A personalized agent-based chatbot for nutritional coaching

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Intelligent systems increasingly support users' behavior change, including exercise adherence, smoking cessation, and healthy diet adoption. Their effectiveness is affected by the personalization degree of advice/coaching and HMI mechanisms. This paper proposes a personalized agent-based chatbot platform assisting the user in healthy nutrition via pervasive technologies leveraging dynamical, multi-modal, and personalized interactions. The system provides diet recommendations and tracks the user's food intake and nutritional behaviors to promote a healthy lifestyle. The study concludes with a user study and performance evaluation.

CCS Concepts: • **Human-centered computing → User studies**.

Additional Key Words and Phrases: nutrition coaching, agent-based chatbot, food chatbot

ACM Reference Format:
Davide Calvaresi, Stefan Eggenschwiler, Jean-Paul Calbimonte, Gaetano Manzo, and Michael Schumacher. 2021. A personalized agent-based chatbot for nutritional coaching. In *IEEE/WIC/ACM International Conference on Web Intelligence (WI-IAT '21), December 14–17, 2021, ESSENDON, VIC, Australia.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3486622.3493992

1 INTRODUCTION

Genetics (e.g., diabetes), psychological (e.g., obesity), and chronic diseases (e.g., hypertension) are increasingly affecting our society. Such different conditions are all (in)directly linked to nutrition aspects. Beyond traditional (in-person) support, researchers strive to provide continuous support in nutrition coaching systems (NCS), exploiting novel/influential technological trends (i.e., natural language justifications [23]). NCS can be specialized on groups with specific demands (e.g., the elderly [8], diabetics [25], or critical consumers [18]). Nevertheless, well-targeted ads (e.g., commercial food recommender systems) have the upper hand in promoting potentially unhealthy but profitable strategies to boost consumeristic interests. Such behavior is exacerbating the already difficult daily living of healthy and at-risk individuals. Promoting poor nutrition quality food increases the unfortunate cases slipping into abusing processed meat, over-sugared snacks, and fast food-like meals. Therefore, persuading and educating individuals about nutrients, meal compositions, and individual needs is crucial. Hence, the need for raising awareness about healthy lifestyles and food teaching is impelling, especially for the new generations. Most of the NCS are vulnerable and prone to ethical and societal criticisms such as being opaque, unfair with different stakeholders, and reducing their users' autonomy by encouraging committed reliance on the system's recommendation (too often repetitive and not really personalized). Additionally, user privacy concerns are a major challenge for NCS. Besides preventing the technical risks of data leaks or de-anonymization attempts, it is important to specify the data's purpose, with what external parties this data are shared with, and to ensure that the ownership of the data is user-exclusive. Finally, current NCS are unidirectional and do not allow dialog-based (e.g., argumentation-based) interactions if not with *paid-for* human interventions.

This paper proposes personalized agent-based chatbots assisting the human users in their daily living via pervasive technologies leveraging dynamical, multi-modal, and personalized interaction/recommendation while tracking the user food intake and nutritional behaviors to promote a healthy life style (e.g., dealing with weight, food disorder, or nutrition-related chronic disease).

The rest of the paper is organized as follows. Section 2 presents the state of the art of the relevant areas such as agent-based chatbots, food tracking systems, and food recommender systems. Section **??** elicits the challenges and formalizes the objectives. Sections 3 and 4 detail design and implementation. Section 5 presents the user study. Section 6 discusses the system and tests. Finally, Section 7 concludes the paper and introduces ongoing and future works.

2 STATE OF THE ART & CHALLENGES

This section overviews agent-based chatbots, food tracking systems, and recommender systems.

Agent-based Chatbots - Recent studies confirm the potential of using multi-agent systems (MAS) to design and deploy conversational agents in different domains [6, 20]. Early studies used agents to implement the several specialized parts of a *single* chatbot interacting with all the users [13]. More evolved solutions adapted the agent-based environment to model multi-source knowledge bases with domain-expert agents [3]. Nevertheless, such approaches hamper the chatbot personalization, compliance with GDPR policies, and agent-to-agent interactions (if possible at all). Hence, relatively more recent approaches use agents as a virtual representation of a given user, abstracting their profile, preferences, and functionalities in a privacy-preserving and GDPR-compliant manner while leveraging social-media chat applications [5]. On this line, more complex solutions rely on platforms such as SPADE to realize the chatbots' back-end, delegating the front-end to existing chat App (e.g., Telegram) or custom chat-like applications (e.g., based on Flutter) [6]. Although tailored front-end apps limit the outreach, they allow overcoming the third-party apps' limitations (i.e., anti-flooding

WI-IAT '21, December 14–17, 2021, ESSENDON, VIC, Australia

ACM ISBN 978-1-4503-9115-3/21/12…$15.00
https://doi.org/10.1145/3486622.3493992

mechanism, multimedia file and caching limitations, and message routing). Concerning the back-end of the agent-based chatbots (the bot/agent brain), the most relevant trend is the introduction of machine learning (ML) techniques into the decision process (thus leading the systems to shift towards Python-based back-ends, with some reliance on proprietary platforms [2, 39]. Concerning the front-ends, most studies relied on web-based technologies to bind the chatbot with a thematic website. However, due to the release of dedicated APIs by popular chatbot platforms such as Facebook, WhatsApp, and Telegram, even the number of agent-based chatbots has skyrocketed [6]. Overall, most of the MAS chatbot systems in the literature present an early stage of development, with only a few exceptions being tested in real-world scenarios [6, 17].

Food Tracking Systems - Understanding and analyzing eating habits and tracking daily calories intake is essential for most dietary models. Recent advancements in speech-to-text input and predictive search algorithms could make meal tracking more comfortable and efficient. Yet, most of the commercial platforms (see [24], or [26]) require to manually introduce data through mechanistic (sometimes overwhelming and counter-intuitive) processes. The social media effect made taking pictures of meals a daily habit. Including such behavior in a meal tracker system would boost the tracking process's acceptance. However, due to technical limitations, early approaches used nutritional experts to analyze the received images, or a crowd-sourced approach. The unbearable workforce to analyze the images decreed the systems not usable on a larger scale. Thus, early prototypes adopted convolutional neural networks (CNN) to improve the performance and accuracy of image recognition. Due to limited data sets and problems related to fine-grained food recognition, portion size analysis, and nutritional data attribution to the image, these early prototypes did not make it outside the labs. More recent approaches such as [29] and [30] as well as the proprietary work of tech companies such as [4] and [7] invested to tackle these problems. Although the accuracy of classifying food outside of a lab environment has remarkably increased over time, these solutions are still unreliable when analyzing more complex dishes and determining the portion size displayed within the picture. Henceforth, they are only partially applicable in NVC.

Food Recommender Systems - Food recommender systems (FRS), similarly to other recommender systems (RS), can employ multiple recommendation techniques. Such techniques include collaborative filtering (leveraging users similarities [14]), content-based filtering (recommending similar items on the basis of similar profiles' previously liked items [35]), Knowledge-based recommendation (based on the user preferences and constraints [9]), and Hybrid recommendation. (combines the techniques mentioned above to overcome the limitations of the single approaches [34]). For example, the disadvantage of unrated items in a content-filtering approach could be offset by combining it with a knowledge-based approach as items in a knowledge-based recommender system contain attributes. According to [37], RS are typically used in the food domain to tackle issues such as proper dietary management, prevention or cure of food-based illnesses, substitution-based suggestions, and group-based food recommendations. Karpati et al. [16] assessed the ethical implications of food recommender systems prevalent in the European market by classifying the systems in those that provide personalization features and those that do not. The study concludes that most modern FRS follow a popularity-focused approach based on content filtering rather than providing personalized recommendations. Moreover, the authors indicate *privacy* (user data management and usage), *opacity* (general explainability of the applied algorithms and the reasoning behind specific recommendations), *fairness* (providing unbiased recommendations) and *robustness* (validation of the underlying dataset) as major FRS ethical concerns.

Challenges and Objectives - Analyzing the state of the art, we can formulate challenges such as: **C1.** To enable the tracking of the food intake in a multi-modal fashion (e.g., pictures, bar codes, manual selection, and vocals notes). **C2.** To integrate data coming from wearable sensors (e.g., smartwatches) into the calorie and behavioral computation to provide enhanced and more tailored recommendations. **C3.** To integrate both proprietary and open-source third-party commercial services such as geolocalization of food-related services, food image recognition AI, and macro-nutritional databases into an agent-based chatbot framework.

3 DESIGN

This paper significantly extends the underlying architecture presented in [6]. It leverages the basic agent structure and databases setup, adding new logic, connectors, and functionalities (see Figure 1) below described.

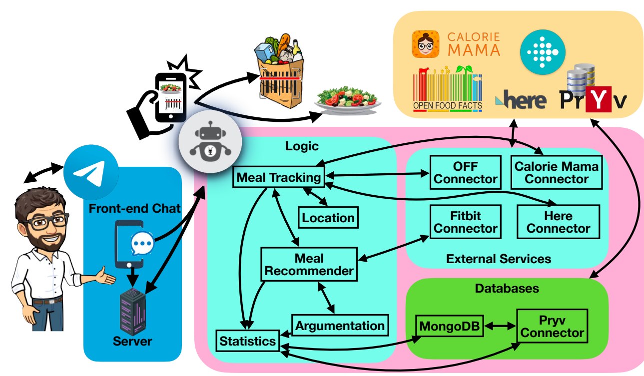

Fig. 1. Chatbot Design Overview

Meal Tracking - The meal tracking functionality is user-centered. According to [15, 31], to create nutritional awareness and nurture a state of mindful eating, the feature should encourage tracking the daily food intake (maximizing its accuracy). Thus, we introduced two procedures: (a) scanning the item's barcode (only viable for industrially packaged food items) and (b) via food pictures (for all the other situations – e.g., home-cooked, composite, and restaurant food). The first step to track is taking a picture (of a/b). If a barcode is identified, the chatbot queries the OpenFoodFacts platform, a crowdsourced food products database [27]. If the item exists, the chatbot can retrieve the product's nutritional information, properly tracked into the user profile. If the picture contains no barcodes (but actual food), the picture is appropriately resized and submitted to the commercial image recognition platform, named Caloriemama, for its processing [4]. Its APIs provides a list of food groups and items sorted by probability, which is simplified and proposed to the user to confirm, contradict, or extend what *seen* by the predictor.

Meal Recommendation - The recommendations are based on the type of meal, time of the day & day of the year, available calories for the day, type of macro-nutrients intake, the user's behavior (active minutes, steps, etc.), and if necessary, their position. At the time of writing, the system employs a static pre-set of food, sufficiently flexible to comply with a broad range of scenarios. Extending such a list and making it dynamic is part of the ongoing works. Finally, the user's choices (i.e., which item is picked among the suggested ones) are recorded and used by the system for the behavioral analysis.

Restaurant Search - Given the lack of real-world infrastructures, this function is a visionary proof of concept. Using the user's GPS location, the system queries HERE GPS platform [12]) looking for nearby restaurants. The idea is to select/prioritize healthy menus/options complying with the user's nutritional needs (including macro-nutrition, compliance with possible allergies, and dressings). Nevertheless, we cannot select a specific food item yet without access to their menus and, henceforth, nutritional values. Such a feature can unveil remarkable business models and opportunities, enabling restaurants to foster a healthy advertisement on the platform. Exposing foods' macro-nutrients should discourage consumeristic behaviors while promoting healthy habits.

Statistics - This functionality serves two purposes: (a) to raise the user's awareness by providing aggregated and intuitive representation of their eating/calorie-consumption behavior. According to [19], regular self-weighing is essential for weight loss, as well as weight gain prevention efforts. Hence, the system encourages the user to introduce their weight methodologically. All these data are summarized into a graphical representation that can show the "current week" progresses on-demand, and it is generated automatically on a monthly basis (see Figure 2); (b) to provide essential understanding for the chatbot, developers, and nutritionists (possibly taking part in future campaigns) of the user's engagement level, adherence to healthy habits, and other possible patterns.

External Data Source Integration - Equipping the chatbot with the knowledge collected by wearable garments can boost the agent's accuracy and the understanding of the user's daily behavior. Indeed, differently from static nutrition support chatbots, the proposed system integrates conventional formulas for calories needs/consumption (e.g., daily total energy expenditure (DTEE) [22, 38]) with the tracked data. At the moment of writing, the system integrates the steps, active minutes, and calories calculated by the FitBit back-end [10].

Periodic Behaviors - To encourage a methodological and consistent behavior, the chatbot implements periodic nudges (released *around* strategic hours of the user's schedule. Their release variability depends on statistical correlations of the user's behavior. Among the periodical nudges, we can mention the weighing reminder, main mails/snacks reminders, and periodical trend overviews.

Data Privacy - The setup to ensure the user control of their data inspires to [6]. In particular, we have designed a data stream-based user profile leveraging the privacy-centric platform Pryv.io [33] (GDPR-compliant).

4 IMPLEMENTATION

The framework is composed of four main components communicating with each other over a Docker network:

The **Communication Server** container hosts Prosody, an XMPP server [32]. Prosody is the communication platform for inter-agent communication. Each registered agent (embodying a human user) can broadcast a message to other agents via multi-user chat or send a message to a specific user via peer-to-peer chat session.

The **Database** component implements a hybrid data model such as storing information coming from Telegram in MongoDB and Pryv contextually. The database component comprises a local MongoDB instance for non-personal data and Pryv.io for user-specific data. The data is modeled as document collections and embedded documents, as both MongoDB and Pryv.io persist data in a document-based JSON format. The *User* object is composed of both data that is stored in MongoDB and Pryv.io. The object uses getter/setter methods to retrieve and manipulate the data during run-time without the overarching system knowing where the data is stored.

The **Underlying Architecure** component uses the SPADE platform [28] to actualize virtual agents. Such a component runs an instance of the admin agent used for general tasks such as querying the database component for specific users and other system dynamics such as Fitbit integration.

The **Core** components are also based on SPADE. A gateway agent bridges the agent community with the Telegram messaging platform, forwarding the messages to the agents related to the given senders. Although EREBOTS supports multiple communication interfaces, the version employed in this thesis employs Telegram IM [36] to maximize the outreach. Indeed, since 2015 (two years after its release), Telegram has provided an API for dedicated bot development, which our system links to using aiogram [1]. Upon receiving a Telegram message, the gateway agent uses the sender's user identifier (i.e., Telegram ID) to determine the existence of a corresponding agent. If the agent exists, the message is directly forwarded to it. Conversely, (new interacting user), a new agent is created before forwarding the message. The agent's primary logic is modeled in the form of a finite state machine (FSM). A state generally comprises an initial function (e.g., sending a message), a function that evaluates incoming messages using regular expressions, and the related necessary actions in case of a match.

Meal Tracking - It begins by asking the user to specify the type of meal (e.g., breakfast, lunch/dinner, or snack) and send a picture (barcode or food). The image is pre-processed attempting to decode a possible barcode via open-source libraries (Opencv2 and pyzbar). If a valid barcode is found, it is sent via HTTP request to OpenFoodFact. If found, the API returns a JSON formatted representation of the item subsequently validated and stored in the DB. Conversely, the image gets resized and sent to Caloriemama via the proprietary APIs. The response (a JSON stored in MongoDB) contains a list of identified food items, their probability, macro-nutrient compositions, portions, etc. Subsequently, the chatbot starts the validation process where it shows to the user the most probable food items seen by the predictor. The process goes through the top five identified elements unless the user indicates that all the element(s) have been already identified. However, if an item is not identified in this process, the user can add it in free text. The latter is used for statistical analysis and to provide feedback to the developers of the predictors. Eventually, the selected food items are stored into the user profile on Pryv.io, completing the tracking.

Meal Recommendation - It provides the user with a list of options (stored in MongoDB) suiting their current state (e.g., missing macro-nutrients and burnt calories). The list of recommendations is currently characterized by elements belonging to several calorie intervals (e.g., 200-400, 500-700, and 800-1000Kcal). The suggested item is subject to the user's remaining calorie budget and preferences. However, only lightweight food options will be recommended if a user has already exceeded their calorie limit. The recommendations are sent to the user as a list of meal images and custom keyboard options to select them. Once a meal is selected, the user receives a link to the recipe and the option to track it directly.

Restaurant Search - As mentioned above, this functionality is still in an early stage. Nevertheless, the user study confirms remarkable potential. Functionally, the user should share their location (a Telegram map marker) to the bot. In turn, the HERE location API [12] allows retrieving nearby restaurants. This list is then parsed and sent to the user in the form of custom keyboard options. The selected option is encoded in a Telegram venue item (consisting of a name, address, and a GPS location) and sent to the user.

Weight Tracking - It is suggested to be a daily routine. The user updates the weight, which is stored in the corresponding Pryv data stream. By doing so, the user's DTEE can be updated appropriately (calculated by multiplying the basal metabolic rate (BMR) [22] with the physical activity level (PAL) [38]). If the user's goal is to reduce their weight, the DTEE will be reduced by 10 percent leading to the user consuming fewer calories than needed to sustain their current body weight. As ongoing work, we are setting collaboration with professional nutritionists to propose reasonable and safe plans.

Statistics - The user can retrieve a statistical overview at any time. The overview is generated by retrieving the user data and then generating an in-memory graphic using matplotlib [21]. This temporary file is then sent to the user. Figure 2 depicts an example of a generated user statistics image. The graph contains two types of information: (i) the blue line represents the history of the user's weight. In this case, the user hovers around 129 kilograms with a slight downwards tendency. The blue dotted line represents the user's weight goal (set by the user during the registration phase), and (ii) the red stacked bar chart represents the tracked meals of the user. The type of meal is differentiated by color. The red dotted line represents the daily total energy expenditure which is the threshold the user should try not to pass in order to lose weight.

External Data Source Integration - In the current iteration of the chatbot, the only integrated data source are Fitbit devices. The user can provide the chatbot with access to their Fitbit activity data by following an OAuth 2.0 authorization code grant flow as defined in [11]. In order to handle the authorization request and to retrieve the access- and refresh token, the chatbot platform includes an agent hosting a simple webserver that acts as a callback server. Upon providing their consent, the chatbot can access data such as daily step count and daily burned calories through exercise. In future iterations, this data can be used to refine the nutritional coaching process.

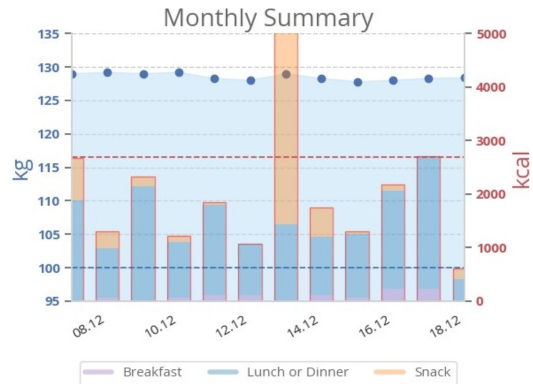

Fig. 2. Example User Statistics

5 USER STUDY

The system has been evaluated by 11 users (referred to as U_1 to U_{11}) for a period of 12 days. The group is comprised of three women and eight men with ages ranging from 26 to 67 years. During the evaluation period, the eleven testers have used the chatbot daily to track their weight, food consumption, and test the recommender and statistics features. An anonymous questionnaire on the quality of experience has concluded the study. Additionally, the generated logs were analyzed to retrieve general information about the system's performance and utilization. Table 1 briefly summarizes participants, goals, and activity level [38]. The majority of testers' feedback is divided in partially vs. fully positive. The participants have appreciated the idea of receiving notification messages at strategic times of the day. Nevertheless, most of the users would prize even more the possibility of tuning the notification intervals. Negative notes from the testers mainly identify two major weak points of the prototype. On the one hand, the *sometimes* unsatisfactory accuracy of the image recognition API has been unanimously criticized by the participants. On the other hand, some participants have defined the Track Meal function as awkward and counter-intuitive. Such an implementation has been "imposed" by some technological constraints characterizing the bridge of Caloriemama and the chat-like user interface. Clearly, such a process must be simplified. A possibility is to migrate towards a custom interface to waive Telegram's limitations and realize some more user-friendly pop-ups or interfaces integrating the verbose chat. Multiple participants (46%)

Table 1. Campaign participants

Individual	Sex	Age	Activity Profile	Goal
U_1	male	32	light	weight loss
U_2	male	35	moderate	weight loss
U_3	female	26	light	maintain weight
U_4	male	26	light	weight loss
U_5	male	28	light	weight loss
U_6	male	28	light	maintain weight
U_7	male	28	moderate	weight loss
U_8	female	66	light	weight loss
U_9	male	67	light	weight loss
U_{10}	female	34	moderate	weight loss
U_{11}	male	37	moderate	maintain weight

developed the conscious eating habit [15, 31], which describes a concept of awareness building that leads to a healthier lifestyle. The functionalities of the proposed system facilitating this habit are the meal tracking (although partially unpleasant) and the recurrent statistics that raise the user awareness about their behavior. Several participants provided constructive suggestions such as (i) providing simpler ways of analyzing the personal food consumption (i.e., macro-nutrients, meal history, more detailed statistics) and (ii) implementing a concept of individual feedback where the bot praises/criticizes the user's food choices. This concept also leans towards another aspect that has been underdeveloped according to tester feedback: personalization. The criticism applies in particular to the food suggestion feature. Although the participants know how quickly their preferences can vary and how environment/context-dependent they are, the participants demanded more dynamism and some faster mechanism to learn their preferences and behave accordingly.

Concerning the use of the system, Figure 3 displays the message response time sorted by day in seconds. In particular, it spans from the platform receiving a message from the Telegram server to when the chatbot completes its operations sending back a message to the user. The average response time is between 1.4 and 1.6 seconds, meaning a fluid interaction flow between user and chatbot. However, looking at Figure 3, we can observe some outliers on 14 and 15 December. They can be attributed to a problem with the allowed quota of requests sent to the Caloriemama API. After resolving the unexpected limitation due to the third-party default policies, the response time normalized again.

Another interesting information extracted from the log is the distribution of the messages over the testing period. Figure 4 provides an overview of the messages received during the test phase organized per user and time of day. It is possible noticing that most messages were sent during breakfast-, lunch- and dinner-time (a possible positive reaction to the chatbot nudges). Additional picks of interactions took place principally in the morning, revealing that most snacks were consumed and tracked during the phase between breakfast and lunch. A reduction in interactions between main meals can be observed starting around the middle of the test scenario in terms of changes over the days. According to user feedback, this change is due to the statistical feedback provided by the chatbot and the act of having to track each meal actively. This led to a positive change in eating habits, as confirmed by several participants.

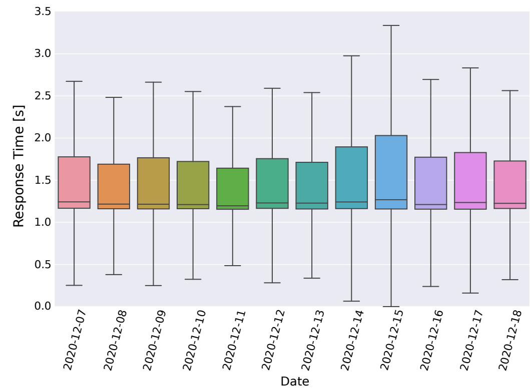

Fig. 3. Message response time per day

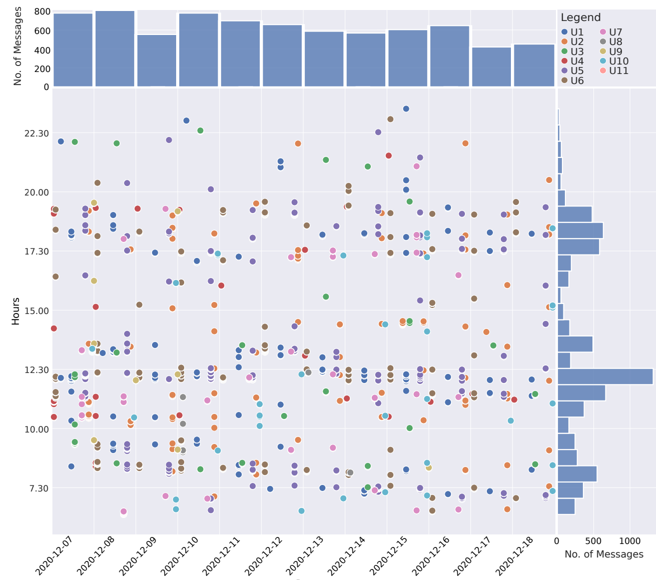

Fig. 4. Distribution of received messages per day/hour

6 DISCUSSION

The underlying architecture of the proposed system relies on the EREBOTS framework [6]. Nevertheless, the system's core has been redesigned and adapted to tackle the nutrition-related scope and challenges. In particular:

Concerning **C1** (multi-modal food tracking), it can be concluded that it has been partially fulfilled. The user can record their daily food intake via the chatbot (either via a picture of the food or the corresponding barcode of an industrial product), specifying serving portions and/or sizes. A majority of users found this function notably helpful. However, the lengthy process interaction has been criticized, especially if tracking complex dishes or due to the poor accuracy of the image recognition system. Tracking meals via simple voice messages is still a work in progress, and surprisingly, it is the most requested extension in the conclusive questionnaire.

Regarding **C2** (wearable sensor data integration), we implemented a connector to integrate Fitbit wearable devices. This connector was used to retrieve and securely store the user's daily calorie consumption within Pryv. However, although available, this data is not yet fully exploited in all the chatbot functionalities.

Finally, concerning **C3** (integration of external services into EREBOTS), several connectors were implemented to include data from third-party services, both open source, and proprietary. The meal tracking feature used the crowd-sourced macro-nutritional database [27], as well as the proprietary food image recognition platform [4]. Additionally, the first proof of concept of the restaurant search functionality was implemented using the geolocation database provided by [12].

7 CONCLUSIONS AND FUTURE WORKS

This paper presented an agent-based chatbot system for nutrition coaching. It extends the EREBOTS framework [6] for personalized nutritional coaching. The key features of the chatbot are the multimodal means of meal tracking (i.e., food image and barcode recognition), the tracking of the user's weight, and the statistical evaluation and visualization of the collected data to provide the user with direct feedback. The resulting platform has been evaluated in a test scenario to ascertain to what extent it satisfies the identified challenges. The tests have confirmed the intuitiveness of the image-based meal tracking (even if the process must be simplified and the addition of vocal interaction has been demanded). Additionally, to improve the meal tracking, the meal recommendations have to be extended by taking more user's choices into account (e.g., taste, dietary constraints, and contextual variants such as festivals and social events). Finally, another significant challenge is to pursue the business model outlined in Section 3 and to integrate restaurants into our platform. To this end, we will need to fundamentally expand the currently implemented restaurant search feature and attempt to collaborate with local establishments.

ACKNOWLEDGMENTS

This work was partially funded by the HES-SO RCSO IsNet grant PERSA. We would also thank Azumio Inc., the owners of Caloriemama.ai, for the access to their platform and generous support.

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