# Towards a Model for Recommender Systems for Reminiscence Therapy in Alzheimer's Disease

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As the most common form of dementia, Alzheimer's Disease is one of the leading causes of death in the world. Because it is a disorder that becomes progressively worse, it is important that people suffering from Alzheimer get the best care at every stage of their procedure. A popular non-pharmaceutical treatment for Alzheimer's Disease is reminiscence therapy, which aims to improve the cognitive abilities and general quality of life of the Alzheimer's patient through their long-term memory. To enhance their reminiscence, it is important that each patient gets in touch with content they have memories from. However, picking the right content can be a difficult and long process, because every patient has a different background and different interests. To solve this, a recommender system could be used to recommend the right content for every patient in an automated approach. This research aims to create a model that can function as the basis for such a recommender system for individual reminiscence therapy in Alzheimer's patients.

Additional Key Words and Phrases: Reminiscence Therapy, Recommender Systems, Alzheimer's Disease, User Profile Ontology, Rule Sets

## 1 INTRODUCTION

As the world's population gradually becomes older, the registered cases of dementia are growing as well [3]. The most common form of dementia is Alzheimer's Disease (AD). AD is a neurodegenerative disease that slowly worsens over time [32]. According to the Alzheimer's Association (AA) [24], AD is generally diagnosed when the patient suffers from general memory impairment and a decline of at least one other cognitive function, like decreasing word comprehension ability, decreasing ability to perform complex tasks involving muscle coordination or decreasing ability to plan and organize regular activities [8].

As AD is not -yet- curable, treatment focuses on delaying the dementia for as long as possible. Existing treatments can be divided into two types: pharmacological treatment (PT) and non-pharmacological treatment (NPT)[35]. PT focuses on treating AD through medication, while NPT focuses on improving the patient's symptoms through therapy. This research will focus on NPT aimed at cognitive intervention. Cognitive intervention can be split into cognitive stimulation, cognitive training and cognitive rehabilitation [9]. Reminiscence therapy (RT) falls under the cognitive stimulation class of NPT, as it has the goal to improve the general cognitive and social skills of the patient [13].

RT aims to do this by exposing patients to senses that could help them to recollect memories from their earlier life[18]. This generally improves the general quality of life of the patients, as they get a more positive look on their life through their memories[6]. Furthermore, as AD patients retain their long-term memory for a relatively long period of time, especially compared to their short-term memory, they can profit from RT during a large part of their treatment[33].

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While RT can be held as group therapy or individual therapy, this research will focus on individual therapy. Over the last two decades, technical advances have made it possible to use multimedia devices in one-on-one therapy. Compared to group therapy, multimedia devices in individual therapy can be constructed in a more personal manner. Such a device can focus more on personal input from the patient's life, like family photographs, personal favorite music and video recordings of events they might have attended. These media could be provided by close family members or friends, or could be retrieved from more general sources that more patients can relate towards. [10]

A recommender system (RS) can be used to find the type of multimedia the patient will respond to in the best way. Such a system can recommend the approach of RT for AD patients based on their personal experiences and connections (e.g. work-related, family, friends). This research aims to find a foundation model from which a rule-based RS for AD patients in individual RT could be constructed. A rule-based RS is the most effective RS when using small amounts of input information and is therefore useful when conducting research in a relatively unexplored area like individual RT. [36]

A rule-based RS has two main building blocks: a user profile ontology and rule sets that can translate the information inside the ontology to useful information that a computer can understand. A user profile ontology gathers all the existing information about the patient, while the rule sets make it possible to combine this personal information with guidelines from professional institutions and studies.

In order for the model to be able to understand all the subtle differences in the patient's needs, a user profile ontology can be created. The user profile ontology can model several important factors of the patient, for example their cultural or socio-economic background. Furthermore, the model also considers the patient's medical status. Patients in different phases of AD gain more from RT if the duration and amount of therapy sessions are tailored to their level of AD.

While the user ontology profile functions as a knowledgebase of the AD patient, the recommendations the RS gives should also be based on the general guidelines of experts or institutions specialized in treating Alzheimer patients. Together with the personal information, a good recommendation can then be stated on the frequency, main topics and media for a RT session.

This research will focus on creating a model that can serve as the basis of a rule-based RS for individual RT by creating a general user profile ontology and collecting data on the rule sets.

## 2 RELATED WORK

This section contains background information on the main topics of this research. To construct a model for a recommender system, we looked at literature containing the relevant terms and looked at comparable studies.

### 2.1 Reminiscence therapy

As explained in the introduction, reminiscence therapy is a NPT that fixates on helping AD patients through activating their long-term memory. It was first proposed by Butler in 1963[7], who introduced the idea of giving more essence to the lives of AD patients through a process called "Life Review". Over the years, it has been doubted whether reminiscence therapy has a significant positive impact on the life and cognitive abilities of AD patients [11][19], with the main critique that there was not enough research conducted in this area. However, as Woods et. al[33] note in their systematic review on RT in 2018, the quality and quantity of research on RT has improved significantly in recent years. In this review they also talk about the different positive effects of group RT and individual RT.

As group RT is held with multiple AD patients together, it has a positive effect on the communication and expression skills of the patient[33]. Furthermore, it could create a form of emotional awareness between them, which is a great addition if they also happen to live in the same nursing facility[22].

Individual RT mainly improves the quality of life (QoL) of the patient in the areas of cognitive ability and improving the general mood[33]. Individual RT oftentimes includes the usage of a multimedia device, which displays or describes an event that happened in the life of the patient. These devices will be described in the next section.

### 2.2 Recommender systems and multimedia devices in Alzheimer studies

Literature usage of a multimedia device was a little more difficult to find, but plenty enough nonetheless [18][21][30]. The multimedia device that was mentioned in a lot of research was the CIRCA (Computer Interactive Reminiscence and Conversation Aid) project set up by Gowans et al. [17] This was the first project to commit to designing a multimedia device that could use personal media from the AD patient, like family pictures and other personal memorabilia. The CIRCA project is also used frequently as a basis in studies that focus on RSs in RT.

In general, there has been plenty research done in the field of RSs in healthcare, some in combination with AD as well [10][23]. A lot of literature is written on either group RT [5] or a specific part of individual RT[2]. The paper that has the most resemblance to this research project is the Memorec project by Bejan et al [4]. They also designed a RS for individual RT, which they based on the CIRCA project. The difference with their research and this specific paper is that they focused mainly on the personalization part of the media of the patient, while this research also tries to take the frequency and duration of therapy sessions into account.

One other example of the usage of a RS in RT is the REMPAD system designed by Yang et al.[34]. This system aims to facilitate group RT by making video recommendations based on participant profiles of the AD patients that are attending the therapy session. In their research they discovered that especially the video recommendation was rated highly by the facilitators of therapy sessions. Because the videos were automatically selected, the system drastically decreased the preparation time for the facilitators. This meant they could focus more on the interactions with the group.

### 2.3 Other recommender systems

As explained in the introduction, we chose a rule-based RS for this research. However, there are other types of RS that could be used to recommend RT for AD patients. Most notably, machine learning and collaborative filtering RSs [1].

#### 2.3.1 *Machine learning recommender systems.*

Machine learning RSs main source of giving recommendations is by analyzing the patient's life and habits beforehand. When it has a good view of this, it can give a recommendation on the best form of RT. The I-CARE project by Schultz et. al[27] is an example of this. They constructed a self-learning RS that takes a basic user profile based on biographical information, and expands this user profile as the user gives feedback throughout therapy. The problem with this type of RS is that it needs relatively much background information on the patient to give a good recommendation. This information is collected throughout the sessions, but the long cold start period could result in users opting out before the recommendations get aimed more towards their liking.

#### 2.3.2 *Collaborative filtering recommender systems.*

Collaborative filtering RSs focus on making recommendations by comparing the patients' interests to interests by similar patients. This way of recommending becomes increasingly better as the group of patients exposed to the RS grows over time. However, it can take a while before this threshold is crossed[28]. Furthermore, given the limitations AD patients have, their feedback may be incomplete or unreliable[23]. This could make it difficult for similar users to get the right recommendation for their RT, which is why this is not the type of recommender system that was chosen for this study.

### 2.4 Rule-based Recommender systems

Rule-based RSs base their recommendations on rules and guidelines of domain knowledge[1]. Combined with a user profile ontology, our recommendation system can be classified as an "ontology-enhanced rule based RS". The user profile ontology entails the personal information of the patient, through which the RS can make a personalized recommendation for different patient.

#### 2.4.1 *User profile ontologies.*

The usage of a user profile ontology combined with a rule-based RS has been used before in withing the topic of AD. Skillen et al.[28] used this approach to assist people with dementia in their daily lives. They combined an ontology model that focuses more on static user characteristics with a model that focuses on the dynamic aspects of the user's life to get a more complete user profile ontology of the life of the user. This resulted in an application that can help people with mild dementia in their daily lives, by for example reminding them that they have to do their weekly groceries and navigating them to the supermarket.

#### 2.4.2 *Rule sets.*

In order to construct the rule sets in the rule-based RS, a knowledgebase on AD and RT needs to be built. To acquire this knowledge, several studies and institutional guidelines were used. A lot of research has been done AD in general, which meant there was plenty of research to be found on RT and the effects thereof [6] [16] [20] [22][29]. Furthermore, institutions like the Alzheimer's Association (AA), Alzheimer's Disease International (ADI) and the

National Institute of Aging (NIA) provide useful information on the general treatment of AD patients. The information from this institutes and studies will be used as a guideline to give a recommendation on what media and topics are best to be explored during the sessions. Furthermore, they will examine how frequent the patient should have RT sessions and will also recommend a duration of each session.

## 3 PROBLEM STATEMENT

Although research on RS for personalized RT for AD patients has been carried out before, little studies include specific ontology enhanced rule based RSs for individual RT. Studies on RS for AD patients mainly focus on group therapy or do not use the rule-based RS we have focused our model on. As mentioned before, we think a rule-based RS has positive features that can make it a viable option as a RS for individual RT for AD patients. Compared to machine learning and collaborative filtering RSs, it struggles less with a long cold start period and requires less participants respectively.
This research aims to create a model that could serve as a basis for a rule-based RS. We will create a basis for a user profile ontology and the knowledgebase that will function as the building blocks for the rule sets. This will be done by answering the main research question and three sub-questions.

### 3.1 Research Question

The problem statement can be translated into the following research question:
Which rule sets should be incorporated into a model for personalized recommender systems for individual reminiscence therapy for Alzheimer patients?

This research question can be answered with three sub-questions:

(1) What information about the patient should be included as properties in their user profile ontology?
(2) How do the properties in the user profile ontology relate to each other?
(3) How can the information in the user profile ontology and reminiscence therapy guidelines be combined to create rule sets?

## 4 RESEARCH METHODOLOGY

The research was conducted through multiple steps, which can be compared to the Design Cycle described by Wieringa [31], shown in figure 1. Firstly, we moved through the phase of investigating the problem by going further through the existing literature on RT and RSs. After this, the user profile ontology and the rule sets were designed, which combined into the rule-based personalized recommendation. The next step was to validate this recommendation along a persona of an AD patient. Lastly, the recommendation of this persona was evaluated and the problem investigated again, as the design cycle suggests. The design cycle is aimed at an iterative process, where after the evaluation the cycle will start again to improve the artifact. Due to time limitations the cycle was only completed once, after which recommendations were given as the conclusion on the main research question.

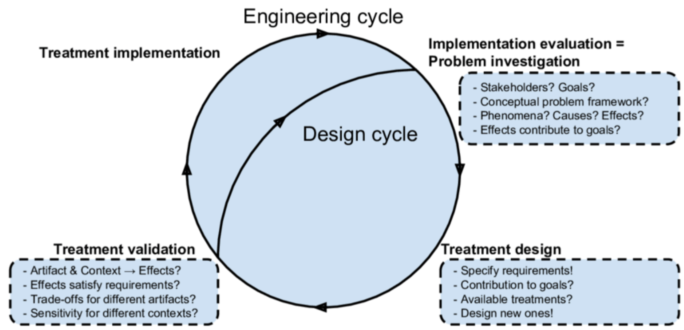


Fig. 1. The Design Cycle as part of the Engineering Cycle[25]

### 4.1 Problem Investigation

First of all, further literature research needed to be done. The strategy to find the right sources was to look into relevant literature on the central topics and use snowball sampling[26] to research this topics thoroughly. This would firstly be done on RT and RSs. We focused on RSs that are in use at this point in the sector of AD and dementia in general, to fully understand the cohesion RSs and RT have. Once this relation was established clearly, literature research into user profile ontology and rule sets in RSs had to be conducted. This time the focus of this literature research lied on how the properties for user profile ontology were chosen, which sources were the best for the guidelines and how the information from the guidelines could be used in combination with the user profile ontology of the AD patient.

### 4.2 Design

When the first steps were completed, the focus was shifted towards the first two sub-questions. To make sure that the facilitators have the relevant and personalized information about their AD patients, the system must consider the patient's relationships, the possible availability of relevant personal media and their cultural and personal characteristics, as well as their capabilities for RT. To make sure this information was visualized in the right way, we designed a user profile ontology. This ontology was made using six work phases which were also used in the research by Alian et al. [1]: (1) scope definition, (2) knowledge acquisition, (3) specification, (4) conceptualization, (5) implementation and (6) evaluation. With more time, this would turn into an iterative design cycle, where we would start with step 1 again after the evaluation of step 6. However, because of limited time we only ran through the six phases once.
For the construction of the user profile ontology, the Flowchart design program Diagrams.net was used. This program provided the right capabilities to give a good visualisation of the properties a patient can have and the relationships between these properties. This was therefore also used for answering sub-research questions one and two.

### 4.3 Validation

Following the construction of the user profile ontology, we focused on answering the third sub-question by researching the possibilities of rule-enabled personalized recommendation that could result from the user profile ontology. To answer this sub-question we combined the literature found on the frequency and duration for RT with the personal media information from the user profile ontology of the AD patient. From the literature on RT, certain rule sets were constructed, which combined with the personal information of the patient, resulted in rule-enabled personalized information. This step in the research resulted in a theoretical model, which was validated with the persona of an imaginary patient.

### 4.4 Evaluation

To validate the model, all the information of the persona was put into a user ontology profile. This, combined with the rule sets resulted in a theoretical rule-enabled personalized recommendation. We then evaluated whether this recommendation would be reliable and realistic and we designed a new problem investigation for the next design cycle.
This is the last step in the design cycle, meaning the final research question can be answered and a conclusion can be written. The process and results of the research will be described in the next section.

## 5 RESULTS

### 5.1 Approach/intro

As explained in the methodology section before, we constructed a model for a user profile ontology and explored various studies and organizational guidelines on RT to create an adequate knowledgebase. Combining this, we will create rule sets.

### 5.2 Profile classes

The user profile ontology can map the differences between AD patients in a coherent way. As all AD patients are different, they will all have different attributes in their personal user profile ontology. These attributes can be divided into user-related classes. Skillen et. al[28] introduced several of these classes in their research for creating a personal application that AD patients could use while they are in the mild dementia phase and might still live at home. They introduced dynamic and static profile classes. Dynamic profile classes are attributes of the AD patient that can change or fluctuate over time. This could for example be their cognitive ability. Static profile classes mainly contain personal information that will not change, like the birthyear of the AD patient.
For our research, we constructed the dynamic profile classes *CapabilityProfile*, *HealthProfile*, *PreferenceProfile*, *EducationProfile* and *InterestProfile*. The information in these classes can change during the time the patient has their RT sessions. The static profile classes designed contained the profile classes *PersonalInformation*, *WorkInformation* and *ActivityInformation*. The attributes in these classes are static and will not change during therapy. One could say that the patient might still be able to go on activities or do small jobs, but as RT is focused on the long term memory of the patient, the information in these classes will be based on activities or working experiences that occurred a longer time ago in the life of the patient.

### 5.3 User Profile Ontology

The model for the user profile ontology was constructed in the application *Diagrams.net*[12]. A model containing the profile classes can be found in appendix A. The model shows the attributes and hierarchy of the profile classes and also notes the various relationships the classes and the profiles have. For example, the *Healthprofile* class has an attribute *HasHealthCondition*. This attribute contains the information of various conditions the patient may have or may contract during the time they are in therapy. Next to the AD condition, the patient could contract a heavy flu which causes their energy and concentration to decrease. This health condition has a connection to the *CapabilityProfile* class, specifically to the *HasCapabilityLevel* attribute. If the patient for example contracts several health problems, their capabilities can decrease and they might not be able to attend the amount of sessions their previous *HasCapabilityLevel* attribute would suggest.
Furthermore, the dynamic and static profile classes also have connections between each other. If for example the *HasHobbies* attribute of the *ActivityInformation* class contains the information that the patient has played a musical instrument before, this can be added to the *HasMusicTaste* attribute in the *PreferenceProfile* class. It is likely that the recommendation on the type of media used in the RT sessions of this patient would then include media containing music related content, and, if possible, containing the specific instrument as well.

### 5.4 Rule sets

Whereas the information from the user profile ontology counts more heavily towards the media recommendation of the RS, a rule sets model cannot be made without a sufficient knowledgebase. Like said before, the guidelines from various studies and organisation can determine how frequent RT sessions need to be planned in order for them to positively impact the patient. Also, they could recommend a certain sequence for a specific session or across different sessions. A knowledgebase like this could help the facilitators of the RT with shortening their preparation time. All the resources required are already available, but combining all the sources and then personalizing the media for every patient can put a lot of working load on the facilitators given the rising amount of patients they have to treat.
To turn the knowledgebase and the user profile ontology into rule sets that can be used in an application, they will need to be written in a specific way that they can be used in a certain code. For this model, we suggest a premise that could be described as an IF –> THEN statement. This would be a simple way to connect the antecedent (cause) to its consequent (effect).

### 5.5 Recommender System

To transfer these rules into a full recommendation, several consecutive IF –> THEN statements should be ran through. They should take all the available information into account and eventually combine into one recommendation. Such a reasoning engine can be programmed in two ways[14];

(1) By first gathering all the available information, and then creating "new" information from this. This new information is then put in the place of the antecedent in a new rule and it

checks whether this can trigger a new clause of a consequent. This is called forward chaining reasoning.

(2) Backward chaining reasoning. This works in the opposite direction compared to forward chaining. It takes a list of hypotheses and chains back through the IF–>THEN clauses to see if it matches the information that was available at the start.

Our model is based on forward chaining reasoning. There are so many available variants of RT, that it can be difficult to create a hypothesis that is fully correct. It would take a long time for a RS to go past all possible options and then track backwards until it has found a match. On the other hand, a forward chaining reasoning RS would work well, as it has relatively much background knowledge on the AD patient and a lot of knowledge on RT in general. Therefore, we think it has enough knowledge to keep going through the IF–>THEN clauses until it comes to a conclusive recommendation on the composition of the RT for the patient.

### 5.6 Persona

To give an example on how the model for the RS would work once it is fully implemented, let us use an example with a persona.

*Assume Peter is a 74-year-old AD patient from Munich, Germany. He was born in 1950, and with his mild AD symptoms gradually moving towards moderate AD symptoms he was recently transferred to a nursing home. Here he will also get his RT sessions. His family have filled out a form with information about him, but there is not a lot of personal media available from his youth and the years after. His family have filled in that he is a relatively introvert person, with few, but close friends he met while playing in a band when he was at University. He was never particularly excited about his job, but did have a few hobbies besides his working life. Next to playing an instrument, he liked to play and watch football and he is a lifelong Bayern München fan. Also, he spent a lot of his time working in his garden. At 74, Peter is still in a good physical shape, although his eyesight has deteriorated over recent years.*

Combining this information, we can focus on working out the right recommendation for Peters RT. First of all, we can deduce from his health profile that visual media would not be the best media to use during his therapy. Considering his interest in gardening and music, it is also more likely that he will have more of a positive sentiment when exposed to aroma or audio. When looking at his user ontology profile, our RS has several routes it can take. When looking at the aroma content for RT, it could use the smells of the flowers in his garden, maybe even combined with the sounds of birds in his garden. Another route it could take is focus on his music interest and let him listen to the instrument he played in his band. However, both these routes miss critical information on how exactly the flowers in his garden smell or which exact instrument he played in the band. Therefore it could dive deeper in his third hobby, football. As Peter was born in West-Germany in 1950 and was a lifelong, the RS could deduce with forward chaining reasoning that he will have likely heard the commentary on the World Cup win of West-Germany in 1974. As this memory could also be enhanced by introducing the smell of grass, this topic could have the best results according to the RS.

### 5.7 New problem investigation and evaluation

Now we have shown how our model should work, the design cycle returns to the evaluation and problem investigation phase again. As the results from the RS of the persona of Peter were only simulated, it is clear that the problem investigation should include some level of implementation of a functioning RS.

## 6 CONCLUSION

In this section, the conclusion of the research will be given with answering the research question and sub-research questions. The first two sub-research questions can be answered using the model of the user profile ontology, while the third sub-research question is answered through the results.

Finally, the main research question can be answered through combining the three sub-research questions and coming to a central conclusion.

### 6.1 Sub-research questions

*6.1.1 Sub-research question 1.* As every patient has got vastly different properties, the information that should be included in their user profile ontology is varied as well. The relevant attributes of an AD patient to recommend their personalized way of RT can be divided into five dynamic profile classes (*CapabilityProfile*, *HealthProfile*, *PreferenceProfile*, *EducationProfile* and *InterestProfile*) and three static profile classes (*PersonalInformation*, *WorkInformation* and *ActivityInformation*). Each of these profile classes contribute to a clear and concise way of mapping the ontology profile of the AD patient through branching out in more detailed attributes of the patient.

*6.1.2 Sub-research question 2.* The profile classes and their attributes have several different relationships with each other. The dynamic profile classes can impact each other through changing conditions of the AD patient and their surroundings. The *HealthProfile* and *CapabilityProfile* are very intertwined for example. If the health of an AD patient worsens, through sickness for example, their concentration and energy level might go down, which could have an impact on their capabilities of following their RT sessions. Of course, this could also go the other way around. In some cases, RT improves the cognitive abilities of the patient, which can help in battling depression that many AD patients suffer from. In this way, the *CapabilityProfile* positively impacts the *HealthProfile*.

*6.1.3 Sub-research question 3.* Next to the personal information of the AD patients, general guidelines on how to apply RT are also necessary to give a good recommendation on the therapy the patients will react to in a positive way. These guidelines were collected from various official sources in a knowledgebase. However, in order to create rule sets and a recommendation, we need a way to combine all this information into a singular recommendation. This could be achieved through forward chaining reasoning. This will be the engine behind the RS and makes sure that all the IF–>THEN statements that are available from the ontology profile and the knowledgebase are considered and in the end will end up with a conclusive recommendation.

### 6.2 Main Research Question

The final result of this research combines all three sub-research questions into a theoretical model that can serve as the base for an ontology enhanced, personalized rule based RS. The user ontology profile, knowledgebase and forward chaining reasoning engine should, when fully implemented, work together as the main components of the RS. The next step will now be to implement them and automate the RS.

## 7 DISCUSSION

In this section the research and the results will be discussed and possible improvements will be addressed. Furthermore, the future work section provides potential follow-up research with a starting goal.

### 7.1 Limitations

The main limitation of this research was the time constraint. If more time would have been available, the knowledgebase of the model could for example have been expanded upon more. Also, due to a planning that would not always go to plan, an interview with an expert could not be planned before the final deadline. This would have made the evaluation section more regarding and would have contributed well towards the final result of the research.

### 7.2 Future work

As said before, this research could be suited to work with as a base for a rule-based RS. However, while implementing the RS would be a logical step in the future, some improvements could be made beforehand to strengthen this model as well.

As said in the limitations, the knowledgebase could still be expanded upon and the evaluation could be improved through the evaluation of an expert on RT. While the knowledge collected so far should give an adequate view of the possibilities of RT, there is definitely more information that could be included here. This should be one of the starting points for possible future research. Furthermore, an evaluation from an expert on RT could help with valuing the model. This expert could give feedback to improve the model first, before another researcher could start with their RS.

If these steps have been taken, the model could be turned into a working RS. For this, an OWL-rule language should be used. A lot of studies use the program Protegé for this, which seems to be a viable option. Furthermore, the knowledgebase should be stored in a place where the reasoning engine can reach its necessary information. The same counts for the user profile ontology, as the RS cannot fully work without the connection between these three components.

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# A USER PROFILE ONTOLOGY

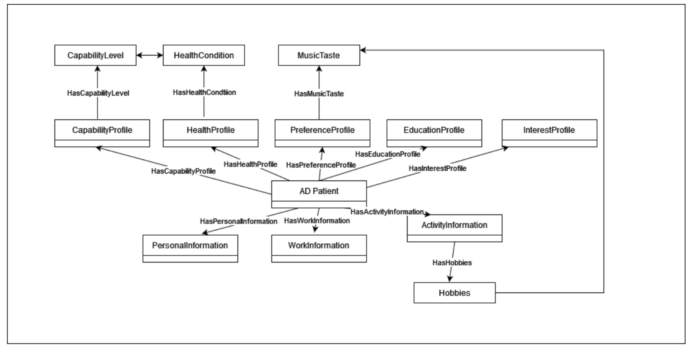


Fig. 2. Basic user profile ontology containing the profile classes and some attributes