A Decision Support System to Propose Coaching Plans for Seniors

Paula Subías-Beltrán*, Silvia Orte*, Eloisa Vargiu*, Filippo Palumbo†, Leonardo Angelini‡,
Omar Abou Khaled‡, Elena Mugellini‡, Maurizio Caon‡
*eHealth Unit, Eurecat, Centre Tecnològic de Catalunya. Barcelona, Spain
†Institute of Information Science and Technologies. National Research Council. Pisa, Italy
‡University of Applied Sciences and Arts Western Switzerland (HES-SO). Fribourg, Switzerland
*paula.subias@eurecat.org, *silvia.orte@eurecat.org,*eloisa.vargiu@eurecat.org, †filippo.palumbo@isti.cnr.it,
‡leonardo.angelini@hes-so.ch, ‡omar.aboukhaled@hes-so.ch, ‡elena.mugellini@hes-so.ch, ‡maurizio.caon@hes-so.ch

***Abstract*—This paper presents the decision support system that has been defined and developed under the umbrella of the NESTORE project. The main goal of the proposed system is to help users in selecting coaching plans by proposing personalised recommendations based on their behaviours and preferences. Recognising such behaviours and their evolution over time is therefore a crucial element for tailoring the interaction of the system with the user. A three-layer system composed of *pathways*, *coaching activity plans*, and *coaching events*, constitutes the so-called coaching timeline on which the analysis is grounded. Various techniques are used to model and personalise the recommendations and feedback. Firstly, the indicators are extracted from disparate data sources, then these are modelled through a profiling system and, finally, recommendations on the pathways and coaching plans are performed through a scoring and a tagging system.**

***Keywords*-decision support system; well-being; active ageing; assistive technology; e-coach; tagging system;**

I. Introduction

Ageing population is growing fast in EU [1]. In this context, ICT can provide solutions for Active and Healthy Ageing, however, the success of novel ICT solutions will depend on users' perception about their efficacy. Active and Healthy Ageing represents a complex intervention because it aims to tackle all the human domains: physical, cognitive, social and nutritional. User-centred care has now made it to centre stage in discussions of quality and, as evidence-based medicine does, considers both the art of generalisations and the science of the individuals [2]. It comprehends strengthening the patient-clinician relationship, helps patients know more about their health, and facilitates their involvement in their own care [3].

The NESTORE[1] project (Novel Empowering Solutions and Technologies for Older people to Retain Everyday life activities), funded by EU H2020 programme, is conceived as a multi-domain system to promote proper healthy strategies with an integrated vision. In this paper, we present the core component behind the coaching plans suggested to the user by NESTORE: the intelligent Decision Support System (DSS), able to analyse users' profile, track the changes and compliance to active ageing guidelines, and provide personalised pathways towards the adoption and maintenance of a healthy lifestyle.

A. NESTORE e-Coach

The vision of NESTORE is to be a companion, a partner, and a mentor [4]. NESTORE e-Coach aims to give advice to older people so that they can maintain their well-being and their independence at home. It is a pervasive conversational agent utilising multiple modalities to communicate with the users: voice, applications, and a tangible interface. The text interaction form is implemented as a chatbot embedded in the NESTORE mobile application. This chatbot acts as a minding mentor that cooperates with the users in building and sustaining their well-being, adjusting to their inclinations and to relevant recorded data. NESTORE provides recommendations for coaching and personalisation in four crucial domains (called henceforth target domains) of the Active Ageing process: a) physical activity (PA), b) social interaction, c) cognitive, and d) nutrition [5]. It is grounded on the Health Action Process Approach (HAPA), a model for supporting behaviour change in health related domain [6]. With respect to other behaviour change models adopted insofar for coaching healthy behaviours (e.g., Theory of Planned Behaviour (TPB) [7]), the HAPA model identifies specific variables that better support the users during the actual phase of behaviour change (whereas TPB identifies only variables affecting the intention-making). It is implemented by matching specific behaviour change techniques to the aforesaid variables and implementing them in the interface [8].

II. Related work

DSSs are computer-based systems designed to be a direct aid to users in choosing and judging the different available options to solve a problem. During recent years research has been made in this area due to the emergence of personalised medicine. Most DSS provide decision support for specific diagnostic or therapeutic tasks. The work related to NESTORE's field of interest can be classified according to their purpose as systems that:

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

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1) give advice, recommend coaching plans and trigger alerts: Coaching plans can give details of dietary requirements, activity levels, targets for PA, blood pressure, and other tests [9].

2) are based on daily life activities: It is important to adapt the recommendations to users' current behaviour. In [10], patients' daily life activities as well as other social elements are used for personalising their services. In a similar manner, [11] proposes to automatically monitor daily activities to detect abnormal events.

3) extend independent living: [12] demonstrates that monitoring technologies to detect activities of daily life of elderly people prolong their independent living.

III. Materials and methods

The DSS can be considered as the intelligence of NESTORE. Its aim is to develop the data analysis elements needed to provide NESTORE e-Coach with tailored feedback based on integrated data sources encompassing the four target domains. For action planning, the DSS helps users scheduling the proposed coaching activities into their calendar, matching their availability with context requirements. Finally, the DSS helps them to adapt coaching activities to their needs and preferences, e.g., lowering the intensity of PA if the perceived required effort is too high.

A three-layer coaching timeline is proposed to adapt better to users' needs and preferences. This layered system allows them to 1) choose a general goal (pathway), 2) select the kind of activities that they prefer (coaching activity plans), and 3) accomplish their objective performing specific training scheduled by the system (coaching events). This makes NESTORE a user-friendly framework that converts general goals into specific actions supporting their accomplishment and, therefore, users' fulfilment.

1) Pathway: High-level goal to which users will commit at the end of the motivational phase, such as "Achieve a healthy diet". During the first two weeks after signing up to NESTORE, the system tracks the necessary data to analyse users' behaviour. Then, it is able to recommend what may benefit users the most. Next, users will select the pathway they want to focus on.

2) Coaching activity plan (CAP): Category of activities that can be stratified into a set of specific activities, such as "increase your calcium intake", which could be fragmented into "add milk to your coffee" or "eat a yogurt as a snack". Each pathway has many CAPs associated to tailor the coaching plan to users' preferences.

3) Coaching events (CEs): Set of activities scheduled by the system throughout the day/week. Its enjoyment and willingness to be repeated are assessed by the user using the five-level Likert scale.

The DSS aims to combine and interpret the different signals coming from extensive sources of information, to provide meaningful, timely, and relevant tools to help users to select the best pathway, CAPs and CEs according to their health status and preferences. Fig. 1 depicts the architecture proposed in this research to accomplish this objective; it is formed by the following parts:

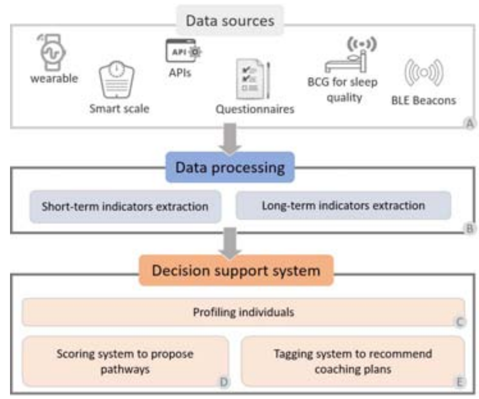

Figure 1. The NESTORE DSS architecture.

A. Data Sources

NESTORE uses different data sources: *hard* and *soft* data sources. The former corresponds to the stream coming from environmental and wearable devices, hereinafter referred as *Sensing system*. The latter consists of derived data coming as a result of computation or fusing strategy, data coming from web and third-party APIs, and data coming from a direct input of the user.

1) Sensing system: It is composed of a wearable device and an ensemble of environmental wireless devices that detect the status of the users' living space and their behaviour.

2) Food recognition: The LogMeal API [13] is used to automatically construct a food diary, based on images captured by the user with a smartphone.

3) Questionnaires: The inclusion of a well-assessed psychological empowering modelling in the system intelligence guarantees an improved adherence with respect to conventional coaching approaches.

4) Context: User engagement is improved by adapting CEs to users' context. A series of context data types like weather or user location have been identified to be used at different stages of the personalisation process.

B. Data processing

This subsystem analyses and interprets the data to create expert-driven indicators that will be used in the DSS.

C. Profiling individuals

NESTORE aims at knowing users "intimately" so it needs to know and understand habits, the environment, the social life and other key information about them, including the health status. To this purpose, it is proposed a two-fold user profile (see Fig. 2) used by the DSS to model the

Figure 2. User profile summarised per category.

user creating a detailed, reliable, and dynamic user profiling, which is the base to build personalised guidance and advice:

- *Static profile*: It is formed by users' demographic and environmental characteristics, preferences and baseline data of the various domains. It is characterised by containing non-varying attributes.
- *Dynamic profile*: It is built dynamically while receiving data from sensors, applications, and contextual APIs. It is foreseen to receive daily indicators about the different domains and also contextual information.

D. Scoring system to propose pathways

NESTORE experts conducted a search of normal values and cut-offs relative to each pathway. Cut-offs adopted in clinical practice, in international recommendations as well as in relevant literature have been included. The most referenced recommendations were selected and will be used as reference values for the evaluation of NESTORE users' daily habits. The standardisation of the thresholds between pathways comes with a three-level scale to measure the users' status per pathway. Expert knowledge and statistical data are used to sort pathways with same scores.

E. Tagging system to recommend coaching plans

Once users choose the pathways and CAPs to focus on, another subsystem of the DSS, the tagging system, comes into play by proposing appropriate CEs to users. NESTORE uses personalisation techniques based on tags to fit users' likings and behaviours. Its foundations have two parts: tags to describe CEs and user profiles, and rating data. As Bonhard showed, the rating overlap between users in combination with profile similarity can be a powerful source of information for a decision-maker when validating a recommendation [14].

Tagging is the process of assigning metadata to content in the form of keywords. Users' profiles are tagged automatically thanks to a given ontology [15] and expert-driven criteria. For example, a lactose-intolerant person who lives in a city with beach, and enjoys swimming will be tagged with [lactose-intolerant, beach, swim]. CEs are tagged based on their requirements; e.g., the CE "Why don't you go to swim at the beach?" will be tagged with [swim, beach], and the CE "Add milk to your tea" will be tagged with [milk]. In this example, the former CE could be suggested to this user, whereas the latter would be filtered out. This constraint-based system is combined with a hybrid recommendation system, which employs collaborative (CF) and content-based filtering (CBF), that all together form the complete tagging system. Fig. 3 shows the workflow of the tagging system.

CF finds users in NESTORE that shared the same interests in the past to predict what the current user will be interested in. We use the rating overlap as a measure to compute the user-based CF. Its implementation is the following:

- A collection of users u_i, $i = 1, \ldots, n$, and a collection of CEs CE_j, $j = 1, \ldots, m$
- An $n \times m$ matrix of ratings v_{ij}, with $v_{ij} = \emptyset$ if user i did not rate product j, where v_i denotes all the ratings made by user u_i
- Similarity between users is computed by adjusted cosine similarity, which takes care of the difference in rating scale

$$u_{ik} = \frac{\sum_{j \in J}(v_{ij} - \overline{v_i})(v_{kj} - \overline{v_k})}{\sqrt{\sum_{j \in J}(v_{ij} - \overline{v_i})^2}\sqrt{\sum_{j \in J}(v_{kj} - \overline{v_k})^2}}$$

  where J is the set of CEs rated by both u_i and u_k
- Prediction for user i and product j is computed $v^*_{ij} = K \sum_{\substack{k=1\ldots n \\ v_{kj} \neq \emptyset}} u_{ik} v_{kj}$ where K is a normalisation factor

CBF generates recommendations from two sources: the tags associated with CEs and the ratings that a user has given to them. We treat each CE as a user-specific classification problem and learn a classifier for the user's likes and dislikes based on CEs' tags. It is able to recommend new and unpopular items, although it highly depends on the quality of the tags; meaningless or lacking tags would lead to an unnecessary set of CEs filtered out.

The outcome of both algorithms is aggregated through a hybridisation strategy which employs both recommendation systems side by side and aggregates their outputs by computing weighted sums of their scores. This parallelised approach acts as an additional post-processing step.

F. Piloting

A four-months pilot study to assess the feasibility of NESTORE in real life conditions is scheduled to start in September 2019 in Italy, The Netherlands, and Spain. Its main objective is to test the effectiveness of the system in a twofold manner a) evaluating the increase of knowledge and awareness about healthy habits and b) assessing behavioural change on the selected pathways. Approximately 90 participants aged 65-75 years will use the system during the study.

IV. Conclusion

The proposed DSS takes advantage of both mHealth (smartphone apps and sensors) and cloud solutions to perform a three-stage processing of the user-generated data at

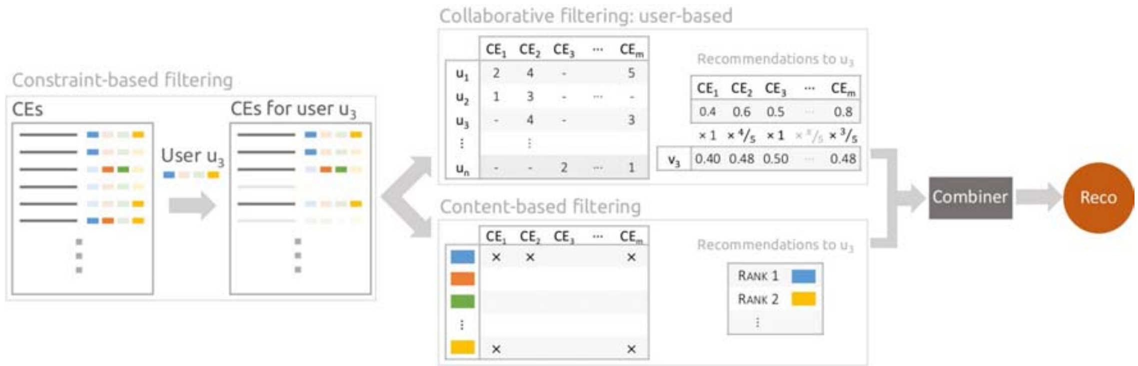

Figure 3. Workflow of the tagging system.

different timespans to provide different levels of feedback and user interaction. The implementation of a DSS embedded into NESTORE architecture, allows NESTORE e-Coach to dynamically adapt to users' profile and needs. A combined analysis performed using different data analysis techniques provides further level of understanding of the status of the final users as it is able to discern users' daily needs and ultimate goals at the same time. Thus, this ability of the DSS provides a significant level of personalisation. An expert-based scoring system is used to rank the pathways according to users' health status, while the proposed hybrid tagging system offers a highly scalable and easily updatable solution for CEs recommendation.

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References

[1] A. Chłoń-Domińczak, I. E. Kotowska, J. Kurkiewicz, A. Abramowska-Kmon, and M. Stonawski, "Population ageing in europe: facts, implications and policies," *Brussels: European Commission*, 2014.

[2] I. McWhinney, "'an acquaintance with particulars...'." *Family medicine*, vol. 21, no. 4, p. 296, 1989.

[3] R. M. Epstein and R. L. Street, "The values and value of patient-centered care," 2011.

[4] M. El Kamali, L. Angelini, M. Caon, G. Andreoni, O. A. Khaled, and E. Mugellini, "Towards the nestore e-coach: a tangible and embodied conversational agent for older adults," in *ACM International Joint Conference and International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers*. ACM, 2018, pp. 1656–1663.

[5] The-NESTORE-Consortium, "D2.1: Models for healthy older people," 2018.

[6] R. Schwarzer, "Modeling health behavior change: How to predict and modify the adoption and maintenance of health behaviors," *Applied psychology*, vol. 57, no. 1, pp. 1–29, 2008.

[7] I. Ajzen, "The theory of planned behavior," *Organizational behavior and human decision processes*, vol. 50, no. 2, pp. 179–211, 1991.

[8] The-NESTORE-Consortium, "D5.1: Definition of intervention techniques," 2018.

[9] M. M. Baig, H. Gholamhosseini, M. J. Connolly, and M. Lindén, "Advanced decision support system for older adults." in *pHealth*, 2015, pp. 235–240.

[10] A. M. Khattak, Z. Pervez, M. Han, C. Nugent, and S. Lee, "Ddss: Dynamic decision support system for elderly," in *Computer-Based Medical Systems (CBMS), 2012 25th International Symposium on*. IEEE, 2012, pp. 1–6.

[11] T. Croonenborghs, S. Luca, P. Karsmakers, and B. Vanrumste, "Healthcare decision support systems at home," in *Proc. AAAI-14 Workshop on Artificial Intelligence Applied to Assistive Technologies and Smart Environments*, 2014.

[12] K. K. Peetoom, M. A. Lexis, M. Joore, C. D. Dirksen, and L. P. De Witte, "Literature review on monitoring technologies and their outcomes in independently living elderly people," *Disability and Rehabilitation: Assistive Technology*, vol. 10, no. 4, pp. 271–294, 2015.

[13] E. Aguilar, M. Bolaños, and P. Radeva, "Food recognition using fusion of classifiers based on cnns," in *International Conference on Image Analysis and Processing*. Springer, 2017, pp. 213–224.

[14] P. Bonhard, C. Harries, J. McCarthy, and M. A. Sasse, "Accounting for taste: using profile similarity to improve recommender systems," in *Proceedings of the SIGCHI conference on Human Factors in computing systems*. ACM, 2006, pp. 1057–1066.

[15] The-NESTORE-Consortium, "D2.3: The nestore specific ontology," 2018.