IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 3, March 2024

DOI: 10.17148/IJARCCE.2024.13389

Revolutionizing Dementia Care: A Brief Survey of Personalized Therapy Recommender Systems

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Abstract: Dementia, with its intricate cognitive and behavioral aspects, presents significant challenges for patients and caregivers. Rehabilitation is a key component of dementia care, holding potential for improved patient well-being. Recommender systems, driven by advanced algorithms and patient data, could transform the patient experience by offering tailored recommendations. Inspired by their success in e-commerce, where demographic filtering, collaborative filtering, and hybrid systems excel, this survey explores the landscape of recommender systems in dementia therapy. It sheds light on how machine learning technology can provide personalized care, enhance patient outcomes, and lighten the load on caregivers. The findings open doors to patient-centered healthcare strategies for addressing the multifaceted challenges of dementia.

Keywords: Dementia, Collaborative Filtering, Content-based Filtering, Demographic Filtering, Hybrid Recommender Systems.

I. INTRODUCTION

In the early 1800s, Esquirol provided a concise description of dementia as a `cerebral condition marked by a decline in sensory perception, comprehension, and volition.' [1] [2]. By articulating these characteristics, Esquirol not only highlighted the cognitive aspects of the disorder, including memory and cognitive deficits in daily activities, but also brought attention to its broader manifestations, encompassing indifference, deteriorating social behavior, sporadic aggression, as well as the emergence of delusional beliefs and hallucinations [3]. Dementia refers to a decline in cognitive function significant enough to disrupt daily life. It's better understood as a syndrome rather than a single disease, with numerous potential causes, including neurological, neuropsychiatric, and medical conditions [4].

Dementia symptoms encompass memory and cognitive issues, language difficulties, motor control problems, reduced independence, social cognition challenges, as well as neuropsychiatric and behavioral changes [5]. These symptoms often lead to falls, delirium, weight loss, incontinence, sleep disturbances, oral health problems, and frailty [6]. Consequently, individuals with dementia may struggle with daily tasks and community engagement [7]. These findings illustrate the extensive reach of the brain alterations caused by dementia. The profound effects of dementia on individuals, families, and communities persist. Rehabilitation, akin to its role in other chronic conditions, proves beneficial. Non-pharmacological approaches can delay functional decline [8], enhance the quality of life for those with dementia [9], and addressing medical symptoms and comorbidities can improve cognitive function. A well-organized, interdisciplinary rehabilitation plan can target individual symptoms and establish meaningful objectives that evolve as the person's needs evolve over time [5].

In the realm of medical rehabilitation, a noticeable scarcity of recommendation systems. Upon the diagnosis of dementia, a comprehensive and personalized rehabilitation plan can be meticulously crafted to cater to the individual needs of the patient. This plan is not only a means of addressing the symptoms and challenges associated with dementia but also a way to provide holistic care and support for the patient throughout their journey [10]. In this context, recommender systems hold the potential to revolutionize the user experience within the realm of rehabilitation therapies. They possess the capability to overcome the limitations associated with traditional data-mining and machine-learning techniques, making them an enticing alternative for therapy decision support. By leveraging advanced algorithms and patient data, recommender systems can provide tailored and timely recommendations, significantly enhancing the efficacy and efficiency of the rehabilitation process. However, it's worth noting that, despite their considerable potential, the application of recommender systems in the medical field remains relatively constrained [10].

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This literature survey focuses on studying recommendation systems and their potential in planning rehabilitation for dementia patients. It's important because it helps us understand how machine learning technology can provide personalized and effective care for individuals with cognitive decline. By looking at how recommender systems can tailor rehabilitation plans and provide specific support, it shows promise in improving patient outcomes and reducing the workload on caregivers. This information can pave the way for more efficient and patient-centered healthcare strategies to address the challenges of dementia.

II. LITERATURE REVIEW

The landscape of dementia care and rehabilitation has undergone a remarkable transformation in recent years, driven by the confluence of healthcare advancements and technological innovations. Dementia, characterized by progressive cognitive decline and functional impairment, poses a significant challenge to individuals, their families, and healthcare systems globally. As the global population ages, the prevalence of dementia is on the rise, emphasizing the urgent need for innovative and personalized therapeutic approaches.

A. Types of Dementia

Dementia is a complex syndrome encompassing a range of neurodegenerative disorders, each with its distinct characteristics and progression patterns. Understanding the different types of dementia is fundamental in tailoring rehabilitation strategies. As outlined by a research study [11], dementia can be categorized into the following types:

1) Alzheimer's Disease (AD): Alzheimer's disease stands as the most common form of dementia, accounting for a significant percentage of dementia cases. It is a neurodegenerative disease which usually affects people at the age of 65 and above. Typically, it starts with mild memory impairment and gradually advances to more severe cognitive deficits, encompassing challenges in language, spatial awareness, and problem-solving.

2) Vascular Dementia: Vascular dementia results from cerebrovascular disease and it usually starts a bit earlier than AD. Frequently triggered by minor strokes that disrupt blood flow to the brain, its most frequent symptom is impaired cognitive function, especially concerning memory. Other symptoms include recalling new events, recognizing familiar objects, thinking difficulties, impaired communication, organizational difficulties, learning new things, or motor coordination.

3) Dementia with Lewy Bodies (DLB): DLB is generally caused by the accumulation of abnormal microscopic protein deposits that damage the brain. Common symptoms include visual hallucinations, fluctuations in cognitive abilities, and motor symptoms similar to those seen in Parkinson's disease. Individuals with DLB may experience rapid changes in alertness and attention.

4) Parkinson's Disease Dementia (PDD): This form of dementia results from the loss of neurons that produce dopamine and the accumulation of specific proteins in Lewy bodies within midbrain neurons. Typical symptoms of Parkinson's disease dementia include tremors, particularly in the hands, slowed movements, limb stiffness, and balance difficulties. In addition to these motor symptoms, individuals may also contend with cognitive challenges.

5) Mixed dementia: As the name suggests, mixed dementia is characterized by abnormal changes in the brain typical of more than one type of dementia. Most frequently, patients with mixed dementia exhibit symptoms of AD, vascular dementia, and DLB. Unfortunately, diagnosing mixed dementia can be quite challenging due to its resemblance to other forms of dementia.

B. Approach to Dementia Rehabilitation

Dementia rehabilitation aims to improve the quality of life and functional abilities of individuals living with dementia. Various approaches and strategies are used in dementia rehabilitation to address the cognitive, emotional, and physical challenges associated with the condition. These approaches can be tailored to the specific needs of the individual and may include:

1) Cognitive therapy: Cognitive therapy focuses on improving cognitive functions such as memory, attention, and problem-solving. It includes structured activities that challenge and stimulate the brain. While cognitive therapy may not yield significant improvements in individuals with moderate to severe cognitive impairments caused by dementia, it can still serve as a valuable tool in maintaining their current health and cognitive status [12].

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Impact Factor 8.102 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 13, Issue 3, March 2024
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Conversely, for individuals with mild cognitive impairment at heightened risk of dementia, cognitive therapy has shown promise in enhancing physical well-being, cardiac health, and cognitive abilities [13]. Furthermore, enhancing patient interaction through the gamification of cognitive therapy holds promise. While cognitive impairment may present initial challenges to participating in cognitive games, the evidence suggests that these activities can have a profound and positive influence on the cognitive well-being of individuals living with dementia [14].

2) Speech therapy: Speech therapy focuses on improving communication skills, including speech and language. It can address difficulties in understanding, expression, and articulation. Speech therapy can help them improve their ability to communicate, understand others, and express their needs and emotions, and thus, the overall quality of life [15].

3) Music therapy: Music therapy involves using music as a therapeutic tool to address emotional, cognitive, and social needs. [16] shows that music can evoke emotions and memories and promote relaxation. Listening to familiar music can trigger memories and improve mood. Additionally, playing musical instruments, singing, or participating in group music sessions can enhance cognitive and emotional well-being.

4) Physical exercises: Physical exercises encompass a range of activities designed to improve physical health and well-being. These activities can include yoga, aerobics, strength training, balance exercises, and flexibility routines. Based on a study in 2011 [17], it is evident that engaging in aerobic exercise is linked to a decreased risk of cognitive impairment and dementia. Moreover, exercise has demonstrated immediate cognitive advantages for individuals with mild cognitive impairment (MCI) or dementia. Exercise can also stimulate the release of endorphins, which may improve mood and reduce agitation.

5) Meditation: Meditation involves mindfulness practices that promote relaxation, reduce stress, and increase self-awareness. It can help individuals focus their attention and manage emotional responses. Meditation can be beneficial in dementia rehabilitation by promoting relaxation and reducing anxiety and stress. Research [18] has compellingly demonstrated that the practice of mindfulness and meditation techniques can have a beneficial impact on the preservation of cognitive abilities in individuals with dementia.

C. Role of Personalized Recommendations in Rehabilitation Therapies

Contemporary cognitive training apps fall short in providing customized games and activities tailored to the evolving needs of individuals with dementia across different stages of the condition. These applications often lack the essential adaptability and personalization required to effectively address the distinct cognitive challenges faced by dementia patients as their condition advances. Furthermore, financial constraints stemming from the expense of therapist accompaniment, spatial limitations in healthcare facilities, and the disruption to daily routines necessitated by the presence of a patient's caregivers all pose significant hurdles to cognitive rehabilitation efforts [19]. And the consequences that extend beyond economic and financial aspects, as it also places a substantial weight on the responsibility of caring for individuals with dementia. Caregivers of dementia patients are frequently reported to encounter various mental health issues, including anxiety and depression [20]. Addressing these challenges requires further research and technological innovation to devise effective solutions. In this study, we delve into various recommendation systems designed for diverse therapeutic approaches.

The substantial amount of data routinely collected in healthcare facilities and even outside clinical settings presents fresh opportunities to enhance medical practices [21]. Developing such an application is a global necessity in the evolving world of technology, with features like Reinforcement Learning to predict patient progress based on user behavior. A study [22], demonstrates their mobile application, which offers a wide range of cognitive exercises, covering attention, concentration, executive functions, language, and memory. These games and activities are powered by Machine Learning technologies such as Reinforcement Learning (RL), Natural Language Processing (NLP), and Hidden Markov Model (HMM). RL predicts the next level based on user learning, while NLP and HMM enable some games to function through speech-to-text communication. The application's primary goal is to monitor a patient's progress while they're at home, allowing them to work on their cognitive abilities independently. This makes it a valuable tool for dementia patients, given the absence of a definitive cure for the condition.

Another study [21], explores the application of recommender system algorithms in therapy decision support within the medical domain. Two approaches are compared, with a Collaborative Filtering (CF) outperforming the hybrid Demographic filtering (DF), which integrates patient data but is affected by less relevant information. The study emphasizes the importance of incorporating more patient information into recommendations when medical history is limited.

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III. METHODOLOGIES AND APPROACHES

A systematic review was conducted to explore therapies recommended for dementia patients. Databases such as Google Scholar, Mendeley, and PubMed were thoroughly explored. This was done using a set of specific search terms, including `dementia therapies', `recommender systems', `collaborative filtering' and `content-based filtering'. The selection criteria for articles encompassed the following prerequisites: (1) English language, (2) relevance to dementia and therapies, (3) clear elucidation of recommender system functionality, and (4) comprehensive reporting of recommender system outcomes. Additionally, relevant books meeting the similar criteria were referenced for better understanding of the surveyed topic.

We will further discuss some renowned recommendation systems employed across diverse domains to deliver personalized recommendations aligned with the unique requirements of individual users. We will investigate the potential of integrating these systems into dementia rehabilitation, leveraging their capabilities to recommend tailored therapies to dementia patients based on their health conditions and specific needs.

IV. COLLABORATIVE FILTERING

Collaborative Filtering has become one of the most impactful recommendation methods. This approach doesn't rely on explicit knowledge about the content or attributes of items but, instead, focuses on patterns of user-item interactions. At its core, collaborative filtering is based on the idea that users who have shown similar preferences or behavior in the past are likely to share common interests in the future. Collaborative filtering suggests items based on the preferences of users with similar tastes or identifies items akin to those previously rated by the user in question. This is achieved through statistical methods that measure the likeness between user or item profiles. Collaborative filtering methods can be categorized into two main groups: Memory-Based and Model-Based techniques [23].

A. Memory-based method

Memory-based methods are also known as neighborhood-based collaborative filtering algorithms. They are relatively simple to implement and understand, and can effectively capture user preferences and deliver accurate recommendations. Here, the user ratings for an item are predicted on the basis of their neighborhoods. These neighborhoods can be defined in one of the two ways.

1) User-based Collaborative Filtering: In user-based collaborative filtering, recommendations are generated by identifying users who are similar to the target user and suggesting items that these like-minded users have enjoyed. First, the neighborhood of the target user is computed using some similarity metric such as Pearson correlation coefficient, cosine similarity, or others. Then, the weighted average of the mean-centered rating of an item in the top-*k* peer group of target user *u* is used to provide a mean-centered prediction. The raw ratings are converted into mean-centered by subtracting the mean of the ratings of the items rated by the target user. Some users may consistently give higher ratings, while others may rate more critically. Mean-centering makes it easier to compare users and items on a common scale. Lastly, the mean rating of the target user is then added back to this prediction to provide a raw rating prediction $\hat{r}_{uj}$ of target user *u* for item *j* [24].

For an $m \times n$ ratings matrix $R = |r_{uj}|$ with *m* users and *n* items, let I_u denote the set of item indices for which ratings have been specified by user *u*, $P_u(j)$ denote the set of *k* closest users to the target user *u* and μ_u denote the mean rating for each user *u* using their specified ratings. The similarity between the rating vectors of two users *u* and *v* is given by sim(*u*, *v*). Then the overall neighborhood-based prediction function is as follows.

$$\hat{r}_{uj} = \mu_u + \frac{\sum_{v \in P_u(j)} sim(u,v).(r_{vj} - \mu_v)}{\sum_{v \in P_u(j)} |sim(u,v)|}$$

2) Item-based Collaborative Filtering: In item-based collaborative filtering, the recommendation process focuses on the similarities between items. It identifies items that are similar to the ones the user has previously interacted with and suggests items with a high degree of similarity. The first step is to determine the top-*k* most similar items to item *t* based on some similarity metric. Similar to user-based collaborative filtering, the raw ratings are converted into mean-centered ratings in order to normalize the rating scales while calculating the similarities between the items. Let the top-*k* matching items to item *t*, for which the user *u* has specified ratings, be denoted by $Q_t(u)$. The predicted rating is calculated using the weighted average value of the raw ratings [24].

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The weight of item j in this average is equal to the similarity between item j and the target item t. Therefore, the predicted rating $\hat{r}_{ut}$ of user u for target item t is as follows.

$$\hat{r}_{ut} = \frac{\sum_{j \in Q_t(u)} sim(j,t).(r_{uj})}{\sum_{j \in Q_t(u)} |sim(j,t)|}$$

B. Model-based method

In model-based methods, machine learning and data mining methods are used in the context of predictive models. In cases where the model is parameterized, the parameters of this model are learned within the context of an optimization framework. Some examples of such model-based methods include decision trees, rule-based models, Bayesian methods and latent factor models. Many of these methods, such as latent factor models, have a high level of coverage even for sparse ratings matrices. Detailed explanation about model-based collaborative filtering can be found in [25].

C. Limitations of Collaborative Filtering

Collaborative Filtering, a widely used recommendation approach, exhibits several limitations that impact its performance and applicability. One of the prominent challenges is the ``cold start" problem, where this method struggles to provide recommendations for new users or items with minimal or no interaction history [26]. It is also susceptible to data sparsity issues, as its effectiveness diminishes when faced with datasets containing limited user-item interactions. Scalability can be a concern, particularly for memory-based CF methods, as they can become computationally expensive for large datasets. Additionally, CF often falls prey to popularity bias, favoring recommendations of popular items at the expense of less-known, niche options. Furthermore, maintaining diversity in recommendations can be a challenge, as CF tends to suggest items similar to those previously liked by users [25]. These limitations have spurred the development of hybrid recommendation systems and alternative recommendation techniques to address these issues and enhance the quality of personalized recommendations.

V. CONTENT-BASED RECOMMENDER SYSTEM

Content-based (CB) recommender systems analyze user's past preferences and the attributes of items they've liked to construct personalized user profiles. These profiles are then used to match users with items similar to their previous preferences, based on item attributes, rather than relying on ratings from other users [27] [23]. Unlike collaborative systems, which incorporate the ratings of multiple users, content-based systems prioritize the target user's own preferences and item attributes for recommendations [28].

As referenced in [29], content-based systems are dependent on two sources of data:
i. The first source of data is a description of various items in terms of content-centric attributes. An example of such a representation could be the text description of an item by the manufacturer.

ii. The second source of data is a user profile, which is generated from user feedback about various items. The user feedback might be explicit or implicit. Explicit feedback may correspond to ratings, whereas implicit feedback may correspond to user actions.

The system utilizes the user profile to suggest relevant items by comparing the attributes of the user profile with that of the items to be recommended. The result is either binary or continuous relevance judgment, computed using some similarity metrics [28].

A major advantage of content-based recommender systems over collaborative filtering is that they do not suffer from popularity bias, and are capable of recommending items that are not rated by any user. Explanations can also be given on why a particular item was recommended which is not possible in collaborative filtering. Although content-based systems help in resolving the cold start problem for new items, they do not help in resolving these problems for new users as they cannot provide reliable recommendations to a new user, or to a user who has rated very few items. Also, analysis of item attributes may not be sufficient to define distinguishing aspects of that item [28] [29].

VI. DEMOGRAPHIC FILTERING

Demographic filtering is a recommendation approach that categorizes users into groups based on their demographic information, such as age, gender, location, or other personal attributes. It then suggests products, services, or content to users by matching their demographic profile to those of similar users who have demonstrated preferences for the same or related items.

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Impact Factor 8.102 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 13, Issue 3, March 2024

DOI: 10.17148/IJARCCE.2024.13389

The key concept is to use demographic characteristics to create user segments and infer user preferences based on the behavior and preferences of others in the same demographic category. This approach is commonly employed to deliver personalized recommendations and content to users with similar demographic profiles, enhancing user experiences and engagement [30]. Demographic filtering can help overcome the cold start problem for new users by providing meaningful recommendations to users who lack interaction history.

VII. HYBRID SYSTEM

A hybrid content-based collaborative filtering system, integrated with demographic profiling, presents a promising solution to address the cold start problem in the content-based and collaborative filtering techniques and enhance the recommendation process. Each of the methods discussed in the previous sections uses different information to create a profile of a user's interests. Demographic methods seek to identify patterns within user profiles who favor specific items. Content-based methods uncover patterns within item descriptions that resonate with particular users. Collaborative methods establish connections by correlating a user's ratings with the ratings of other users to make personalized predictions for that user [27].

The hybrid approach combines elements of content-based and collaborative filtering approaches. It starts by creating user profiles based on demographic information such as age, gender, and location. Then, it incorporates content-based analysis by considering item attributes and user demographic data to make recommendations. User profiles and item attributes are used to identify preferences, and similarity metrics are applied to find items that align with a user's demographic characteristics and content preferences. This approach leverages both user-specific and item-specific data to provide more accurate and personalized recommendations, particularly suitable for users with limited interaction history or when demographic attributes strongly influence preferences [31].

VIII. LIMITATIONS

Due to the limited scope of recommender systems in healthcare-related studies, we encountered constraints in conducting a comprehensive survey. As depicted in Table I, collaborative filtering methods exhibited superior accuracy when prior user interaction data was available [32] [33]. However, as demonstrated in [34], demographic filtering techniques provided better recommendations than collaborative filtering, particularly when faced with the cold start problem. Hence, the integration of demographic profiling alongside collaborative filtering is deemed essential for enhancing recommendations [35]. Expanding on this approach, [31] highlights the effectiveness of a hybrid recommender system that combines collaborative filtering, content-based filtering, and demographic filtering to deliver exceptional results. Nevertheless, it's worth noting that extensive research studies focusing on such hybrid models within the domain of dementia and healthcare remain scarce.

TABLE I COMPARISON OF RECOMMENDER SYSTEM ALGORITHMS USED IN THE FIELD OF HEALTHCARE

Algorithm	Purpose	Precision	Accuracy	Reference
DF	Recommendation for Autism Spectrum Disorder	-	83.8%	M. Kohli et al. [34]
CF	Recommendation for Autism Spectrum Disorder	-	71.26%	M. Kohli et al. [34]
CF	Pharmaceutical therapy recommendation system	77%	-	F. Gräßer et al. [33]
CF + DF	Recommendation for psoriasis therapy	78.51%	-	M. Kohli et al. [35]
CF	Recommendation of input variables to a system providing physical therapy	-	85.76%	W. Ismail et al. [32]
CB	Emotion-based recommender system for tinnitus patients is proposed	-	-	K. A. Tarnowska [36]

IX. CONCLUSION AND FUTURE SCOPE

In summary, the survey of recommender system algorithms has revealed their notable successes in diverse fields, offering substantial potential for the creation of personalized therapy recommendations in the realm of dementia rehabilitation. While the application of recommender systems in healthcare remains relatively limited, there are noteworthy examples of studies that have successfully integrated these systems to deliver personalized therapies. The promising outcomes achieved in these studies suggest that the experiences and insights gained from other domains can be effectively replicated in the context of dementia care.

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Among the explored recommender system approaches, demographic filtering emerges as a powerful tool, capable of generating superior personalized recommendations. By harnessing patient data, it addresses the common challenge of the cold start problem, which often hampers the effectiveness of collaborative and content-based filtering methods. This approach opens avenues for tailoring therapies to the specific needs of dementia patients, ultimately enhancing their quality of care and life.

Moreover, the survey underscores the immense potential of hybrid recommender systems. By amalgamating collaborative filtering, content-based filtering, and demographic filtering, these systems exhibit the capacity to deliver recommendations of exceptional quality. Although research on such hybrid models in the context of dementia rehabilitation is currently limited, their promise in optimizing therapy recommendations is evident.

In conclusion, the survey not only sheds light on the applicability of recommender systems in healthcare but also underscores the need for further research and implementation in the field of dementia rehabilitation. These systems hold the promise of revolutionizing the patient experience, improving healthcare outcomes, and lightening the burden on caregivers. The path forward involves robust investigations into their real-world application, ethical considerations, data privacy safeguards, and the seamless integration of these technologies into the clinical settings where dementia patients receive care.

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International Journal of Advanced Research in Computer and Communication Engineering
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