Chapter

BECOME: A Modular Recommender System for Coaching and Promoting Empowerment in Healthcare

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Abstract

In this chapter, we present BECOME (Behavior Change recOMender systEm), a modular Recommender System built to cope with issues like personalization, adaptation, and delivery of contents pertinently designed to solve idiosyncrasies of various topics in the healthcare field. The main objective is to empower citizens or patients to make informed decisions to improve their health condition. It deals with a double-edged personalization process as one of the key aspects to fostering self-empowerment: content dynamically personalized and adapted as new information is gathered and flexibility in the strategies and timings of the delivery. Thus, we take personalization one step further by not only tailoring the content, which is the standard customization strategy, but also adapting its timings and complexity in a dynamic manner while dealing with the feeling of having an entity (the coach) behind, ready to help. To show the modularity of the system and the diverse ways of interaction, different studies representing various use cases are presented.

Keywords: healthcare, personalization, behavior change, nutrition, physical activity, sleep, reinforcement learning, tagging system, gamification

1. Introduction

Data has been created massively in healthcare, specifically data related to the main pillars of health (physical activity, wellness, nutrition, and sleep), thanks to the digitization of health records and the use of wellness-monitoring devices [1]. According to [2], AI and data technologies are the principal enablers to provide key indicators derived from the analysis of such data to propose personalized plans that are able to prevent and deal with health problems. Based on that, healthcare providers are starting to off-load certain parts of the care pathways to AI-based automation, aiming to readjust healthcare delivery pathways, in particular the ones related to public health. Recommender Systems and Decision Support Systems are the two main methods that are facilitating this change by (a) generating self-awareness and thus self-empowerment, (b) enhancing and sustaining motivation through gamification and personalization techniques, and (c) changing behavior [3]. Understanding people's behavior in complex and distinct environments and interactions between a changing population is crucial for the required personalization. To do so, it is important to exploit new data sources (e.g., nutritional intake derived from gamified approaches) to better identify people's needs, patterns, and profiles, with the aim of identifying risk behaviors and patterns. It is also important to monitor the population in the different environment settings in regard to the main pillars of health as well as monitor the perceived knowledge of the implications of certain behaviors. It is important to promote healthy lifestyles, such as diet and physical activity, and give recommendations, and also, the qualitative assessment is essential to ensure accomplishment. One effective strategy to promote personal lifestyles is coaching [4] through healthy messages.

In this chapter, we present the BECOME (Behavior Change recOMender systEm) recommender system and the various use cases that rely on it. BECOME was properly defined and put into practice to encourage users to adopt and maintain healthy habits by informing them of their present situation and the effects of a certain trend. It enables personalized medicine since it is built on data from diverse sources and is dynamically fed by sensor data, standard and ad hoc questionnaire responses, and other data sources. These data are used to characterize participants in order to construct tools that are tailored to users' preferences and needs. BECOME follows an Integrated Care approach [5], coping with the transformation of the healthcare management via its digitalization, putting the participant in the center of the model, and taking an active role in the decisions and in narrow and effective collaboration with professionals from different assistive models. Thus, this solution has no barriers of age or socioeconomic status, efficiently meeting the needs of a very diverse population, with a clear objective: to promote improvement of the user's quality of life by providing them with a set of engaging advice, suggestions, and recommendations. The system has been designed and developed as part of two European projects, the PEGASO F4F FP7 project[1] and NESTORE H2020 project,[2] and enriched with different layers of the system and different use cases. After describing the main features and components, this chapter introduces how BECOME has been used for different use cases.

2. A modular recommender system

BECOME is supported by a micro-services-based backend called xCare [6] and typically by a frontend in the form of an app, which provides details about (a) the current profile of the individual, including user status and other derived data; (b) understandable, structured, and directed plans for the user for a specific time frame; and (c) a workable intervention planning of the activities and events to be carried out

[1] https://pegasof4f.ro/

[2] https://nestore-coach.eu/

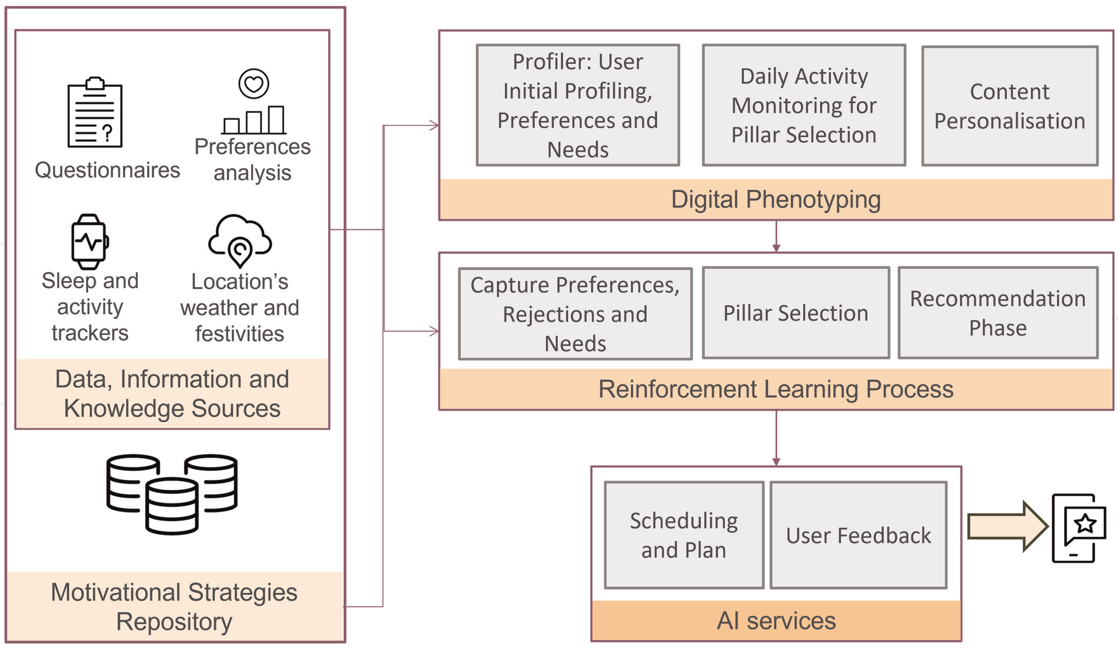

Figure 1.
BECOME modules.

by the participants to encourage behavior change. **Figure 1** sketches the overall system, showing the generic and modular manner in which it is built. This versatility makes it simple to integrate it with other environments, engines, or systems. In the following section, we show how each of the modules works.

2.1 Motivational strategies repository

The Motivational Strategies Repository contains a number of strategies that have been shown to improve the quality of life (QoL) and, in particular, the health-related quality of life (HRQoL) in chronic diseases. These strategies are based on a pool of over 1000 recommendations that are ready to enable customization and personalization to users based on their preferences as well as the monitoring of several indicators with proven significance. The repository contains ideas, events, activities, and proposed actions to foster behavior change on the main pillars of health and is grounded on domain expert knowledge from different areas of interest (e.g., nutritionists, psychotherapists, and psychosocial rehabilitation professionals), international guidelines (e.g., the World Health Organization), and evidence-based literature to set referenced cutoffs. It is dynamically fed and enriched with experiences and knowledge as new use cases are added.

The recommendations for behavior change extend beyond task-oriented activities and educate and reinforce healthy lifestyle habits by showing contrasted information on various topics of medical interest. Hence, it fosters user-centered recommendations with a flexible, dynamic, and multi-domain framework, rather than the classical disease-centered support. This approach provides omni-comprehensive user profiling and improves the self-adaptation of the entire system. All recommendations have been exhaustively tagged for this purpose, allowing proper personalization of contents (see Section 2.3.3). This tagging is what truly makes the difference, since it not only provides the whole understanding of the repository contents (see **Figure 2**) but also allows to easily filter, classify, and thus adapt contents to any use case. The tags of

Figure 2.
Cloud of tags used.

each recommendation include the following aspects: (a) *Pillar*, to identify the pillar related to the recommendation; (b) *Class*, to distinguish between Activity (e.g., "Why don't you train your muscles today?"), General knowledge (e.g., "Benefits of drinking water"), or Motivation (e.g., "Congratulations, you reached your goal today"); (c) *Season*, to indicate if a content is specific to a particular season; (d) *Day of week*, to indicate if a content must appear on a particular day of the week; (e) *Moment of day*, to indicate if a content must appear on a particular moment of the day (morning, midday, afternoon, or night); (f) *Need*, to specify if a recommendation requires any specific item; (e) *Subclass*, to classify the content if needed; (f) *Topic*, to allow adding other labels to the content; and (g) *Attachment*, to enable adding multimedia contents to improve the user experience. Text messages, images that complement text, videos that provide a different perspective on a subject and help users to fully understand it, and soundscapes—interactive nature-themed sounds with embedded videos that feature biological, geophysical, and climatic noises—are just a few of the different kinds of materials included in this repository.

2.2 Data, information, and knowledge sources

Gathering the information and knowledge from several sources is key to achieve a successful personalized recommendation process. In order to categorize potential sources, we used the terms active, passive, and contextual. Active sources include all the flow of information generated on the active interaction of the user with the system. Passive sources are those elements that measure the interaction of the user with the system but in an indirect way, without requiring the user's intervention. Finally, contextual sources refer to all that information that can be obtained from the users and from their environment without requiring any input from them. The distinction between passive and contextual sources is that users can alter passive, but they cannot alter the contextual ones.

2.2.1 Active data: questionnaires, surveys, and user input

Standard and non-standard questionnaires are useful to profile the user at the beginning of the recommendation process and to monitor their status and change of behavior during the intervention. Standard questionnaires are scientifically validated and commonly used to capture the nutrition habits of the user [7] and the quality of life [8, 9]. Other non-standardized questionnaires and surveys are useful to track the daily habits (e.g., fruit consumption, hours of sleep, etc.) and to fetch the preferences of the user. The last form of active data is the user's interaction with the recommendations. This interaction includes the ratings (or likes and dislikes) that the user may have given to a recommendation. The time spent visualizing the material and the hours of the day and week that these activities occurred may be considered as passive data gathering. All the information can be captured by the user interaction with an app or a web-based survey. However, an interesting way of dynamically capturing structured and non-structured user inputs is the use of intelligent conversational agents (i.e., chatbots) that can offer a more engaging experience resulting in higher quality data [10].

2.2.2 Passive data: wearables, mobile, and ambient sensors

Sensors on a smartphone, a wearable device, or other environmental sensors are used to automatically gather passive data about the user. These automatically obtained data provide a way to capture unique digital behavioral markers while also lessening the strain on patients that is generally associated with active data collection. Wearables, mobile, and ambient sensors may be used to (a) *measure anthropometric, musculoskeletal characteristics, and balance* with, for example, a smart scale; (b) *monitor physical activity* through commercial smart bracelets such as Fitbit that have a proven high accuracy for measuring physical activity (number of steps, heart rate, and distance) [11]; (c) *monitor sleep* through ballistocardiographic systems [12] or smart bracelets; (d) *monitor heart rate variability [13] and electrodermal activity [14] to assess psychophysiological stress* via smart bracelets to complement the subjective assessment of stress captured via questionnaires, surveys, and user inputs; and (e) *track social behavior* through Bluetooth Low Energy (BLE) beacons to measure social interactions [15].

2.2.3 Contextual data

Weather has an impact on people's daily life. Its health implications, however, are yet not completely understood. It may cause physical symptoms and/or have an impact on mental health, raising disease mortality and morbidity rates [16]. The most important variables that impact both bodily and mental moods are temperature and humidity [17]. Therefore, it is essential to gather this data and use it to provide context-sensitive advice to prevent severe temperatures. Other factors such as air, noise, water pollution, and availability of green urban zones have shown great influence on people's physical and mental health [18]. All these factors can be tracked by the use of Application Programming Interfaces (APIs) by tracking the localization of the user. BECOME may also benefit from clinical data supplied by hospitals in order to get a more comprehensive understanding of the user. We can learn interesting and useful information about the user thanks to the Hospital Information System (HIS), which enables recording and managing patient health records and appointments. Clinical data is transferred following the Health Level Seven (HL7) protocol, which enable the transference and exchange of data between healthcare providers. Furthermore, to have the whole image of the user, BECOME may also consider the Standardized Medical Prescription to know the real prescribed drugs or health products by clinicians.

2.3 Digital phenotyping: digital data collection for personalization

Digital phenotyping [19], also known as personal sensing, is the in-the-moment assessment of the human personal traits at the individual level utilizing information from digital devices. This type of personalization is a strategy that develops ad hoc solutions based on the unique biological traits, environment, needs, and lifestyle of an individual. It has proved its efficacy in a variety of healthcare settings, including prevention, disease management, risk assessment, risk reduction, diagnosis, and therapy [20]. Different facets of the recommender contain personalization traits that are relevant. The most obvious one is probably the personalization of content to the user's preferences, but other factors, hidden between the user interaction with the recommender, can be also captured and used to improve the experience.

2.3.1 Profiler: user initial profiling, preferences, and needs

User profiling is necessary to be able to personalize recommendations and thus increase adherence to BECOME. To do this, it is necessary to monitor the user for a period of time in order to measure the variables of interest and thus avoid a cold start. This monitoring period allows us to collect information about the user's lifestyle (e.g., does the use have a sedentary lifestyle?), preferences (e.g., type of diet), routines (e.g., at what time does the user have breakfast? And lunch?), or needs (e.g., weight reduction). The user profile may also include data that come or are inferred from the sensors, which have been entered manually (e.g., self-reported), and so on. And later, these will be enriched with the context of each user. For example, the weather and the temperature in the user's area. All this information is quantified and translated into scores that match the tags from the content database. By doing this, the user will start receiving recommendations according to their preferences. During the process of recommendation and the interaction with BECOME, this scores will evolve to capture dynamic user-system interaction and to take into account the long-term user engagement, two of the main pillars of reinforcement learning approaches for recommender systems [21]. The issue of new user cold start could be enhanced by including some strategies proposed in recent literature such as cross-domain collaborative filtering using matrix factorization models [22], enhanced content-based algorithms using social networking [23], ontology decision models [24], and using social network textual information to model user interest and item [25].

2.3.2 Daily activity monitoring for pillar selection

BECOME is made to make the user aware of which area of health is being worked with in order to prevent overwhelming them during the process of changing their behavior. The term "pillars" refers to these facets of health. The recommender can work with various pillars depending on the use case. For instance, a healthy user can concentrate on the four pillars of health: physical exercise, diet, well-being, and sleep. By recording and analyzing data from active, passive, and contextual sources, these factors are quantified and converted into a score. BECOME calculates these scores over a predetermined time period (for instance, one month) and determines which pillar is the best for that user. There are various ways to determine which of the pillars is the most appropriate. Choosing the pillar where the subject scored the lowest is the simplest strategy. However, this is not always the optimal strategy, as a person may not be able or motivated to concentrate on a certain area of their health, that being the reason why it is receiving a low score in that pillar at the first time. Because of this, more intricate methods might be used by documenting the historical evolution of pillars over several days or months. With this knowledge, BECOME might suggest work to the user in the pillar with the most potential for transformation. The ability to suggest or automatically choose a pillar to work on is another feature that can be customized. The user must make an intention to either take a preventative action or modify risky behaviors in favor of other healthier ones, according to the behavioral change theory known as the HAPA model (Health Action Process Approach) [26]. According to this view, it is preferable to allow the user to choose which component of health would be the focus rather than selecting one for them. However, for vulnerable populations, such as the elderly or those with moderate to severe mental health conditions, it would be easier to automate the selection process to simplify the interaction. It is important to keep in mind that the goal is to encourage a healthy lifestyle. Although these recommendations may be divided into pillars, they are actually interconnected; thus, changing one component of health would also affect the others.

2.3.3 Content personalization

In BECOME, personalization is focused not only on the user's own features and attributes but also on the types of content that the user can access. The person's susceptibility to one form of content or another will depend on their personality. By doing this, we can apply less weight to things that are not as relevant to the user and emphasize those that the user is paying more attention to. The parameters subject to customization in terms of content diversification are, on the one hand, the class of recommendation that users may receive:

- **General knowledge recommendations:** Users may require further information regarding a particular risky behavior in order to successfully change their behavior (for example, understand the effects of sedentarism on cardiovascular diseases).

- **Activities recommendations:** Other users could require guidance for actions to improve an unhealthy behavior (for example, receive a recommendation on hiking trails in their area).

- **Gamification:** Some users might prefer a system where the advice is presented as a game and the habit modification is left to be implied (for example, a game that suggests the user to pick digital treasures hidden on the streets of their city).

- **Monitorization of activities:** Last but not least, other users might desire tips on activity monitoring. For instance, if a user wears a smart bracelet, they might prefer to know whether they are more or less sedentary than people of a similar age and lifestyle.

Gender, spatial ability, previous knowledge, and levels of literacy and digitalization [27] of users may make them also prone to have preferences in the different type of multimedia that the recommendations may have.

2.4 Reinforcement learning process

The methods that let BECOME learn from user interactions are what give it its uniqueness. The learning process involves two steps: first, it identifies the most relevant content by examining how users engage with different themes, content categories, and multimedia types; second, it determines when a user is most likely to benefit from advice. This strategy is based on what is known as the "Reinforcement Learning" methodology [21, 28]. To provide context for the reader, we consider the following three stages as the foundation for the recommendation process. In stage 1, the recommender collects fundamental information from active, passive, and contextual sources about users and builds a quantified user profile (user Digital phenotype). The aim is to capture initial preferences, rejections, and needs, which enable the personalization of future advice, as well as to have the first whole picture of the user. In stage 2, it selects the pillar to work on through scoring strategies defined in order to obtain a score for each pillar of the system. This phase is crucial since it allows the user to concentrate on working on a single element, which is better for fostering behavior change. After a predefined number of weeks, the pillars' scores are updated. This enables the selection of the pillar to work on, allowing the evaluation and monitorization and determining whether the recommendations they are receiving are having a successful impact on their behavior. Finally, it comes to the recommendation phase, which is based on the feedback and interactions with the previously issued recommendations. The scheduling of the recommendations over the entire week is also part of this step and is based on the user's interaction with the recommendations. As explained in Section 2.1, each recommendation is tagged with different topics and classes to enable proper personalization of contents. This tagging system allows the creation of the quantified user profile, a matrix where each pair of topic and class receives a score. To avoid recommending the same topics and classes, an exploitation/exploration approach is used. This approach is controlled by a factor named *epsilon*, which measures the proportion of exploitation versus exploration. One strategy is to keep *epsilon* constant along time (for instance, with a value of 90% of exploitation and 10% of exploration). Other approach is to start with higher percentages of exploration (lower *epsilon* values) and decrease the exploration along time (increase *epsilon*).

A predetermined number of recommendations to be programmed are chosen for each week. With a probability set by *epsilon*, the algorithm randomly selects one of these recommendations for the exploitation/exploration paradigm. A topic/class pair is chosen at random from the ones that are available if it falls under exploration, and it is chosen from those that scored in the top decile if it falls under exploitation. The topic/class pair is then used to select a recommendation. All of the recommendations for the week are repeated using this process. Depending on the use case, two methods are used to penalize the already sent recommendations: either they are subjected to a penalty factor [29], or after being sent, they are programmed with a latency time that prevents them from being reprogrammed for a predetermined period of time.

2.4.1 Scheduling and planification

Once the recommendations are selected, they are intelligently programmed along the week and during the day. On the one hand, each recommendation is tagged with the correct day of the week and time of day on which that should be sent, as described in Section 2.1. For instance, a recommendation for a working day will only be sent from Monday through Friday and only in the early morning or midday. On the other hand, the likelihood of reading a recommendation in the pair "day of the week"/"time of day" is quantified for each user using a second matrix. One fact that must be known in order to correctly plan recommendations and initialize this matrix is the daily routines of the users. For example, sending a recommendation regarding good practices for better sleep will be more relevant if it is sent before going to bed than if it is sent while having breakfast. One way to infer this information is through the use of sensors such as those described in Section 2.2 that allow to detect: when users go to sleep and wake up (sleep monitoring), when they eat (home-space monitoring), or when they are doing physical activity (activity monitoring). Once the recommendations are selected, they are scheduled starting from those that are more restrictive (the ones that have less days or times to be scheduled) using the information provided by the previously mentioned matrix. The exploitation/exploration paradigm explained in the previous subsection is maintained. The *epsilon* value controls if the scheduling is performed in an exploitation or exploration fashion, by respectively selecting the pairs day/time on the top decile of the matrix, or randomly. For those recommendations falling into the "Activities" class and depending on the use case, the user may also be provided with the possibility of scheduling or blocking future time to take that recommendation into practice. This is one key aspect of the HAPA model [26], which makes the behavioral change more effective.

2.4.2 User feedback

The reinforcement learning process employs the user interaction with the recommendation to learn from it and subsequently update the weights of the quantified user profile (topic/class and day/time matrices). To measure the feedback, several approaches can be considered depending on the use case. With the active feedback, the users actively show interest on the recommendation. They may rank the recommendation, for example, by using a star rating system, like and dislike buttons, or answering future questions about the recommendation (for instance, questions asked by a conversational agent). Other types of active feedback could be adding the recommendation to favorites. Also, in the case of Activities, blocking future time to take that recommendation into practice is considered part of the active feedback. With the passive feedback, users interact with the recommendation, for example, by reading or ignoring it. The time spent reading a recommendation is also a continuous feature that could be used to measure their interest in the content. In the case of interactive recommendations, the number of clicks and the playback time are also considered.

Feedback is then translated into a score that is used to update the quantified user profile on each interaction with the recommendation. In the case of the topic/class matrix, active and passive feedbacks can be negative (disliked or ignored) or positive (liked or spent a lot of time reading or playing the content). In the case of the day/time matrix, the paradigm is slightly different, as any interaction with the content (even a negative one) is considered positive, as what is reinforced is the times and days that the user mostly interacts with the content.

2.5 A human-centered approach

BECOME is designed to serve the needs of users by personalizing the human-system interactions to properly adapt to each user. It is a modular system that offers flexibility to users by allowing users not to have to adhere to or accept all modules in order to benefit from BECOME. This flexibility is illustrated, for example, in the data that the system will use to profile users. Only the information that users want to provide will be used to profile them to later obtain their own version of BECOME. This means that it is not necessary for users to accept the deployment of sensors or to answer all questionnaires to obtain meaningful recommendations. Thus, BECOME prioritizes user decisions over system performance. Strengthening users' autonomy in decision-making related to the use of BECOME is the key to their empowerment. Another example is that users can choose to not receive recommendations from certain pillars. Thus, the scope of BECOME is as wide as users want it to be.

BECOME is a system that promotes transparency in communication with the patient. It offers a view with access to all the data it collects, such as responses to questionnaires, or infers, such as the indicators that are calculated to assess the status of the patient. This transparency allows users to understand the basis for the recommendations made by the system and to validate their appropriateness. The recommendations are also accompanied by an explanation supporting the rationale for the suggestions made. Thus, the user can understand not only what information recommendations are based on but also the potential impact of the recommendations in order to be well-informed and make a free decision on whether or not to act on the recommendation.

Another element that highlights the human-centered essence of BECOME is that it accepts the dynamism of individuals and therefore allows data to be updated. In other words, BECOME embraces changes in users' routines and preferences and adapts to them. This is done, for example, by overwriting the answers to certain questionnaires that are sent out periodically, such as the one that assesses the frequency of food consumption or the quality of life questionnaire. It also offers the option for users to decide how often they want to receive messages from BECOME. Giving agency over the control of notifications to the user makes BECOME adaptive to the user's needs and preferences by speaking the user's language.

3. Use cases, interfaces, and interaction

In the following, we show how BECOME has been tailored to various use cases such as encompassing different stages of life, covering specific pathologies, or delivering content in a unique way.

3.1 PEGASO F4F: optimizing lifestyle in teenagers

With a holistic and multidisciplinary approach, the project PEGASO Fit-for-Future (Personalized Guidance Services for Optimizing lifestyle in teenagers through

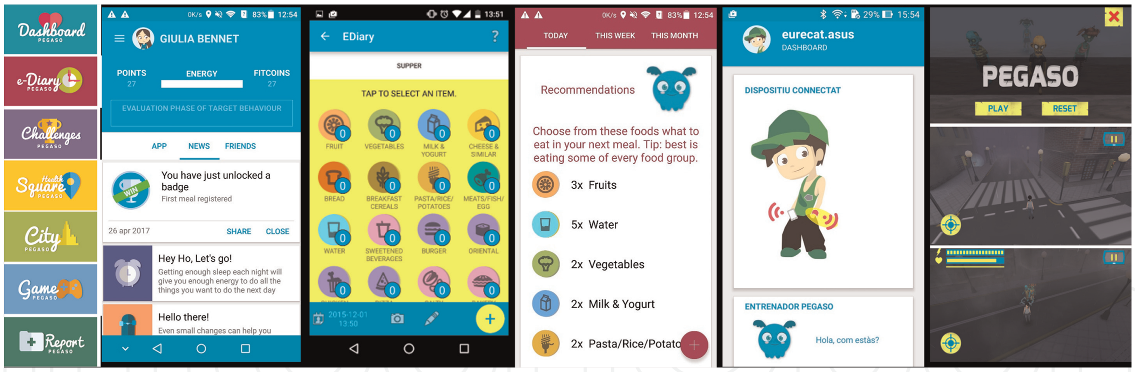

Figure 3.
The PEGASO F4F apps.

awareness, motivation, and engagement) [30] seeks to challenge teenagers in their fields of study and areas of interest while fostering a long-lasting shift toward healthy lifestyles. All in all, it is an ICT system that includes game mechanics to influence behaviors in order to fight and prevent overweight and obesity in the younger population by encouraging them to become co-producers of their wellness and take an active role in improving it. As we can see in **Figure 3**, the PEGASO F4F application, games, and gamification approaches are offered to teenagers to promote sustainable behaviors geared toward achieving healthy lifestyles. It contains a behavior-change platform (BCP), targeting teenagers in preventing obesity and related comorbidities [31]. The BCP was the basis for BECOME and the first Motivational Strategies Repository. It contains 45 different recommendations, most of which were centered on general knowledge to help educate teenagers about how to change their behavior with regard to three pillars of health: nutrition, physical activity, and sleep. No machine learning methods are used; instead, the artificial intelligence technologies rely on case-based and rule-based approaches. BECOME is divided into two modules in PEGASO: short-term analysis and long-term analysis. The short-term analysis' main objective is to assess user's daily habits to be able to provide feedback to the teenager. It processes user data coming from disparate sources in order to analyze which factors may have a negative impact on health and suggest corrective interventions through BECOME. The long-term analysis is built upon weekly and monthly data stored in a semantic repository, and they are used to evaluate trends in behaviors and to assess changes.

3.2 NESTORE: personalized coaching plans for seniors

NESTORE is a project from the H2020 EU program that aims to combat ageism, enable autonomy, and support healthy aging. Its acronym stands for Novel Empowering Solutions and Technologies for Older people to Retain Everyday life activities [32]. NESTORE proposes to support healthy older adults to sustain their well-being and the capacity to live independently by promoting customized coaching plans for well-being. This was made possible by transforming the original version of BECOME into an innovative, multidimensional, cross-disciplinary, and personalized coaching system that, leveraging ICT social connectivity, supports older adults by encouraging them to become co-producers of their well-being and health by considering the main domains of active aging: physical activity, nutrition, cognition, and social interaction. The design of coaching plans aims at stressing the recommendations that best guide users to extend their independent living and postpone functional decline. This resulted in the development of the second version of BECOME, in which personalization was enhanced further by the addition of the following framework, which allows for a deeper understanding of the user and the ability to tailor recommendations to the user's unique requirements and situations. NESTORE's version of BECOME chooses the most appropriate set of structured and non-structured Coaching Events (CEs) for each user and sends the recommendations at the most adequate time. The Motivational Strategies Repository was enhanced by adding over 450 recommendations, some of them focused to elderly people needs, and it was published to a web page to facilitate the introduction of expert criteria. After some iterations, this resulted in a rich repository of recommendations and their metadata. In NESTORE, we added many kinds of tags to BECOME: domain-specific (e.g., to create the grocery list of nutritional CEs), time-related (to indicate the most appropriate time slots to send a specific CE), language (to describe if the CE is language-specific and to define the communication language of a user), and preferences (to describe the likings of users), among others. The selection of the recommendations was done through a tagging system composed of four modules: a constraint-based system combined with a hybrid recommendation system [29], which employs collaborative (CF), content-based filtering (CBF), and log filtering.

3.3 CarpeDiem: self-management system to promote healthy habits in general population

CarpeDiem [33] aims at adapting, personalizing, and delivering motivational, informative, and gamified strategies through an Intervention Planner and a Recommender System with the aim of promoting healthy habits in the general population. The main goal of the platform is to help participants in selecting coaching plans from three pillars of health: nutrition, physical activity, and sleep. CarpeDiem's recommender system is built over BECOME, which was improved during the execution of this project by: (a) enriching the Motivational Strategies Repository with additional entries concerning the health pillars addressed, especially sleep recommendations, (b) adding the definition and implementation of a holistic scoring system that offers quantifiable metrics to enable the analysis of people with comparable behaviors and to determine which of them are connected, and (c) including gamified elements such as the Missions, which are groups of coaching plans (recommendations) presented in an engaging and stimulating way, challenging the user to accomplish nutrition goals based on the food groups with the worse score.

CarpeDiem's frontend is a smartphone app (see **Figure 4**) with an advanced interface that assists and entertains the user to provide them with education on healthy habits, trigger alarms and nudges, and motivate them to comply with personalized goals. It contains personalized interfaces such as a calendar to record progress, visualization of daily progress, presentation of scoring and comparison with other users to promote competitiveness, and display of recommendations and selector" I like/I do not like" to know the users' preferences.

3.4 CarpeDiem coach: promoting healthy behaviors among elderly people

CarpeDiem Coach is a special use case of the abovementioned CarpeDiem, but it was created to address the specific needs of the elderly population with the support of

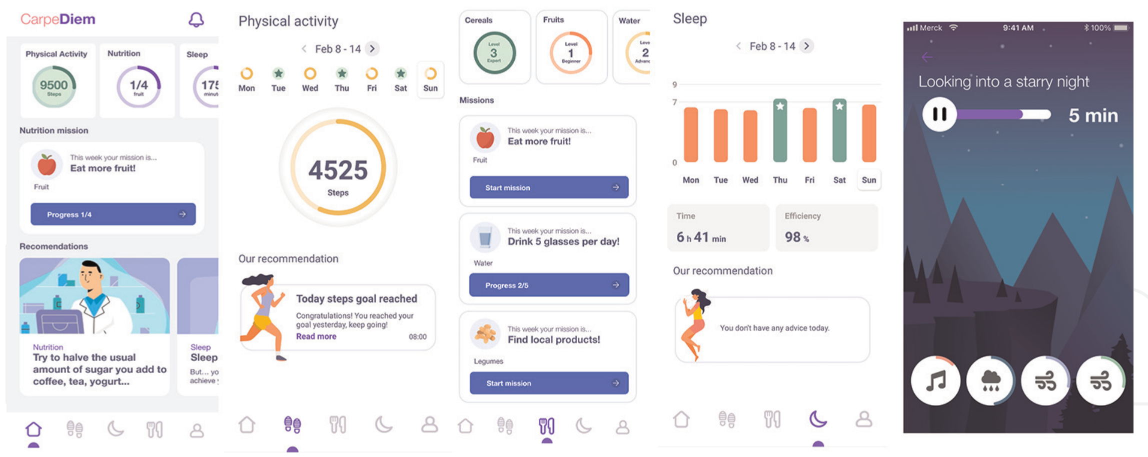

Figure 4.
CarpeDiem app.

the project PECT Maresme.[3] To that end, it provides intelligent and automatic support to prevent the risk of decline in older adults. CarpeDiem Coach proposes recommendations in the form of coaching plans to support healthy older adults to sustain their well-being and the capacity to live independently while detecting bad behaviors that can lead to physical decline.

The project presents a health and social welfare technological innovation centered on the person and supported by a mobile device and a smart bracelet for patient monitoring. What truly makes this use case different is the intuitive, easy-to-use, and simplified interface with customized functionalities, generated after a co-creation iterative process where designers, developers, and elderly volunteers periodically met to lay the foundations of the application, enabling to create a system that perfectly met their specific needs and requirements. The creation of an app tailored to the unique requirements of this vulnerable population type allows for the inclusion of the digital age and all of its related benefits for the promotion of healthy lifestyles (use of countless digital resources to improve nutrition, physical activity, rest, use of telemedicine, improve communication with family and friends, etc.).

This use case was used to enhance the Motivational Strategies Repository with over 100 recommendations tailored to the older demographic and to improve the Reinforcement Learning algorithm to make it more robust.

Figure 5 presents the mobile app's front page, consisting on a virtual coach and a friendly agent that delivers tasks to users, encouraging them to answer a questionnaire or to read a recommendation to improve their QoL. This design concept comes from previous research on finding new ways to stimulate elderly to use the mobile applications and to facilitate their navigation through the interfaces in the app [34].

3.5 Healthy habits promotion for adults with schizophrenia

How lifestyle, typically associated with physical health, nutrition, and good sleep, may also connect to mental health and psychological well-being is a topic of growing academic and therapeutic attention [35]. The case of people with schizophrenia is especially sensitive. They present lower levels of quality of life resulting in a lower life

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[3] https://matarociutatcuidadora.cat/

Figure 5.
CarpeDiem coach app.

expectancy than the general population, with approximately 75% of deaths resulting from preventable medical conditions, such as cardiovascular disease and diabetes [36]. Most doctors agree that in addition to treating symptoms, focusing on topics like living well by developing one's own resources and abilities, recognizing one's own strengths, or forging a positive identity can help people recover from schizophrenia and its related symptoms [37]. Thus, it is crucial to provide adapted and personalized recommendations to change their way of lives. For this use case, BECOME is packaged inside a mobile application and a professional's back office that connect patients with their psychiatrist and primary care doctors. By using the application, the patient is able to answer follow-up questionnaires (both hetero- and self-applied) and monitor their daily habits via short questions and a smart bracelet. BECOME uses all this information to profile the user and provide automatic recommendations. Some of these activities are mindfulness sessions, physical activity exercises, doctor's appointments, and so on. Furthermore, the system is connected to a chatbot (a conversational agent) named *Tothom*. It has great potential because it not only helps patients 24 $\times$ 7 by providing information, companionship, understanding, advice, and emotional support but also allows professionals to track their patients' mood swings by observing how they communicate using natural language, therefore avoiding the interaction barrier that exists between an application and the human. Offered advice through *tothom* is based on BECOME, which suggests positive practices around sleep (sleeping at night, respecting the hours of sleep per day, not attending the mobile in the minutes before going sleep, etc.) in an extremely personalized fashion. *Tothom* is especially sensitive to suggesting activities that are shared with family, friends and pets, mentioning their names, as this type of personalization increases the commitment, aiding with the change of behavior [38].

3.6 Supporting cardiac patients in improving the QoL

Cardiovascular diseases are a common, serious, and a global healthcare issue, and rehabilitation is crucial for maximizing functional recovery and the quality of life. Effective cardiac rehabilitation comprises medical evaluations, prescriptive exercise, education and counseling, and behavioral interventions, among others [39], and it has predominantly been offered as a supervised and inpatient service. Nevertheless, the need for introducing it outside the hospital has recently appeared to widen access and participation, and nowadays, telemedicine is attempting to bring innovative and optimal tools to accomplish it [40].

In these terms, recent research has suggested that cardiac rehabilitation may incorporate behavioral modification and psychosocial support as a means of secondary prevention [41] and that digital health solutions have a strong influence on improvements in physical activity, quality of life, and rehospitalization [42]. To capture this scenario, a use case of the PECT Bagess[4] project aims at supporting cardiac patients and healthcare professionals by providing a tool for both home-based and center-based cardiac rehabilitation sessions. Its main objective is to support the planning and monitoring of those sessions, including personalized advice and reminders, with the overall goal of improving patients' quality of life and professionals' efficiency.

This use case involves a smartphone application for patients and a backoffice for clinicians. The app consist of a series of features including questionnaires to capture patients' data, recommendations and advice (based on BECOME), training sessions' prescriptions and virtual environments to attend the sessions, chat to promote effective communication, and an alerts system that sends warnings to users when some cases occurred. As an specificity of this use case, BECOME has been improved to include a specific module to recommend the training intensity of the next training sessions, differentiating between aerobic and strength training. Both intensities are based on user variables such as maximum heart rate and age as well as on questionnaires after training, which include Borg's Scale and the presence of symptoms during and after the session, not only allowing intensity calculation but also improving patients' safety. Furthermore, by analyzing training data tracked by Polar smart watches,[5] the system sends reminders about fulfilling their weekly sessions of exercise as well as about the importance of having healthy habits, based on other user data (e.g., BMI, abdominal perimeter, mental health, diet, etc.).

3.7 Recommendations of health multimedia content

Recommendation systems can also be used to empower people as patients. The use case that is presented in this section aims at educating patients and achieving effective two-way communication through technology and multimedia content. In particular, we present a system capable of recommending health multimedia content to patients through their medical journey with the ambition of providing the right information at the right time. This system has two main target users: patients and healthcare professionals. The aim of the system in relation to the former is to foster their empowerment, while in relation to the latter, it aims to make it easier for healthcare practitioners to prescribe content to their patients by providing more tools to move

[4] https://bagess.cat/
[5] https://www.polar.com/es/ignite2

toward personalized medicine and to optimize the time available to attend visits and, in turn, improve the care provided. Thus, this system facilitates the dissemination of medical content to a greater number of actors in the ecosystem. To accomplish this purpose, three different data sources are used: one characterizes the patients, another the audiovisual content, and the last one structures information about health conditions. By exploiting this data, we can understand patients' needs at a specific point of their medical journey together with their learning preferences so as to find the most adequate audiovisual item based on its content and learning requirements.

The implementation of BECOME in this use case integrates the classic recommendation methodologies: content-based filtering and collaborative filtering. In addition to these two techniques, another type of filtering evaluates the ideal viewing sequence based on the viewing history and the corresponding interactions. This functionality can predict the most appropriate recommendation sequence for each patient based on their medical history.

4. Conclusion

BECOME's overall goal is to create an emotional connection between users and the platform by creating the impression that they have a kind of "coach" who is aware of their wants and preferences and offers recommendations when they are needed in a tailored fashion. For such a purpose, the inclusion of knowledge-processing algorithms and reasoning techniques is being implemented through the Recommender System so that, for instance, recommendations are personalized in terms of which kind of activities are proposed, when they are sent—frequency, time of the day, and so on, the total amount of recommendations to administer, and their priority. Thus, we take personalization one step further by not only tailoring the content, which is the standard customization strategy, but also adapting its timings and complexity in a dynamic manner while dealing with the feeling of having an entity (the coach) behind the app, ready to help. It is based on contents and knowledge validated by professionals from various fields of health, and these contents are made available to users through easy-to-use and adapted-to-profile interfaces. The system also continuously generates new knowledge from participants' evolution on the Quality-of-Life indicators. It motivates and fosters adherence with complementary tools as the gamification provides in terms of missions or challenges. One of the strengths of BECOME is that it can be easily introduced in different interfaces, depending on the use cases as well as on the preferences of the user. Interfaces range from more classical mobile apps with advanced features (user can monitorize themself, schedule activities, play games, etc.) to simplified versions with smart interactions, useful for users with lower digital literacy. In addition, it is possible to insert BECOME into a conversational interface, such as chatbots or voice services (e.g., Alexa, Siri, etc), focusing on improving how people interact with systems by means of a more natural way of communication.

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Conflict of interest

The authors declare no conflict of interest.

Notes/thanks/other declarations

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