https://doi.org/10.31891/csit-2026-1-7

UDC 004.8: 159.9: 78.08

TECHNOLOGY FOR SELECTING MUSICAL GENRES TAKING INTO ACCOUNT HUMAN MENTAL HEALTH BASED ON MACHINE LEARNING

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Received: 04/02/2026
Accepted:11/03/2026
Published:26/03/2026

The research considers the technology of intelligent selection of musical genres taking into account human mental health based on machine learning methods. The relevance of using music therapy as an effective non-drug approach to improving emotional state, reducing stress, anxiety and preventing psychoemotional disorders is substantiated. Modern scientific research on the influence of music on mental health is analyzed, as well as existing approaches to recommender systems in the field of healthcare. A comparative analysis of the performance of various machine learning methods for the task of classifying and predicting the user's psychoemotional state is conducted, based on the results of which the most relevant algorithm is selected. Hyperparameters are selected and optimized in order to increase the accuracy, stability and generalization ability of the model. A concept of a system that provides personalized selection of musical genres according to the individual psychological characteristics of the user is proposed. The compliance of the developed technology with the principles of explanatory and responsible artificial intelligence is outlined, in particular with regard to the transparency of decisions, the ethics of data use and the minimization of potential risks. The consistency of the research results with the UN Sustainable Development Goals is shown, in particular in the context of ensuring well-being, mental health and access to innovative digital technologies in the field of healthcare.

Keywords: mental health, musical genres, machine learning, recommendation systems, intelligent music selection, personalization, psycho-emotional state, explanatory artificial intelligence, responsible artificial intelligence, sustainable development.

Introduction

Mental health is a growing issue today, as more and more people struggle with stress, anxiety, depression, and insomnia. Lack of support, high levels of psychological distress, and limited access to effective treatments exacerbate the problem. Addressing mental health issues may require a holistic approach that combines medical treatment with more natural and accessible methods. One such method is music, which can improve mood and reduce stress and tension. This research is directly related to several Sustainable Development Goals. In particular, the research is fully relevant to SDG 3 Good Health, as finding new, effective, and accessible ways to support mental health is an important challenge today. It is also relevant to SDG 4 Good Education, as knowledge about how music affects mental health can inform educational programs and increase psychological literacy. The connection with SDG 10 Reducing Inequality is important, as music is accessible to almost everyone, regardless of age or social status, and can serve as a universal means of emotional support. In addition, caring for the mental well-being of society helps to build a more cohesive and resilient environment, which is in line with the principles of SDG 16 Peace and justice.

Available scientific data confirm that the regular use of music as a means of emotional self-regulation helps reduce stress and anxiety, which defines it as one of the most accessible ways to strengthen mental health.

The impact of music is individual and depends on musical preferences, the tempo of the composition and the emotional state of the person. In addition, the same music can affect different people differently due to individual tastes and different psycho-emotional states, and regular listening to certain tracks can enhance the therapeutic effect. That is why this emphasizes the personalized selection of recommendations. Therefore, technologies that can automatically select musical recommendations according to a person's psycho-emotional state are becoming relevant.

Available scientific data confirm that the regular use of music as a means of emotional self-regulation helps reduce stress and anxiety, which defines it as one of the most accessible ways to improve mental health [1]. The study [2] combines advances in music research from neuroscience, psychology, and psychiatry to connect the specific foundations of music in human biology with its specific therapeutic applications.

Domain analysis

The study [3] examines the application of Indian classical music and machine learning algorithms to predict and treat anxiety. The aim of the work is to develop a system that assists professionals in treating patients with mental disorders using Indian classical music and machine learning. For this, a dataset was used that includes physiological parameters such as heart rate, blood pressure, sweating, age and gender, as well as musical compositions (ragas) recommended by professionals. The study tested various machine learning algorithms, including logistic regression, SVM, KNN, Random Forest and decision trees, with the SVM model showing the best accuracy of about 87.23%. For practical implementation, a Flask (Python)-based web application was created that allows users to listen to audio files and track their anxiety levels.

The study [4] focused on applying emotional content analysis of music to create therapeutic playlists. The paper presents an optimized sentiment n-gram classifier (OSC) model designed to detect the emotional context of musical pieces. This model allows to automate the process of creating playlists that meet the emotional needs of patients, in particular in the treatment of stress and anxiety.

The study [5] deals with the assessment of the effectiveness of music therapy using machine learning methods. The study involved 320 healthy participants who listened to music for 9 minutes. The level of relaxation was measured using a visual analog scale (VAS) before and after listening. Participants were divided into three categories: increase, decrease, or no change in the level of relaxation. A decision tree was created to predict the effect of listening to music on relaxation. The results showed an overall accuracy of the model of 0.79. Analysis of the decision tree structure revealed important factors that influence the effectiveness of music therapy, including the initial level of relaxation, the combination of education and musical training, age, and frequency of music listening.

The study [6] focused on using physiological signals (EDA, BVP, skin temperature, pupil dilation) and machine learning methods to improve music therapy. The study involved 24 participants who listened to 12 different songs from 3 different genres. Physiological data were collected during the listening session: electrodermal activity (EDA), blood pulse (BVP), skin temperature (ST), and pupil dilation (PD). 34 features were extracted from each signal, and six different feature selection methods were applied to identify the most significant indicators. The data was then processed using a neural network, which achieved high accuracy in classifying music genres (99.2%) and participants' emotional reactions (98.5%). The study also proposed a new technique called "Gingerbread Animation" to visualize physiological signals in video, making them more human-readable and suitable for computer vision methods such as CNN.

The research [7] focuses on using deep learning techniques to identify emotions in music and apply this knowledge to music therapy. To analyze musical compositions, characteristics of key, rhythm, timbre and loudness were extracted and then processed by a convolutional neural network (CNN). The model classified songs into six emotions – happiness, sadness, anger, surprise, fear or neutral – with an accuracy of about 80%. The results demonstrate that such approaches can help tailor musical compositions to users' emotional needs and facilitate personalized music therapy.

The study [8] is devoted to developing a model to predict the effectiveness of music therapy using a combination of Support Vector Machine (SVM) and Artificial Neural Networks (ANN). The aim of the work was to determine which factors – such as age, gender, education level and musical preferences – influence the therapeutic effect of music, and to predict its effect on relaxation. The authors compared different machine learning algorithms, including decision trees, random forest, SVM, ANN and their hybrid, and found that the hybrid SVM-ANN model provided the highest prediction accuracy. The project [9] is investigating the application of machine learning to assess depression levels based on socio-economic and demographic data to detect mental disorders earlier and offer personalized approaches. KNN, neural networks, decision trees, random forest and gradient boosting models were compared using MSE and R^2 Score metrics. KNN and MLP showed high accuracy and ability to take into account local patterns, neural networks are effective for complex nonlinear dependencies. The results emphasize the importance of choosing a model depending on the characteristics of the data and the level of interpretability, creating a basis for further research in the early detection of mental disorders.

A study using the PICO search strategy [10] identified 23 commercially available MDT technologies targeting adults with stress, anxiety, and depressive mood problems. They were classified according to five approaches: user musical preferences, affect parameterization, mood tuning and compensation, neural synchronization, and bio- and neurofeedback. The authors note that basic research in the field of neuroscience and music therapy confirms the effectiveness of these approaches, and the first applied results are encouraging. At the same time, it is emphasized that research into digital music therapies is at an early stage, so larger and more diverse samples are needed to fully realize their potential in promoting mental health and well-being.

The study [11] presents EmoHeal, a comprehensive system that provides personalized three-level support. It analyzes the user's text using an advanced XLM-RoBERTa model and identifies 27 subtle emotions. Next, emotions are transformed into musical parameters using a knowledge graph based on the principles of music therapy (GEMS model, iso-principle).

The CLAMP3 model is used to select audio and video content, which helps to gradually guide the user through three stages - match, guide, and target - from the current state to a calmer one.

The results of the experiment with the participation of 40 people showed a significant improvement in mood ($M=4.12$, $p<0.001$) and high accuracy of emotion perception ($M=4.05$, $p<0.001$). The strong correlation between emotion recognition accuracy and therapeutic effect ($r=0.72$, $p<0.001$) confirms the effectiveness of this approach.

The results obtained prove that EmoHeal can become a scalable and scientifically based tool that implements the principles of music therapy using artificial intelligence.

MediMusic [12] is a B2B service that uses artificial intelligence and machine learning to create audio fingerprints that mimic the brain's response to music. Music is then used as a kind of medicine to reduce pain and anxiety.

The system automatically generates personalized playlists based on predictive analysis that help reduce heart rate and levels of the stress hormone cortisol, as well as stimulate positive hormonal responses - dopamine, immunoglobulin-A and oxytocin. It also helps improve breathing and cognitive functions.

As the user listens to music through the app, their heart rate is monitored to refine the playlist in real time using the Digital Drip system (biofeedback loop). Performance metrics are provided for healthcare facilities to demonstrate cost-effectiveness and cost savings.

MATCH (Music Attuned Technology – Care via eHealth) is an innovative mobile app designed to support family caregivers of people with dementia [13]. Its goal is to help caregivers effectively use music as a therapeutic tool to improve the emotional state and behavior of their residents. The app combines virtual training that teaches caregivers music therapy strategies with an intuitive music interface that allows for easy creation of personalized playlists.

16 caregiver-caregiver pairs living in the community participated in the prototype study. After completing the training, caregivers created their own playlists in the app and applied the skills learned at least twice a week for 8 weeks. To assess the effectiveness of the application, the researchers used quantitative methods: Neuropsychiatric Inventory Questionnaire (NPI-Q) – to measure mental state symptoms, Cohen-Mansfield Agitation Inventory - to assess the level of agitation or aggression, acceptability indicators of the mobile application and virtual training.

The study [14] notes that traditional music therapy suffers from a number of problems that lead to its lack of popularity. However, thanks to the rapid development of artificial intelligence (AI), especially AI-generated content (AIGC), it offers an opportunity to solve these problems.

The research [15] uses statistical and machine learning methods to select a sport based on a human morphofunctional indicators.

Dataset structure

The study used a dataset from Kaggle. The Music & Mental Health (MxMH) dataset was created to find a connection between people's preferences and their mental state [16]. It contains information about favorite genres and styles of music, the number of hours listened to per day, as well as an assessment of psychological state. Such data can help to better understand how music affects a person's emotional and mental state and make music therapy more effective.

From a psychological point of view, this area of study has several important meanings. The data obtained are useful in that they allow us to understand which genres of music reduce stress levels and which, on the contrary, can increase it. This helps music therapists select music according to a person's mental needs. Such studies also have a preventive value, as they help to form recommendations for the widespread use of music as an affordable way to reduce psychological stress. In addition, knowledge about the effects of music can be useful for each person to improve and maintain their own psychological health, especially during difficult periods. In addition, music can be useful in adapting to society, increasing motivation and improving processes such as: attention, memory, concentration and creativity. Figure 1 shows the distribution of listening frequency of each of the 16 genres available in the dataset. Figure 2 shows the most popular genres. Table 1 shows the statistics of listening to the most popular music genres, and Table 2 shows the least popular ones.

It should be noted that this study uses only generalized and depersonalized data, which makes it impossible to identify specific individuals. Personal information of users, in particular information that may directly or indirectly indicate the identity of the respondent, is not collected, stored or processed. The collection of empirical data was carried out through a questionnaire, which was conducted in compliance with the ethical norms of scientific research and the principles of confidentiality. A separate item in the questionnaire provided for informing respondents about the purpose of the study, the nature of the collected data and the possibility of their further use in a generalized form. Participation in the survey was voluntary, and each participant provided informed consent to the processing and publication of the results exclusively in aggregate form. This approach meets modern requirements for the protection of personal data, ethical standards for conducting scientific research and the principles of responsible use of artificial intelligence [15].

Within the framework of this study, data from a selected thematic dataset was used to build and train a machine learning model, which meets the scientific and practical tasks and contains relevant features for analyzing the psycho-emotional state of users. The specified dataset provided the opportunity to conduct experimental verification of the proposed technology, evaluate the performance of the model and compare different machine learning algorithms.

At the same time, the developed technology is not rigidly tied to a specific dataset and is universal in nature. If necessary, it can be adapted to work with other datasets, in particular with expertly verified, clinical or interdisciplinary datasets that meet the requirements of quality, representativeness and ethics. Such flexibility ensures the scalability of the proposed approach, the possibility of its further improvement and integration with new sources of information, and also increases the potential for practical application of the technology in real mental health support systems.

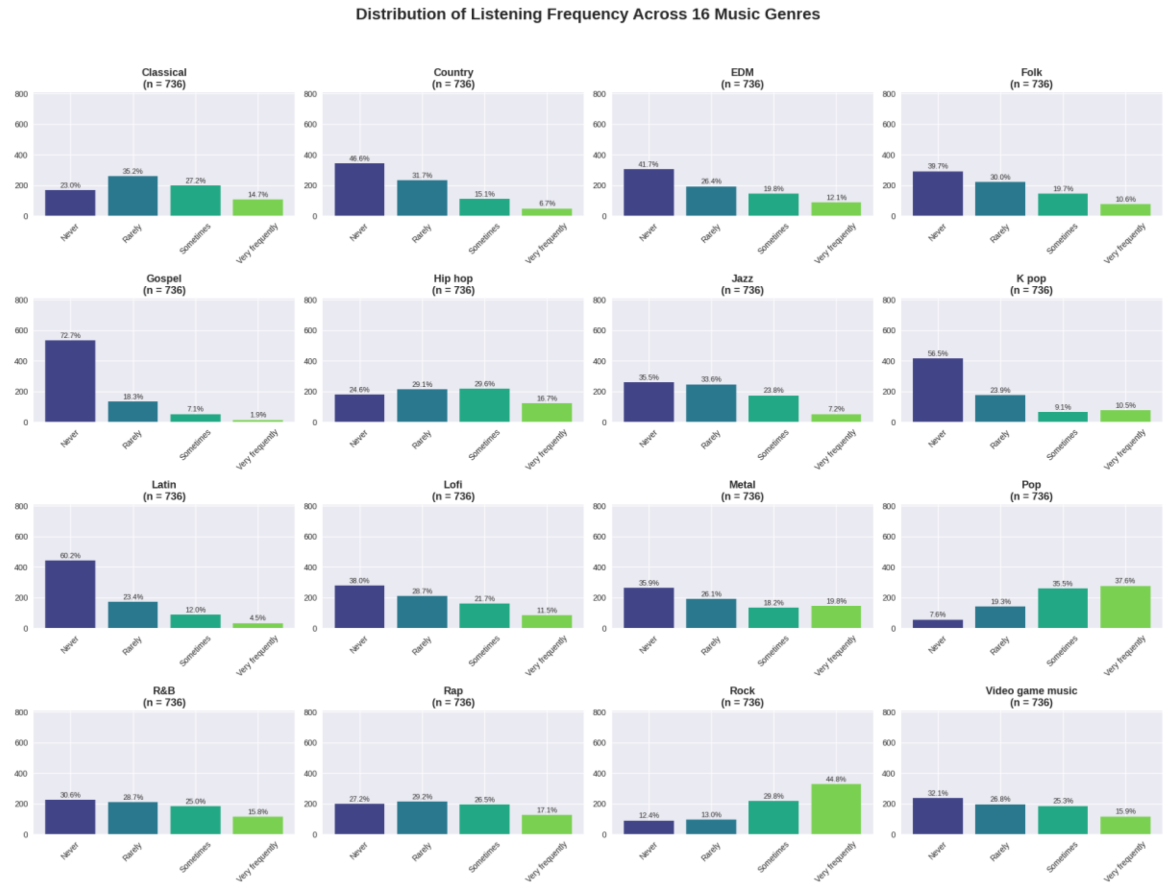

Fig. 1. Distribution of Listening Frequency Across 16 Music Genres

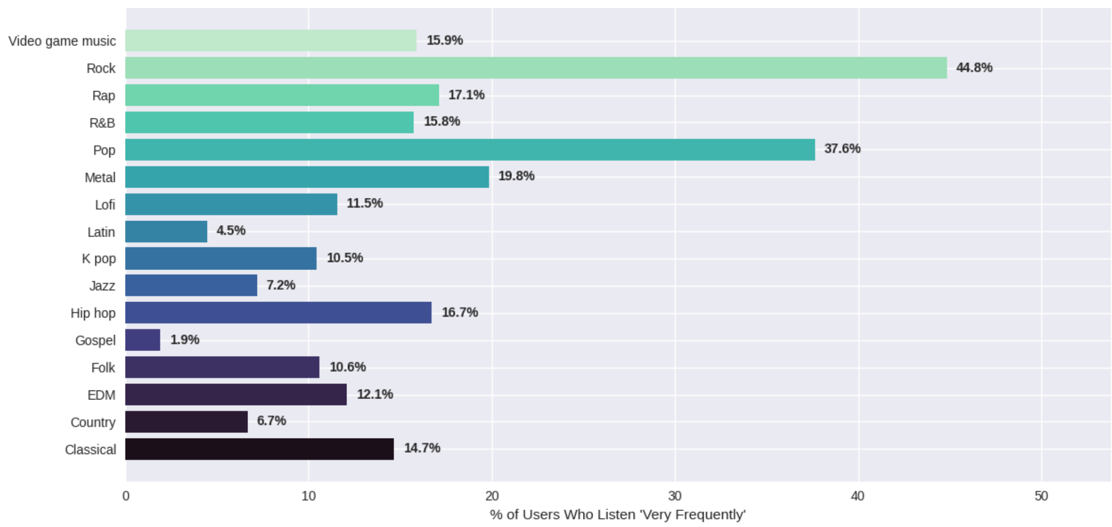

Fig. 2. Popular genres

Experiments

To create a recommendation system, 16 music genres and 14 features were analyzed based on user survey information presented in the dataset. The input features are:

– anxiety level;
– depression level;
– insomnia level;
– obsessive-compulsive disorder (OCD) level;
– age;
– average time listening to music per day (in hours);
– tempo of the song (BPM);
– listening to music while working;
– ability to play musical instruments;
– whether a person creates their own music;
– whether the user is inclined to search for new genres;
– whether the user listens to songs in a foreign language;
– primary streaming service;
– favorite genre.

Table 1

Most popular music genres

Genre	Share among users who listen most often (%)
Rock	44.84
Pop	37.64
Metal	19.84
Rap	17.12
Hip hop	16.71
Video game music	15.9
R&B	15.76
Classical	14.67

Table 2

Least popular music genres

Genre	Share among users who listen most often (%)
Gospel	1.90
Latin	4.48
Country	6.65
Jazz	7.2
K pop	10.46
Folk	10.6

Several machine learning models were selected for the study, including linear regression, decision trees, gradient boosting and its variations XGBoost and CatBoost. None of the considered methods gave an acceptable result for the multiclass recommendation problem. The Macro F1 metric score was lower than or equal to 0.2. Thus, it was decided to apply the technology of selecting model hyperparameters. MultiLogloss CatBoost was chosen as the model. Hyperparameter selection was carried out using the Optuna method. Tuning the model to solve the given problem allowed to significantly improve the performance. The model performance metrics are given in Table 3.

Figure 3 shows the F1 score for each music genre. The F1 score for Gospel and Latin is explained by the low number of users listening to these genres, and therefore the low interest in these genres.

Figure 4 shows the Top-k ranking, which determines the probability of a given genre being in the top k rankings. This means that for 74% of users, at least one of the 3 most popular recommended genres is truly therapeutic for them, based on self-reported improvement and frequent listening.

Since, among the 16 possible genres, on average, about 5 are actually helpful for each person, the model finds at least one real helper in the top 3 for 3 out of 4 users.

Table 3

Model performance metrics

Metric	Value
Macro F1	0.33
Micro F1	0.43
Mean Avg Precision	0.455
Top-1 Hit Rate	0.682
Top-3 Hit Rate	0.743
Top-5 Hit Rate	0.764
Avg true genres	4.91
Avg predicted	3.16

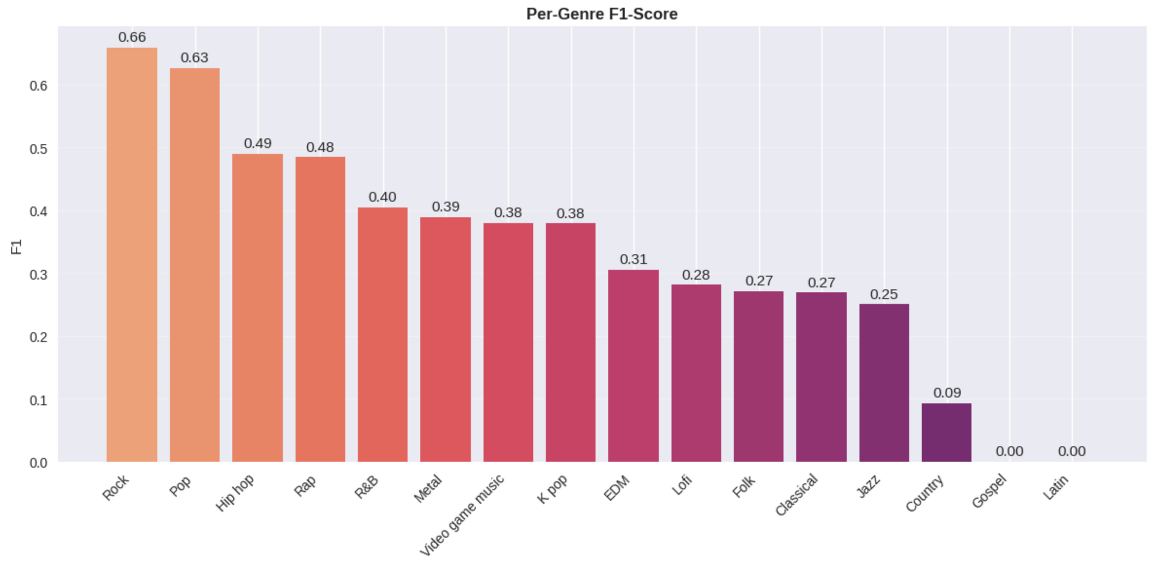

Fig. 3. Per-Genre F1-Score

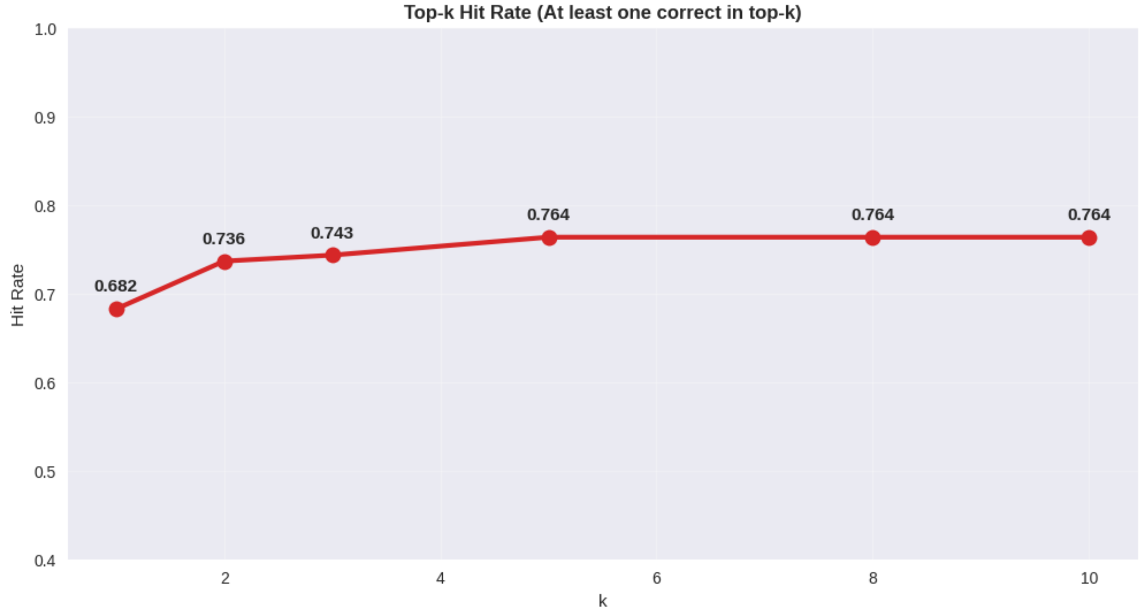

Fig. 4. Top-k Hit Rate

The results obtained show that the impact of music on a person's mental state depends not only on the genre and duration of listening, but also on the context, social conditions and motivations of the user, which is important for more accurate personalized therapeutic recommendations. It should be noted that the impact of music depends not only on the genre and amount of listening, but also on the context, social factors and motivations of the user, which helps to more accurately personalize therapeutic recommendations.

Let's consider the principle of operation of the developed technology. Let there be a user whose survey results in the following parameters:

– Anxiety: 9;
– Depression: 8;
– Insomnia: 7;
– OCD: 5;
– Age: 28;
– Hours per day: 4;
– BPM: 135;
– While working: 1;
– Primary streaming service: "Spotify";
– Fav genre: Rock.

After processing the results, the system calculates the probability of a therapeutic effect for each genre. The result for the given input parameters is shown in Fig. 5.

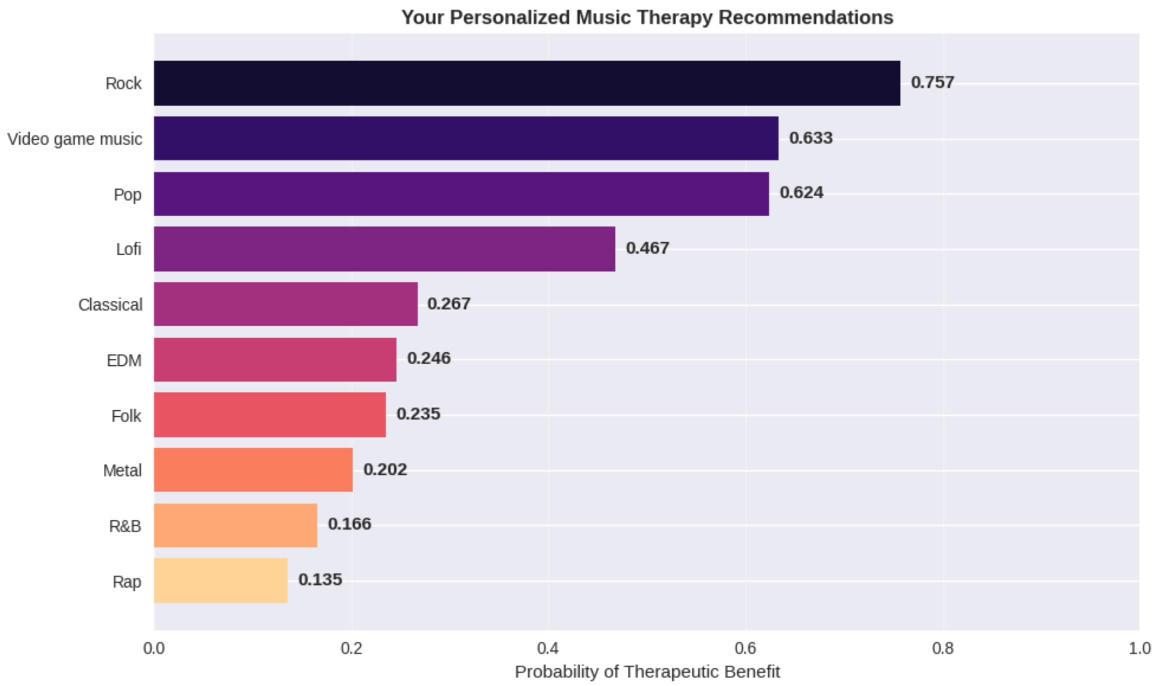

Fig. 5. Example of personal recommendations

Ethical aspects

According to the requirements of the EU AI Act, this project falls under the category of limited risk law, as it works with data on mood and preferences, but does not make critical or medical decisions. That is, the system does not perform medical diagnostics, but only provides recommendations. Also, according to the law, the user is informed about the use of artificial intelligence, gets the opportunity to manage their data, and can refuse recommendations at any time.

In accordance with the ethical principles of HLEG AI, the project ensures complete security, privacy and understandable operation of the algorithm for the user. The user independently reports his emotional state, manages his musical preferences and can change or delete data at any time. The system does not draw conclusions about the user's mental illness and does not offer advice that can replace a doctor. Recommended music is used only as an auxiliary tool to improve the emotional state, but the user himself chooses whether to use it. The user can always view, change or delete his data, as well as control exactly which data the system processes.

The system collects only the data necessary for music analysis and recommendations, namely: music preferences, listening history, emotional state data, as well as technical data such as user actions, recommended music, and interaction time. The data that the user specifies when registering or logging in is used only for personalization. The privacy policy informs that the data is not transferred to third parties, is not used for medical analysis, and can be deleted by the user at any time.

Explainable AI (XAI) is quite important in the project, since the user must understand why the system recommends this particular music track to him according to his psycho-emotional state. The main principles of XAI that the system adheres to include clarity, transparency, and accountability, which means that behind each human decision there is a clearly defined mechanism that can be explained.

In the dataset on which this project is built, you can see the permissions column, which records the users' permission to provide the necessary information.

To make the system as transparent as possible and in line with the principles of XAI (Explanatory Artificial Intelligence), modern methods such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanation) were used. The system also adheres to the following XAI principles: control (you can change your data at any time) and clarity (explanation of the system's operation).

The SHAP method allows you to determine which factors have the greatest influence on the formation of a specific music recommendation, for example, emotional state, genre preferences, sleep time. For example, this method can show that the recommendation was formed due to a high level of stress, a sad mood, or due to previous positive data on the recommended music.

Figure 6 shows SHAP Global Impact on Genre Prediction.

Figure 7 shows an example of SHAP Dependencies: How Anxiety Affects Predicted Lofi Frequency.

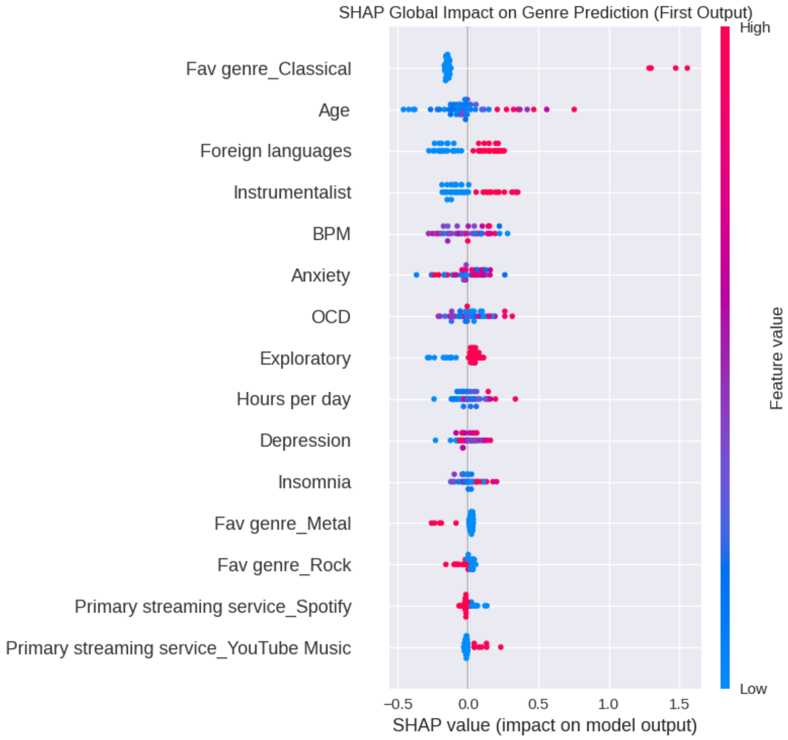

Fig. 6. Example of personal recommendations

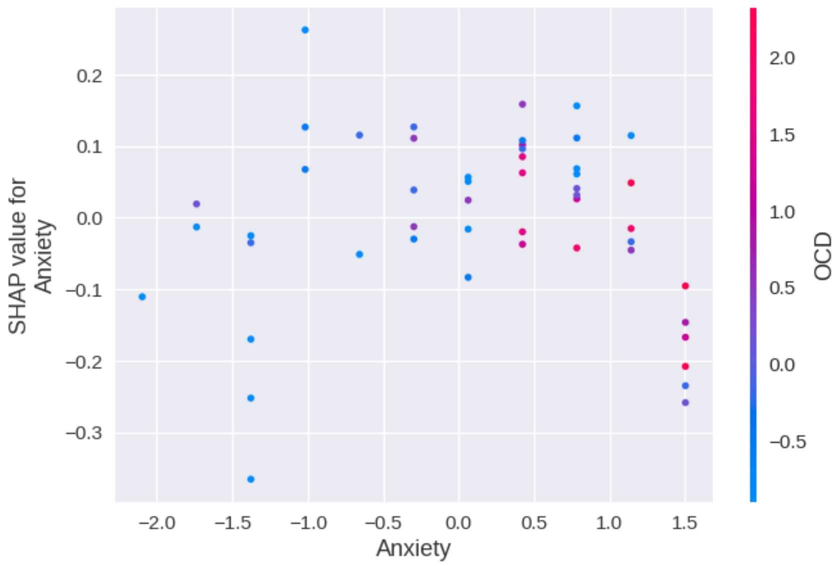

Fig. 7. SHAP Dependence: How Anxiety affects predicted Lofi frequency

LIME helps explain why this particular track was recommended for a certain emotional state. That is, it allows the user to show in real time what indicators influenced a certain recommended music - for example, the model predicts that the mood will improve after listening to the corresponding track. This makes the system's operation transparent and understandable for each user.

The system not only processes data, but also takes into account the user's psychological factors, including emotional state and reactions to music, so that recommendations are truly personalized and beneficial for emotional well-being.

Conclusions

The study developed a personalized machine learning-based system capable of recommending music genres that will create a therapeutic effect for people based on their mental health, listening habits, and music preferences. An evidence-based digital tool was created that can support music therapy interventions and improve mental well-being.

The MultiLogloss CatBoost machine learning model and Optuna hyperparameter tuning technology were used. This approach resulted in a solution that allows 74% of users to choose at least one of the 3 recommended genres that will be truly therapeutic, based on self-reported improvement and frequent listening. Thus, the developed model finds at least one true helper in the top 3 for 3 out of 4 users.

In further studies, it would be advisable to take into account the personality traits and coping strategies of the participants to explain individual differences in the response to music therapy. The improvement of the technology also implies that the recommendations can also take into account the motives for listening to music and the emotional needs of the user to increase the psychological effectiveness of music therapy. It is also advisable to use auxiliary methods such as Feature Permutation Importance to assess the importance of features, which will make it possible to determine whether the emotional state is the key feature or whether the model relies more on the user's musical preferences. It is also worth considering clustering methods, such as k-means, to identify users with similar musical preferences and emotional states. The developed technology complies with the principles of responsible artificial intelligence. The results of the study are also aligned with the Sustainable Development Goals and contribute to the achievement of goals 3, 4, 10 and 16.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

Conceptualization, Vitalii Alekseiko, Olena Petiak and Bohdana Bondarchuk; methodology, Vitalii Alekseiko and Olena Petiak; software, Vitalii Alekseiko and Bohdana Bondarchuk; validation, Olena Petiak and Tamara Petruk; formal analysis, Tamara Petruk; investigation, Olena Petiak and Tamara Petruk; resources, Bohdana Bondarchuk; data curation, Vitalii Alekseiko and Bohdana Bondarchuk; writing – original draft preparation, Vitalii Alekseiko and Bohdana Bondarchuk; writing – review and editing, Olena Petiak and Tamara Petruk.

DECLARATION ON THE USE OF GENERATIVE ARTIFICIAL INTELLIGENCE TOOLS

During the preparation of this work, the authors used Grammarly in order to: grammar and spelling check; DeepL Translate in order to: some phrases translation into English. After using these tools and services, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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ТЕХНОЛОГІЯ ПІДБОРУ МУЗИЧНИХ ЖАНРІВ З УРАХУВАННЯМ ПСИХІЧНОГО ЗДОРОВ’Я ЛЮДИНИ НА ОСНОВІ МАШИННОГО НАВЧАННЯ

У дослідженні розглядається технологія інтелектуального підбору музичних жанрів з урахуванням психічного здоров’я людини на основі методів машинного навчання. Обґрунтовано актуальність використання музичної терапії як ефективного немедикаментозного підходу до покращення емоційного стану, зниження стресу, тривожності та профілактики психоемоційних розладів. Проаналізовано сучасні наукові дослідження впливу музики на психічне здоров’я, а також існуючі підходи до рекомендаційних систем у сфері охорони здоров’я. Проведено порівняльний аналіз ефективності різних методів машинного навчання для задачі класифікації та прогнозування психоемоційного стану користувача, за результатами якого вибрано найбільш релевантний алгоритм. Гіперпараметри вибрано та оптимізовано з метою підвищення точності, стабільності та узагальнюючої здатності моделі. Запропоновано концепцію системи, що забезпечує персоналізований підбір музичних жанрів відповідно до індивідуально-психологічних характеристик користувача. Окреслено відповідність розробленої технології принципам пояснювального та відповідального штучного інтелекту, зокрема щодо прозорості рішень, етики використання даних та мінімізації потенційних ризиків. Показано узгодженість результатів дослідження з Цілями сталого розвитку ООН, зокрема в контексті забезпечення благополуччя, психічного здоров’я та доступу до інноваційних цифрових технологій у сфері охорони здоров’я.

Ключові слова: психічне здоров’я, музичні жанри, машинне навчання, рекомендаційні системи, інтелектуальний підбір музики, персоналізація, психоемоційний стан, пояснювальний штучний інтелект, відповідальний штучний інтелект, сталий розвиток.