Data Decentralisation of LLM-Based Chatbot Systems in Chronic Disease Self-Management

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ABSTRACT

Chronic patient self-management is crucial for maintaining physical and psychological health, reducing pressure on healthcare systems, and promoting patient empowerment. Digital technologies, particularly chatbots, have emerged as powerful tools for supporting patients in managing their chronic conditions. Large language models (LLMs), such as GPT-4, have shown potential in improving chatbot-based systems in healthcare. However, their adoption in clinical practice faces challenges, including reliability, the need for clinical trials, and privacy concerns. This paper proposes a general architecture for developing an LLM-based chatbot system that supports chronic patients while addressing privacy and security concerns. The architecture is designed to be independent of specific technologies and health conditions, focusing on data protection legislation compliance. A prototype of the system has been developed for hypertension management, demonstrating its potential for motivating patients to monitor their blood pressure and adhere to prescriptions.

CCS CONCEPTS

• **Applied computing → Health informatics**; • **Security and privacy → Database and storage security**; Social aspects of security and privacy; • **Computer systems organization → Distributed architectures**.

KEYWORDS

chatbot, personal data store, healthcare data privacy, hypertension

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1 INTRODUCTION

Patient self-management is demonstrated to play a central role in patient care, since it has a beneficial impact on both physical and psychological health status, as well as reducing the pressure on the health systems [5, 7]. In particular, patient empowerment and engagement are essential, especially in those health conditions that are mainly managed at home. Chronic diseases are a prominent example in this context, since the correct acquisition of vital signs and the adherence to the therapy are mainly in charge of the patients during their day-to-day life. One way of empowering patients is to encourage them by providing, for instance, regular reminders based on objectively measured levels of adherence [20], *e.g.* on how many measures have been acquired during the last week, or on the type and frequency of physical activity [23].

The literature on self-management recognises the crucial role played by digital technologies, especially wearable and *mobile*, which are considered enablers for effective patient-centered care and empowerment [13, 17]. Among others, *chatbots* are emerging as a powerful tool for supporting patients in managing their chronic conditions. The goal is to deliver to patients personalised motivational messages aimed at (i) keeping patient engagement in self-management habits high, (ii) make them aware of their adherence and performance with respect to clinical prescriptions, and (iii) motivate them and, accordingly, possibly improve their healthy habits. Investments into AI assistant messaging could affect patient outcomes. If more patients' questions are answered quickly, with empathy, and to a high standard, it might reduce unnecessary clinical visits, and it may affect health behaviours, including medication adherence, compliance (eg, diet), and fewer missed appointments.

The release of large language models (LLMs), for understanding (NLP) and generating (NLG) natural language, substantially increases the literature in this field and potentially will improve the adoption of chatbot-based systems in healthcare [4]. A critical example is given by autoregressive generative pre-training transformer (GPT), whose performances are continuously improving, evolving in various version —to date GPT4 has already been launched and GPT5 is under-training. ChatGPT is actually one of the most famous examples [9]. Even though they are showing extraordinary performances and are leading change in multiple contexts – such as in software engineering by writing and debugging code –, until now they are not yet adopted in clinical practice to support patients' needs, since *(i)* their reliability in medicine is still to be demonstrated, *(ii)* large clinical trials must be conducted before adoption, and *(iii)* critical privacy issues arise once interacting with such systems and feeding them with patients' sensitive data. However, investigating the potentialities and issues of the adoption of LLMs in medicine is worthy. In particular, they demonstrated to answer user queries with empathy, a skill considered crucial in the clinical context this paper discusses, where patient engagement and trust strongly depend on the ability of the chatbot to mimic human behaviours and responses.

Accordingly, in this paper we propose a first discussion on how LLMs may be adopted as a grounding technology for developing a chatbot-based system that supports chronic patients in managing their condition. Out of the three main issues outlined, we focus in this paper on how the privacy and security of patients data may be managed. In particular to where and how acquired sensitive data, such as vital signs, are stored, and if these data can be used in the LLM-based frameworks nowadays available.

The contribution of this paper is the definition of a *general architecture* in which we identified the key components for building such a system with respect to data protection legislation, independently of the specific technologies adopted and of the specific health condition it will be applied to. The system enables acquisition, storing, and analysis of users' data, but also mechanisms for user's empowerment and engagement on top of profiling evaluation and motivational messages. An instance of this system has been developed in the context of *hypertension chronic disease*, and the chatbot has been programmed and trained to interact with hypertensive patients, specifically for motivating them in acquiring Blood Pressure (BP) measures, following prescriptions, monitoring the evolution of pressure, and possibly generating alerts if the vital signs exceed the safe range.

The reminder of this paper is organised as follows. Section 2 outlines the main aspects related to the use of LLM in the healthcare domain, giving some background and motivation for the design of the proposed system architecture. Section 3.2 presents the system architecture. Section 4 discusses on the specific use case, showing some results on the implementation of a prototype of the system. Section 5 outlines some related works. Finally, Section 6 provides some concluding remarks.

2 LARGE LANGUAGE MODELS IN HEALTHCARE

LLMs are becoming increasingly common and are already being used in content marketing, customer services and a variety of business applications. Recent advances reveal that LLMs are impressive learners: they are able not only to extract, summarise, translate, and generate textual information, but also to develop impressive reasoning capability [22]. Nevertheless, it is unclear how well they will perform in specific domains with precise and difficult real-world questions, especially in fields such as medicine where high and complex reasoning is required, evaluating a diverse set of information, from the context the patients live to their clinical conditions, and grounding on a ever-changing medical knowledge. Before discussing the potentiality and limitation of LLMs in medicine, it is worth mentioning that these models were not developed to provide healthcare, and their ability in different healthcare scenarios is still unexplored, thus opening a set of challenges for research in this field.

Since their onset and, particularly, since the recent widespread diffusion, the scientific and clinical communities are discussing the potential benefits, issues and challenges of their adoption and exploitation in clinical activities, management and research [9]. The common agreement is that LLMs have the potential to be a game changer, but also that we are not quite ready to play and further research is needed to address critical issues of their application in healthcare.

A critical analysis of LLMs in healthcare is proposed in [4], where four main categories of possible applications have been identified: *(i)* support of clinical practice, *(ii)* scientific production, *(ii)* misuse in medicine and research, and *(iv)* reasoning about public health topics. Moreover, for each of the four categories, the paper proposes the results of the interactions with a notable LLM-based system, ChatGPT, in order to evaluate its effective performance and concrete applicability. Generally speaking, results show a huge potential of such strategies in each category but, since the focus of our work falls into the first one, henceforth we refer to the preliminary evaluation that has been discussed in literature within this category. In this context, LLMs can enable the extraction of knowledge from medical texts, such as electronic health records (EHRs), clinical notes, and research papers, and its proper exploitation once answering user questions. Moreover, a peculiar skill LLMs showed that is worthy of attention, is the capability to engage human-like conversations and to be perceived as trustable, reliable and emphatic. For instance, [2] shows that a set of patients, that receive responses in a public online forum both from physicians and from a LLM-based chatbot, preferred chatbot replies, rating both the quality and the empathy of the chatbot-generated responses higher than those of physicians. This skill is crucial in the context of self-management of chronic conditions we are discussing in this paper: the adoption of LLMs can increase patient engagement and accordingly, compliance with medical prescriptions, such as measures acquisition and therapy adherence.

Given these premises, that particularly demonstrated promising results in the use of LLMs for interacting with patients, further research is necessary before any definitive conclusions can be made regarding their potential effect in clinical settings. In particular, we organise here the limitations we found in literature, in three main categories:

Trustability: LLMs still lack the medical expertise and context needed to fully reason on the causal relation between symptoms and diagnosis, as well as to precisely identify the proper sets of treatments for different conditions. Moreover, they can be influenced by any bias present in the data they were trained on: this could be particularly concerning in medical contexts, where certain demographic groups may be under-represented [11].

Ethics: Ethical concerns and of the dangers derived from LLMs adoption for self-care is another big issue that must be addressed: who's responsible? where can be set the line between self-care and professional advice?

Privacy: Another issue, that arises when it comes to LLMs in medicine, is how patient privacy can be protected [21] (for instance, ChatGPT was banned in Italy in early April due to privacy issues): first of all these language models tend to capture sensitive information in the sentence, which leaves the adversary a window for privacy breach; secondly, the use of patient health records must observe the privacy laws, such as the Health Insurance Portability and Accountability Act (HIPAA) through accessing protected health information (PHI) [19] in the case of the US, or General Data Protection Regulation (GDPR) in case of EU [12, 27]. For instance, since ChatGPT does not support services covered under HIPAA, the use of ChatGPT for healthcare workflows would violate the terms of use: deidentifying patient messages by removing unique information to make them HIPAA/GDPR compliant could change the content enough to alter patient questions and affect the chatbot responses.

In this paper, our primary focus lies in developing a comprehensive system architecture capable of providing recommendation services for individuals with chronic illnesses. Thus, addressing potential legal issues surrounding the utilisation of sensitive data is our primary concern. We believe that privacy should be our foremost consideration, and as such, we strive to strike the delicate trade-off between safeguarding sensitive information and delivering practical natural language processing. Our approach is based on filtering sensitive data at the first stage of the system. This way, clinical data remain confined to the healthcare domain, securely stored within the patient's Personal Data Store (PDS), ensuring that no sensitive information is transmitted externally. Filtered, non-sensitive data can then be safely passed to more advanced external LLM, enhancing the empathetic nature of the conversation. Admittedly, this approach has its limitations, as discussions pertaining to the patient's health status remain relatively simplistic, and the broader discourse cannot be contextualised based on their health condition. However, in the absence of a sophisticated language model integrated within the healthcare system, we assert that this solution presents a viable alternative. Further research in this area is certainly warranted.

3 SYSTEM ARCHITECTURE

In recent years, the integration of technology in the healthcare sector has gained significant attention, due to its potential to enhance patient care and improve operational efficiency. One such technological advancement is the utilisation of distributed systems in healthcare, which enables the seamless sharing of information across multiple entities. In this section, we explore the design of a distributed system architecture that should surmount the typical limitations of a classic Client/Server model.

The goal of the system is to *empower* and *engage* patients, so as to improve their health conditions and quality of life, by *pro-actively* recommending activities and *re-actively* responding to queries and registering health data, and to safely manage and store their data. Accordingly, the system is composed by two main components sharing a common core providing services for data storage, and natural language processing (NLP) and generation (NLG). Before diving into the architecture, we motivate our design by describing the functional and non-functional requirements gathered through co-design sessions with both clinicians and patients.

3.1 Requirements

The gathered requirements either inform the functionalities that the system should deliver (e.g. send reminders to patients once a day), or what properties the system must exhibit (e.g. flexibility). The following sections describe both.

3.1.1 Functional. The functionalities that the system must deliver can be roughly categorised as *pro-active* or *re-active*, depending on whether interaction is initiated by the user or not.

- Pro-active functionalities are: (P_1) sending messages to inform the patient about their *adherence* to prescriptions, and (P_2) sending messages to ask the patient to input health data.
- Re-active functionalities are: (R_1) responding to a set of specific requests for (aggregated) health data issued by the patient, and (R_2) responding to a set of specific disease-related queries issued by the patient.

The description of how each functionality is actually delivered is in Section 3.4.

3.1.2 Non-functional. Non-functional requirements regard either some metrics of performance that the system should deliver, or the technical (legacy) constraints it must abide to. Such requirements are as follows:

- each patient has a personal data store (PDS) that addresses concerns related to privacy, security, and data protection, which are essential qualities of a system handling sensitive information;
- the client interface for the chatbot will be the Telegram messaging app[1], chosen for its wide adoption, device compatibility, and capability of supporting custom bots.

The description of how each functionality is actually delivered is in Section 3.2.

3.2 A Distributed System Architecture

A possible architecture of such a kind of healthcare system can be based on a client/server model, where a centralised server acts as the main hub for processing and storing data, while client devices interact with the server to access and manipulate information. This architecture is being widely used in various, or better, almost all healthcare applications and has proven to be a reliable and scalable solution. Indeed, the client/server model offers advantages such as centralised data management and ease of maintenance. Moreover, assuming that the central server is maintained by the healthcare system, this solution does not raise privacy concerns related to sensitive data protection. It thus can easily set up to comply to data management regulations, such as the EU GDPR [27].

However, there are some recognised concerns related to a client/server system architecture:

Single Point of Failure: One major drawback of the client/server model is its reliance on a central server. If the server fails or experiences downtime, the entire system becomes inaccessible, rendering it unusable for critical healthcare operations.

Scalability and Performance: As the number of users and data volume increases, the centralized server may become

[1] https://core.telegram.org/bots

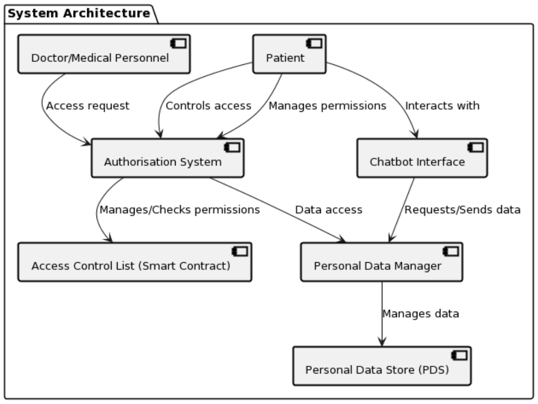

Figure 1: System architecture.

overloaded, leading to decreased system responsiveness and delays in delivering timely healthcare services.

Data Privacy and Security: In healthcare, data privacy and security are paramount. Although efforts can be made to ensure data security, any breach or unauthorised access to the server compromises the privacy of all stored data. Thus, while a centralised data management can comply to data protection regulations, the potential for data breaches still raises concerns regarding patient confidentiality.

Data Sovereignty : Data sovereignty refers to the concept that individuals should have control over their own data, including where it is stored, how it is processed, and who has access to it [27]. In the context of healthcare, data sovereignty is of utmost importance as it involves sensitive and personal information. Clearly enough, in a client/server solution the data is produced, maintained and owned by the specific (local) healthcare administration. If not properly handled, this can lead to issues if, just to make an example, the patient relies on a private healthcare system but then decide to change doctor.

To address the mentioned limitations of a client/server based solution, we propose a decentralised system architecture for the chatbot healthcare application. While some components of the system remain deployed on a server, the rationale is to design a solution that allows patients to have full control of their data, while at the same time granting access to the authorised healthcare personnel, through the use of proper access control policies.

Figure 1 provides a representation of the overall system. In the rest of the section, we are going to outline its key aspects (Subsection 3.3), and then we specifically focus on the chatbot system, which is the main component under consideration in this work (Subsection 3.4).

3.3 Decentralised Personal Data Storage

The distributed system architecture is designed to empower each user with a Personal Data Store (PDS) where their personal data, obtained from interactions with the chatbot, can be stored. Whenever new data is generated, it is added to the user's PDS, through a personal data manager, and it is used to update the patient's profile [26]. The system incorporates a traditional authorisation system, ensuring that only the user is authorised to input or update their data [3]. However, the system also enables authorised healthcare professionals, such as doctors, to access and potentially contribute to the data, based on the patient examinations.

At any given time, the patient retains the ability to add or remove doctors (or other relevant actors) from the list of authorised users with access and writing privileges to their personal data. This can be achieved through an access control list implemented as a smart contract.

Medical professionals with access to the data can retrieve and potentially aggregate it to perform analyses. The system allows them to utilise the data for gaining insights and generating valuable information that can support diagnosis, treatment, and research. By enabling data aggregation, the architecture promotes collaborative and data-driven decision-making in healthcare.

3.3.1 Personal Data Store (PDS). The Personal Data Store (PDS) serves as a pivotal component within the decentralised system architecture. Each user is allocated their own PDS, which acts as a secure repository for storing their personal data. This data is acquired through interactions with the system, such as chatbot conversations or other relevant healthcare activities. The PDS is decentralised, indicating that data of different users can be distributed across distributed nodes within the system. However, at the level of the single user, the PDS acts as a centralised location to maintain control over his/her personal health information, allowing to manage and update patients' data efficiently. A Personal Data Manager is put in front of the PDS. This component is in charge of handling data reads and writes, as well as simple data aggregation, e.g., mean calculation of data retrieved in a time interval (see below).

To interact with their respective PDS, patients can utilise the chatbot Interface. The chatbot acts as an intermediary, providing a user-friendly interface for patients to access and manage their personal health data. Patients can interact with the chatbot to input or update their data, ensuring they have control over the information stored in their PDS.

The implementation of each single patient's PDS can be based on different alternatives, ranging from a traditional and centralised personal cloud storage (e.g. Azure, Google Drive, etc.) up to decentralised file storage systems, such as the InterPlanetary File System (IPFS) [3]. The former, private and proprietary solution is more likely and easy to manage from a user perspective, and it is completely compatible with our system, as long as the data content can be referenced and data can be accessed by the medical personnel, once they have the keys to decode ciphered data. According to the latter solution, ciphered data can be published and stored in the peer-to-peer system in a pseudo-anonymous way. In this work, we are not going into the specific implementation details. However, according to this solution it is possible to track all data changes in the PDS by logging all the updates into an associated DLT. This solution provides guarantees in terms data integrity and traceability. The interested reader can find a detailed description and implementation in [27].

3.3.2 Personal Data Manager. Each patient can request, through the chatbot interface, to manage and inspect their data, such as to be informed with some aggregate values, such as the average, over a period, to remove some entries, to visualise the trend of some stored data in a specific time window. This component is in charge to manage such a kind of requests, by accessing the PDS and properly inspecting and elaborating data. As already mentioned, in the current implementation of the system, the personal data manager performs basic data management functionalities. However, this component could be equipped with more sophisticated data analysis models and embedded in more complex federated learning architectures.

3.3.3 Authorisation Mechanism. To maintain data privacy and control, the system employs a robust authorisation mechanism. This mechanism ensures that only authorised individuals, namely the user and authorised healthcare professionals, can access and modify the data within the PDS. The user is the ultimate authority when it comes to granting or revoking access privileges. Additionally, the system enables users to dynamically manage their list of authorised healthcare professionals, granting or removing access permissions as required.

The access control is implemented using a Smart Contract-based Access Control List [25]. This access control list contains a list of authorised users who are allowed to access and interact with the patient's data. The Smart Contract ensures transparency and security in managing access permissions, enabling patients to dynamically add or remove authorised healthcare professionals from their access control list.

3.3.4 Data Retrieval and Analysis. Authorised healthcare professionals, such as doctors, can retrieve and utilise the data stored in their patients' PDS for analysis purposes. This includes accessing relevant patient information, perform data aggregation as well various analytical operations to gain insights. These analyses can range from individual patient assessments to population-level studies, enabling evidence-based decision-making and enhancing the quality of care. Since access it is based on a smart contract access control list, data accesses by healthcare professionals adhere to the permissions granted by the user, ensuring privacy and data sovereignty.

3.4 The Chatbot

The chatbot has 6 main duties, meant to support the delivery of functionalities P_1, P_2, R_1, and R_2:

- collect data from the patient, defining how many measures must be acquired per week, at the minimum
- inform patient about anomalies in the measures
- aggregate data (weekly or monthly average)
- provide full history data to the patient upon request
- visualise data plot
- hold an empathetic conversation with patient

Its abstract workflow is also simple:

(1) periodically, as configured, check whether patient data is missing (this could be done with a different period, e.g. weekly for weekly average)
(2) in case it is, generate a message to request patient input on specific data (e.g. systolic and diastolic pressure)
(3) in the case input validation succeeds, send back a confirmation message
(4) otherwise guide the patient through troubleshooting (e.g. "input lower value first, higher then")
(5) simultaneously, be ready at all times to reply to patient's inquiries (e.g. about entered data, their aggregation or visualisation)

The chatbot elaborates patient input through Natural Language Processing (NLP) and generates feedback through Natural Language Generation (NLG).

Ad-hoc Interpretation The first level manages the interpretation of the sentences that include vital signs values. This component is crucial and can not admit any misinterpretation since data acquired will be used for managing the disease. As such, the interpretation of the inputs including numbers is parsed with an algorithm developed ad-hoc for the specific pathology. This solution also preserves data protection, since no sensitive information is transmitted externally;

Wit.AI: The second level manages the requests on data inspection that the patient may ask. For instance, it understands requests on data aggregation, such as providing mean values over a period of time, or showing plot of measures in a specific time window. This component is in charge of the Wit.AI library[2]. It foresees a training process based on keywords and on "intent" – a set of functions that the application is able to perform in response to a user's action – and "utterances"– a set of sentences the application is able to understand –, as required by the Wit.AI API. The Wit.AI App must be trained on the clinical problem addressed, since the vocabulary is rather specific. Every time a user enters a sentence, the trained Wit.AI App will estimate which intent must be triggered. Adding new sentences and evaluating how the App responds (which intent it selects) constitutes the training phase, thus making the App ready to properly recognise new sentences entered by the user. We stress the fact that this module is in charge of understanding the intent to be triggered, not executing it. The execution is in charge to the personal data manager, so as to avoid any sensitive data disclosure. Thus, for instance, Wit.AI can understand that the patient would like to know an average value of a measure acquired during the last week, but the calculation is performed by the personal data manager.

LLM via GPT3: In order to understand, and answer properly and empathically to a varied set of sentences the patient may input – whose content is rather unpredictable, thus making the Wit.AI training impossible – the third level of this system exploits a LLM. In particular we interacted with GPT3 through the API available.

The NLP/NLG component is implemented in such a way that the three levels are mutually exclusive and the call of a higher level is possible only if the first ones failed in understanding the sentence. In this way, we protect patients sensitive data, such as their vital signs measures, while we let more general conversation on different aspects of the disease, or whatever the patient may ask, to an impressive high-performance NLP/NLG that can understand and interact with the patients making them perceiving the system as trustable and empathetic.

[2]https://wit.ai/

4 CASE STUDY

In this paper, we instantiated the system presented in Section 3.2 to support HBPM. The software project has been developed in C#, using the .NET technology, together with other software technologies, such as PostgreSQL, Amazon Web Services, Telegram API, Dashboard, and Wit.AI. These technologies were maintained due to their essential functionalities for the system's operation.

4.1 Clinical background and motivations

Arterial hypertension still remains the strongest modifiable risk factor for cardiovascular disease worldwide. Despite extensive knowledge about ways to prevent and treat hypertension, the global incidence and prevalence of hypertension and its cardiovascular complications are still elevated, mainly due to inadequacies in prevention, diagnosis, and control. According to the Global Burden of Disease Study, hypertension is the leading cause of cardiovascular diseases and one of the major risk factors responsible for 20% of all deaths [6]. The treatment of hypertension has shown clear benefits in reducing cardiovascular risk however, *blood pressure management* is currently suboptimal in a significant proportion of hypertensive patients. The current inadequate management of hypertension might be in part related to the limitations of using only office blood pressure (BP), which has led to increasing use of out-of-office BP [10]. Adoption of home BP monitoring (HBPM), in particular, has had an exponential growth, favoured by technological progress, such as small, accurate, user-friendly, and relatively inexpensive BP monitoring devices. However, the way patients measure their BP is often incorrect, which makes it difficult for physicians to interpret values appropriately and therefore to make correct decisions on treatment. Furthermore, only half of the patients share BP data with physicians and most patients still report BP values on paper not allowing an appropriate estimation of means [15].

4.2 Chatbot configuration for HBPM

To compute the daily adherence, we defined prescription compliance as a function of the number of measurements the patient acquires per week, namely $g = 3$.

The Wit.AI App is trained by creating the intents: "agree", "disagree", "pressure_get_all", "pressure_info", "pressure_mean_day", "pressure_mean_week". For each intent a varied set of sample utterances in Italian are provided, which are then used by Wit.AI to perform model training. A set of different utterances are then added.

(1) At first, ad-hoc interpretation of the incoming message is attempted. In the context of this case study, incoming messages containing a couple of numbers are interpreted as pressure measurements (with some heuristics to filter out unwanted matches). A confirmation message is sent back (i.e., *Is 120 your systolic pressure and 80 your diastolic pressure?*). If data is validated, the measures are added to the database. The ad-hoc parser accepts a wide range of separators, words, and other characters, in order not to constrain users into using a fixed message format;

(2) Messages that are not matched by the ad-hoc interpretation step, are forwarded to Wit.AI for intent detection. According to the intent detected, a different response is generated. For instance, an utterance like *Could you please send me a graph of all measurements?* would be matched by Wit.AI to the intent "pressure_get_all", that generates a graph of all past user measurements and sends it back. An utterance asking for guidance, like *How can I send you my measurements?* or *What should I do?* will match the intent "pressure_info", providing a short guide on how to use the chatbot and how to send daily measurements;

(3) If no intent is detected or if the match is uncertain, ChatGTP is invoked to generate a conversational response (with no effect other than keeping the dialogue credible and empathetic).

The chatbot appears as in Figure 2. Screenshots are in the Italian language, since the system is designed for Italian users and has been evaluated, through a closed loop process, by Italian physicians involved in the project.

5 RELATED WORKS

The impact of Internet of Things in healthcare as enabler of disease self-management is well discussed in the literature [14]. The literature shows that mobile health interventions can promote change in a range of behaviours, both in healthy and chronically ill populations, by easing the process of data acquisition and storage, promoting healthy lifestyle, close monitoring of health conditions and possibly therapy adherence [14].

Diverse efforts have been proposed in the literature. Given the huge amount of papers in the field, we focus here on works specifically devised for the hypertension disease, mainly supporting digital BP acquisition and storage. A comprehensive review of 186 mobile apps available in the two major app stores, Apple Store and Google Play, is presented in [1]. Main drawbacks identified are: *(i)* the need for patients and health care professionals to trust the apps, *(ii)* privacy and security issues, *(iii)* difficulties associated with installation and use, especially by elderly or disabled.

In recent years, chatbots have been introduced in the field as a mean to mediate the interaction among the digital system and the user, preventing errors, promoting constancy and accuracy, and grounding on messaging apps such as Telegram and WhatsApp, which are now almost universally used [16, 24]. In the context of hypertension, a paper presenting a chatbot for hypertension – strongly related with our work – is [8]. There, a Telegram chatbot is presented with the same goal of supporting patients in recording BP acquisitions. However, it is based on a predefined set of sentences, responding to messages that must be formatted properly.

[18] is a first work of us that steps forward by exploiting AI services to make the interaction with user more flexible: it enables the chatbot to understand different data formats that may be adopted by the user and it adequately answers to a different set of questions. However, it still lacks the capability to engage patients in conversations that make it perceived trustable, reliable and emphatic. This is the reason why we extended our previous work by adding a third level that grounds on LLM, thus enabling an extremely wider capacity of our chatbot to understand and respond patients.

Finally, [8, 18] do not discuss neither manage the privacy issue we are dealing with in this paper.

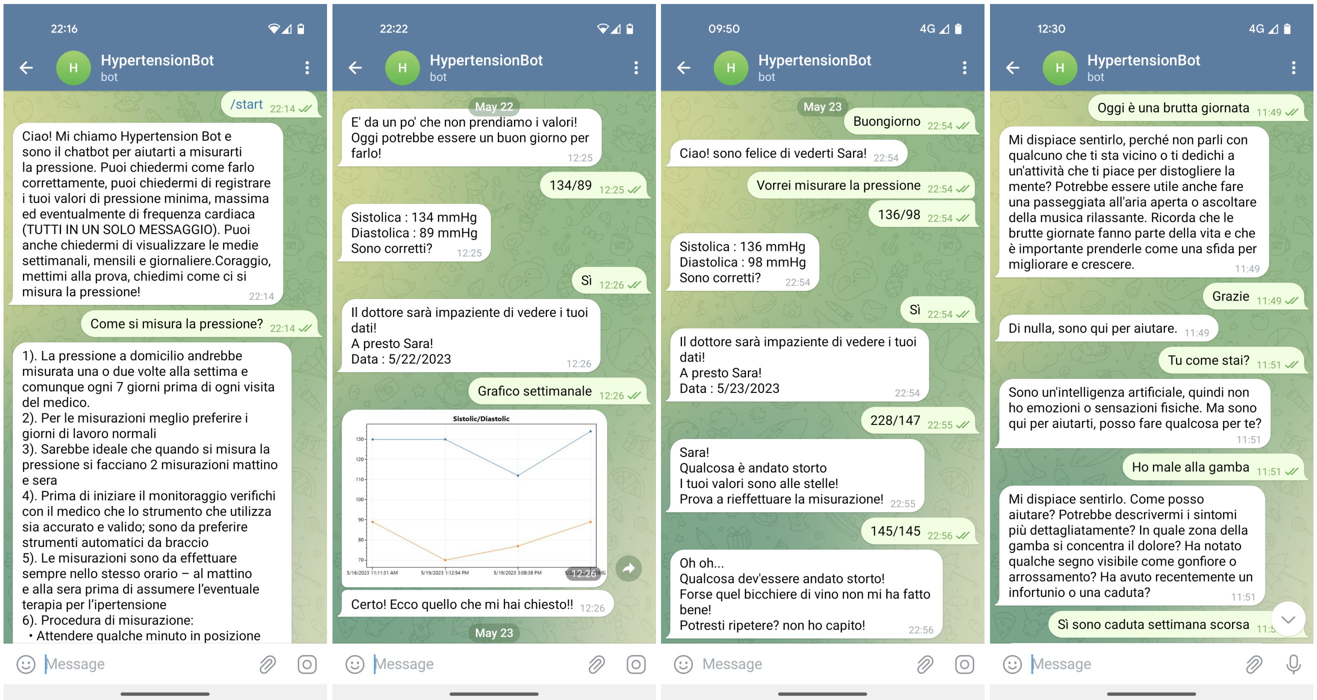

Figure 2: Telegram chatbot. Since the chatbot has been specifically devised for Italian patients, the language is Italian. For the sake of the readers, from left to right, the chatbot *(a)* provides the user with prescriptions on when and how they can measure they have to acquire their BP, *(b)* suggests the user to acquire BP since too much time has been passed from the last acquisition, verifies that the data entered are correct, by prompting the patient, and provides a plot as a response to the request "weekly chart", *(c)* alerts the patient if entered values are out of the safe range, and *(d)* holds an emphatic conversation with the user who complains about a bad day and leg pain.

6 CONCLUSION

We described a general purpose architecture to promote patient empowerment through a mobile healthcare solution: a recommendation system interfacing to patients in natural language via a chatbot. The framework is designed in a modular way, so as to be flexible (configurable) regarding (i) the disease, (ii) the deployment infrastructure, (iii) the criteria for sending recommendation messages, (iv) the natural language "spoken" by the chatbot (currently, Italian), (v) the patient interface (e.g. a mobile app replacing the Telegram app), (vi) as well as the clinicians interface (currently an ad-hoc web application used for monitoring). The system design presented in this paper is specifically tailored to prioritise data protection and uphold the principles of self-sovereignty. By incorporating a PDS for each individual, we grant users control over their own data, thereby fostering trust and ensuring compliance with data protection regulations. This approach not only safeguards sensitive information but also empowers individuals to manage their personal data.

The developed system has been deployed for HBPM and tested with clinicians, and it is currently under evaluation by a restricted group of volunteers, featuring both healthy individuals as well as hypertensive patients. Future work will report on such an evaluation from both user satisfaction and usability perspective, and a quality of life and health improvement one.

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