POLYHYMNIA Mood – Empowering people to cope with depression through music listening

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ABSTRACT

Depression is one of the largest sources of burden of disease in the worldwide and the development of flexible, timely and easily accessible interventions is considered to be a critical direction for the future. We propose that Mood Regulation (MR) via music listening may be a viable tool support these aims if people have adequate support to make music selections that underpin healthy MR strategies. To this aim, we developed a new app (*POLYHYMNIA Mood*) that automatically generates personalised music playlists for mood elevation and the reduction of depression symptoms. In this paper, we provide an overview of *POLYHYMNIA Mood*and report the results of a preliminary evaluation of its effectiveness and acceptability. Results suggest that listening to *POLYHYMNIA Mood*playlists over a period of 4 weeks led to a large reduction in negative affect and a clinically significant reduction in depression symptoms. Whereas these results should be interpreted cautiously due to the small sample size and the lack of a control condition, they provide support to our approach.

CCS CONCEPTS

• **Applied computing** → **Sound and music computing**; **Health informatics**; • **Human-centered computing** → *Empirical studies in HCI*.

KEYWORDS

Music Listening; Mood Regulation; Depression; Health Intervention; Web App; Machine Learning

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1 INTRODUCTION

Depression is one of the most common and serious types of mental illness worldwide. According to the World Health Organization (WHO) [24], depression affects 322 million people of all ages worldwide and is predicted to become the greatest cause of disability by 2030. Unfortunately, the care that the mental health sector can provide is limited, and a large proportion of the affected population does not have access or receives insufficient treatment. According to the National Institute for Health and Clinical Excellence (NICE) [23], the most common and effective interventions include medicines and psychological therapies. Nonetheless, pharmaco-therapies have several major limitations that limit their effectiveness (e.g., slow onset of action, long periods until actual remission, poor response to antidepressants [25], low remission rates (30-35%), non-adherence to treatment, high costs). Psychotherapies, although relatively more successful [12], have average waiting times of 6 to 9 months [16] and many people cannot access them. Furthermore, a large number of people suffering from depression who do not seek professional help [21] or do not receive adequate treatment for their condition [26].

In this context, the development of easily accessible interventions is a critical direction for future strategies to cope with the incidence of depression. Such interventions should be easily accessible whenever needed to empower people to deal with their condition and keeping depressive symptoms below clinical thresholds, through a reduction of the intensity, duration, and frequency of depressive symptoms in a timely fashion [22]. Unfortunately, such topics have received little research effort [3], and there is an urgent need to conceive new interventions to reach a very large number of people and allow them to cope with their condition independently, timely and in a personalised way.

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1.1 Music, Mood Regulation and Depression

Mood regulation via music listening may be a viable and cost-effective intervention with the potential to reach a wide range of untreated people in a timely way and empower them to cope with their condition at any stage. Indeed, the ability of music to express and induce emotions [15] and act as a powerful tool for Mood Regulation (MR) [31] are demonstrable and research shows that music listening is a commonly used, efficacious, and adaptable device to achieve regulatory goals [35], and a way for people to cope with negative experiences by alleviating negative moods and feeling [18].

Since low mood is a core symptom of depression, music emerges as a potential therapeutic tool, and evidence from two systematic reviews of randomised control trials (RCTs) indicates that music listening over a period of time can lead to a reduction in depressive symptoms [5, 6]. Additionally, music interventions may overcome important challenges in the treatment of depression: they are self-administered, can bring timely treatment to a wider population, are arguably low cost (subscriptions to online music streaming services cost as little as £9.99 per month), and being a passive activity, may lead to higher rates of adherence compared to other treatments due to motivational difficulties to actively engage with treatment when living with depression.

Utilising adaptive MR strategies is vital for mental health [1, 8] and musical mood self-regulation can have harmful effects due to the adoption of unhealthy regulatory strategies that are underpinned by inadequate musical selections. Indeed, people are more likely to use music for MR when already in a low mood [27, 28], and when doing so they often listen to music that expresses the emotions they are experiencing with the aim of releasing/expressing negative feelings (Discharge strategy; [29]). This strategy is functionally equivalent to rumination (a maladaptive MR strategy with potential long-term negative effects on mental health [5]), and various studies show that adopting this strategy has leads to an inability to improve or even worsening of mood (e.g., [20, 34]). Hence, it is of paramount importance to explore strategies that help promote well-being and help listeners to effectively regulate negative emotions by choosing adequate MR strategies and selecting music which supports them.

1.2 Promoting the adoption of healthy MR strategies

Using music for mood elevation involves selecting a healthy MR strategy and matching music selections to this strategy [30], which requires that the listener recognises the emotions expressed by music and the impact of it on their mood. Nonetheless, such process implies a degree of emotional skills and competence which cannot be taken for granted (especially for people with depression), and also that people are aware of the potential consequences of adopting different strategies. Moreover, whereas general purpose music playlists could provide a solution to this problem, individual music pre-dispositions and preferences are central to a successful mood regulation process [32] and have a decisive role in successful interventions [6, 33]. Consequently, if the potential of music to help people coping with depression is to be harnessed, there is a crucial need to develop methods and tools to systematically select music that is tailored to a specific listener in such a way that promotes healthy MR strategies.

In this context, automatically generated user-specific music playlists may provide a large-scale solution to empower people to cope with depression effectively. Music Emotion Recognition (MER) is a transdisciplinary area of research focused on estimating the emotional impact of music through the computational analysis of musical properties. The basic premise of MER is that music communicates and induces similar emotional states in all listeners because musical parameters (e.g. rhythm, melody, timbre, dynamics) encode affective information that is implicitly decoded by listeners. Both music psychologists and computer scientists have provided plenty of evidence that listeners construe emotional meaning by attending to structural aspects of the acoustic signal at various levels [10, 14]. Furthermore, in our past work we have shown that the emotions conveyed by music can be consistently predicted using Machine Learning techniques (e.g., [9–11]). Such work has paved the way for the application of computational models to the automatic selection of music based on its potential affective content and opened new avenues to explore the development of new technological tools for the automatic selection of music for the treatment of depression. This technology has the additional advantage of permitting the generation of user-specific playlists that focus on individual preferences which promotes a stronger involvement in listening to music and the effectiveness of the interventions [6].

1.3 About this paper

We are currently developing a new type of intervention to empower people to use music effectively for coping with depression in everyday life. The aims of the work reported in this paper are the following: (1) to present a new web application (*POLYHYMNIA Mood*) that supports the creation of personalised music playlists; (2) to preliminary evaluate the effectiveness of two playlist generation strategies for mood elevation and the reduction of depression symptoms; and (3) to preliminary evaluate the acceptability of this approach.

2 POLYHYMNIA MOOD

*POLYHYMNIA Mood*is a web application that allows users to automatically generate new music playlists based on their current and target moods. From a technical perspective, it is functionally divided into two core modules: a server backend (where all the processing power is concentrated) and a (lightweight) client frontend (see Figure 1).

The current version works in tandem with Spotify (https://www.spotify.com/). The first time users login to *POLYHYMNIA Mood*they are asked to authenticate their Spotify account and grant permission to access information regarding their saved tracks and playlists (and for creating new playlists). Then, users can select which music tracks they want to add to their personal *POLYHYMNIA Mood*Music Library, and these tracks will be used when generating new personalised playlists (the library can be updated anytime the user wants). Participants were asked to include as much music as possible and as diverse as possible in terms of emotional character (in order to generate playlists that can target a wide range of moods). They were also encouraged to add more music to their libraries if they

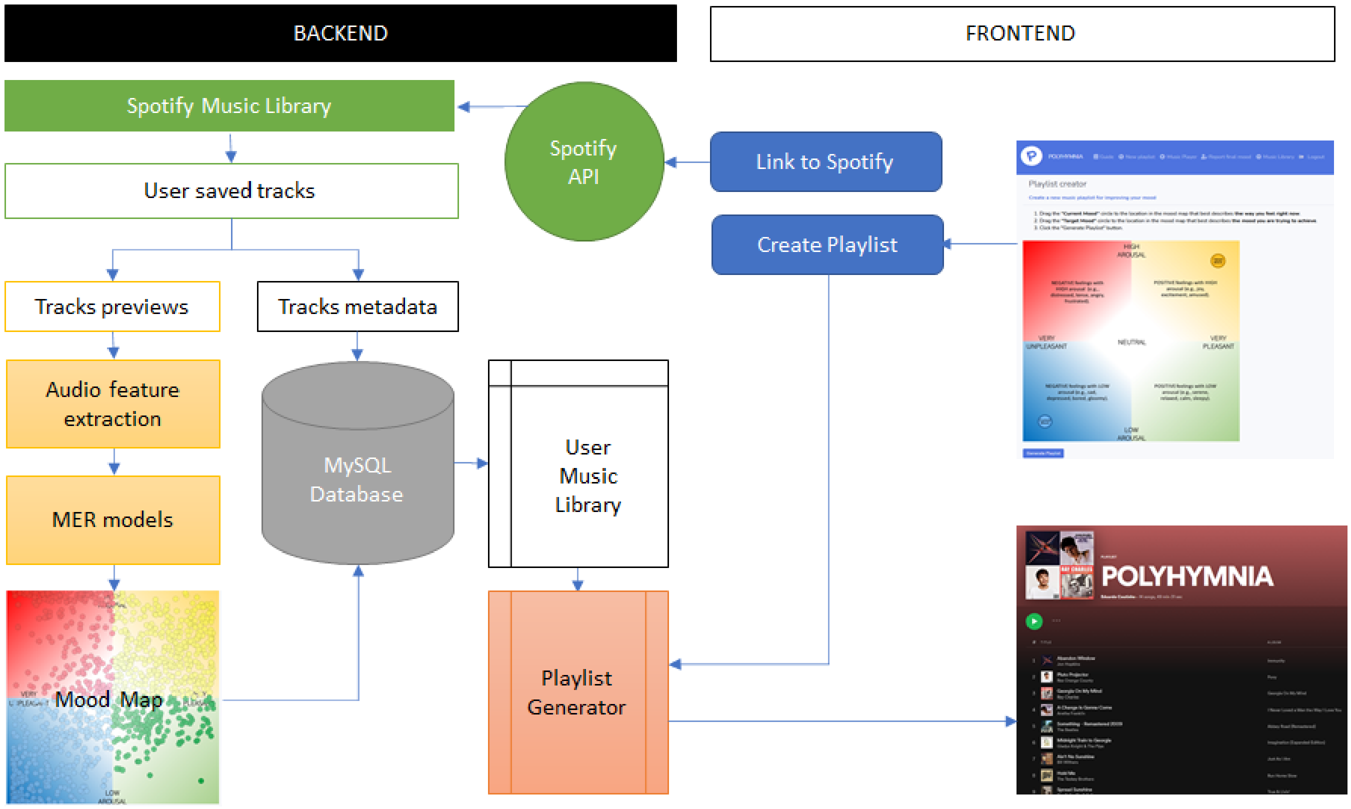


Figure 1: *POLYHYMNIA Mood*: system overview.

believed that it was not very diverse in terms of its emotional character (which they could determine by inspecting a music library Mood Map included within *POLYHYMNIA Mood*; see Figure 2).

Once these steps were completed (and every time the library was updated - either by adding or removing music), *POLYHYMNIA Mood*retrieves all the available information pertaining to the selected tracks from Spotify through its API. Along with general information about the tracks, *POLYHYMNIA Mood*also downloads the 30 seconds audio previews (when available), which are used by *POLYHYMNIA Mood*MER models for estimating the potential emotional impact of each track (see 2.1. From this moment onward, each time users want to regulate their mood they can use *POLYHYMNIA Mood*to generates a new, personalised music playlist (see 2.1.1. Tracks can then be listened to on *POLYHYMNIA Mood*or on Spotify (app or web player).

2.1 Music Emotion Recognition

The playlist generation is underpinned by Machine Learning models that automatically estimate the affective content of a given music track through the analysis of music structure. With these estimations, POLYHYMNIA catalogues a given user's music library and create a Mood Map for each user music library. The general approach for model development was similar to that adopted in our previous work (e.g., [11]). In brief, we used the used the MediaEval Database for Emotional Analysis of Music (*DEAM*; [2]) to develop our models, which includes 1802 songs belonging to 14 musical styles and Arousal and Valence annotations for each track (in this work we used the static annotations, i.e., a single pair of Arousal and Valence values per track). During development, the *DEAM* dataset was split into 5 distinct partitions and a nested cross-validation procedure was used (for each cycle we used 3 folds for training, 1 for validation and another for testing the models). As inputs to our model we used the same feature set used in [11]. Prior to training our regressors, for each fold, both the input features and the target annotations were standardised to zero mean and unit standard deviation, and we applied the Boruta feature selection algorithm [19] on each fold to optimise the input feature set.

In relation to the models, we tested a variety of traditional Machine Learning regressors - Support Vector Machines for regression (SVR), kernel ridge (KR), random forests (RF), k-Nearest Neighbours (kNN), Gaussian Processes (GP), Gradient Boosting (GB) and Multi-Layer Perceptrons (MLPs). Where possible, we also tested single- and multi-task learning frameworks. For each nested cross-validation inner fold, the hyper-parameters of the traditional regressors (e.g., the kernel function of SVRs) were optimised via grid search. Those of the MLPs (number of hidden layers and units per layer), activation functions, optimisers, and dropout rates were fine-tuned using Bayesian methods for hyper-parameter optimisation [4]. All models were implemented in Python 3.7 using Scikit-Learn and PyTorch. From the analysis of the test errors, we found that a SVR with Laplacian Kernel achieved the best results for Arousal

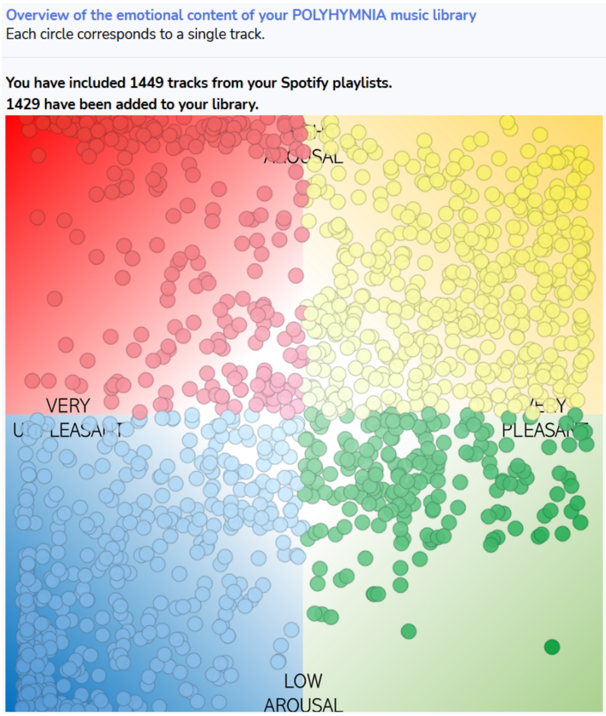


Figure 2: *POLYHYMNIA Mood*: mood map view.

($RMSE = 0.047$) and a RF was the most accurate model for predicting Valence ($RMSE = 0.110$). These two models were used in *POLYHYMNIA Mood*to estimate the emotions expression by each tracks in the users music libraries.

2.1.1 Playlist generation. Evidence from MR research shows that initially mood-congruent responses may spontaneously reverse over time, i.e., there is an active reversal toward mood-incongruent responses [13]. In the music domain only one study has addressed this issue [7]. Results show that listeners with low rumination tendency are compelled to initially select music that is congruent with their low mood, but, over the time course of listening, they gradually tend to select music that is more positively valenced (i.e., incongruent with their initial low mood). People with high rumination tendency do not exhibit this temporal pattern in music selection and fail to achieve mood elevation. Therefore, the interactions between MR strategy and listener characteristics is a fundamental aspect of the effectiveness of the mood elevation process. Musical emotion trajectories that gradually move from low mood congruent music selections towards positively valenced musical selections may help people with tendency for rumination to regulate their mood in healthy ways.

Given its potential for promoting mood elevation, we decided to use this strategy (which we called "dynamic") to generate personalised music playlists with POLYHYMNIA Mood. In practice, we generate a sequence of tracks that progressively transitions from music congruent with the participants mood at the moment of the playlist generation (e.g., sad) to music that is congruent with a target (positive) mood stipulated by the listener (e.g., serene, cheerful). This is achieved by finding the closest tracks (minimising the euclidean distance) to each point on a sequence of equidistant points sampled from a line starting at the the user current mood and ending at the target mood. Once the closest tracks are determined a random track is selected from this set (this is done to allow more variability in the generated playlists).

In addition this strategy, we created a second method that generates a set of music tracks that match a random static mood sitting within users current and targets moods. The aim of this "static" strategy is to offer a comparison condition to the "dynamic" method, whilst avoiding the potentially negative effects of listening to music that matches the participants' low mood. In practice, it mirrors a strategy whereby people will listen to music to divert and forget negative thoughts by listening to music that expresses a different affect (and it is similar to Diversion [29]).

3 EVALUATION

We conducted a pilot uncontrolled trial to preliminary evaluate the effectiveness and acceptability of this type of guided music listening intervention.

3.1 Methodology

Adult participants (18 years of age or older) were invited to a pilot trial evaluating the effectiveness of *POLYHYMNIA Mood*in supporting their MR goals over a period of 4 weeks as well as the acceptability of the approach. Participants were asked to use *POLYHYMNIA Mood*every time they decided to listen to music for MR. In each listening session, participants reported their current and target moods (see Figure 3), and a new playlist comprising 14 tracks (approximately 45 minutes of music) was automatically generated. Participants were randomised to receive 1 of the 2 personalised playlist types described in Section 2.1.1 (i.e., "dynamic" or "static"). At the start and at the end of the intervention period, participants completed measures of depression severity (Patient Health Questionnaire; PHQ-9 [17]) and general mood (Positive and Negative Affect Schedule; PANAS-SF [36]). Participants also completed a series of questions at the end of the study about the ease of use, perceived efficacy, and willingness to recommend *POLYHYMNIA Mood*to friends and family. This study received ethical approval from the University of Liverpool (review reference 5999).

3.2 Results and Analysis

Twenty-four people participated in the study and 12 randomly were allocated to each playlist type before the intervention started. Pre-intervention PHQ-9 scores showed that 8 participants had symptoms of clinical depression (PHQ-9>=10) at the start of the study. The main analysis aimed at determining whether depression severity and the amount of positive and negative affect changed because of the intervention, and we employed a Three-Way Mixed ANOVA with presence of clinical depression at baseline (*PCDB*, 2 levels: $PHQ-9 < 10$ / $PHQ-9 >= 10$) and playlist type (*PT*, 2 levels: dynamic/static) as between-participants factors, time (*T*, 2 levels: pre-/post-intervention) as within-participants factor, and PHQ-9, PANAS-P and PANAS-N scores as outcomes.

3.2.1 Effectiveness. The ANOVA results revealed a main effect of time ($F(1, 20) = 14.771, p = .001, \eta_p^2 = .425$) and a significant

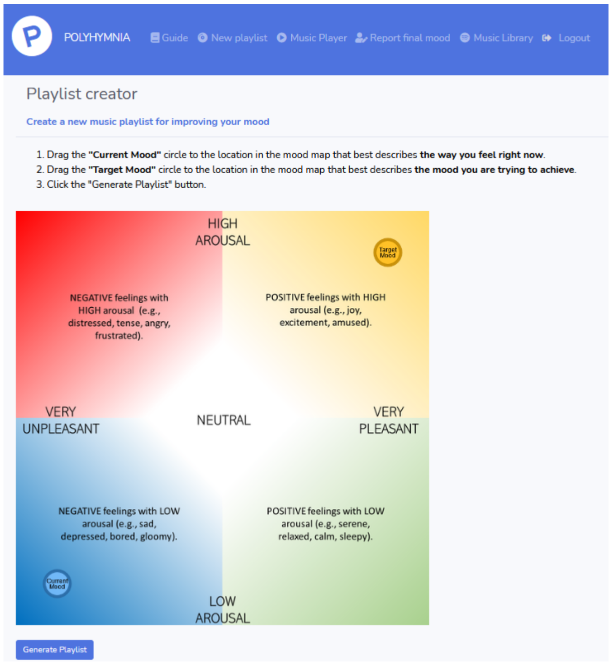


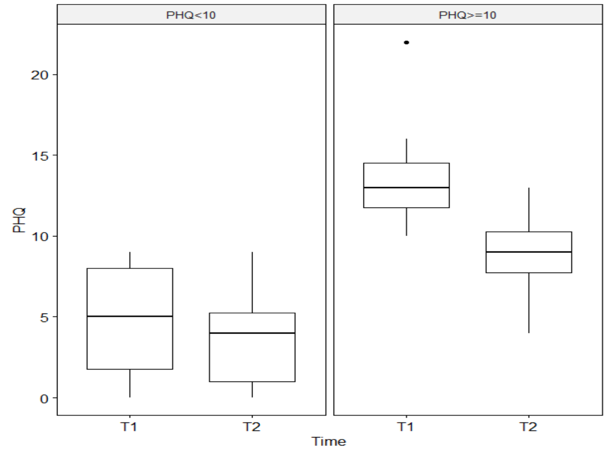
Figure 3: *POLYHYMNIA Mood*: playlist generation view.

$T * PCDB$ interaction ($F(1, 20) = 7.866, p = .011, \eta_p^2 = .282$) on PHQ-9 indicating that the depression scores of people with clinical depression at the start of the study decreased as a result of the intervention ($M_{pre} = 13.3, M_{post} = 7.9$). This reduction is clinically significant (5 or more points; see Figure 4a). We also found a main effect of time on PANAS-N ($F(1, 20) = 59.959, p < .001, \eta_p^2 = .750$) showing a large reduction in negative affect from pre- to post-intervention periods ($M_{(pre)} = 23.8, M_{(post)} = 14.1$; see Figure 4b). No significant effects on PANAS-P (positive affect) were found.

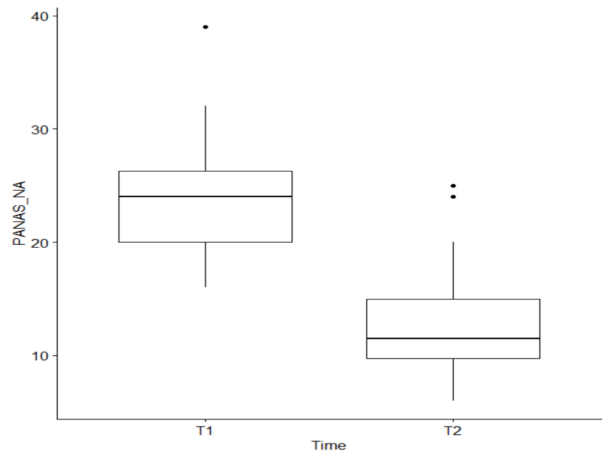
3.2.2 Acceptability. Over the intervention period, participants created and listened to an average of 14 playlists (i.e., an average of 3 to 4 times a week). Usability of the *POLYHYMNIA Mood*app was rated as "Easy" ($M = 4.1$, on a 5-point scale ranging from "very difficult" to "very easy"), it was used 50-70% of the times participants wanted to regulate their mood, and its perceived effectiveness for regulating low mood was rated at 7 (on a 10-point linear scale). On a 10-point scale (ranging from "not at all likely" to "extremely likely"), participants with clinical depression at the baseline would more likely ($p < .05$) recommend *POLYHYMNIA Mood*to friends or family (compared to those without clinical depression at the baseline; $M_{PHQ>=10} = 9.1, M_{PHQ<10} = 6.9$).

4 CONCLUSION

In this paper we proposed that music listening has the potential to help people elevating their mood and reducing depression symptoms, but also alerted to the fact that music listening can be harmful, especially for those people with a tendency for rumination. In this context, we have suggested that it is fundamental to support people adopting healthy MR strategies and empower them to do so when they most need. To do so, we proposed that personalised, automatically generated playlists that implement dynamic MR strategies have the potential to help people elevate their mood and reduce depression symptoms, and we provided preliminary evidence of the effectiveness of this approach: (1) there was a statistically and clinically significant reduction in depression scores for those participants that started the intervention with clinical depression symptoms; and (2) there was a statistically significant large reduction in Negative Affect for all participants. We also determined that this approach was generally well accepted by all participants (especially those with depression symptoms). In sum, we provided preliminary evidence that automatically generated, personalised music playlists can reduce negative affect as well as depression symptoms in people with symptoms of clinical depression. Nonetheless, these results should be interpreted cautiously due to the small sample size and



(a)



(b)

Figure 4: Visualisation of main effects and interactions. (a) Average PHQ-9 before and after the intervention for participants with ($PHQ >= 10$)and without ($PHQ < 10$) clinical depression at the baseline. (b) Average (across all participants) PANAS-NA before and after the intervention.

the lack of a control condition. Indeed, our central aim was to test the approach and not yet to fully evaluate its effectiveness. Current and future future work will focus on providing a more robust evaluation, as well as explore different MR and playlist generation strategies, improve the MER models, and add a variety of new features to improve the usability of the app and the effectiveness of the approach. Our ultimate aim is to conduct a full Randomised Control Trial.

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