Music Recommendation System for Old People with Dementia and Other Age-related Conditions

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Keywords: Music Recommendation System, Music Metadata Mining, Music Information Retrieval, Digital Ageing, Dementia, Music-based Intervention, Machine Learning Algorithms, Music Repository.

Abstract: The worldwide increase in life expectancy can be accompanied by age-related degenerative conditions such as dementia. Dementia poses significant challenges for which music is a beneficial non-pharmacological intervention. Based on research and clinical expertise we developed a web-based system, termed Tamaringa, that builds and displays customized playlists. The recommendation mechanism incorporates an old person's age, birthplace, and popular songs from their youth. That particular range is known as being most accessible to seniors in terms of memory. Although there are a lot of repositories containing metadata and information about music, there is no single repository that addresses all our requirements in terms of specific metadata, range query application programming interfaces (API) capability and popularity information. This study explores the APIs of several repositories in order to populate our internal database with suitable songs that are required for accurate personalized recommendation. A preliminary promising pilot enabled twenty-four residents in an assisted living facility in Israel to engage and enjoy the music recommendation system. Personalized playlists were created using the system; the medical staff reports were positive. Further research will help to develop our system and eventually to integrate its use both in assisted living facilities and at home.

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1 INTRODUCTION

According to the World Health Organization (WHO), life expectancy is increasing around the world. Aging presents challenges such as isolation, loneliness, as well as currently incurable diseases like dementia and Parkinson’s. It is estimated that approximately 50 million people are affected worldwide by dementia (WHO, 2017). The care of people with dementia has become a focal point for policy makers, researchers and healthcare providers, who recognize the need for competent and effective services (Prince et al., 2016). Studies show that music is an effective non-pharmacological intervention for people with dementia. It has an ameliorating effect on agitation (Levingston et al., 2014; Ziv, Granot, Hai, Dassa & Haimov, 2007), it improves well-being for the person with dementia (Baird & Thompson, 2018), and supports the caregiver in providing the best care possible (Ray & Fitzsimmons, 2014; Särkämö, et al., 2014).

The use of music can be crucial in the care of people with dementia. Music-based intervention mostly includes listening to familiar music. Usually a customized playlist is gathered and recorded, either manually or on a spreadsheet. Such music-based interventions are not documented in digital repositories and are thus unavailable for the purpose of creating more accurate playlists for each person. In this paper, we describe a system we have developed, termed Tamaringa, that automatically builds customized playlists and then stores them in a scalable system that allows for fast playlist display on demand.

Nowadays, music streaming systems, such as Spotify (Eriksson et al., 2019) and YouTube (Airoldi et al., 2016), that recommend customized playlists to their listeners are popular. These systems are unsuitable for people with age-related conditions in several ways: The recommendation algorithm is not adapted for cognitive difficulties; Spotify provides general and calm playlists for old people without any specific profiling or comprehension regarding the use of music that taps into long-term preserved memory

Allalouf, M., Cohen, A., Sabban, L., Dassa, A., Marciano, S. and Beris, S.
Music Recommendation System for Old People with Dementia and Other Age-related Conditions.
DOI: 10.5220/0008959304290437
In *Proceedings of the 13th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2020) - Volume 5: HEALTHINF*, pages 429-437
ISBN: 978-989-758-398-8; ISSN: 2184-4305
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in the case of dementia and other related conditions; Youtube recommendation algorithm is based on averaging the preferences of people from different ages and origins and not suitable for elderly people that mostly prefer music from their past. In addition, old people in general and those with dementia require easier human-computer interface than the one that is provided by the regular desktop or smartphone for Spotify or YouTube (Finamore et al., 2011). Thus, it is not practical to expect they will handle their own playlist by themselves or ask their caregivers to handle a unique playlist for each person.

The MUSIC & MEMORY® (Thomas et al., 2017) organization helps people in nursing homes and other care organizations who struggle with a wide range of cognitive and physical challenges to find renewed meaning and connection in their lives through the gift of personalized music. They train care professionals how to set up personalized music playlists, delivered on digital devices, for those in their care. But they do not provide an automatic system such as the one presented here. The Tamaringa platform identifies personal musical preferences related to preserved memories and builds an appropriate playlist accordingly.

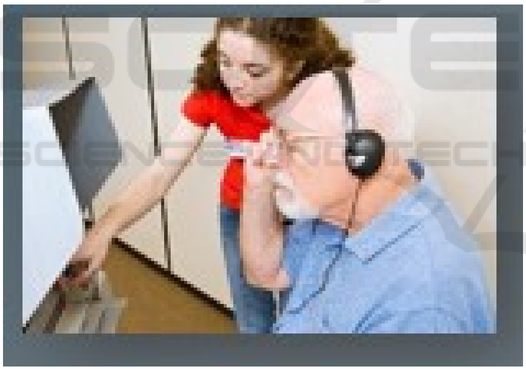

Figure 1: Web Application guided by an instructor.

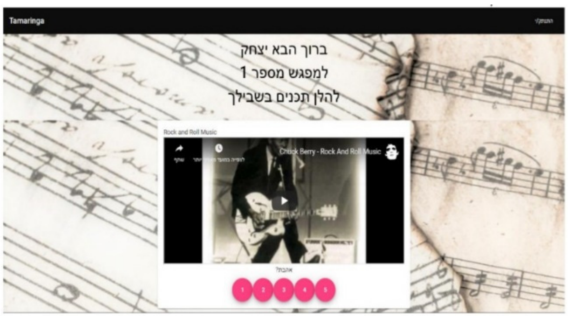

Figure 2: Suggested playlist with buttons to rate the song.

2 MUSIC REVIVES YOUR SOUL

Until now, customized playlists were put together by a close family member, hand-written on a sheet of paper, and given to a caregiver or to nursing home staff to play for the person with dementia. As the music sessions were played at the discretion of the caregivers and were not monitored, they could not be modified to generate more precise playlists, and behavioural or other well-being measurements were at best mediocre.

The Tamaringa platform automatically builds customized playlists, based on where and when people were born, where they grew up, where they went to school and university, their ethnicity, religious and social background, and their taste in music, among other things. Suggested playlists are kept in storage and played on demand in a simple interface that can be operated by the end-user (Figure 2). The results of patients' preferences and reactions to the chosen playlist (such as verbal comments, singing, or reduction of agitation) are saved to the internal database by an instructor or family member in order to create better playlists and hone baseline target profiles.

In this work we followed the Music Information Retrieval (MIR) modelling as surveyed in Schedl et al., (2014) that categorizes two main classes: user profiling and context, and music content and context. In particular their survey focused on user-centric music retrieval as well as how to recommend music based on the user's profile and preferences. User profiling is described in Section 2.1. The music recommendation algorithms that are described in Section 2.3 are based on having the relevant music information and metadata in the system (described in Section 2.2).

2.1 User Profiling

A preliminary pilot was conducted in a nursing home in Israel. Israeli society is culturally diverse and only twenty-two percent of the elderly were born in Israel (Myers-JDC-Brookdale, 2018). Old people may have grown up in other countries and may speak various languages. The elderly participants in the nursing home were from different cultures, spoke different languages and were at different stages of dementia. Lack of memory was evident, as well as other neuro-psychological symptoms such as agitation, depression, verbal and physical aggression and refusal of medical treatment.

People between the ages of 75-95 in Israel have usually immigrated from a variety of countries over the world, at different stages of their lives. We identified and split the residents into several groups with regard to their origins. For example, 90-year-olds who arrived from Russia would probably like war songs such as the Red Army choir *Smuglianka* https://www.youtube.com/watch?v=n7hHlh2IusY or Dark is the Night by Mark Bernes from 1943 https://www.youtube.com/watch?v=Wdx7fkss6kU. Younger people around 75-years-old would prefer music from Soviet films like *Kidnapping, Caucasian Style*, a Soviet comedy film from 1967 (https://en.wikipedia.org/wiki/Kidnapping,_Caucasian_Style).

As an example, 85-year-olds who arrived from Arabic-speaking countries (Iraq, Syria, Egypt, Morocco, Tunis and Algeria), and who speak Arabic, would prefer Arabic songs e.g. Umm Kulthum and Farid al-Atrash. The 70-85-year-olds who came from North African countries and spoke French in addition to Arabic, had been influenced by French culture and songs by French performers like Edit Piaf, Jacques Brel and Nana Mouskouri, and they would probably elicit positive reactions. Old people who were in Israel in their twenties would like the Israeli and Western songs that were played during the years 1940-1970. Thus, in order to recommend suitable music, we had to define their profile by their age, the period corresponding to their twenties, their first language, place of birth and other attributes.

The nursing home where we applied our system established computer rooms with instructors who could offer help, where the residents could come and watch video content and listen to music. As depicted in Figure 1, each person has a pair of headphones and his/her own computer. The participant received personalized content that fitted his or her profile, operated by an instructor in the room. It was evident that the residents at different stages of dementia were eager to come to the computer room. We realized that it was important to accompany music with a video rather than only playing the audio. Usually, the role of the instructor was to suggest a suitable content to the person and follow the resident's reactions. We learned that music that they liked in their twenties pleased them very much and increased their motivation to return to the computer room. This is in accordance with previous research which shows that the majority of seniors' accessible songs are from earlier decades of life (Cohen, Baily, & Nilsson, 2002).

Hence, the instructors suggested music that fits the background of each person. In this sense it is similar to a regular customized MIR (Music Information Retrieval) application that recommends music for the user based on the user's cultural background, interests, musical knowledge, and usage intention, among other factors. But Tamaringa also learns the person's preferences given their tendency to remember and react more positively to music from their past rather than unfamiliar or recent songs.

2.2 Music Metadata Retrieval

Our recommendation system contains relevant information about music content that is kept in an internal database that is used for the recommendation pool. To populate the database, we pulled the information automatically from external repositories using software tools. The information about songs that we looked for included detailed information such as the name of the performing person or band, the name and the language of the song, creation or recording date, the year of release, the country of origin, the tags that characterize the song and popularity ratings for a song at a relevant period. In order to retrieve songs from several years, we required the repository Applicative Programming Interface (API) to allow year range query.

The need for this diverse information became problematic due to several reasons. We encountered difficulty in gathering this music metadata. Although there are a lot of repositories containing metadata and information about music, there is no single repository that addresses all our requirements in terms of specific metadata, range query API capability and popularity information.

In addition, we found that information about songs from the mid-1950s, for example, that was taken from several repositories, contained contradictions and was vague. Therefore, to build the database that would serve as the basis for the music recommendation system, we examined several repositories, each with different programming APIs.

2.2.1 Youtube

Study of the YouTube API showed that the metadata of songs in YouTube usually include the title of the song, the performer's name and the comment of the user who uploaded it (https://developers.google.com/youtube/v3/getting-started) . These features did not help in characterizing the songs in the way we needed. Still, we used YouTube to display the songs, as will be described later.

The popularity rating of each song is also a difficult parameter to meter. We can find today's popularity rating of a song from the 1930s. But there

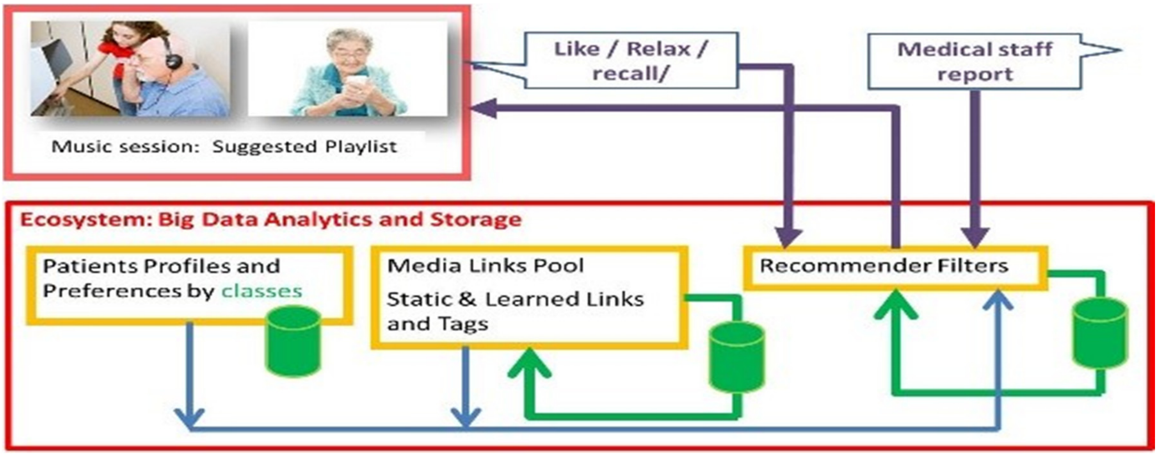

Figure 3: Tamaringa Workflow.

is no way to evaluate its popularity back in the 1930s. The Billboard-Hot-100 shows the best 100 songs in USA (only) every week since 1901 to today (https://www.billboard.com/charts/hot-100). There is no way to query Billboard about the popularity of a certain song since it does not provide any API or access to its internal database. Thus, we assumed that a song that was then popular will have a large number of *plays / likes* on YouTube today and relied on this information for the popularity rating a of a song.

Another requirement of our project was the ability to view and play a song while remaining in the context of our application without being transferred to another application such as YouTube. It is clear that YouTube is the main platform for this, because it is the largest system, with extensive content.

At the beginning of the project it was not possible to get a link to the song by its name, since the songs are characterized by a unique ID for YouTube. YouTube considerably improved the documentation and client API for many languages, including Javascript, on the 27th of October, 2017, (https://developers.google.com/youtube/v3/revision_history#april-27,-2017) and we could obtain a link to the video by the name of the song and the artist. And thus, we overcame the difficulty and were able to play any song that would appear in the playlist.

2.2.2 Musicbrainz

MusicBrainz's extensive research shows that it contains a lot of songs' metadata but after a long investigation in MusicBrainz API (https://musicbrainz.org/doc/Indexed_Search_Syntax#Overview) there were many difficulties in searching for specific information such as the first publishing date of a song by year and by its original geographical area. A song's metadata on MusicBrainz contains the year of release and in which country, based on the year and location the album was released. But there could be more than one album containing the same song, each album with a different publishing date or location. So, according to many tests, and verification of Google data on songs, we realized that the best way to get the most accurate information was to take the first year of publication listed.

MusicBrainz does not contain a popular rating, which is very important to our recommendation tool; the popularity data is meanwhile taken from the YouTube using the Video ID that was fetched from MusicBrainz. We found that MusicBranz API does not fit such massive search and retrieval. One connection session allows, before terminating, not more than 16 requests to the MusicBranz server; each request can fetch up to 100 songs, which adds up to the retrieval of 1600 songs' metadata in one connection.

In order to get the metadata of several hundred thousand songs published in a certain and geographical location, we downloaded and stored all the information about the songs from 1880 to 2018 (121,348 Records). The data was saved in JSON files containing 100 songs in each file, and stored in our MongoDB server with the information that was relevant to us. Additional information like the song's rating or views, and the ability to play it, was fetched and stored from other repositories.

2.2.3 Last.fm

Like MusicBrainz, Last.fm (https://www.last.fm) displays information about songs from different periods. Unlike MusicBrainz, the Last.fm repository

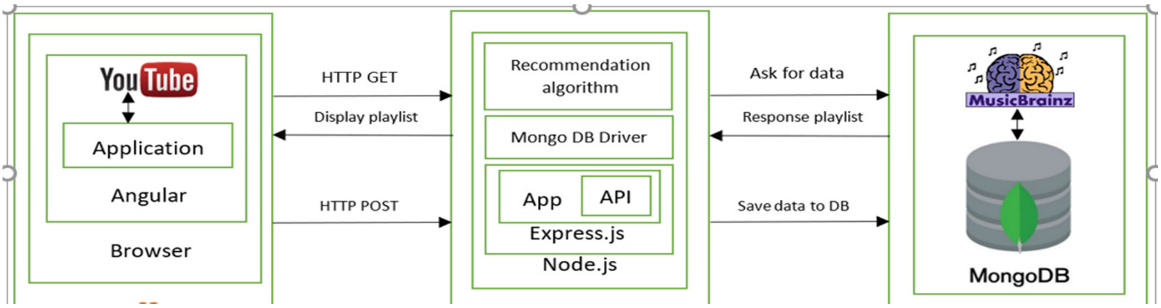

Figure 4: System Architecture.

shows a range of songs using the API for a certain period of time, but a manual check for the parade of songs we received found that the songs are out of date and do not show the hits for that period. A thorough examination of various forums brought to our attention that the database has not been updated since 2015. It was decided to abandon it and continue research.

2.2.4 Discogs

We conducted another study in the Discogs (https://www.discogs.com) repository. Discogs provides a lot of information about songs, such as year of publication and information about various record companies. Discogs did not fit our need because of several reasons that disqualified its use. The site is mainly focused on electronic music and does not fit the songs we were seeking for elderly people. The information in Discogs is categorized by complete albums rather than specific songs. Finally, the information is not categorized according to geographical location, which is very critical to this work.

2.3 Music Recommendation

A prototype of the recommender application is depicted in Figure 3. The system is composed of a web-based and mobile application that displays a recommended playlist that is customized to the profile and needs of the end-user. The person's reactions to this playlist will be monitored, stored and used to improve it. The application is illustrated in the upper left-hand box of Figure 3. The system provides monitoring of the person by the medical staff filling out a report regarding their psycho-social behaviour before and after the music session. A scalable ecosystem (illustrated in the lower box of Figure 3), learns to match a list of songs, filtered by tags, to a certain profile of an elderly person.

The recommendation filter determines the makeup of the playlist created as a result of this matching process. The system has to build a new dataset for each type of recommendation algorithm and continuously analyse the data for more updates. Storage of the vast amounts of data around the world warrants the use of big data technology for scalable and reliable systems. As stated in 2.1, an old person's profile is characterized by their details such as: year of birth, country of origin and language. The system calculates the years when the person was 15-25 years old. The recommendation algorithms and playlist composition work in two stages as follows:

Stage 1:
The population (for example all the residents of a long-term care facility) are clustered together into one group by country of origin, language and year of birth. That is, all participants who were born in Arabic-speaking countries in 1940 and whose language is Arabic (in addition to Hebrew) were under the same group. The cosine similarity distance is used in order to set similar groups.

Each group of residents having similar parameters is assigned initially to the same playlist. A playlist of 25 songs with the highest rating by year, country of origin and the song's languages will be extracted from the database. Currently, our main load of data was retrieved from MusicBrainz and contains information on each song including year of release, country of origin and language. The play popularity rating is determined by relevant information on YouTube.

Stage 2:
The first time a person logs into the system, the recommender filter (Figure 3 on the right) randomly displays 10 default video songs from the playlist (containing 25 songs) using the YouTube ID that is kept in the internal database. It is important to note that the video is displayed within the framework of our application and is not transferred to the YouTube environment. Thus, we have full control over the content that is displayed to the old person. In addition to the video of a song, the song's name and the

performer's name will be displayed. The software uses YouTube API to fetch the video by its YouTube ID and display it.

The old person himself (or the instructor according to the person's reactions) is able to rate the songs on a scale of 1-5. 5 - songs he liked / knew, 1 - didn't like / didn't know. The rating is kept in the internal database to be used the next time this person enters the system, in order to improve his playlist.

When the user ranks the list of songs presented to him, the recommender filter uses the collaborative filtering with the cosine similarity as the distance in order to calculate the similarity between this person's preferences and the rest of the group. The next time this person logs in the system the playlist is refreshed and displays songs that he liked in the past along with songs that others in his cluster group liked.

2.3.1 Example of 1970 Playlist for People from the UK

The following example presents the recommendation process for three 70-year-old people, Emma, John and Sam, who speak English and came from the UK. (The presented names are pseudonyms). All of them were assigned the same playlist with 25 songs; it is listed in column 1 and 2 (Table 1). This playlist was created using our clustering mechanism as explained before.

When Emma logged into the system for her first time, 10 random songs were presented to her, one after the other, and Emma ranked them according to her taste. The order of the presented songs to Emma with her rank score is presented, from the top downwards, in the third column of Table 1. Columns 4 and 5 present the top downwards order of songs presented to John and Sam respectively and the ranks they allotted to each song.

The preference vectors of each one of the users were updated with the given ranks. The similarity between each pair of users was calculated using the collaborative filtering with similarity distance; The similarity distance we have used takes into account that one person may consider 4 as a very high rate and another considers 5 as a high score. It was found that preferences of Emma and John are more similar than the others. Thus, the second time Emma logged into the system, her playlist was updated as can be seen below (Table 2). The four first songs are those that she liked more than the others. The next four songs are those that John liked and the last two were new songs from the initial playlist.

Table 1: Playlist display for Emma, John and Sam at their 1st login presented in columns 3, 4, and 5.

Initial UK73 Playlist		First Login		
song	artist	Emma 1st login	John 1st login	Sam 1st login
Bohemian Rhapsody	Queen			
Wish You Were Here	Pink Floyd	5		
Smoke on the Water	Deep Purple			5
A Day In The Life	The Beatles		2	
Alone Again (Naturally)	Gilbert O'Sullivan		1	4
Angie	The Rolling Stones	5		
Roundabout	Yes	2	2	
Can't You Hear Me Knocking	The Rolling Stones			
Stand by Me	John Lennon			4
Rainy Days and Mondays	Carpenters	4	4	1
Suspicious Minds	Elvis Presley	1	1	
Money	Pink Floyd	4		
Lonely This Christmas	Mud		3	
Wild Horses	The Rolling Stones		3	1
The Way We Were	Barbra Streisand	2	2	
I'm Not in Love	10cc	4	4	
Bang a Gong (Get It On)	T. Rex			3
Us and Them	Pink Floyd	2		
Morning Has Broken	Cat Stevens		3	4
Have a Cigar	Pink Floyd			5
Brown Sugar	The Rolling Stones			
It's Only Rock 'n' Roll	The Rolling Stones	3		5
Firth of Fifth	Genesis			1
24 Hours	Ace			
Alive	Bee Gees			

Table 2: Emma's updated playlist presented to her on her 2nd login.

Second Login	
Emma 2nd Login Playlist Order	
Wish You Were Here	Liked before
Angie	Liked before
Rainy Days and Mondays	liked before
Money	liked before
I'm Not in Love	John Liked
Lonely This Christmas	John Liked
Wild Horses	John Liked
A Day In The Life	John Liked
Smoke on the Water	New Song
Bohemian Rhapsody	New Song

3 SYSTEM PROTOYTPE ARCHITECTURE

The architecture of the system is depicted in Figure 4. The client side was developed in Angular. The server functionalities were developed in NodeJS and include the recommendation mechanisms and the interaction with repositories APIs and database servers. The internal storage for the metadata of the songs is MongoDB. The songs' metadata was downloaded and updated from MusicBrainz and YouTube, as explained in Section 2.2.2, into MongoDB in JSON format which is the most prevalent format for serializing content (Humphrey et al., 2014). MongoDB was selected because of its fitness with JSON in terms of document creation and indexing. MongoDB has replication capabilities and works well for scalable big data storage, as is required in our system.

4 PRELIMINARY PILOT USING TAMARINGA

A preliminary pilot enabled 24 residents in an assisted living facility to try and use the system described above over a period of three months. The activity was suggested to the residents as part of other activities offered in their assisted living facility. Residents were free to access the computer room and were also invited by staff members to try the system. The instructor helped each resident to operate and formulate their customized content. The residents who participated included those with dementia, those who are wheelchair-bound with/without cognitive decline, and those who have other age-related conditions, such as stroke survivors. Some residents had a weekly meeting in the computer room, some asked to attend few times a week, and most of the residents with dementia, when asked, expressed their wish to attend again.

For three months, the resident entered the computer room regularly on certain days at certain hours or by his/her request and was presented with the customized playlist (as described in Section 2.2). During the sample period, the professional staff observed the behaviour of the residents and gave their impressions regarding changes in the residents' psycho-social behaviour. Though no systematic data was gathered.

According to the staff report, it seemed that all the residents shared their enjoyment with others after the experience. They told their friends, staff members, and family about the content they watched. Some residents continued singing their preferred song afterwards, some stated that watching their preferred songs helped them to forget their worries. The instructor in the computer room documented moments of joy, laughter, and singing. Pivotal moments were with residents who had previously refused to participate in any suggested activity, and after realizing they could watch their preferred content, kept asking to attend. Further investigation using validated assessment tools will help to understand the impact of using customized content via the suggested system.

5 RELATED WORK

In addressing a disease that destroys memory, preserved musical memory serves as an important tool for enhancing quality of life (Baird & Samson, 2015). Individualized music evokes memories, despite memory loss, particularly by means of songs associated with the early decades of seniors' lives (Dassa & Amir, 2014). The theory-based intervention of individualized music has been evaluated clinically and empirically and was found to be beneficial in reducing anxiety and agitation, eliciting memories and in promoting communication among people with dementia (Gerdner, 2012).

A communication barrier is most evident in the case of dementia. In an exploratory research case study, a personalized database was formed with the help of spouses who visit their partners with dementia in a long-term care facility. The database included preferred music and personal photos and helped to evoke a reaction and facilitate communication between the couple. Although the process of preparing the data was very powerful for the spouses, it demanded extensive preparation. The main challenge is to create a feasible procedure that will allow caregivers to have the use of a personalized database (Dassa, 2018).

Old people are having a lot of difficulties accessing and operating modern applications (Zajicek, 2006; Sayago & Blat, 2009) and our vision is to create a suitable interface for the elderly, yet not to exclude communication with another person who will guide and accompany this process. The design of Tamaringa application follows this vision.

Music Recommendation aims to suggest suitable music to users by inferring their music preferences. Different kinds of ancillary information have been applied to boost recommendation accuracy. A typical example is to add temporal dynamics and music taxonomy bias (i.e., artist, album, and genre) (Koenigstein et al., 2011). Another research study explored how the usage of the user's demographic information in collaborative filtering and additional user's characteristics improve the tailoring of a more suitable playlist (Schedl et al., 2015; Schedl & Hauger, 2015).

In recent years, more research efforts have been devoted to explore user-related contexts in music recommendation. Music popularity trends and user's current location context were taken into consideration to facilitate personalized music recommendation (Cheng & Shen, 2014). Several works (Koenigstein & Shavitt, 2009; Schedl et al., 2010; Hauger & Schedl, 2012) considered the popularity of a performer or a music piece highly relevant, specifically in order to estimate the popularity of music releases and promising artists. For this purpose, different data sources have been investigated: search engine page counts, microblogging activity, query logs and shared folders of peer-to-peer networks, and play counts of Last.fm users.

6 CONCLUSIONS

Conventional medical treatment does not counteract the progression of the course of deterioration in the case of dementia, nor does it help recall those memories thought to be lost. Pharmacological solutions also have a limited effect on the symptoms. Personalized music sessions can help memories re-emerge and revitalize the spirit of those with dementia. Music was proved to reduce behavioural symptoms and elicit physical activity. Our Tamaringa system prepares customized media and music playlists in order to improve the daily lives of people with dementia, those with other age-related conditions, and their caregivers. For this purpose, we explored several music repositories for their suitability to retrieve relevant metadata into an internal database of songs suitable for recommendation.

The music recommendation process, and the architecture of our system, is different than the work that was done so far in several aspects. The starting point for the recommendation is based on the characteristics of the old person, such as birth year and place, followed by the music search and filter. The information about the songs cannot be found in an online social media and should be retrieved from static repositories. Finally, the popularity back in the years the songs were released cannot be retrieved by the same mechanism we have today. Hence, in order to be able to recommend correctly the suitable songs for the old person we had to include the metadata of these songs in our internal database. We explored several repositories and decided to use the MusicBrainz data and API.

Our next step will be to conduct a full assessment scale research that will explore the benefits and impact of our system on specific socio-behavioural symptoms among people with dementia and other age-related conditions. We also aim to further develop our system to match the necessary requirements in the field of gerontology. We believe that adding the use of personalized music using this system could benefit well-being and promote communication between people with dementia and their caregivers in assisted living facilities, and at home.

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