AI-Driven Personalized Music Therapy via Hybrid Recommender Systems

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ABSTRACT
Music is widely regarded as nourishment for the human mind and a universal cultural expression that supports emotional well-being. Its capacity to modulate emotional states, promote adaptive behaviors, and mitigate mental health challenges underscores its significance as a component of therapeutic interventions. However, selecting appropriate music genres, identifying optimal listening durations, and designing effective AI-driven personalization mechanisms remain significant challenges. This paper proposes a framework and presents the development of a personalized music recommendation application, guided by the Design Science Research (DSR) framework, to support intelligent music-based therapeutic interventions. Recommender systems assist users in navigating vast music libraries by extracting meaningful patterns from large-scale datasets and aligning recommendations with individual preferences. Following the DSR process of problem identification, artifact design, development, and evaluation, the proposed framework integrates collaborative filtering with content-based techniques using Cosine Similarity and Count Vectorization. Python APIs and datasets sourced from a popular music platform are utilized to implement and validate the model. Given music's historical and cross-cultural role in emotional regulation, an intelligent recommendation approach can significantly enhance therapeutic outcomes. Managing extensive user interaction logs and diverse music metadata introduces computational complexity, requiring efficient algorithmic design. Experimental results demonstrate effective genre prediction and improved personalized recommendation performance using standard evaluation metrics. This research emphasizes the importance of user mood, behavioral trends, and activity patterns in advancing AI-enhanced music therapy systems.

Keywords
Music Therapy, Recommender System, AI-based Music Recommendations, Mental Health, Cosine Similarity.

1. INTRODUCTION
Listening to music has been consistently recognized for its positive impact on both physical and mental well-being. In various healthcare settings, including nursing homes and palliative care facilities, board-certified music therapists are employed to complement traditional treatments for a diverse range of illnesses and disease processes.

Music, being a ubiquitous activity, engages virtually every individual on the planet. Music therapy, as a therapeutic approach, involves utilizing music to address social, emotional, cognitive, and physical needs, aiming to achieve specific goals such as anxiety reduction, pain control, mood enhancement, communication facilitation, and relaxation induction. This inclusive form of therapy proves beneficial for individuals of all ages and across various conditions, encompassing mental health disorders, developmental impairments, neurological disorders, and physical disabilities.

The therapeutic modalities can range from singing, playing instruments, and creating music to improvisation and simply listening to music. In the contemporary context, where mental health issues are prevalent and the global health crisis has exacerbated stress and pressure on individuals and communities, there is a heightened need for increased support and attention to mental health services and resources. Simultaneously, the vast amount of information available on the internet has made information discovery challenging and time-consuming.

1.1 Recommender systems
Recommender systems have emerged as a solution to this issue, automating the recognition of user interests and suggesting relevant information. Building recommender systems aims to alleviate information overload by extracting the most relevant knowledge and services from vast datasets, providing personalized offerings that enhance the overall user experience. In the digital age, recommendation systems have become integral components for improving user interactions across various platforms. This is particularly evident in scenarios where there are hundreds of millions of user activity records and an extensive catalog of music pieces, making accurate, targeted, and efficient suggestions a challenging task. The surge in popularity of internet streaming services, such as Spotify, Pandora, or Apple Music, has further highlighted the need for effective Music Recommender Systems (MRSs). Content-Based Filtering (CBF) and Collaborative Filtering (CF) are the two primary information filtering techniques into which recommender systems are generally divided according

to their suggestion criteria, which can be either item qualities or user behavior.

1.1.1 Content-based filtering (CBF)

Users' preferences (rating behavior) are the basis for the content-based filtering (CBF) recommender system. It extracts the similarity of features or qualities between users and items based on item kinds or users. For example, an item will be suggested to the user with a variety of possibilities based on the user's rating and the similar item the user has already rated. There are numerous options for alternative similarity measures to utilize in user-to-user or item-to-item similarity assessment because of the diversity in items and user behaviors. Known as the keyword-specific recommender system, CBF uses terms to illustrate its items [33, 34, 35]. A vector space is used to represent the features. The degree of similarity between things or users is represented by the distance of the vectors. To compute the similarity, score the Cosine or Euclidean similarity equations are used:

$$sim(x, y = \frac{\sum_{i=1}^{n} x_i \times y_i}{\sqrt{\sum_{i=1}^{n} x_i^2}\sqrt{\sum_{i=1}^{n} y_i^2}} \dots\dots\dots (1)[34]$$

$$dimsim(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} = \|x - y\|_2 \dots\dots\dots (2)[34]$$

In this case, sim(x,y) indicates similarity and dissim(x,y) indicates dissimilarity between items and users, where x and y are the vectors of the items or users. This study employed cosine similarity, which makes use of the equation, in the KNN implementation [34].

1.1.2 Collaborative Filtering (CF)

Among recommendation algorithms, collaborative filtering (CF) is one of the best. By grouping users who exhibit similar behaviors and suggesting new products based on the group's interests, it functions based on group characteristics [33]. For creating tailored suggestions, CF finds similarities between objects or user behavior. In general, there are two forms of collaborative filtering: item-based filtering and user-based filtering. The user-based collaborative filtering used in this paper makes use of normalized data. Using user rating data, a m×rating matrix R(m,n) is created, where m stands for the number of users and n for the number of goods [34]. For example, the collaborative filtering similarity between user a and b is expressed as sim(a,b) when comparing their behavior. The CF approaches are further classified as Memory based and Model-based approach, as follows:

(a) Model-Based CF

In [34], KNN and ALS were used to implement this method, where rating trends are summarized offline using this method. By splitting the user-item interaction matrix into two lower dimensional matrices with latent variables, the model-based CF, an unsupervised learning approach, employs a dimensionality reduction mechanism to address typical problems like scalability and data sparsity in RS.

(b) Memory-Based CF

The user's matrix, also known as the interaction or utility matrix, and the ratings in the form of items are kept in a memory that must be online to be processed. The anticipated rating is then determined using this interaction matrix. Assume that user A has viewed films 1, 2, and 3. User B has viewed films two and three. Movie 1 will be suggested to user B in memory-based CF. Memory-based CF learns the interaction/utility matrix in this manner. The memory-based technique can also be divided into two categories: item-based (IB CF) and user-based (UB CF). In all cases, the cosine metric of similarity/dissimilarity was used to calculate the similarity between the user and the object.

$$\text{Usersim}(u_t, u) = \frac{\sum_{i \in I_{u,u_t}} (R_{u,i} - \bar{R}_u)(R_{u_t,i} - \bar{R}_{u_t})}{\sqrt{\sum_{i \in I_{u,u_t}} (R_{u,i} - \bar{R}_u)^2}\sqrt{\sum_{i \in I_{u,u_t}} (R_{u_t,i} - \bar{R}_{u_t})^2}}$$

…………………. (3) [34]

Here, $\mathbf{u_t}$: The target user for whom we are making predictions. $\mathbf{u}$: A neighbor user in the system. $\mathbf{I_{u,u_t}}$: The set of items co-rated by both user u and user u_t. $\mathbf{R_{u,i}}$: The rating given by user u to item i. $\bar{\mathbf{R}}_\mathbf{u}$: The average rating given by user u across all items they have rated. $\mathbf{R_{u_t,i}}$: The rating given by target user u_t to item i.$\bar{\mathbf{R}}_{\mathbf{u_t}}$: The average rating given by target user u_t across all items they have rated. [34].

(c) Hybrid RS (CBF and CF combined)

The combined approach to recommendation, which often uses CBF along with both memory and model-based CF, is more varied and gets beyond the drawbacks of each separate method. Individual CF and CBF approaches have several drawbacks (which are not covered in this study), but by combining CF and CBF heuristics, hybrid RS overcomes most of these issues and may suggest a wide range of available items to users [35, 36].

The similarity matrix can be computed and used for recommendation in applications. The item recommendation system makes predictions about user behavior based on past user behavior and item similarity.

This paper delves into an analysis of how different musical genres impact mental health across various age groups. As music enthusiasts gain access to millions of songs through these streaming services, the importance of addressing listeners' musical enjoyment becomes apparent, specifically in the situation of therapeutic needs. This requires consideration of intrinsic, extrinsic, and contextual aspects, as well as additional interaction information. Factors influencing appropriate music recommendations include user preferences, personality, emotional state, trending lists, preferred artists, weather, location, gender bias, and more. Experiments in psychology and neuroscience explore the intricate relationship between individuals' moods and their musical preferences.

Research findings suggest that acoustics play a crucial role in eliciting emotions, particularly in happy music, while lyrics gain significance in sad or angry music. However, the multitude of alternatives poses a challenge in combining these factors effectively to produce optimal results. Musical choices may also be influenced by the occasion being commemorated, highlighting the dual nature of music as both personal and universal, capable of influencing the listener's mood and expressing emotions. Machine learning, a field leveraging statistical methods and mathematical algorithms on extensive datasets, plays a crucial role in creating models capable of making predictions, providing advice, and detecting anomalies. Recommender systems, one of the most effective applications of machine learning in business, utilize algorithms such as collaborative filtering and content-based filtering. Collaborative filtering suggests items based on popularity among individuals with similar preferences, while content-based filtering focuses on an individual user's preferences, utilizing historical data to generate personalized recommendations.

This study falls under the category of content-based filtering, where machine learning algorithms operate on numerical attributes, requiring the transformation of text-based music data into vector representations through a process known as vectorization. This enables the recommender system to process natural language data effectively, recommending music based on the frequency of occurrence of each word in a phrase and associating it with the entire collection of terms in the original dataset. While there has been considerable emphasis on content-based approaches in music information retrieval, a quantitative investigation reveals a gap in research dedicated to the intersection of music and recommendation. The study aims to address this gap and contribute to the understanding of the relationship between music genres and mental health issues across various age groups.

As recommender systems extend beyond music to areas like movie recommendations, they play a pivotal role in enhancing user satisfaction and saving time. With the analysis of user lifestyle and activities, recommender systems can tailor recommendations based on reactions to posts, searched content, movies watched, and more. The flexibility of recommender system parameters and the incorporation of deep neural network models demonstrate their adaptability to evolving user preferences and needs. In summary, this study endeavors to construct a recommender system based on current user queries, recommending similar music to users who meet specific criteria set by the recommender system.

The system has been fully implemented and is ready for use. The subsequent sections of this paper include the Background Study in Section 2, the proposed system architecture and methodology in Section 3, the findings analysis in Section 4, and concluding remarks and future directions in Section 5.

2. LITERATRE REVIEW

The integration of musical therapy in mental health treatment has emerged as a burgeoning area of study, evident from the growing body of works and algorithms dedicated to this subject. Markus et al. conducted an analysis on the essential qualities required in a music recommender system, providing insights into current challenges and prospects for the industry [1]. Shahrzad et al. explored the correlation between song lyrics and mood, employing a data-driven methodology and nearly one million songs [2]. Utilizing state-of-the-art natural language processing models, they found that lyrics, rather than acoustics, play a more crucial role in predicting mood. Kozhevnikov et al. delved into the advantages and disadvantages of categorization techniques, vectorization methods, and classification algorithms [3]. In addition to traditional classification methods, the study explored neural network approaches, particularly convolutional neural networks.

The research identified measures for assessing the effectiveness of trained classification models. Markus et al. presented several recommender systems using Deep Learning, highlighting the intricacies of the music domain in recommendation system research [4].

This review organizes discussions around key elements such as task, recommendation technique, neural network type, input data, and input data type (standard or sequential music recommendation). It also addresses primary challenges faced by music recommendation systems, especially in the context of current deep-learning research. Kim et al. employed Short-time Fourier transform (STFT) and Dynamic K-means Clustering Algorithm in 2003 to extract sound wave attributes and provide personalized music choices [6]. They demonstrated the ability of STFT to quantify musical properties and introduced K-means clustering for offering options from different genres. Cheng et al. developed a hybrid method for individualized music suggestions using collaborative music filtering, considering both content and context [7].

The proposed technique utilized timbre texture, rhythmic content, and pitch content for categorizing music information. Ahmed et al. introduced a movie recommendation system in 2018, utilizing K-means clustering to identify individuals with shared interests before creating neural networks for personalized movie recommendations [8]. Kim et al. presented an accelerometer-based music recommendation system in 2019, considering contextual factors such as emotional and physiological condition, location, time, and activity levels [9]. Dong et al. proposed a fusion deep learning model in 2020, incorporating both audio and lyrics data for music recommendations [10]. CH et al. described a personalized music recommendation system in which they used lyric-based mood prediction and employed collaborative filtering and content filtering approaches [9]. Sakurai et al. introduced the use of knowledge graphs for music recommendation in 2022, offering a solution to the cold-start issue [12].

In the realm of psychological treatment, Dan Wu et al. suggested translating human EEG into music to communicate mental states through music [21]. Hillecke et al. proposed therapeutic approaches involving the use of music, emphasizing the role of recommendation systems in selecting appropriate music for treatment [22]. The present literature review highlights the diverse methodologies and technologies employed in the field of music recommendation systems, showcasing their potential impact on mental health treatment and therapy. The proposed study introduces a music recommendation system based on Cosine Similarity and Count Vectorizer algorithms, contributing to the ongoing efforts to harness the power of technology and music for holistic well-being.

3. MATERIALS AND METHODS

3.1 Music Data Set

The data utilized in this visualization project was sourced from the Kaggle website [29]. This dataset is designed to explore potential correlations between an individual's musical preferences and their disclosed psychological state, if any. The hope is that these discoveries could offer valuable insights into the advancement of Music Therapy (MT) or simply contribute intriguing new insights into the workings of the human mind. A snapshot of the data table is shown in Table 1.

Table 1: Music Data Sample [29]

File Name	Song ID	Genre	Song Name	User ID	Rating	Feeling	Gender
pop1.mp3	1	POP	Beyond	180	5	relaxing	M
pop1.mp3	1	POP	Beyond	176	3	energizing	M

pop1.mp3	1	POP	Beyond	176	3	happy	M
pop1.mp3	1	POP	Beyond	176	4	joyful	M
pop2.mp3	2	POP	To climb	177	2	dreamy	M
pop2.mp3	2	POP	To climb	175	3	happy	M
pop2.mp3	2	POP	To climb	175	3	neutral	M
pop100.mp3	101	CLASSIC	The one that got…	70	5	joyful	M
pop100.mp3	101	CLASSIC	The one that got…	72	3	relaxing	M

3.2 Data Cleaning

In the transformation phase, data cleaning is conducted to ensure that the data is in its optimal condition for subsequent graphical visualizations. This process involves gaining a comprehensive understanding of the dataset's features and identifying any instances of outlier values. In some attributes, such as BPM, Primary streaming service, Instrumentalist, Music effects, and while working, there exist Null values. To address this, a strategy is employed to impute these Null values appropriately. For numerical attributes, the Null values are replaced with the mean, while for categorical attributes, they are substituted with the mode. By implementing the provided Python code, the dataset undergoes a transformation where Null values are substituted with the corresponding values, facilitating a more robust analysis and visualization.

3.3 Exploratory Data Analysis

After importing the necessary libraries and datasets, the initial step involves preprocessing the data, which includes addressing any missing values. The provided code enables us to assess and handle missing values, and in this instance, no missing values were identified. This preparatory phase is essential for facilitating data visualization and analysis. Through exploratory analysis, we can delve into several research questions. The first inquiry pertains to the age groups that exhibit a high frequency of music listening. Visual evidence, in the form of a histogram derived from the dataset [29], highlights that individuals within the age range of 15-25, with a particular emphasis on those around the age of 20, are the most avid music listeners.

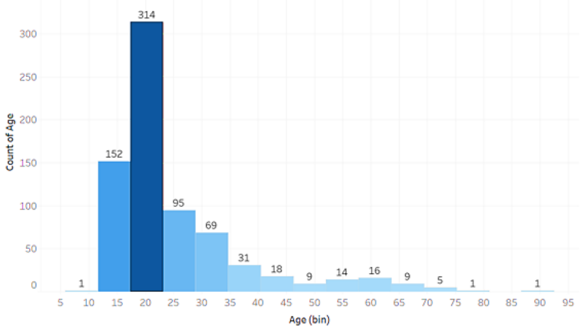

Figure 1. Music listener by age

From the above figure 1, histogram, most of the participants are under 25 years old in the dataset. Most participants listen to music for between 1-4 hours a day. Some people spend many of their days listening to music. While working, performing other chores, or in a career that involves music, there may be background noise. The second research inquiry pertains to the popularity of various streaming services as indicated by the data at hand.

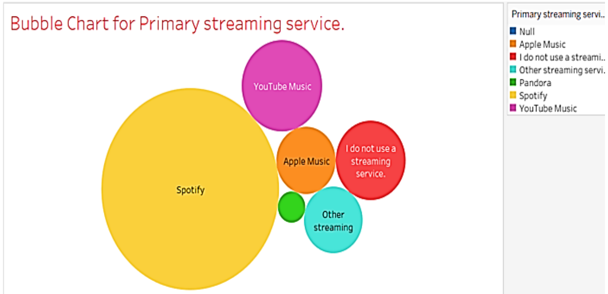

Figure 3. Music streaming services

In figure 2, the bubble chart above illustrates the prevalence of different streaming services among the study participants. The chart reveals that "Spotify" emerges as the predominant primary streaming service, with approximately 62% of all participants opting for it. A noteworthy observation is that Spotify's user demographic skews slightly younger when compared to Apple Music's users. Conversely, Pandora boasts the oldest user base overall, with a median user age just shy of 60 years. The third research inquiry revolves around the willingness of individuals to engage in music listening during their work activities.

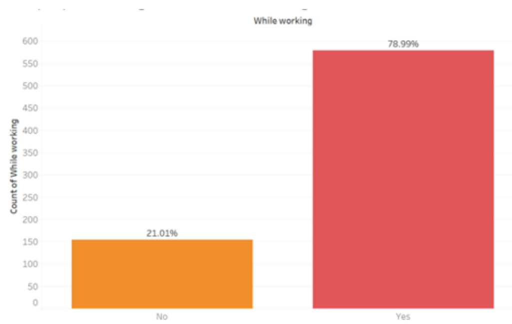

Figure 3. Percentage (%) of people listening to music while working.

As depicted in Figure 3, the bar graph above illustrates that a substantial 78.99% of individuals choose to listen to music while they work. Furthermore, another question arises: what is the distribution of the number of hours respondents spend listening to music per day, and how does this distribution evolve as the number of hours increases from 0 to 24? Additionally, is there a subset of respondents who claim to listen to music continuously for the entire 24-hour duration of a day?

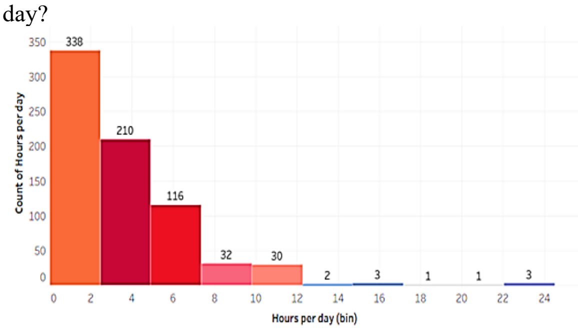

Figure 4. Number of hours listening to Music.

Most survey participants listen to music for 0 to 5 hours each day. After this point, the proportion of respondents who listen to music for five or more hours each day starts to decline nearly exponentially. A few respondents assert that they listen to music 24 hours per day. Another question that emerges is how the duration of music listening varies among individuals who exhibit extreme rankings in various mental health categories, such as insomnia and OCD.

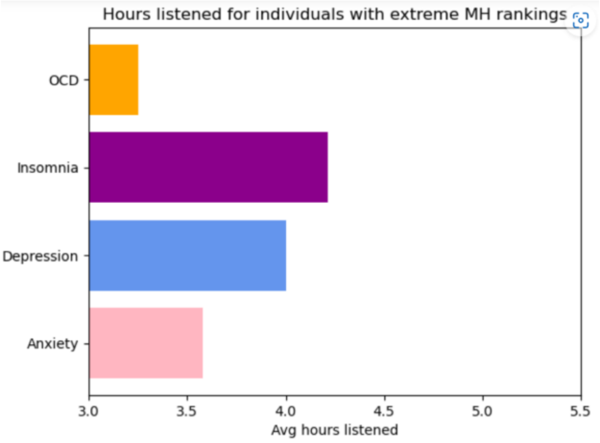

Figure 5. Hours listened to individuals with extreme MH ranking.

An additional inquiry that surfaces is the extent to which the duration of music listening differs among individuals displaying extreme rankings in different mental health categories, including conditions such as dementia.

3.4 Research method

This paper uses a mixed research approach with Design Science Research (DSR), which is a well-known research paradigm widely used in Information Systems, Computer Science, and Engineering. It is particularly useful for developing practical artifacts that address specific problem domains, such as personalized music recommendation systems. These “useful data artifacts” (UDAs) play a critical role in data analysis for system design and machine learning applications [51].

To improve performance analysis using machine learning techniques, a useful data analysis artifact based on ML within a Design Science Research framework was proposed in [52]. This approach can be adopted to develop an effective personalization framework. Machine learning algorithms, such as clustering and classification techniques, can be evaluated using standard performance metrics, including accuracy and F1-score [52]. Figure 6 (modified from [52]) shows the adopted design science approach used in researching artifacts and machine learning algorithms.

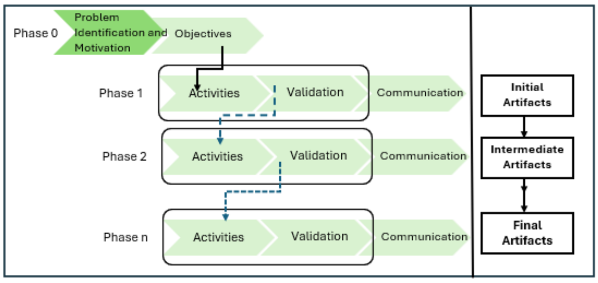

Figure 6. Design Science Framework (adopted from [52]).

This paper adopts the design principles and the framework [52], with machine learning algorithms in music recommendation system design and personalization.

4. MUSIC RECOMMENDER SYSTEM

Making product recommendations that are relevant to the desires of the customers is the main operational objective of a recommendation system. This study has led to the creation of a content-based personal music framework that can stream music and recommend the songs that are most like it.

4.1 The Framework

The framework is split into two sections: the server, or backend, which houses a music database, and the client side, which may access and stream music data from the gaana.com server. The framework and image design of the implemented system are shown in the accompanying figure 7. The biggest and most well-known music streaming service in India, Gaana, has an enormous song library.

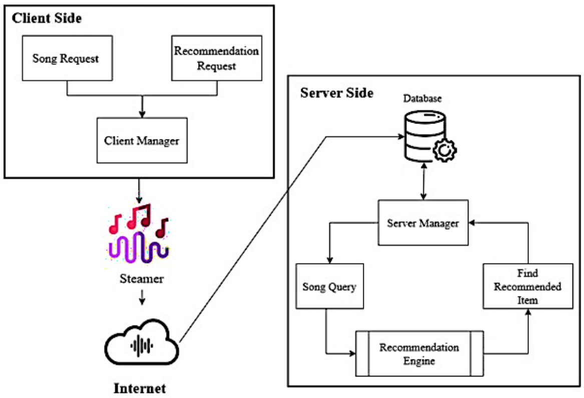

Figure 7. Content-Based Personal Music Framework Diagram

In this study, the music metadata, such as song title, album title, song URL, duration, singers, composers, lyricists, tags, artwork, etc., are fetched from the Python library (Beautiful Soup, Request) and stored in an Excel spreadsheet using Pandas. Despite having a vast music collection, the library could only calculate roughly 5000 (Five Thousand) pieces of music's metadata at a time. Pandas (A Python Library) has accessed data from the Excel sheet to process the data. The recommendation algorithm can do without some more columns like album_id, duration, release_date, lyrics_url, etc. The content-based personal music framework is shown in figure 8.

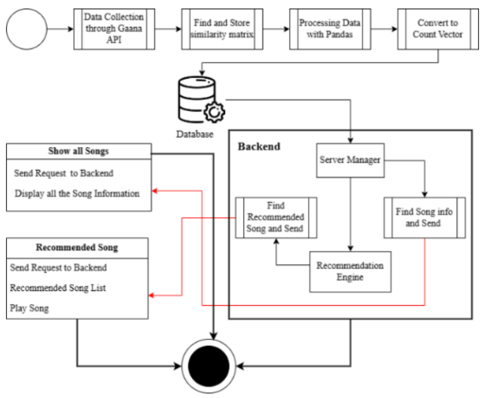

Figure 8. Content-Based Personal Music Framework Diagram

To prevent any form of inaccurate output, the procedure removed any duplicate data and null or empty values. For the recommendation system to produce the right results, whitespace has been eliminated from every value; otherwise, the whitespace would transform each value into a different value. To further use the data for the suggestion component, the essential column is finally concatenated into a single column called "keywords" and stored in a new Excel file (with artifacts).

The system then uses the Cosine Similarity and Count Vectorizer from the Python library. The system analyzes the 'keywords' column to determine how similar each music is to every other song and then stores the similarity matrix in a different database. Finally, we may suggest songs that are comparable using the similarity matrix. The text must first be processed to remove words, a procedure called tokenization, before the data can be utilized for predictive modeling. These words must first be encoded as integers or floating-point values to be utilized as inputs in machine learning techniques.

Table 2. Count Vectorization

Array Item	This	is	The	first	document	Second	And	Third	one
cvText [0]	1	1	1	1	1	0	0	0	0
cvText [1]	1	1	1	0	2	1	0	0	0
cvText [2]	1	1	1	0	0	0	1	1	1
cvText [3]	1	1	1	1	1	0	0	0	0

Observations from the above execution of process –

a. The table 2 shows 9 unique terms.
b. The document has 4 text samples, each rendered as a table row.
c. Each cell carries a number representing the word count in the text.
d. All words are lowercase.
e. The words in the columns are randomized.

Table 3. Indexing of the count vectors

0	1	2	3	4	5	6	7	8
1	1	1	1	1	0	0	0	0
1	1	1	0	2	1	0	0	0
1	1	1	0	0	0	1	1	1
1	1	1	1	1	0	0	0	0

A song can have a variety of qualities such as artists, composers, albums, tags, and so on. All those qualities were converted to term-frequency vectors in the preceding section using count vectorization. These vectors are used to calculate the cosine similarity for each song with the most common frequency vectors. The mathematical expression for cosine similarity between two non-zero vectors is:

$$Similarity = \cos(\theta) = \frac{\vec{A}.\vec{B}}{\|A\|\|B\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i{}^2}\sqrt{\sum_{i=1}^{n} B_i{}^2}} \quad (4)$$

As an Example of finding the similarity:

$$A = [1,1,1,1,1,0,0,0,0]$$
$$B = [1,1,1,0,2,1,0,0,0]$$
$$C = [1,1,1,0,0,0,1,1,1]$$

First, we need to calculate the dot product of each two vectors –

$$A.B \ = \ 1 \times 1 + 1 \times 1 + 1 \times 1 + 1 \times 0 + 1 \times 2$$
$$+0 \times 1 + 0 \times 0 + 0 \times 0 + 0 \times 0 \ = \ 5$$
$$A.C \ = \ 1 \times 1 + 1 \times 1 + 1 \times 1 + 1 \times 0 + 1 \times 0 + 0 \times 0 + 0 \times 1 + 0 \times 1 + 0 \times 1 \ = \ 3$$
$$B.C \ = \ 1 \times 1 + 1 \times 1 + 1 \times 1 + 0 \times 0 + 2 \times 0 + 1 \times 0 + 0 \times 1 + 0 \times 1 + 0 \times 1 \ = \ 3$$

Second, we figure out the Magnitude of vectors –

$$\|\|\|A\|\|\| = \sqrt{12 + 12 + 12 + 12 + 12 + 02 + 02 + 02 + 02} = \sqrt{5}$$
$$\|\|\|B\|\|\| = \sqrt{12 + 12 + 12 + 02 + 22 + 12 + 02 + 02 + 02} = \sqrt{8}$$
$$\|\|\|C\|\|\| = \sqrt{12 + 12 + 12 + 02 + 02 + 02 + 12 + 12 + 12} = \sqrt{6}$$

Finally, we may determine cosine similarity by dividing the dot product by magnitude.

$$Similarity(A,B) = \frac{\vec{A}.\vec{B}}{\|A\|\|B\|} = \frac{5}{\sqrt{5}\sqrt{8}} = 0.790$$
$$Similarity(A,C) = \frac{\vec{A}.\vec{C}}{\|A\|\|C\|} = \frac{3}{\sqrt{5}\sqrt{6}} = 0.547$$
$$Similarity(B,C) = \frac{\vec{B}.\vec{C}}{\|B\|\|C\|} = \frac{3}{\sqrt{8}\sqrt{6}} = 0.433$$

In the preceding example, it can be shown that document A is more like document B than document C. Document C, once again, resembles document A more than document B. As a result, if we need to offer or recommend the most familiar document in comparison to document A, document B will be the most suitable and acceptable.

The recommendation handler modifies the similarity matrix by indexing all values and ranking the similarity from highest to lowest. This information may now be utilized to get the highest similar song index for each song. The data is then transformed and dumped by a python package called pickle for actual recommendation on the system's backend server. Python provides Pickle modules for serializing and de-serializing Python objects such as lists, dictionaries, tuples, and other data structures. There is a method on the flask-based backend server that takes song index as input. It then determines the first ten song indexes stored in the similarity matrix that are most like the given index. The music information is retrieved in the front end by using the API using the index. Our Content-Based Personal Music Framework recommended music to the user in this manner.

4.2. The Proposed Model Design

The 'react-hls-player' ReactJS module is used to broadcast music via the m3u8 file format. Music and video playback systems use the M3U8 file format to store playlists. The playlist is made up of an Internet web route, also known as a URL, and metadata about each song on the list (playtime duration).

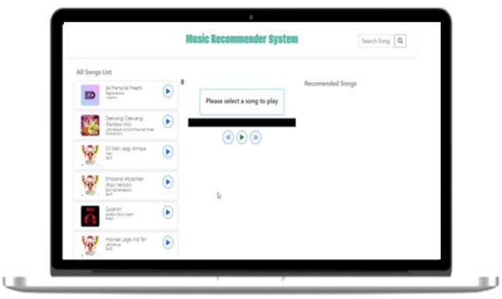

Figure 9. Home Page

Figure 9 depicts the first home page with no song selected. All the songs from the database are listed alphabetically on the left side. Users can play individual songs by scrolling through the music list and clicking the play button next to each one. It displays currently playing song information with audio controls in the middle section. Before recommending a song, it requests that you select or play it. The recommended songs list will appear on the right side (figure 10).

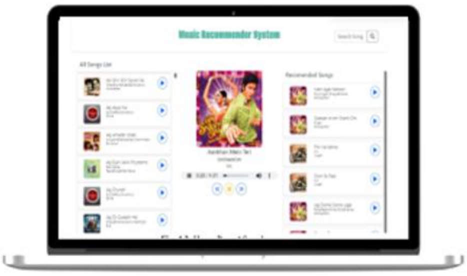

Figure 10. Song Play and recommendation

4.2 The Recommendation System

Based on the user's interests and needs, our Content-Based Personal Music Framework may offer the most similar music to the user. The utility and efficacy of recommended songs must be evaluated. The system is designed as a web-based music player to test this in practice. When testing is run, it is discovered that it may recommend songs that sound the most like the consumers who hear them. The goal of any recommendation system is to increase product sales. Companies usually use recommender systems to increase profitability. The recommender system recommends items that are relevant to the user, which leads to greater product sales and profit for the firm. Even though the recommender system's primary goal is profiting maximization, we will go over a few operational objectives that must be met to achieve this objective in the sections that follow.

4.2.1 Relevance

The main operational goal of a recommendation system is to suggest items that are pertinent to consumers. Relevance by itself, though, is insufficient to provide an effective recommendation system.

4.2.2 Diversity

The variety of a recommender system is another operational goal. There should be several different ways to recommend things. Repetitive suggestions may be the reason a recommendation system fails.

4.2.3 Serendipity

By promoting unexpected things, the recommendation system's significance might be raised. In that it comes as a surprise to the user, serendipity differs from variety. Given that it enables users to discover new areas of interest, serendipity is one of the most crucial elements of a good recommendation system.

4.2.4 Data Collection

The biggest and most well-known music streaming service in India, Gaana, has an enormous song library. We retrieve the music data, such as song title, album title, song URL, duration, singers, composers, lyricists, tags, artwork, etc., using the Python library (Beautiful Soup, Request), and we save it in an Excel spreadsheet using the Python library (Pandas). Even though there was a sizable music collection, we would only get roughly 5000 (five thousand) pieces of music information for the library's calculating cap. 3.9.

4.2.5 Data Preprocessing

Microsoft Excel (xlxs) files are used to store the data that web scraping produces. Pandas (A Python Library) can be used for Tasks involving data processing. For our recommendation system, several more columns—such as album_id, duration, release_date, lyrics_url, etc.—are useless. To prevent any sort of inaccurate outcome, this research deleted any duplicate data and null or empty values, removed whitespace, and combined several columns into one. 3.10.

4.2.6 Relevant parameters

The top hit songs, highest-rated songs, song genre, and user behaviors are not included in this study's analysis of various factors. These factors can be combined to enhance system performance and produce a more relevant and practical music suggestion. The inclusion of the parameters can have a considerable influence on the suggested model's accuracy. Since the parameter data will be extracted as raw data and require processing to be converted into visible information, they also comprise data analysis and mining.

Figure 9 shows the currently playing song information such as song title, album title, artist name, album artwork, and buttons to control music such as play/pause, next, previous. The presently playing song's recommended/related song is now displayed on the right side. It offers three associated tracks with the album title and two with the artist's name.

5.PERSONALIZED RECOMMENDATION

Music therapy is widely applied in personalized dementia care. For example, Gerdner [40] proposed a dementia care model that established person-centered music intervention and demonstrated its effectiveness in improving patients' mood, reducing agitation, and enhancing social engagement. The conceptual model has been further refined in recent studies [41], where a prototype was developed incorporating a reaction-based game and a self-designed protocol for structured data collection and preprocessing to improve implementation and evaluation.

5.1 Personalization

Music-based care has been validated in numerous studies [42], [43] and is widely recognized as a complementary clinical treatment, demonstrating significant reductions in depression and anxiety compared to traditional approaches [42]. Beyond behavioral improvements, neurological evidence further supports the effectiveness of personalized music therapy, showing that distinct brain activity patterns are associated with different types of music [43]. Strong empirical findings indicate that personalization enhances patient engagement and contributes to cognitive benefits [44]. In addition, the use of portable devices, such as tablet-based systems [45], enables the automated delivery of personalized music interventions, thereby improving accessibility and scalability in dementia care settings.

The integration of recommender systems into dementia care has further demonstrated potential for improving healthcare quality. An insightful study [46] emphasizes the role of a knowledge-graph-based recommender system in delivering personalized care to dementia patients while simultaneously supporting caregivers. This approach shows considerable promise in enhancing care quality and personalization. However, the study also highlights the need for continuous system optimization based on caregiver feedback and systematic evaluation of effectiveness, identifying these as important directions for future research. Furthermore, a recent study [47] applied machine learning technique, specifically Random Forest and Support Vector Machine (SVM), to the publicly available music dataset *Emotify* [29], illustrating the growing use of data-driven models in personalized music recommendation research. Hence, with the content based personal music recommendation, a personalized recommender engine can be proposed as figure 11, and the recommendation steps can be extended with the gray-box modeling. Figure 12 shows the steps it can take do a user towards personalized music selection based on the artifacts.

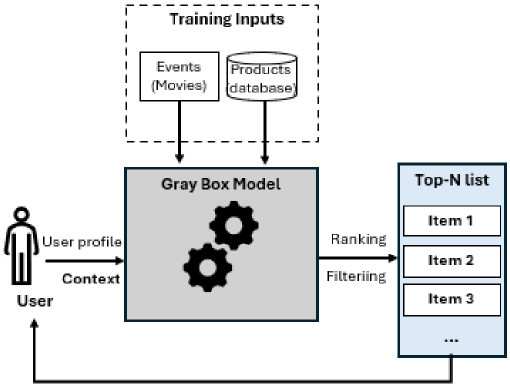

Figure 11. Personalized recommender engine (modified from [18]).

5.2 Recommender engine

To provide recommendations, personalized recommendation systems for music-based therapy examine users' past interactions and interests. The personalized recommender engine [46], which uses AI and machine learning algorithms to analyze user behavior and interaction data to provide tailored recommendations, is at the core of these systems. For instance, the system may classify users according to age groups, including children, adults, and seniors, and assess their past music consumption. It makes music recommendations based on this data, considering the users' past and present likes. The two main components of such a system are (1) the gathering, storing, and indexing of behavioral or personal activity data, and (2) real-time information retrieval facilitated by AI and machine learning algorithms (refer to Figure 10). This is explained in [47].

Through browser cookies, application-based tracking systems, or automatic web crawling, previous user behavior data is gathered with the consent of the user. To facilitate effective random access and quicker retrieval, this data is first cached, if necessary, and then indexed in the recommender system database. Using collaborative filtering techniques, predictive machine learning algorithms like Alternating Least Squares (ALS) and K-Nearest Neighbors (KNN) are used in the second step to produce suggestions.

5.3 Personalize Recommendation

According to [47], the personalized recommender systems use both observable and unobservable user inputs, making them gray-box models. Machine learning algorithms process these inputs to produce insightful suggestions. The possibility of biased recommendations, in which the system reinforces preexisting preferences and may limit exposure to a variety of content, is a drawback of personalized recommender systems.

AI technologies like deep learning and machine learning are used to combine user behavioral data, music selection behavior, and product information, like different music genres, to provide the personalized recommendation. individual needs of users. By examining the user's past behavior, preferences, interests, attributes, categories, and musical qualities, the system forecasts the user's musical preferences and offers tailored recommendation outcomes [30, 31]. Figure 12 shows the detailed steps with user, music database, machine learning algorithms applied on artifacts and final music recommendation.

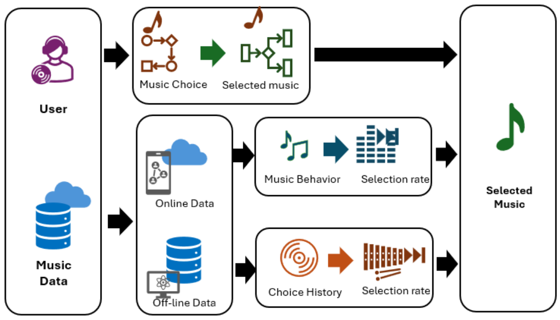

Figure 12. Figure Functional diagram of personalized music recommendation

To increase recommendation accuracy and customer happiness, the suggested personalized recommendation system continuously updates the recommendation algorithm in conjunction with real-time user behavior data and the suggestion strategy. These features enhance user experience and provide commercial advantages. Based on the sample data (as shown in Table I) and ML algorithms automatic and personalized music identification can be performed.

A gray-box recommender system combines interpretable observable similarity with latent factor modeling derived from data-driven learning. Accordingly, the gray-box similarity equation integrates both observable feature-based similarity and latent embedding-based similarity into a unified framework [48 -50]. The gray-box similarity score is defined as:

$$S_{gray}(u,i) = \alpha \cdot \mathrm{Sim}_{obs}(x_u, x_i) + (1-\alpha) \cdot \mathrm{Sim}_{latent}(p_u, q_i) \quad (5)$$

Were,

- x_u= observable feature vector for user u
- x_i= observable feature vector for item (music) i
- p_u= latent embedding of user u
- q_i= latent embedding of item (music) i
- $\alpha \in [0,1]$= balancing parameter

The common choice is the use of cosine similarity (4) in both cases. Thus, the

Observable similarity:

$$\mathrm{Sim}_{obs}(x_u, x_i) = \frac{x_u \cdot x_i}{\| x_u \| \| x_i \|} \quad (6)$$

And, the Latent similarity:

$$\mathrm{Sim}_{latent}(p_u, q_i) = \frac{p_u \cdot q_i}{\| p_u \| \| q_i \|} \quad (7)$$

Thus combining (6) and (7), the equation (5) represents the gray-box similarity,

$$S_{gray}(u,i) = \alpha \frac{x_u \cdot x_i}{\| x_u \| \| x_i \|} + (1-\alpha) \frac{p_u \cdot q_i}{\| p_u \| \| q_i \|} \quad (8)$$

Equation (8) for gray-box modeling can be extended with KNN and alternating least square (ALS), to have better performance [50].

A practical gray-box similarity function with KNN and ALS is defined [50] as:

$$S_{gray}(u,i) = \alpha \cdot \frac{\sum_{j \in N(u)} w_{uj} \, r_{ji}}{\sum_{j \in N(u)} | w_{uj} |} + (1-\alpha) \cdot (p_u^T q_i) \quad (9)$$

Where:

- $N(u)$= K-nearest neighbors
- w_{uj}= similarity weight
- $p_u^T q_i$= ALS latent prediction

6. RESULTS

To justify music recommendation performance, we explore more on the music dataset [29], where the findings indicate the potential for developing recommendation systems with music therapy capabilities. The researchers highlighted the system's ability to assist music therapists in classifying patient-centric musical genres. It's worth noting that this requires therapists to code and pretrain the model.

6.1 Findings

Figure 13 shows the currently playing song information such as song title, album title, artist name, album artwork, and buttons to control music such as play/pause, next, previous. The presently playing song's recommended/related song is now displayed on the right side. It offers three associated tracks with the album title and two with the artist's name.

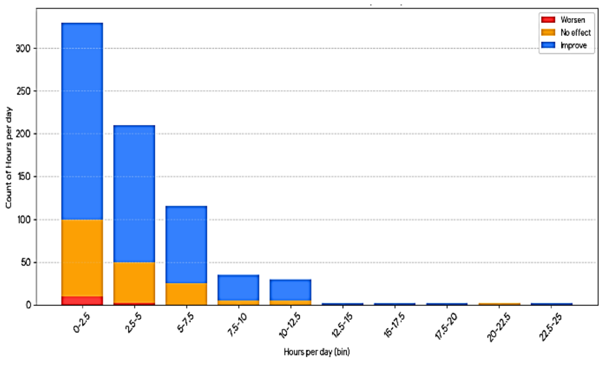

Figure 13. Listening to songs per day vs. mental status

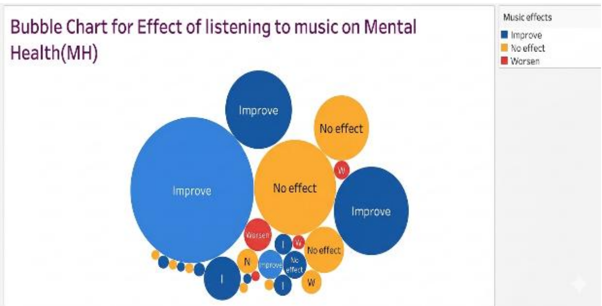

Figure 14. Effect of listening music on mental health

Comparing not listening to any music at all to listening to it for extended stretches of time throughout the day, improvements and no effect from music are demonstrated. However, listening to music between 0-6 hours a day is the majority that worsens mental health issues. The horizontal bar graph, tree map and side-by-side graphs in figure 14, figure 15, and figure 16 respectively, shows the impact of music on mental health.

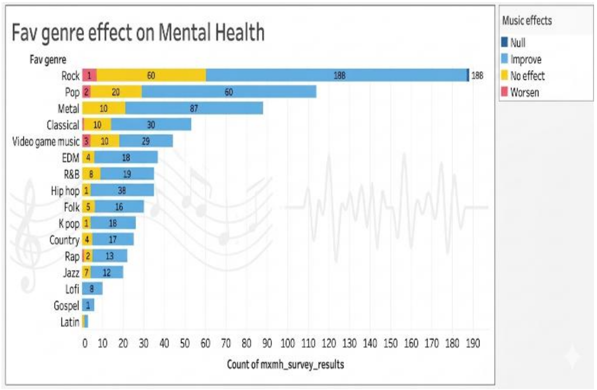

Figure 15. Mental status in different genre listeners

The assumption used in these graphs is that the participant's favorite genre is the one they listen to the most. The music genre breakdown graph above shows that the three genres that are most frequently listened to are rock, pop, and metal. This graph demonstrates that listeners who improved their mental health symptoms across all musical genres. The musical genres that the participants who did have worsened symptoms prefer are rock, rap, pop, and classical.

We employed multiple machine learning algorithms on the "Emotify" dataset using 10-fold cross-validations. The algorithms include Random Tree, LogitBoost, Bagging, Naïve Bayes, and Random Forest. The resulting classification accuracy, precision, recall, and f1-score are documented in Table 3. The ROC curves in Figure 16 and Figure 17 shows the performance of the best (LogitBoost) and the worst (Naïve Bayes) algorithms, respectively.

Table 3. Machine Learning Algorithms

Classifiers	Accuracy	Precision	Recall	F-Score
Random Tree	64.63%	0.728	0.789	0.758
LogitBoost	81.62%	0.817	0.950	0.879
Bagging	68.95%	0.734	0.872	0.797
Naïve Bayes	67.40%	0.749	0.803	0.775
Random Forest	69.35%	0.749	0.844	0.794

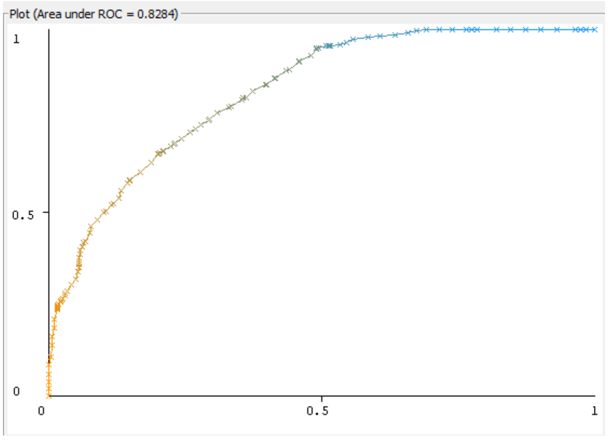

Figure 16. ROC curve for LogitBoost ML Algorithm

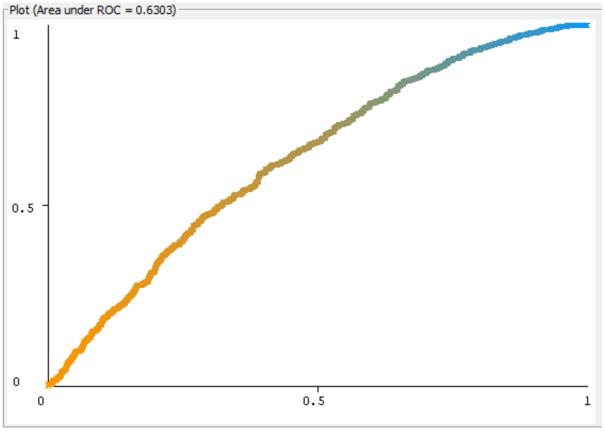

Figure 17. ROC Curve for Naïve Bayes ML Algorithm

6.2 Analysis

It is surprising to see that most of the participants who don't listen to any music at all are under 40. The majority of those who listen to music for more than 6 hours are under 30. Although most participants in this survey are under 25, this makes it difficult to draw conclusions about the listening preferences of older people. It would be interesting to observe the trends for a participant age group that was more evenly distributed.

- Overall, 75% of participants claimed that listening to music made their mental health symptoms better, 23% said it had no effect, and 2% thought it made their symptoms worse.
- According to self-reported scores, most participants exhibited more severe symptoms of anxiety and sadness, while sleeplessness and OCD were the least common conditions.
- Most of the individuals reduced their mental health symptoms by listening to music for 1-4 hours per day.
- Only 5 of the individual's favorite musical genres were shown to have deteriorating impacts. Participants from all genres reported improvements in their mental health symptoms, demonstrating that each person's response to music differs.

7. CONCLUSION

In conclusion, our investigation suggests that music has a positive impact on mental health symptoms, particularly in dementia patients. Future studies should involve a larger pool of volunteers aged 25 and above to comprehensively examine the effects of music on individuals between the ages of 30 and 80. Exploring the influence of music at different times of the day, such as early morning or late evening, could yield valuable insights.

Transitioning to the realm of recommendation systems, we acknowledge the critical role of user interface in machine learning systems. However, our current tools and methods are constrained by a limited dataset of 5000 entries, compounded by the scarcity of music data online, hindering the generation of a sufficiently extensive list of user preferences for precise user-based suggestions. To address this challenge, our upcoming research project aims to create user preferences by extracting data from diverse sources, thereby enhancing computational capacity and reducing reliance on third-party libraries.

The forthcoming iteration of our system will prioritize the essential factors outlined in subsection 3.7, striving for heightened accuracy and user satisfaction. Additionally, efforts will be directed towards refining the User Interface and recommendation algorithm to offer a broader array of options, enhance user experience, and deliver more accurate outcomes.

Shifting our focus to the development of a music recommendation system, our approach involved employing a content-based recommendation algorithm. Despite potential performance differences compared to industry giants, our system provides users with reliable music recommendations. Our study extended beyond recommendation systems to encompass various data science approaches, Python libraries, and insights into the workings of machine learning.

The proposed Content-Based Personal Music Framework, validated through numerous test cases, successfully recommends music with sound characteristics similar to users' preferences. This advancement reconfigures assistive technology [53]–[55] toward therapeutic technology. In essence, the system demonstrates its ability to suggest music that closely aligns with the tastes of its users.

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