not all patients could be included due to the exclusion criteria of the two use cases. These criteria were illiteracy and the inability to manage a cellphone. However, if the patient spends his/her recovery period with a capable informal caregiver, the telemonitoring can still occur, which happened with some patients from CardioFollow.

The user experience of the selected patients might be improved by attending to the degree of patient's literacy and adjusting the dialogue to improve the engagement with the CA. This could be done by having different dialogue-frames given the patient's literacy level.

Patients mentioned the importance of having a non-invasive tool that at specific timings can provide support when needed. After diagnosis, patients tend to look for adapted normality. A supportive tool that empowers patients by capacitating them to take their own decisions and feel safe from home, might be the key to giving them this adapted normality.

6 CONCLUSIONS

In this work, we successfully defined a generalized design of a rule-based task-oriented chatbot, which we then applied to two different use cases. Our initial experiments showed that offering a conversational-based interface to collect PROMs is an efficient way to keep the end-users - the patients - engaged. Mobile phones are ubiquitous, so most of the population can benefit from this way of outcome collection. Using SMS or Whatsapp as an outcomes collection channel is a good way to interact with patients because nowadays anyone carries their cell phone with them, thus being able to respond quickly to what is requested. Although the interface is simple and easy-to-use, managing a mobile phone requires some level of digital literacy, thus not being useful for every type of patient. Both use cases described in this paper, were developed with the objective of being extended to collect outcomes from patients with other health conditions.

From our experience, telemonitored patients feel safer and more engaged regarding their health status, so this work is a starting point to pose remote patient monitoring as a way of preventing clinical complications, due to its close follow-up, and of leading to an increase of the patients health literacy level. Moreover, from the clinical team point of view, having the possibility to analyze more outcomes will help to make better clinical decisions and adopt a more personalized treatment for each patient.

Finally, regarding the chatbot and web application development, including the clinical team in the process is of the utmost importance for two reasons. First, they are the domain experts with the necessary knowledge to identify the requirements for such systems to be of any use. Second, they are the end-users, and user experience is extremely important within this context. Ultimately, the developed systems must serve the clinical team, not the opposite.

7 FUTURE WORK

Both of the use cases described above took place within the context of cardiothoracic surgery in Portugal. Thus, intuitively, future work lies in expanding these conversational agents to other contexts, which will require further development to adapt to specific requirements that might arise. However, these two use cases are still undergoing as depicted in Table 1. There is currently no way to show to the patient a summary of his/her latest measurements, so developing a way of showcasing this data is a priority in the near future. Regarding user interaction, increasing the intelligence of the chatbot might be a way of decreasing input errors and giving advice. This can be done by suggesting, predicting or correcting the user's input.

ACKNOWLEDGEMENTS

The authors would like to acknowledge the Roche Diagnostics and the cardiothoracic service of the Hospital de Santa Marta for their contributions to carrying out the study. This research has been supported by the project DSAIPA/AI/0094/2020 from the Fundação para a Ciência e Tecnologia AI 4 COVID-19 Program.

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