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A Recommendation System for Personalized Daily Life Services to Promote Frailty Prevention

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Abstract. Frailty is a clinical syndrome that commonly occurs in older adults and characterizes an intermediate state between robust health and the loss of autonomy. As such, it is crucial to identify and evaluate frailty to preserve the abilities of older adults and reduce the loss of their functional capabilities. This paper proposes a personalized service recommendation framework designed, to assist senior citizens in selecting appropriate services, to prevent frailty and improve autonomy.

This framework is based on a multidimensional evaluation of the elderly person, considering both user's status information and service-related data. It defines a four steps recommendation process, including personal characteristics identification, needs identification, service types identification, and service identification. To support this, both knowledge-based and rule-based approaches are defined and employed to generate personalized recommendations that align with the individual's specific needs. The effectiveness of the proposal is evaluated using different representative scenarios, of which an example is described in detail that demonstrates the developed recommendation process, algorithms and relevant rules.

Keywords: Recommendation process · Recommender Systems · Elderly · Frailty

1 Introduction

Well-being is essential for successful ageing. Studies link well-being to maintaining functioning, engagement, and life satisfaction in later life [1]. However, ageing can cause a decline in well-being due to resource loss. This decline can lead to problems such as social isolation and depression, further decreasing the person's well-being. This process of functional decline is related to frailty, a concept that

is related to vulnerability and adverse health outcomes due to physiological decline [2]. Prevention plans aim to slow deterioration through tailored solutions such as physical activity, but selecting suitable options can be difficult due to the broad availability and diversity of services, as well as various factors such as cost, quality, expertise, location, and individual preferences and needs.

In this context, recommender systems provide customized services that cater to users' needs. By generating personalized recommendations, these systems offer the most suitable services that align with the unique needs of elderly individuals, aiming to improve overall well-being and prevent frailty. However, several challenges must be addressed before developing and implementing such systems. Our research aims to define and formalize essential knowledge for making personalized recommendations based on user needs. We identify knowledge for characterizing users and services, determine the necessary representation for embedding it within a suitable software structure, and define mechanisms and algorithms for implementing it in a recommendation system.

To address these challenges, we examined surveys and assessment tools used to evaluate frailty. Key elements were identified for defining frailty and intrinsic capacities, allowing for a better understanding of individual status through survey responses. The proposed recommender system uses this data to identify appropriate services and construct tailored prevention plans based on the specific needs and preferences of the person.

In this paper, we first provide an overview of the well-being of the elderly, with a particular emphasis on the use of recommender systems and their role in promoting healthy ageing and preventing frailty among the elderly population. In the third section, we introduce our proposed recommendation framework, Senselife. In the fourth section, we describe the details of the proposed recommender engine, exploring the algorithms used and the four-step recommendation process. In the fifth section, we present a use case to illustrate the effectiveness of the recommender system. Finally, we conclude with a summary of our key findings and offer perspectives for future research.

2 Background

2.1 Well-being

The World Health Organization [9] has emphasized the importance of promoting well-being in older adults for healthy ageing and maintaining a high quality of life. Recent research has emphasized the importance of promoting well-being in older adults, as poor quality of life has been linked to frailty. Frailty, which is characterized by a loss of resources in physical, social, and psychological domains [14], can be prevented by promoting interventions like physical activity and social engagement. [5] have found that higher levels of well-being are associated with a lower risk of developing frailty, while frailty is linked to poorer quality of life and well-being [4].

Promoting a complete approach to well-being is essential for preventing frailty and enhancing the overall quality of life for older adults. Therefore, it

is necessary to prioritize frailty prevention and well-being promotion in older adults to achieve healthy ageing and prevent or slow down the progression of frailty.

Recommender systems (RS) offer a potential approach to managing frailty and enhancing well-being in older adults. RS deliver personalized recommendations based on user preferences and contextual information [12].

Several RS have been developed to help older adults manage frailty, including Nestore [11], CARE [13] and others [3]. Nestore assesses frailty and recommends services based on individual needs and environment [11]. CARE, on the other hand, uses context-specific recommendations based on sensor data to link well-being subcategories to potential activity recommendations [13]. Other RS focus on specific components such as nutrition [3].

In the context of frailty prevention, RS can evaluate data from numerous sources, such as electronic health records, wearable sensors, and self-reported data, to assess an individual’s health condition and situation, and design a preventive plan to their personal requirements and preferences. In the next section 2.2, we will focus on some of the existing systems and compare them to our objectives.

2.2 Existing Recommender Systems

We present an overview of existing systems that share similarities with Senselife’s functional scope. Senselife is designed around six essential functions, namely:

1. Describing one’s environment
2. Expressing one’s needs, preferences, desires and satisfaction
3. Frailty Evaluation
4. Benefit from and evaluate services available in one’s environment
5. The proposed services fit coherently into one’s usual life and schedule
6. Follow-up provided by close ones and healthcare professionals

Table 1. Existing systems comparison

Application	1	2	3	4	5	6
ICOPE [10]	◐	○	●	○	○	●
NESTORE [11]	◐	●	◐	◐	●	◐
CARE [13]	●	◐	◐	○	○	◐
NutelCare [3]	○	◐	○	◐	○	○

○ = Not supported ◐ = Partially supported ● = Fully supported

While ICOPE does not function as a recommender system that suggests services, it is a valuable tool developed by the World Health Organization (WHO)

to assist healthcare professionals in assessing frailty. Although there are other systems available, none of them fully cover the functional scope of Senselife. The system that comes closest is NESTORE, but there are differences in how data is collected and used to generate recommendations. Senselife’s approach to data collection and analysis sets it apart from other systems, making it a unique and innovative solution in the field of healthcare technology.

3 Proposed Recommender System

Our proposed recommender system addresses the challenge of managing frailty in older adults by utilizing self-evaluations to provide personalized recommendations tailored to their unique needs and preferences. The system recommends services aimed at enhancing the functional abilities of older adults, matching the supply and demand of services available in the elderly environment.

To achieve this, the Senselife framework comprises three main components: data collection, recommendation generation, and service consumption and usage, as shown in Figure 1. Defining and utilizing knowledge to create personalized recommendations for each user is a primary challenge. Achieving this requires a deep understanding of users and service characteristics, determining the appropriate format for representing the knowledge, and integrating it seamlessly into the framework’s software structure.

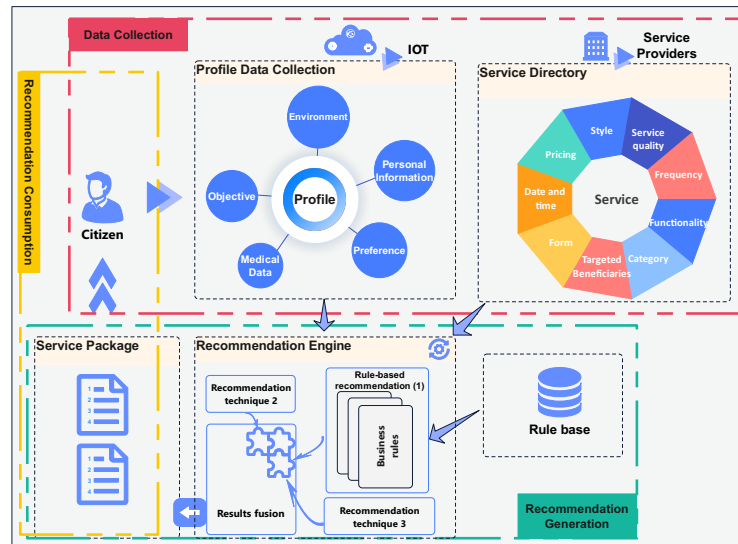


Fig. 1. Senselife framework

3.1 Profile & Service Models

Data collection is the first component of the Senselife framework, and it involves gathering information on both citizens and the services that will be recommended to them. We created two models to help with this process: one for user profiles and another for services. These models assist in identifying and categorizing the data required to generate appropriate suggestions.

User profiling is an important part of Senselife that helps to improve the relevance and quality of recommendations. It involves gathering and evaluating information about target users' preferences and behaviours to better understand their needs and interests. On the other hand, the service model is used to define the key attributes of different offered services and guide the service provider when they introduce new services on the framework.

3.2 The Rules Base

The rule base is an essential element of Senselife's recommendation engine. It contains different types of rules that have different purposes and will be used in various steps of the recommendation process. Figure 2 depicts the typology of rules in our system. It defines six rule types, as follows:

- **Constraint Rule:** This type of rule imposes some constraints on the system. If the constraints are not respected the recommendation can be stopped or modified. An example of constraint rules is the *ConsiderationRules* applied at the beginning of the need identification step of the recommendation process (see section 4.2).
- **Action Rule** (also known as a "condition-action" rule): This type of rule is commonly used in artificial intelligence and expert systems to represent knowledge in the form of logical statements. In the need identification step (section 4.2), there are 3 types of action rules. The first one is *NeedCreation* rule, which is used to create new Needs and add them to the profile if conditions are met. The second one is *PriorityRules*, which can modify needs priority based on the conditions. Finally, *ClassificationRules* are used to classify the identified needs based on Maslow's hierarchy of needs [8].
- **Privacy Rule:** These rules consider the user's privacy preferences and restrict the information that is used to generate recommendations.
- **Association Rule:** These are used to identify patterns of co-occurrence between different person's characteristics and populate the knowledge database by adding new relations. (section 4.1)
- **Recommendation specific Rule:** According to [7], these are usually called "beyond accuracy" objectives. These rules can define diversity, serendipity, novelty, and coverage of recommender system to enhance its performance.
- **Filtering Rule :** These rules are used to filter the service recommendation. These filters can be contextual or demographic depending on the citizen's preferences and the service provider obligations. These rules are used in the final step of the recommendation process (section 4.4).

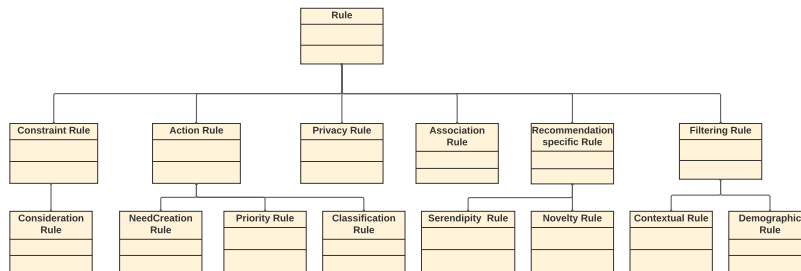


Fig. 2. Rule typology

4 Recommender Engine

For its second component, i.e. recommendation generation, Senselife framework utilizes a recommendation engine to provide personalized services for frailty prevention. Due to the complexity of the citizen and service models, the recommendation engine employs a multi-phase approach to associate the user’s needs with appropriate services. This approach involves generating a citizen profile, identifying the user’s needs, and selecting suitable service types using knowledge bases. Details regarding these phases will be discussed in the upcoming sub-sections.

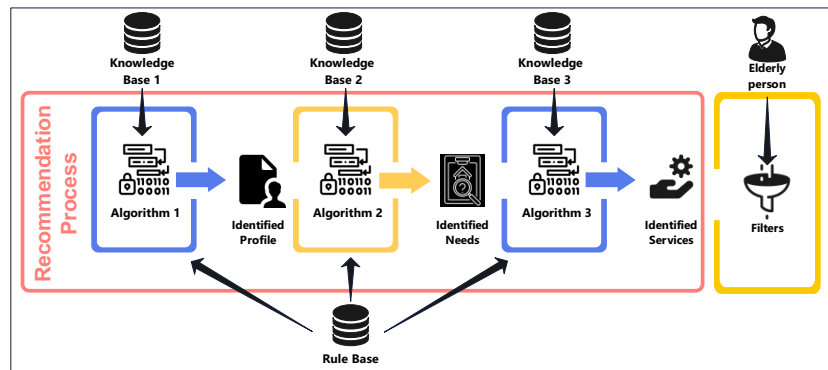


Fig. 3. Recommendation Engine overview

4.1 Personal Characteristics Identification

The first phase of the proposed recommendation system is crucial, it aims to systematically and thoroughly identify the personal characteristics of elderly individuals. However, the identification of these characteristics thoroughly can be

challenging. For example, the common method to capture information is to use a survey or a questionnaire, however for detailed information and for the elderly population that can be tedious and often leads to low engagement. To address this issue, we plan to implement an intuitive survey that leverages a knowledge database containing connections between various attributes of an individual. This survey will be dynamic and adapt to the user’s responses to previous questions. The knowledge database helps to select the most relevant questions, making the survey more efficient while gathering essential information. For instance, for a person with an ear problem, the system can adapt the questions to focus on the affected characteristics, such as the ability to perform household chores or the quality of sleeping, while it omits questions that are less relevant, such as whether the person has a driver’s license.

For a well-connected knowledge, one that identifies common characteristics with prevailing patterns amongst its members, it requires creating a knowledge base with a significant amount of data from real target elderly individuals. Association rules [6] will be used to identify hidden patterns and relationships between different characteristics of the elderly that may not be immediately apparent, leading to the identification of more connected and relevant survey questions.

Algorithm 1 Need Identification Algorithm

Require:

Input: *profile* : an instance of the class Citizen, containing all the characteristics
PC identified in the previous step

Ensure:

Output: *profile* : the same input instance with the added needs

```

1: ConsiderationRules(profile.characteristics)
2: for all need in Knowledge DB do
3:   charPerNeed ← GroupCharacteristics(need, profile.PC)
4:   if charPerNeed NOT empty then
5:     profile.need ← NeedsCreation(profile, charPerNeed)
6:   end if
7: end for
8: for all need in profile.needs do
9:   PriorityRules(profile, need)
10: end for
11: for all need in profile.needs do
12:   ClassificationRules(profile, need)
13: end for

```

4.2 Need Identification

Once the survey data is collected, it will be used to create a citizen profile. Algorithm 1 will then determine if a citizen is eligible for recommendations by

applying *ConsiderationRules*, which may include verifying the score of an activity of daily living survey. Once eligibility is confirmed, the generated characteristic-profile helps to identify citizen’s needs using both knowledge and rule bases. The initial set of needs and their priorities can be identified in the first step using the knowledge base. In the second step, *PriorityRules* are used to modify the needs priorities, if necessary. The purpose of these rules is to detect associations between needs and characteristics (see section 5 for further explanation).

In the final step of the second phase, *ClassificationRules* use Maslow’s hierarchy of needs [8] to assign general priorities to the identified needs. This ensures that we prioritize the most fundamental needs first, and then move on to addressing the less important ones. As a result, the need has two types of priority. The specific priority, which is based on the data provided by the citizen, and a general one, which displays the importance of the need in relation to other needs according to Maslow’s hierarchy.

Algorithm 2 Service Types Identification

Require:

Input: *profile* : an instance of the class Citizen, containing all the characteristics PC and the identified needs in the previous steps

Ensure:

Output: *profile* : the same input instance with added Service Types

- 1: **for all** need in *profile.needs* **do**
 - 2: *serviceTypesPerNeed* \leftarrow CheckConnectedServiceTypes(*profile*, *need*)
 - 3: *updatedSTPerNeed* \leftarrow CheckObligatoryPC(*serviceTypesPerNeed*)
 - 4: *updatedSTPerNeed2* \leftarrow CheckRelatedPriority(*updatedSTPerNeed*)
 - 5: *updatedSTPerNeed3* \leftarrow CheckRelatedNeeds(*updatedSTPerNeed2*)
 - 6: UpdatePofile(*profile* , *updatedSTPerNeed3*)
 - 7: **end for**
-

4.3 Service Types Identification

After identifying the citizen’s needs, the service type identification algorithm is executed, an example is depicted in Algorithm 2. Using the knowledge base and the identified needs, the algorithm identifies all related service types. However, there are some specifications for certain service types that need to be taken into consideration. To address this issue, dedicated functions have been implemented.

At the end of this step, a list of service types is identified and proposed to the citizens for confirmation. This list is generated based on the identified needs and the service types that are applicable to the citizen’s profile. The citizen can review the list and confirm which service types they are interested in. This process ensures that the citizen receives personalized recommendations that meet their specific needs and preferences.

4.4 Services Recommendation

The final phase of the recommendation process involves scoring the services available in the database using a matching formula 1 that considers citizen's preferences \mathbf{p} and service attributes \mathbf{s} .

$$Sim_{tot}(p, s) = \frac{1}{|I|} \sum_{k \in I} Sim_k \quad (1)$$

The formula matches citizen preferences for services with service attributes, such as cost, location, timing, and rating. These attributes make up the set I . To calculate similarity scores between a citizen's profile and a service, the similarity of each attribute must be calculated using formula 2.

$$Sim_k = \frac{1}{1 + \sqrt{\sum_{i=1}^N |r_i - r'_i|^2}} \quad (2)$$

For example, this formula calculates the similarity between a citizen's preference for the "Cost" attribute and the real value of "Cost" for a service. If a citizen wants both free and paid services, the cost preference vector in the profile would be $v_{profile} = (r_1, r_2) = (1, 1)$, and the cost preference vector for a paid service would be $v_{service} = (r'_1, r'_2) = (0, 1)$. In this case N is equal to 2 since the attribute cost has two possible values.

Personalized recommendations are added to the citizen's agenda, ensuring time and location suitability. By considering preferences and service attributes, the system provides customized recommendations that meet the individual's specific needs, as well as increasing satisfaction and quality of life.

5 Use Case

The following use case illustrates the recommendation process. Mr James, a retired 75-year-old, completed the survey, which identified 7 personal characteristics (Figure 4).

The survey identifies personal characteristics with varying levels that help the system understand the challenges faced by elderly users. For example, assigned levels of 1 indicate the lowest level of difficulty, while values of 0 indicate no issues. Some characteristics are binary, indicating whether or not they exist. For example 1 for living alone characteristic and 0 if not. These levels reflect the difficulty of performing specific activities and will be used by the *NeedCreation* Rules in the future. After identifying personal characteristics, the system uses Algorithm 1 to identify the needs. *ConsiderationRules* are applied to verify the system's ability to help the citizen. For example, one of the rules applied in this use case is the following:

Rule 1 *Profiles with a frailty score (ADL¹) greater than 4 are ineligible for consideration.*

¹ ADL: Activities of Daily Living survey.

<https://www.alz.org/careplanning/downloads/katz-adl.pdf>

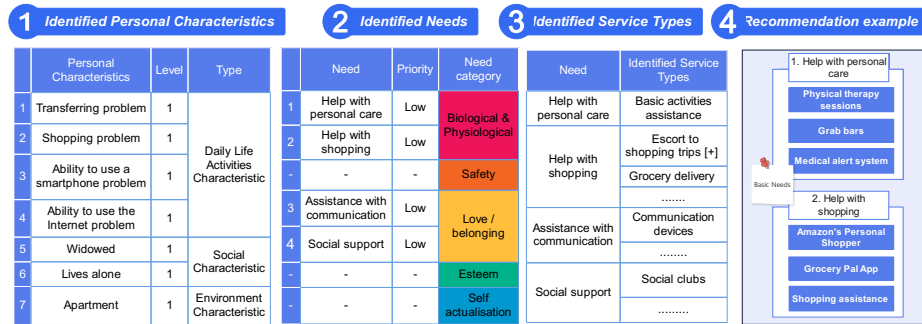


Fig. 4. Recommendation process results in each of the 4 steps

Determining a person's frailty status is a significant role played by the consideration step. The system collects user data by asking questions inspired by frailty surveys. With the help of rules, the system can interpret this data like a healthcare professional. For example, the ADL survey shows that if a person has four or more out of six problems, it indicates severe functional impairment, which is expressed by the rule. James' profile meets all system requirements as defined by the *ConsiderationRules*. Needs are created and assigned priorities using the *NeedCreation* Rules, which are based on the knowledge base. Rule 2 guides the creation of the social support need based on related characteristics. In James' case, two characteristics trigger Social support need with low priority: "widowed" and "living alone".

Rule 2 *Social support need is deemed low priority if one or two related characteristics are present.*

The creation of some other needs is straightforward. For instance, if the "Shopping problem" characteristic is present in the user's profile, the system will automatically generate the need *Help with shopping*. The priority of this need is determined directly by the characteristic level. In this case, rule 3 is triggered:

Rule 3 *Help with shopping need is deemed low priority if the "Shopping problem" characteristic has a level of 1.*

PriorityRules are applied to identified needs in the second phase, revealing relationships between different needs that require special attention. For example, if a person is unable to communicate effectively and living alone, Social support priority might increase to ensure necessary assistance. If someone cannot perform daily activities and communicate properly, Help with personal care priority should increase to ensure appropriate attention and safety.

Rule 4 *A high-priority Assistance with communication need and "living alone" characteristic are factors that warrant an increase in the priority level of a citizen's Social support need.*

In James' case, nothing will be changed since his Assistance with communication need has low priority.

Finally, the *ClassificationRules* will be applied to find out which are the basic needs and those optional based on Maslow's hierarchy of needs.

Rule 5 *Help with personal care and Help with shopping are part of the basic need level*

At the end of the need identification step, the list of needs is added to James' profile (see fig 4 part 2). The next algorithm will be responsible for identifying the service types. It will go through the needs sequentially, one by one, respecting their priority order. In James' case, it will start with the need "Help with personal care". For this need, four service types (ST) are identified in the first phase. In the next one, three ST out of four are eliminated by the *CheckRelatedPriority* function. One ST addresses high-priority needs, while two others address medium-priority needs. Only Basic Activities Assistance ST remains, addressing low-priority needs like James' Help with personal care need.

In the second iteration of algorithm 2, the Help with shopping need is addressed. The iteration involves identifying the Escort to shopping trips ST, which is linked to two needs: Help with shopping and Social support. Consequently, the relevance of the ST is heightened by *CheckRelatedNeed*. This change is denoted by a '+' symbol next to the service type name in figure 4.

The third need on the list is Assistance with communication, with four service types identified in the first phase. *CheckObligatoryPC* eliminates two of them (1) sign language interpreters and (2) speech therapy, which require a "Speech problem" characteristic that James does not have. These are some examples of the constraints of service types. They are defined in the knowledge database and utilized by various functions in algorithm 2 to eliminate unnecessary service types that do not align with the citizen's profile.

Finally, the recommender system calculates scores for available services and recommends the top 3 for each need. Recommendations respect the priority of each need and are presented to the citizen. Figure 4 shows an example of a recommendation of the two first needs for James's profile.

6 Conclusion

The paper proposes a personalized recommendation framework that prioritizes the well-being of the elderly and aims to prevent frailty. It defines a four-step recommendation process, which generates personalized recommendations aligned with specific needs. Further, two algorithms were developed for needs identification and service type identification. We assessed the effectiveness of the proposed framework through a series of scenarios and provided examples of rule applications, an example of a use case scenario is described above.

To evaluate the framework using real-world data on a scale, we plan to develop a prototype and conduct usage testing with a group of elderly individuals. The Senselife framework's final component involves monitoring the consumption

and use of recommended services, allowing for continuous improvement through user feedback. The prototype's usage data will further enhance the framework's recommendation capabilities, leading to better outcomes for elderly citizens.

References

1. Ann Bowling and Paul Dieppe. What is successful ageing and who should define it? *Bmj*, 331(7531):1548–1551, 2005.
2. Andrew Clegg, John Young, Steve Iliffe, Marcel Olde Rikkert, and Kenneth Rockwood. Frailty in elderly people. *The Lancet*, 381(9868):752–762, 2013.
3. Vanesa Espín, María V Hurtado, and Manuel Noguera. Nutrition for elder care: a nutritional semantic recommender system for the elderly. *Expert Systems*, 33(2):201–210, 2016.
4. Howard Fillit and Robert N Butler. The frailty identity crisis. *Journal of the American Geriatrics Society*, 57(2):348–352, 2009.
5. Guilherme Eustáquio Furtado, Adriana Caldo, Ana Vieira-Pedrosa, Rubens Vinícius Letieri, Eef Hogervorst, Ana Maria Teixeira, and José Pedro Ferreira. Emotional well-being and cognitive function have robust relationship with physical frailty in institutionalized older women. *Frontiers in Psychology*, 11:1568, 2020.
6. Erna Hikmawati, Nur Ulfa Maulidevi, and Kridanto Surendro. Adaptive rule: A novel framework for recommender system. *ICT Express*, 6(3):214–219, 2020.
7. Marius Kaminskas and Derek Bridge. Diversity, serendipity, novelty, and coverage: a survey and empirical analysis of beyond-accuracy objectives in recommender systems. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 7(1):1–42, 2016.
8. Abraham Harold Maslow. A theory of human motivation. *Psychological review*, 50(4):370, 1943.
9. World Health Organization. *World report on ageing and health*. World Health Organization, 2015.
10. World Health Organization et al. Integrated care for older people: guidelines on community-level interventions to manage declines in intrinsic capacity. 2017.
11. Silvia Orte, Paula Subías, Laura Fernandez Maldonado, Alfonso Mastropietro, Simone Porcelli, Giovanna Rizzo, Noemí Boqué, Sabrina Guye, Christina Röcke, Giuseppe Andreoni, et al. Dynamic decision support system for personalised coaching to support active ageing. In *AI* AAL@ AI* IA*, pages 16–36, 2018.
12. O Ribeiro, S Almeida, L Teixeira, J Santos, and A Marques. A recommender system for personalized physical activity and nutrition recommendations for older adults with frailty. *Journal of Ambient Intelligence and Humanized Computing*, 10(2):635–644, 2019.
13. Thomas Rist, Andreas Seiderer, Stephan Hammer, Marcus Mayr, and Elisabeth André. Care-extending a digital picture frame with a recommender mode to enhance well-being of elderly people. In *2015 9th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth)*, pages 112–120. IEEE, 2015.
14. Johanna Engelberta Hendrika Maria Schuurmans. Promoting well-being in frail elderly people: Theory and intervention. 2004.