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HELENA: An intelligent digital assistant based on a Lifelong Health User Model

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ABSTRACT

Digital Assistants are overgrowing in the mobile application industry and are now implemented in various commercial devices. So far, their use in the health domain is limited and often narrowed to remote monitoring of specific patient pathology. The main contribution of this paper is HELENA, a conversational agent endowed with healthcare knowledge that supports users in managing their lifelong health user model (LHUM) by providing simple services.

The proposed platform has been evaluated in a user study involving 160 participants who gave feedback on the digital assistant and the profile conceptualization. The results showed that LHUM is comprehensive and inclusive (76.25% positive feedback), and the users appreciated that all personal health data were available in one single profile (83.75% positive feedback). Furthermore, the user interaction was pleasant, functional, and efficient. Also, measurement management, data sharing, and food diary management have been broadly appreciated. The outcomes of our investigation suggest that adopting a lifelong comprehensive user profile by digital assistants is a promising research direction.

1. Introduction

The implementation of information and communication technology in the medical field is commonly referred to as eHealth (or digital health), which consists of using information technology for the benefit of human health (El Benny, Kabakian-Khasholian, El-Jardali, Bardus, et al., 2021; Srivastava, Pant, Abraham, & Agrawal, 2015). Applications for monitoring patients usually adopt wearable smart sensors and devices to monitor vital parameters such as heart rate, blood pressure, blood saturation, and body temperature. These devices are often connected to the Internet or mobile platforms via Bluetooth technology (Sebestyen, Hangan, Oniga, & Gál, 2014; Zhang et al., 2021). This puts the world of eHealth within reach of the end-users, who can gain a huge advantage in dealing with daily activities that affect their health.

In this user-centered vision of eHealth, digital assistants can play an important role. For instance, voice-based digital assistants, such as Siri and Alexa, are rapidly becoming adopted by consumers (Brill, Munoz, & Miller, 2019). Recent studies have shown high user satisfaction when using conversational devices and personal digital assistants in eHealth, but the perception of their limited reliability is still a problem (Abdul-Kader & Woods, 2015; Omrani, Rivieccio, Fiore, Schiavone, & Agreda, 2022).

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It is crucial to provide reliable eHealth services based on explainable models that support decision-making. It is necessary to design systems that support the physician in making informed and timely decisions and provide an empathetic, easy-to-use, reliable interface to improve user experience and increase trust.

The contributions of this work are:

- the conceptualization of LHUM, a Lifelong Health User Model, which is a comprehensive clinical user profile fed with data coming from the interaction with the users or from other systems. LHUM could be exported in standard formats and shared among physicians treating the patient;
- the design and implementation of HELENA, a healthcare digital assistant exploiting LHUM to provide personalized services. HELENA allows users to monitor personal health status through a text-based interface (i.e., a chatbot), as well as a classic graphical interface with buttons and labels;
- the definition of a privacy-aware and transparent process for lifelong monitoring of the patient's health status;
- an experimental session to assess user satisfaction with HELENA.

2. Related work

Emerging technologies are reshaping the healthcare sector in several ways: how consumers access it, how and which providers deliver it, and what outcomes must be achieved. Such ecosystems could be enabled by a combination of: (i) A holistic user model to integrate information that today is fragmented across different information systems (Musto, Narducci, et al., 2020); (ii) Advanced data analytics and artificial intelligence personalization engines to generate insights for patients and their community of caregivers (Bakator & Radosav, 2018; Polignano, de Gemmis, & Semeraro, 2021); (iii) Continuum of care interaction models, patient-caregiver (Lund, Ross, Petersen, & Groenvold, 2015); (iv) Pro-active monitoring of patient's health status (Polignano et al., 2020); (v) Refinement of AI-driven care solutions for healthcare, social and community facilities (Musto et al., 2021).

In this ecosystem, Digital Assistants (DAs) play an important role. They are software or hardware components that interact with users and execute textual, or voice commands (Abdul-Kader & Woods, 2015; Valera Román, Pato Martínez, Lozano Murciego, Jiménez-Bravo, & de Paz, 2021). In the last few years, DAs have benefited greatly from the advancement of Natural Language Processing, Artificial Intelligence (including deep learning), mainly due to the abundance of data on the web and the mass diffusion of smartphones. Their use has become very common in mobile healthcare applications and has grown significantly in recent years, completely revolutionizing the relationship between patients, physicians, and healthcare providers (Sreedevi, Harshitha, Sugumaran, & Shankar, 2022). According to recent literature, most personal assistants in eHealth (Preum et al., 2021) are developed to support only elderly people (Coşar et al., 2020) or people affected by specific problems, such as Alzheimer's disease (Aljojo et al., 2020), Parkinson's disease (Orozco-Arroyave et al., 2020), heart failure (Echeazarra, Pereira, & Saracho, 2021), diabetes (Rehman et al., 2020), nutrition diseases (Parra, Favela, Castro, & Morales, 2018). Only in a few cases, DAs do not focus on a specific disease. A comprehensive review of the DAs in eHealth can be found in Islas-Cota, Gutierrez-Garcia, Acosta, and Rodríguez (2022).

In this paper, on the ground of the lessons learned from previous work, we propose a modular digital assistant that collects medical data and comprehensively organizes them according to a holistic view of the patient. The system is general, i.e., does not refer to any specific disease, and was conceived by redesigning our previous system HealthAssistantBot (Polignano et al., 2020). The resulting agent is complete, versatile, and accessible through an independent mobile application. This makes the system also more dynamic and adaptive to user needs.

3. Lifelong Health User Model

User profiling is nowadays a common practice over the web, which began with seminal work by Kobsa, Koenemann, and Pohl (2001), who proposed a keyword-based representation of the web user. Since then, many strategies have been proposed to exploit the "digital footprints" that people leave on the web (i.e., social networks, web services, purchases, preferences, searches, etc.) to build a user profile (Polignano, Basile, Rossiello, de Gemmis, & Semeraro, 2017; Polignano, Gemmis, Narducci, & Semeraro, 2017; Polignano, Narducci, de Gemmis, & Semeraro, 2021; Song, Lee, & Moon, 2019), a representation of his/her interests and preferences to be used for personalization and adaptation purposes. Among possible user profile facets (Cena, Likavec, & Rapp, 2019), we focus on the *physical and mental state*. From this perspective, we defined the *Lifelong Health User Model (LHUM)* as the composition of eight relevant aspects. LHUM is a comprehensive *clinical* representation of the user, which can be used to record clinical events during his/her entire life, therefore it can be regarded as a kind of lifetime clinical diary. An overview of LHUM is depicted in Fig. 1. The eight boxes are the aspects that we have chosen to include in the model. Details of each of them are provided in the rest of the section.

Hospitalizations - A hospitalization must involve a continuous stay in the healthcare facility for a defined time. We consider it as valuable data to store: the name of the health facility, the dates of beginning and end of hospitalization, the reasons for hospitalization, any visits, treatments received or diagnosis, name and surname of the doctor who took care of the patient, prescriptions, admission risk level. These data are formalized as complex objects strictly dependent on the domain. In general, we expect only a few data stored in this aspect to be updated frequently.

Medical Examinations - A medical or clinical examination is a situation in which a physician examines a patient for any possible signs or symptoms of a medical condition or to assess his/her general health. It generally consists of questions regarding the patient's symptoms or perception of health status. It may be routine, specific, or comprehensive, and might end with a diagnosis and a

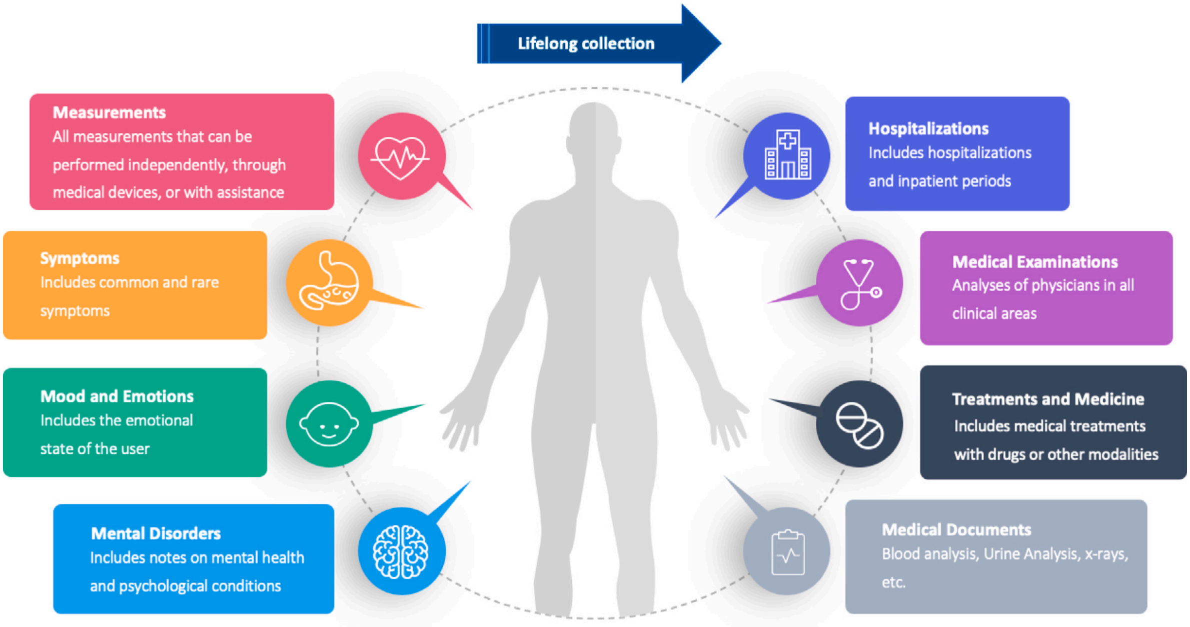

Fig. 1. The proposed Lifelong Health User Model (LHUM).

prescription. We decided to include in this aspect: the name and surname of the doctor who took care of the patient, specialization, place, type of examination, date, reason, diagnosis, and eventually, medical treatment or prescription. Similarly to hospitalizations, these data are formalized as complex objects strictly dependent on the domain. Also for this aspect, we expect only a few data stored in this aspect to be updated frequently.

Treatments and medicines - Therapies may include drugs to be taken at a specific time with a specific dosage, activities to be performed, treatments to be adopted, or new habits to take. It is essential to include treatments and medicines in a specific section of LHUM because they are among the most important aspects examined by a doctor when a quick overview of the patient's health state is needed. These data are also dynamic, time-dependent, and usually stored for a short or medium time, except for those related to chronic diseases. For this reason, we decided to store such data as a complex object that contains: the name of the treatment, the name and surname of the doctor who prescribed it, the name and quantity of the medicine, days of the week on which medicines are to be taken, start and end date of the prescription.

Medical Documents - This section of the LHUM includes all patient medical information regarding clinical documents generated from routine, specific, or comprehensive examinations. These documents should be collected and archived to allow the patient to view and share them when necessary with the referring physician. Such data is formalized as a simple triple, document name, date, and document itself. This data type has long-term validity and is not affected by volatility or frequent updates.

Measurements - This is the most dynamic aspect of LHUM, as it refers to vital parameters that the patient can measure autonomously, having the appropriate medical instruments or with the help of doctors/nurses. Measurements include: blood pressure and beats per minute, blood glucose level, blood oxygenation level, body temperature, weight, the total amount of calories taken in a day, the total amount of liquids taken in a day, etc. Each measurement is formalized as a triple consisting of the type, date and time of the measurement, and observed value. These data are very time-variant and punctual. They provide a current picture of the patient's health and are often used in the development of digital assistants and personalized health services (Echeazarra et al., 2021; Radziszewski et al., 2016).

Symptoms - Any abnormal health condition that generates discomfort in the patient. Symptoms may be felt frequently or rarely, with low, medium, or high intensity. It is always necessary to record the date and the time when a symptom occurs, the type of symptom felt, and its intensity. These data are also time-dependent and can provide an overview of the patient's health status at a given time. Symptoms are often exploited by automatic disease diagnosis systems (Kononenko, 2001).

Mood and Emotions - This is one of the two aspects of LHUM that take into account the psychological traits of the user. The emotional state of the patient can be collected as a discrete (Ekman, 1999) or continuous (Gerber et al., 2008) value associated with a date and time. These data can be acquired explicitly, i.e., by asking the user to reveal his/her mood, or implicitly, i.e., by inferring the user's mood either from his/her behavior or the content posted on the web. From several emotional surveys on the same day, it is also possible to deduce a more stable value representing the mood of the patient (Zhang, Zheng, & Magnenat-Thalmann, 2016).

Mental Disorders - Mental health involves our psychological and social well-being. It affects how people think, feel and act. It also helps determine how people handle stress, relate to others, and make choices. Mental health is essential at every stage of life,

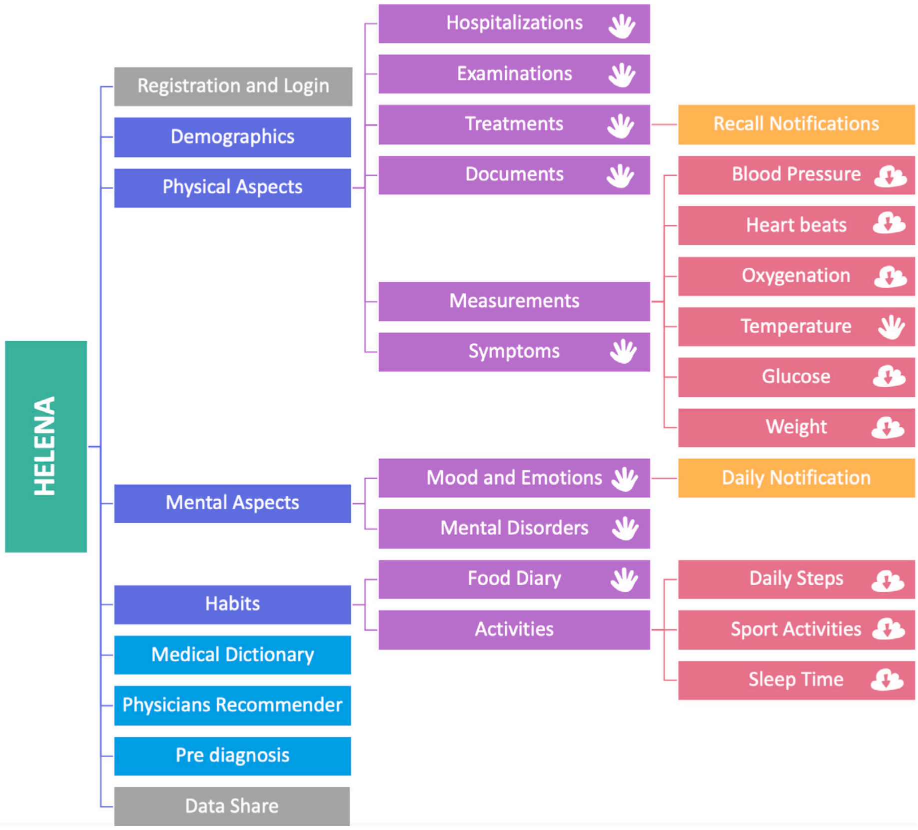

Fig. 2. The HELENA digital assistant architecture. Functionalities marked with the cloud icon can be automatically collected from users' smart devices. Those marked with a hand icon should be manually reported by the user.

from childhood and adolescence through adulthood. Collecting information regarding the mental health of the patient is relevant: for instance, small signals may be recorded that can lead to an early diagnosis of mental disorders such as depression. This section is similar to that of storing symptoms but focuses on mental health aspects. Examples of information that can be stored in this section are: confused thinking, feelings of worry, panic, sadness, uncontrollable emotions, loss of interest, and change in sleeping habits. As for symptoms, these aspects are recorded as a triple given by the name of the symptom, date and time, and its intensity.

LHUM is proposed as a part of a holistic and comprehensive user profile (Musto, Polignano, Semeraro, de Gemmis, & Lops, 2020) that can be easily accessed, shared, and updated during the patient's lifetime. Despite being complete enough to describe a person's physical and mental state, it still needs to be enriched with more data to be compliant with this holistic view. Examples of further data to be included in LHUM are: gender, date of birth, habits, such as the amount of physical activity performed daily, sleeping time, or food and water taken daily.

4. HELENA: An intelligent digital assistant for smart healthcare

This section presents the architecture and implementation details of HELENA, a digital assistant that allows users to store, access, share, and update information regarding their health profile.

4.1. Architecture of the platform

The HELENA platform consists of independent modules that manage the lifelong health user model (LHUM), demographic and habits information, and provide simple health-related services. Fig. 2 depicts the organization of the platform, which has been designed by adopting user-centered techniques and strategies (Abras, Maloney-Krichmar, Preece, et al., 2004) to ensure high usability and user experience.

4.1.1. Features

HELENA provides a set of features: (i) application features that include functions for registration and login, and data sharing; (ii) management features that allow the classic operations of creation, updating, reading and deletion (CRUD) on the user profile; (iii) health services to support end users in common tasks.

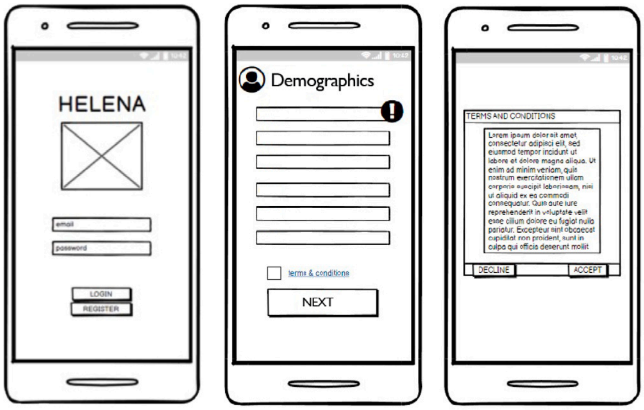

Fig. 3. A sketch of the login and registration screen.

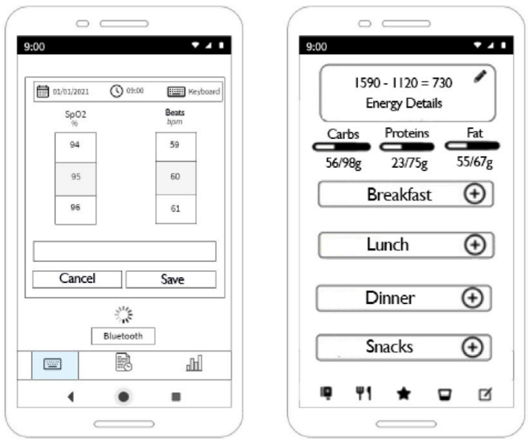

Fig. 4. A sketch of the monitoring screen on the left side and the food diary screen on the right side.

Application Features. They are represented using gray blocks in Fig. 2, and include login and registration and data sharing. Login and registration allow users to register a personal account on the platform. During the registration phase, the user, in addition to providing a username and password, must accept the terms of service. EU General Data Protection Regulation (GDPR) (Voigt & Von dem Bussche, 2017) allows us to store sensitive health information anonymously and use it only with the user's explicit consent to offer innovative features. In addition, the user may also add demographic data, as depicted in Fig. 3. The Data Share feature allows the user to share or export all the information entered into the platform. Specifically, the user can send his/her data to an email address of choice, e.g., a physician, or export them in a compressed package (zip format) containing a PDF report and any additional documents uploaded to the platform.

Management features. They are represented using blue blocks in Fig. 2, and include specific information such as demographic data, physical aspects, mental aspects, and habits. Demographic data contains details about the avatar, name, surname, date of birth, registered address, phone, and tax code. This information can be created, read, updated, or deleted anytime. The physical aspects section includes modules for the management of hospitalizations, medical examinations, treatments, records, measurements, and symptoms. Each of these exactly mirrors the representation proposed in the LHUM profile. Data can be created, read, updated, or deleted. Moreover, the user can set a notification that will remind him/her to perform the treatment on a specific day and at a particular time. Measurements are divided into different blocks: blood pressure, heart rate, blood oxygenation, temperature, glucose level, and weight, and the user can manually enter the different measurements on a specific date or through Bluetooth Low Energy smart devices (i.e., functionalities marked with the "cloud icon") when possible. The transmission takes place through a Generic Attribute Profile (GATT): this defines the structure of the data and how they are transferred. It uses a generic data protocol called the Attribute Protocol (ATT), which stores the device's services, characteristics, and related data in a simple lookup table using 16-bit IDs for each entry in the table (Panwar & Misra, 2017). The HELENA platform, as a client, sends a request command to the device to obtain, through its services and characteristics, the data collected from the user. They are then collected and stored in the user profile. Fig. 4 shows a sketch of the monitoring section. The mental aspects are currently included in the platform through a section about emotions and mood and one about mental disorders. This information is collected by sending a push notification message

Fig. 5. The color palette used in HELENA. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

which asks the user how he/she feels at that time. The user can choose between the five emotions of Ekman (1999): anger, surprise, disgust, enjoyment, fear, and sadness, plus the one of neutrality. Through a slider, the patient can select the intensity of the emotion felt on a scale between 1 to 10. The section on mental disorders proposes an open field that the user can freely fill in. Finally, as for the habits section, we decided to provide the user with the ability to monitor food assumed during the day and activities performed. The monitoring of food is implemented through a food diary that allows the user to record for each meal, i.e., breakfast, lunch, dinner, and snacks, the food assumed. The user can search for any food by typing a query in a search area connected to a search engine (i.e., ElasticSearch[4]) fed by the list of foods released by the Swiss Nutrient Value Database.[5] If an appropriate response is retrieved, it is added to the diary; otherwise, the user can add the food manually by filling in the appropriate fields with nutritional values. Fig. 4 shows a sketch of the food diary section. The section regarding activities is very similar to the monitoring section. The user will be able to manage information regarding the number of steps taken that day, the sleeping hours from the previous night, and any sports activity performed, with the corresponding duration in minutes. As a future development, a solution is being planned to collect this information directly from wearable devices such as fitness trackers.

Health Services. At the current stage of implementation, three services have been designed: a medical dictionary, a recommender system of physicians, and a pre-diagnosis service. The medical dictionary allows users to type a single term query in a search area connected to a search engine based on ElasticSearch, whose database was populated with medical data extracted from MSD Manuals, patient version.[6] This service is basically a *"searchable"* medical guide to symptoms and diseases, providing the user with verified and reliable information. The user is shown an excerpt from the guide and a link to read more about the topic. The recommendation and pre-diagnosis services are similar to those described in Polignano et al. (2020).

4.2. User interface

We developed both a "Graphical User Interface" that ensures the classical interaction with the digital assistant by using buttons and input fields, and a "Conversational User Interface", that allows for simple interaction through voice and text.

4.2.1. Graphical user interface

By Human Centered Design (HCD), we mean a group of methods and principles to support the design of products or services that are useful, usable, enjoyable, and meaningful. In order to follow the HCD guidelines, we started by sketching the platform interface using wireframes (Yang, Zimmerman, Steinfeld, & Tomasic, 2016). A wireframe is a two-dimensional drawing that serves as a visual guide to illustrate how a platform will work. It does not cover the whole design of the app, but only the key screens and interface elements. A wireframe is not a high-fidelity graphic design and does not contain detailed design elements such as logos, font specifications, and actual images. Instead, it is something like an architectural plan or schematic diagram. As the next steps, we focused on choosing shapes and colors. It was decided to use soft, rounded shapes since they convey a feeling of harmony and protection. The circle, in particular, is connected to the meaning of community, love, and unity and requires less cognitive effort from the user's eyes. Square shapes are more difficult to process at a cognitive level. Moreover, an important role is also played by the movement of the eyes on shapes: with right angles, the path is often abruptly interrupted, while on softer shapes, this does not happen (Troncoso, Macknik, & Martinez-Conde, 2009).

For the color palette, we went towards various shades of green and blue since they convey a sense of tranquility, helping to overcome anxiety and stress related to medical treatments, and indeed, those colors are usually chosen to paint hospitals' rooms. The color theory defines green as relaxing as blue, but simultaneously with the same energy as yellow (Agoston, 2013). Blue is associated with calm, tranquility, professionalism, cleanliness, and confidence. Following these guidelines, we have chosen the palette for HELENA (see Fig. 5).

The wireframes realized were evaluated with a restricted set of 20 users with mixed computer competence, 60% men and 40% women, aged between 20 and 35. We described the project objective and proposed to simulate a possible interaction with the wireframes, focusing more on the colors, position, and form of the proposed graphical elements. In the end, they were asked to fill in a questionnaire to evaluate the effectiveness of the designed interface. The questionnaire contains the following five questions, and users could answer using a 3-point Likert scale, i.e., not so much, well enough, and very much:

- Q1: "Does the color palette feel relaxing to the eyes and evoke a sense of serenity?"
- Q2: "Are layout and shape of elements easy to use and understand?"

[4] https://www.elastic.co/

[5] https://valorinutritivi.ch/en/

[6] https://www.msdmanuals.com/home

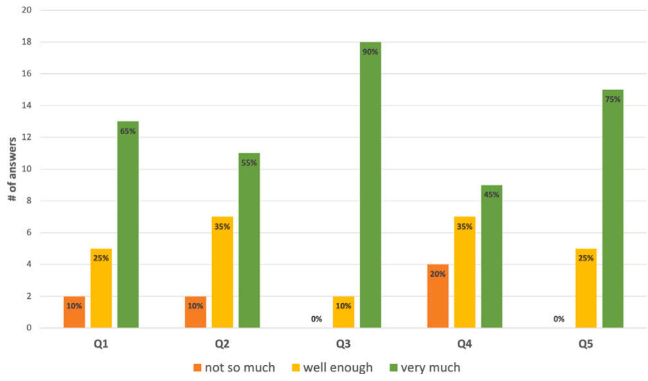

Fig. 6. Preliminary user study for evaluating the wireframe model.

Fig. 7. Resulting graphical user interface of the platform.

- Q3: "Is the position of the buttons adequate for easy usage?"
- Q4: "Are the icons easily understandable?"
- Q5: "Is the purpose of the application clear and understandable from the platform functionality?"

Results of the questionnaire in Fig. 6 show that the layout of the elements could, in some cases, be unclear to users and that the used icons were not exhaustive. This led us to investigate more on the structure of the graphical interface and on the design of new icons more focused on the medical domain. We took inspiration from commonly used applications, e.g., those developed by Google through its material design.[7] We introduced pictures to have a user-friendly interface and to differentiate it from other competitors. The resulting graphical interface of the platform is shown in Fig. 7. At the moment, it is realized only for the Italian language, but we intend to extend it to English as well.

[7] https://material.io/

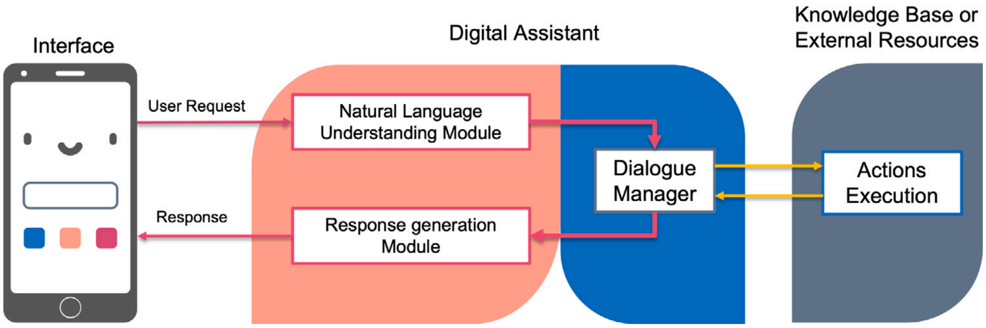

Fig. 8. Chatbot architecture.

4.2.2. *Conversational user interface*

Conversational User Interfaces (CUI) are a type of digital interface that allows users to interact with the software following the principles of human-to-human conversation. Thanks to a conversational interface, users can tell the software what they need, getting a response through a more flexible structure than the classic, more structured graphical user interfaces.

The architecture of our chatbot is depicted in Fig. 8. Any request received by the chatbot is processed by the Language Understanding Module, which infers the user intention (Intent) and extracts the associated information (Entities). Once the user request is interpreted, the chatbot must determine how to proceed, i.e., to deal with the information directly, to request more context information, or ask for clarification. The Dialogue Manager module is responsible for this decision. When the request is fully understood, the Dialogue Manager decides which Action to perform or which information must be retrieved to answer correctly to the user request. Actions are functions able to retrieve information or interact with the platform. Information can be retrieved from the Knowledge Base or any other external resources, and the Response Generation module produces a human-like natural language response by filling in a predefined answer template (Dahiya, 2017). The different intents are handled by invoking internal HELENA functionalities for LHUM profile management and smart services invocation.

Our chatbot allows three types of interaction using text, buttons, and voice. Buttons make answers to the chatbot's questions easy for the user, while voice commands facilitate users having difficulty with typing, e.g., older people. Voice messages are transformed into a textual form using a Speech-to-text function and then managed as standard text.

Intent Recognizer. Intents are split into two main groups: *profile-related intents*, and *services-related intents*. The goal of *user-related intents* is to manage all facets of the user profile, including LHUM, demographics, and habits. Specifically, these intents allow users to: (i) ask what information is encoded in the profiles (e.g., what is my last stored blood pressure?); (ii) add new information in the user profile (e.g., add pasta with pesto to lunch). Service-related intents are mapped to the smart services offered by HELENA. Services can be invoked in retrieval and recommendation mode, i.e., by explicitly submitting a request (e.g., I want to know what headache means) or asking for a recommendation (e.g., can you suggest a physician nearby?). In total, our system is trained to catch 45 intents.

Entity Recognizer. An additional task performed by the *Natural Language Understanding module* is the recognition of relevant entities, such as numbers, dates, and quantities. They can be part of the user text when he/she provides numerical values in the monitoring section. To design this component, we relied on Dialogflow, which provides a Natural Language processing pipeline for predefined system entities (e.g., dates, times, colors, email addresses, etc.) or for creating custom entities.

Dialog Manager and Response Generation module. Once intents and entities have been obtained from the Natural Language Understanding module, the Dialog Manager module deals with the appropriate invocation of system services to interact with the HELENA platform. These services can be data modification or interaction/retrieval services that provide a list of elements, such as the user profile data, which are then passed to the response generation module. The information is encapsulated in a fixed natural language sentence template to generate an understandable and human-like sentence in a completely unsupervised fashion.

Fig. 9 reports a screen of the chatbot implemented in HELENA. The only language supported by the chatbot is Italian (the text in the figure is reported in English to facilitate understanding).

4.3. *Implementation*

HELENA platform is developed through an Android architecture for mobile devices (Gandhewar & Sheikh, 2010). Java code is written using Android Studio.[8] The powerful online service Google Firebase API,[9] which allows to save and synchronize the data processed by web and mobile applications, was also used to let the user interact with the various logical functions of the app. In addition, each functionality provided by the application is implemented following the separation of concerns (SoC) pattern (Kulkarni

[8] https://developer.android.com/studio

[9] https://firebase.google.com/

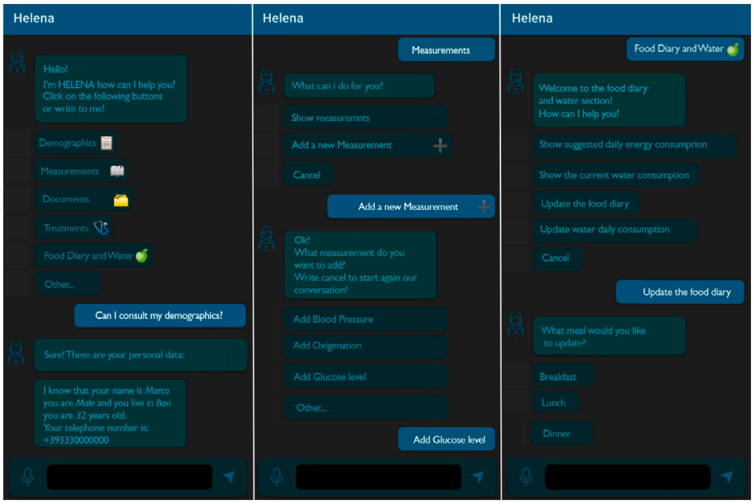

Fig. 9. Screen of the chatbot implemented in HELENA.

& Reddy, 2003). Each of the five functionalities is independent of the other and is reusable in other projects or extensible. The use of each of the basic hardware device features, such as Bluetooth, Storage, Microphone, etc., was appropriately prompted to the user via the Android security screens. At any time, the user can decide to remove these permissions partially or entirely.

In order to design a usable user interface and meet the needs and requirements of the users without neglecting good design, graphical screens were developed using the Figma tool.[10] Figma is a browser-based UI and UX design application with enjoyable design, prototyping, and code-generation tools. It is primarily web-based, with additional offline functionalities enabled by desktop applications for macOS and Windows. The complementary Figma Mirror apps for Android and iOS allow importing screens produced with Figma to mobile devices.

The conversational interface is developed through Google Dialogflow platform,[11] which provides a Web user interface called "Dialogflow console", used to create, build and test agents able to manage conversations with end-users through an NLU module that classifies natural language sentences. The communication between Dialogflow and HELENA was implemented through a function uploaded to Google Cloud, developed in Node.js. The Node.js function interposes itself in the communication between the application and the platform. In particular, the platform sends to the Node.js function the input provided by the user. The function sends the data to Dialogflow, which recognizes the intent and returns the response to the Node.js function that sends it back to the HELENA platform. It takes care of the application to show the response to the user in its user interface. All other components belonging to the backend of the platform, i.e., functions for operationally changing the user profile or providing smart services, have been developed in Java and exposed as RESTful Web Services[12] directly from the mobile application.

5. Experimental evaluation

We carried out a user study to assess both the effectiveness and usability of the platform. To this purpose, we addressed the following three research questions:

- RQ1: *completeness and effectiveness of the conceptual model*. Which facets of the LHUM do the users consider more relevant? Is the user profile complete and effective?
- RQ2: *usability (i.e., Efficiency, Emotional Feeling, Functionality, Control, Simplicity of Use, Global Perception) of the two user interfaces, i.e., graphical and conversational.* How effective are the graphical and conversational user interfaces?
- RQ3: *effectiveness* of the platform. Considering the platform in its entirety, how effective is it? What are the most effective features of the platform?

5.1. Experimental protocol

The study involved *160 participants*, chosen through the "availability" strategy, i.e., they were willing to take part in the study without any reward (Carmagnola, Vernero, & Grillo, 2009). Therefore, participants were recruited on a voluntary basis among

[10] https://www.figma.com/
[11] https://cloud.google.com/dialogflow
[12] https://restfulapi.net/

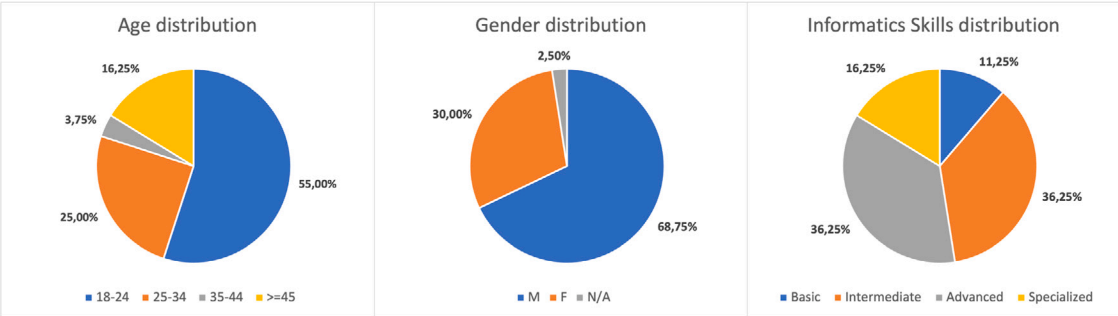

Fig. 10. Experimental sample characteristics.

students of the University of Bari. The distributions of age, gender, and computer skills in the dataset are reported in Fig. 10. Participants are mostly male (68.75%), aged in the range 18–24 (55%), and having good computer skills (88.75% in total reported intermediate, advanced or specialized computer skills). Given the majority of young people in our sample, it was not surprising that almost all participants had strong capabilities in the use of IT devices. In the short term, this group could be the target of the outcomes of our work.

The study was organized into five sessions:

1. *Introduction and training.* In a preliminary meeting, participants were given details about the HELENA project, the LHUM model, and the protocol of the study. We explained the meaning of LHUM aspects and the way they are managed in the mobile platform. After showing the platform installation procedure, we held a short training session on how to interact with HELENA features. The meeting ended with a Q&A session.
2. *Data collection and Confidentiality.* Participants were given a consent form that informed them that data collected during the study would only be used for scientific research. In particular, the form referred to art. 4 of the EU General Data Protection Regulation (GDPR), which defined "data concerning health" as "personal data related to the physical or mental health of a natural person, including the provision of health care services, which reveal information about his or her health status". Furthermore, the form explicitly informed participants that, according to art. 9 of the GDPR, processing of data concerning health is prohibited, with some exceptions, one of which applies when the data subject has given explicit consent to the processing of those personal data for one or more specified purposes, such as scientific research. After participants gave their written consent to participate in the study, they were requested to fill in a short questionnaire (Q1) asking for: gender, age, computer skills, and level of education. Moreover, we also asked to answer the following four questions by using a five-point Likert scale:
   - Q1-1: How often do you search health-related symptoms on the Internet for self-diagnosis? (1-never, 5-often)
   - Q1-2: How often do you search the Internet for health information? (1-never, 5-often)
   - Q1-3: According to your experience, how accurate is self-diagnosis on the Internet? (1-not accurate, 5-very accurate)
   - Q1-4: How satisfied are you with the time spent to reach a self-diagnosis of your symptoms? (1-not satisfied, 5-very satisfied)

   These data are used to get a first overview of the characteristics of the experimental sample collected.
3. *Collecting feedback on LHUM.* We collected feedback from participants, based on the experience they had with LHUM during the training phase, through a questionnaire consisting of seven questions (Q2):
   - Q2-1: According to your needs, what is the most useful aspect of LHUM?
   - Q2-2: According to your needs, what is the least useful aspect of LHUM?
   - Q2-3: Do you think LHUM is complete and comprehensive? (yes, no, do not know)
   - Q2-4: Do you find LHUM helpful for storing all your health data in one place? (yes, no, do not know)
   - Q2-5: Would you use LHUM to share your health data with physicians and specialists in the future? (yes, no, do not know)
   - Q2-6: Would you use LHUM continuously throughout your life? (yes, no, do not know)
   - Q2-7: Do you have any suggestions to improve LHUM? (open-ended question).
4. *Usage of the platform.* In order to evaluate the interaction with the platform by using different interfaces, a *between-subject* protocol was applied. Participants were split equally into two groups by preserving the sample characteristics, and each group was assigned a specific interface, graphical or conversational. Then, each participant interacted independently with the platform, with no possibility of confrontation with other participants, in a quiet and friendly place in our laboratory.
5. *Evaluation.* After the interaction, participants were asked to fill in a SUMI (Software Usability Measurement Inventory) (Kirakowski & Corbett, 1993) questionnaire (Q3) in order to collect their feedback about the usability (i.e., Efficiency, Emotional

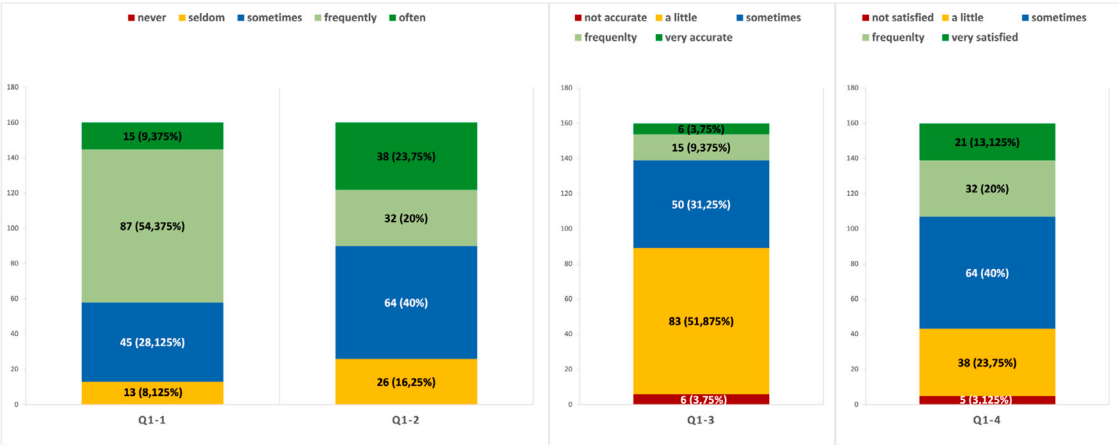

Fig. 11. Results obtained from Q1, the preliminary questionnaire. The graph shows the number of answers for each category and the corresponding percentage.

Feeling, Functionality, Control, Simplicity of Use, Global Perception) of the platform. This kind of questionnaire focuses on questions that include elements of perception in terms of usability and software-side functionality. It provides a valid and reliable method for comparing different versions of the same product and providing diagnostic information for bug fixes and future developments. It consists of a 50-item questionnaire divided into batches of 10 that allow answers through a linked scale composed of three values: “Agree”, “Uncertain”, “Disagree” (Arh & Blažič, 2008). The questions relate to five analysis traits:

- *Application efficiency*: this trait refers to the user’s perception of how the software enables him/her to perform tasks quickly, efficiently, and economically or, on the contrary, that the software hinders his/her performance.
- *Emotional reaction elicited in the user*: this is a psychological term that identifies emotional feeling. In this context, it refers to the user who feels mentally stimulated, in a pleasant or unpleasant way, by the interaction with the software.
- *Availability of relevant functions*: refers to the user’s perception of how the software communicates in a useful way and helps him/her solve operational problems.
- *Possibility of user control:* the extent to which the user feels that he/ she, and not the software, is in control of the execution of a task.
- *Ease of learning*: the ease with which a user begins to learn the functionality of the software.

Furthermore, the SUMI questionnaire also has a global score that refers to the general satisfaction of users when using the software. It is calculated by evaluating the 25 statements of the questionnaire that are the most relevant elements in terms of usability (Arh & Blažič, 2008). In addition to the 50 items, the questionnaire includes two more questions and one feedback request. The purpose of these three questions is to obtain a general assessment. Therefore we asked: (i) what is the most efficient functionality of the platform; (ii) the areas in which the software can be improved; (iii) to provide an overall feedback about the whole platform, on a scale from 0 to 5.

5.2. Discussion of the results

The results obtained from the questionnaires highlight the need, in everyone’s daily life, for tools that help people manage their health data. In fact, according to answers to Q1, reported in Fig. 11, most of the participants use the Internet to search for health-related symptoms. In particular, 63.75% of them frequently or often search the Internet for self-diagnosis (question Q1-1), while 43.75% frequently or often seek health information, not strictly linked to symptoms or diseases (question Q1-1).

Two main observations emerge from these data. The first is that people pay great attention to their health and keep themselves informed about health issues in general. The second is the risk of “cyberchondria” (Marino et al., 2020), which is the tendency to search obsessively and compulsively for symptoms to self-diagnose, significantly increasing the level of anxiety and stress. This leads people to seek multiple medical opinions on Internet, often trusting false information, and then breaking the trust relationship with their physician. Answers to question Q1-3 show that participants are not very happy with what they get from the Internet: 51.875% of them found the results only “a little bit accurate”, while 31.25% reported them as “sometimes accurate”. Participants are quite satisfied with the time needed to reach a self-diagnosis on the Internet (question Q1-4), maybe because of the time saved compared to queuing at medical centers. To conclude the analysis of the preliminary questionnaire, the tendency of people to search the Internet for health issues leads us to suppose their openness toward intelligent tools that support them in taking care of their health.

Research Question 1. The results of questionnaire Q2, regarding the effectiveness of LHUM, are analyzed. Results in Fig. 12 show that the most helpful aspects of LHUM are, in this order: Measurements, Treatments, Symptoms, and Medical Examinations.

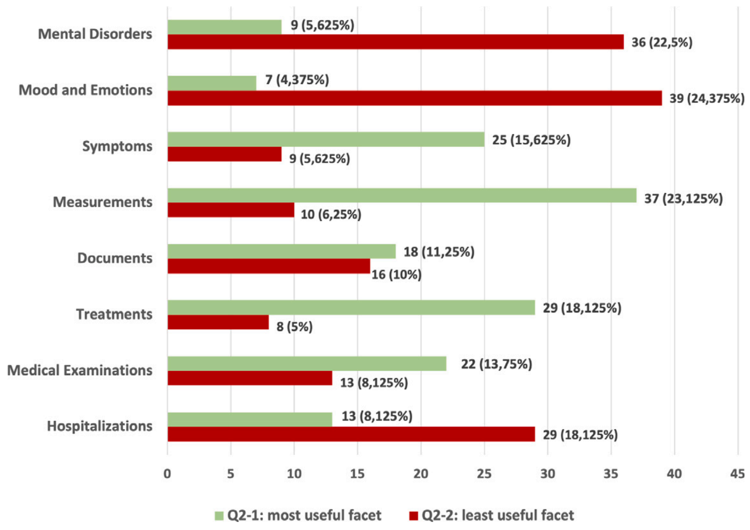

Fig. 12. Results obtained from the Q2 questionnaire, questions 1 and 2. The graph shows the number of answers for each category and the corresponding percentage.

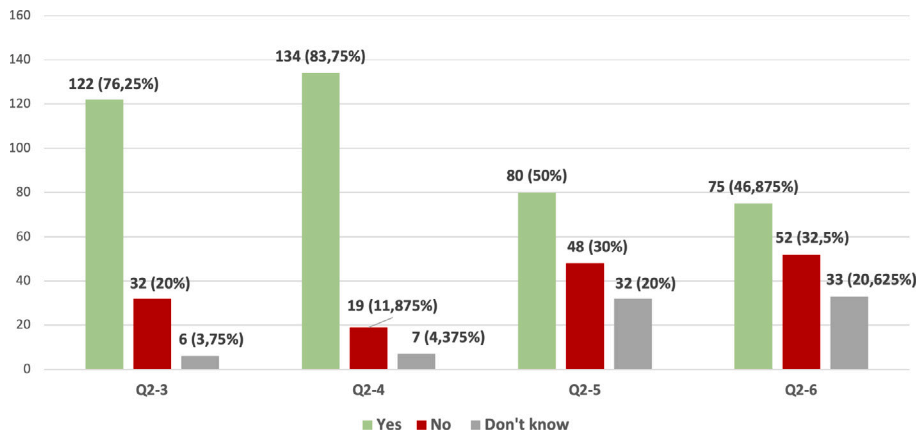

Fig. 13. Results obtained from the Q2 questionnaire, questions from 3 to 6. The graph shows the number of answers for each category and the corresponding percentage.

On the contrary, Mood and Emotions, Mental Disorders and Hospitalization are those considered not very useful. A neutral opinion emerged for the facet “Documents” used to collect medical reports. 11.25% of the participants consider it the most relevant feature and 10% the least relevant for LHUM. We can assume that these perceptions are due to the clinical situations of a large part of the sample. Probably, many users have a reasonably good health situation that includes fairly classic and widespread diseases that usually require frequent monitoring and some medication to be taken.

It is worth noting the low usefulness given by participants to the aspect related to mental health. People tend to underestimate the importance of being mentally healthy. Problems such as depression or anxiety are increasingly common and often debilitating. The COVID-19 pandemic has exacerbated these issues and promoted the spread of these diseases. It is important for people to become aware of the gravity of these problems and intelligent systems can help in this task.

According to the results shown in Fig. 13, 76.25% of participants believe that LHUM is comprehensive and inclusive, and 83.75% of them found it helpful for storing all personal data in one place. Nonetheless, from responses to Q2-5 and Q2-6, a certain skepticism emerges among participants regarding the use of LHUM in the future and throughout their lives: only 50% of them are willing to use it daily in the future and only 46.875% for the rest of their lives. These outcomes show us that, despite the perceived effectiveness of these new technologies, people are reluctant to adopt them on a daily basis in the long term. Valuable suggestions for possible future extensions of LHUM were collected through the open-ended question Q1-7: participants proposed to include an area to store information concerning functional rehabilitation, choices regarding organ donation, blood group, and emergency contacts. These aspects will be taken into account for future work to extend LHUM.

To conclude, the answer to the first experimental question is that LHUM is helpful to users and it is complete and comprehensive. However, the lesson learnt is that it is necessary to work to: (i) improve aspects of security and privacy, (ii) make users aware of the

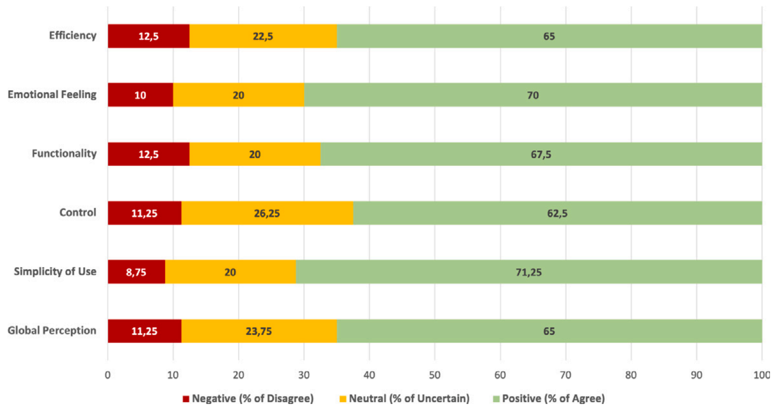

Fig. 14. Results obtained from the Q3 questionnaire, graphical interface.

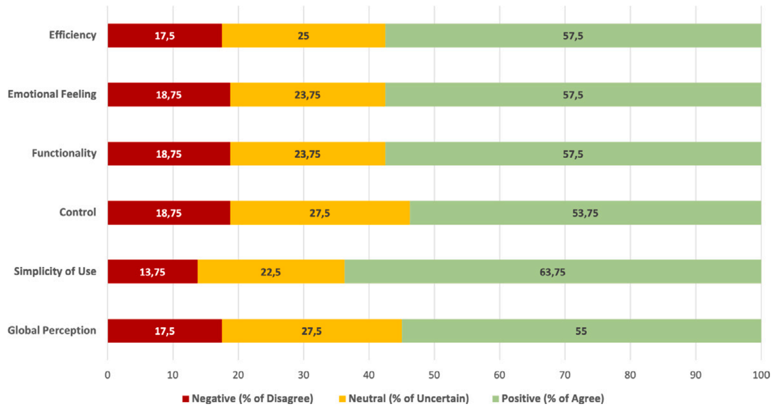

Fig. 15. Results obtained from the Q3 questionnaire about the conversational interface.

importance of monitoring mental health as well, (iii) highlight the benefits that can be obtained by using this profile for long-term data collection.

Research Question 2. To answer this question, we analyze the outcomes of questionnaire Q3 separately for the two groups of participants using the two different interfaces. Fig. 14 shows the results for the group of 80 participants using the graphical interface. As described in Section 5.1, we adopted 5 analysis traits and an overall score ("Global Perception", last bar in the graph). The scores reported in the graph were calculated as in Arh and Blažič (2008), i.e., for each analysis trait, we simply computed the percentages of "Disagree", "Uncertain", "Agree".

The most positive feedback was observed on "Simplicity of use", with 71.25% of positive answers, "Emotional Feeling", with 70% of positive answers, and "Functionality", for which positive answers were 67.5%. In general, participants were satisfied with the interaction via the graphical interface, as shown by the 65% of positive feedback on "Global Perception". On the other hand, improvements are needed mainly regarding "Control", for which we observed 26.25% of uncertain answers, and "Efficiency", whose uncertain feedback was 22.5%. A small part of the participants, around 11% of the sample, was not satisfied at all with the interaction using this kind of interface, perhaps because of any bugs or malfunctioning.

Fig. 15 reports the responses to the SUMI questionnaire regarding the interaction with the conversational agent. The main outcome is that 55% of participants are satisfied with this kind of interaction (i.e., positive feedback on "Global Perception"), but the overall perception of usability decreased, compared to 65% obtained by the graphical interface. The most positive feedback was observed on "Simplicity of use", with 63.75% of positive answers, then on "Emotional Feeling", "Functionality", and "Efficiency", whose positive answers were 57.5%. On the other hand, 27.5% of participants are in general moderately satisfied (i.e., neutral feedback on "Global Perception"), and suggest some improvements, in particular about "Control" and "Efficiency".

These outcomes depend on the complexity of the interaction with a conversational agent, mainly due to the number of utterances often needed by the agent to understand the user's requests. Moreover, the extraction of intents and entities from the dialogue is prone to errors that can end in a stalemate. This can cause a sense of loss of control and confidence that the user does not feel with the other kind of interaction.

To conclude, the answer to Research Question 2 is that the platform achieved an acceptable usability (i.e., Efficiency, Emotional Feeling, Functionality, Control, Simplicity of Use, Global Perception) using both the graphical and the conversational interfaces,

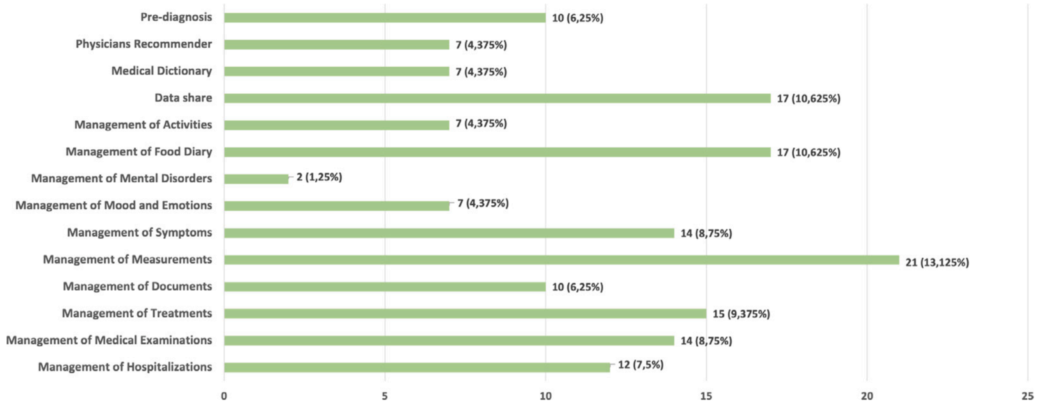

Fig. 16. Results obtained from the Q3 questionnaire about the most efficient functionality of the platform. The graph shows the number of answers for each category and the corresponding percentage.

even though some differences emerged. In particular, the former was easier to use, pleasant, and functional than the latter, perhaps because users are more used to interacting with traditional interfaces rather than with dialoguing agents. On the other hand, the conversational interface was pleasant, functional, and efficient.

Research Question 3. To answer this question, we analyze the responses given by both groups to the last three questions of the Q3 questionnaire, asking for: (i) the most efficient functionality, (ii) suggestions for improvements, (iii) overall evaluation score on a scale between 0 and 5.

Results, reported in Fig. 16, show that the most useful functionalities are "Management of Measurement", achieving 13.125% of positive feedback, "Data share", and "Management of Food Diary", both with 10.625%, of positive feedback. Less appreciation has been shown both for smart functionalities, whose positive feedback ranges between $4.375\% and 6.25\%$, and "Management of Mental Disorders", which achieves only 1.25% of positive feedback. However, participants generally appreciated almost all platform features, which can be considered quite effective and efficient. The average value of the overall evaluation score was $4.4[+/-0.704]$, which demonstrates the effectiveness of the platform. Suggestions for future developments include extending and improving the smart services offered. These can be improved, for instance, by adding new adaptation and personalization features. To conclude, the answer to Research Question 3 is that the overall feedback on the platform is excellent. However, there is room for future improvements, especially in LHUM management and smart features.

6. Implications and limits of the work

The HELENA platform differs significantly from our previous project HealthAssistantBot (Polignano et al., 2020), a simple Telegram chatbot offering basic functionalities for managing demographic information and treatments, and health information monitoring. HELENA was designed to overcome the lack, in the health domain, of a comprehensive and maintainable profile. For this purpose, we propose LHUM (Lifelong Health User Model), a health model that covers all possible aspects of daily patient life, with the advantage of storing, in a single digital container, health data that are usually spread in many heterogeneous sources. From this perspective, LHUM can be seen as a component of a broader holistic user profile that includes further data, such as information about the habits and abilities of users. Currently, the services managed by our digital assistant are quite limited, as well as the vertical data that could be potentially collected. In the future, we will work to extend and centralize the platform and add new functionalities. These features make HELENA a platform that strongly differs from previous related work. At its current stage, HELENA is a prototype. Further work and experimental evaluations are needed to reach the objective of a release for the scientific community. The user study described in Section 5 was helpful to have a preliminary evaluation of the work done so far, but it has some limitations. For example, the group of participants is unbalanced toward 18–24 and 25–34 aged people. A more balanced dataset would allow for a more realistic evaluation, despite the younger population being the main target for our platform. This issue is also due to the limited possibility of recruiting a homogeneous experimental sample in the University environment. Therefore, our goal for the next evaluation is to involve, in the study, also physicians and people suffering from chronic diseases, who need constant monitoring. For this purpose, we started a collaboration with CITEL - Telemedicine Research Center, Internal Medicine G. Baccelli Policlinico di Bari, a research center connected with the main hospital in Bari, that can actively involve stakeholders. We will design a user study that could be performed both in a "natural" use scenario (i.e., simulating a real context of use) of the platform, and also in a "lab-controlled" use scenario, with the possibility of recording the interaction of patients with the platform, in order to detect difficulties that user might not express through an explicit questionnaire. A more robust evaluation will move HELENA toward a validation stage from a clinical perspective as well, a key step for the official release.

Another limitation of the platform is privacy management. In the current prototype version, several actions have already been taken. In particular, when registering to the platform, the user accepts a Term of Services where consent is asked for General Data Protection Regulation 2016/679 (GDPR) and EU regulation (EC) No 45/2001 along with Directive 95/46/EC that describes several possible anonymization strategies for sensitive health data and protection towards retroactive identification strategies. Furthermore, under recital 161, the GDPR states that for "consent to participate in scientific research activities in clinical trials", the relevant provisions of Regulation (EU) No 536/2014 of the European Parliament and the Council shall apply. Under this recital, informed consent means a subject is free and voluntary express his/her willingness to participate in a particular clinical trial after having been informed of all aspects of the clinical trial that are relevant to the subject's decision to participate. Furthermore, user data are stored in a cloud database, Firebase, which offers very high-security standards, allowing individual users to access only the portion of the database containing their data. Users are also anonymized as they are associated with a unique id, which is known only to the application making the calls and encrypted through a public–private key system. For Android applications, an attempt has already been made to create an app that does not allow hijacking and decompiling operations, but this aspect needs further development.

The current prototype of HELENA is an Android app. The only supported language is Italian. We will work to implement a multi-language version available on many platforms (Android, ioS, etc.). The project is supported with a grant by the Apulia region, Italy, and cannot be released publicly due to the constraints of the grant.

7. Conclusions and future work

This work proposed HELENA, a platform to manage users' health information stored in a lifelong health user model (LHUM). The main aim of our work was to design a comprehensive medical user profile filled with data from heterogeneous sources, that are easy to manage and share, and that can be used in the long-term. The main advantage of this kind of profile is to store health information in a single digital place for a lifetime. LHUM is composed of eight aspects that focus only on medical aspects: Hospitalizations, Medical Examinations, Treatments, Documents, Measurements, Symptoms, Mood and Emotions, and Mental Disorders. These aspects are then embodied in a holistic user profile that includes additional facets such as demographics, habits, and user skills and activities. The proposed profile can be considered a complete source for developing personalized, intelligent services that meet the growing needs of users in digital medicine.

In order to show how to manage the LHUM model, we developed an intelligent digital assistant that provides many functionalities to the end-user, including CRUD operations and health-related services. The agent has both a classic graphical and a conversational interface. The graphical interface has been realized following user interface design guidelines with human-centered design logic. In particular, wireframe prototypes, validated through a preliminary study with users, were adopted. Colors have been chosen according to the latest studies of visual perception to ensure pleasant interaction. The conversational interface is realized through chatbot logic. Many user intents have been defined in order to understand users' needs. Voice or textual input given by users is analyzed to extract the Entities associated with recognized intents (e.g., the user is asking for last blood pressure). Then, corresponding Actions are performed to build a human-like response. The actions carried out are the management of LHUM or the use of smart services.

A user study involving 160 participants has been carried out to assess the effectiveness of LHUM, the usability (i.e., Efficiency, Emotional Feeling, Functionality, Control, Simplicity of Use, Global Perception) of the two interfaces implemented, and the overall effectiveness of the platform. Excellent results were observed from the analysis of the questionnaires filled in by participants. In particular, LHUM was found to be complete and helpful in keeping all health data in one place. The less appreciated facet was that concerning mental health, perhaps due to the fact that users underestimated the importance of being mentally healthy. The two interfaces met the users' needs and showed acceptable usability, efficiency, and effectiveness. The graphical interface was more appreciated than the conversational one, maybe because participants are more used to interacting with this kind of interface. Finally, the overall judgment on the platform was very positive, with a feedback score of 4.4 over 5.

In future work, we will continue to develop the proposed lifelong health user model by extending aspects, reducing redundant parts, and improving robustness to allow extensive daily use. The proposed digital assistant will be enriched with intelligent features for personalization and adaptation. In particular, we will focus on recommending doctors and healthcare facilities, automatic diagnosis, and advanced reporting. Moreover, before releasing the assistant publicly, we plan to perform an extensive evaluation of the platform in collaboration with CITEL - Telemedicine Research Center of the University of Bari, Italy. For health applications, it is fundamental to ensure that everything works correctly and that data security is guaranteed to preserve users' privacy and sensitive data.

CRediT authorship contribution statement

Marco Polignano: Methodology, Software, Writing – review & editing. **Pasquale Lops:** Conceptualization. **Marco de Gemmis:** Formal analysis. **Giovanni Semeraro:** Supervision, Data curation.

Data availability

The authors do not have permission to share data.

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