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Songs Perceived as Relaxing: Musical Features, Lyrics, and Contributing Mechanisms

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Abstract

How we listen to music has been changing rapidly in the last years, with online streaming becoming more predominant. Besides the gain in accessibility for the listeners, the growth of online services also affords easier access to data for musical analyses. A growing body of research has been showing that daily life music listening serves varied functions, from affect regulation to social bonding. More specifically, the reduction of stress responses is quite pertinent in the contemporary world, and recent studies have highlighted the importance of adequate musical choices. This study aimed to identify the characteristics of music that individuals perceive as favorable to relax and to compare it to the music perceived as unfavorable to relax. Furthermore, the study intended to explore the possibilities offered by the application programming interfaces (API) of services such as the music streaming *Spotify* and the lyrics database *genius* as sources for future work. Answers were collected through an online survey, where the participants provided examples of music tracks (favorable and unfavorable to relaxation). They also rated the contribution of several musical mechanisms to the (in)efficacy of the examples. Musical features were pulled from the Spotify API and the lyrics were retrieved from the genius API through the R package *spotifyr* and then analyzed. The discriminant functions for musical features and perceived mechanisms (Wilks' lambda: .611, $\chi^2(20) = 257.57$, $p < .001$) and for all the variables when lyrics were present (Wilks' lambda: .555, $\chi^2(26) = 202.80$, $p < .001$) were statistically significant. Relaxing and non-relaxing music was successfully distinguished by perceived mechanisms, Spotify features, and two variables related to lyrics. The largest contributors for the discriminant function were the mechanisms *aesthetic value*, *genre/preference*, and *familiarity*, following by the Spotify features *energy* and *loudness*.

Introduction

Our need to relax is a fundamental one: it helps us to recover from stress, anxiety, and tension, and thus fosters our well-being and mental health. The process of relaxation can be defined as physiological (e.g., progressive muscle relaxation) or affective. In this paper, we adopt the latter approach to studying relaxation. Importantly, for clarity, a differentiation should be made between the strategy 'relaxation' and the affective goal 'to relax'. In the paper, we refer to the latter. Affect regulation is an umbrella term encompassing all the efforts of altering or creating an affective change, whether positive or negative (Baltazar & Saarikallio, 2016).

When feeling tense, anxious, or stressed, one expected goal is to relax. We define relaxation as an affective goal operationalized as a decrease in arousal levels and a slight increase in valence. Individuals seek to relax through varied activities – here we focus on music listening, which has consistently been found to serve different functions and help to achieve several goals (for a review, see Baltazar & Saarikallio, 2016). Music listening is often used for affect regulation (Van Goethem & Sloboda, 2011) and, more specifically, for relaxing (Thayer, Newman, & McClain, 1994). Previous studies have shown that individuals increase their music listening when feeling more stressed (Getz, Marks, & Roy, 2014) and that there are several beneficial outcomes when they do so (Pelletier, 2004). Relaxation through music listening has been found to occur in an interplay of musical mechanisms and regulation strategies (Baltazar, Västfjäll, Asutay, Koppel, & Saarikallio, 2019; Saarikallio, Baltazar, & Västfjäll, 2017). Baltazar et al. (2019) conducted an experiment where participants selected relaxing and non-relaxing music and also adequate and inadequate strategies for the goal of relaxing/calming down. After a stress-inducing task, the participants were asked to relax by listening to music and employing the regulation strategy instructed. It was observed that both variables had a significant impact on the success of stress reduction, meaning that when listening to the "right track" and using the "right strategy" the participants relaxed the most. Furthermore, the effect of listening to adequate music (versus inadequate) seemed to be larger than the one of the regulatory strategy.

The selection of music for each moment and the affective goal is often described as immediate, automatic, effortless (DeNora, 1999). Indeed, generally, individuals are quite successful in attaining their desired states through self-selected music and, importantly, their selections are usually more helpful than the ones made by experimenters or experts (Groarke, Groarke, Hogan, Costello, & Lynch, 2019; Liljeström, Juslin, & Västfjäll, 2012). This suggests that familiarity and musical preferences play a crucial role in emotion induction and regulation through music listening.

Previous literature generally describes relaxing music as having a slow tempo, medium pitch, soft non-percussive timbre, gentle contours in melody, flowing beat, simple rhythmic structures, consonant harmony, major mode, and soft loudness (for reviews on the matter, see Tan, Yowler, Super, & Fratianne, 2012; Västfjäll, 2002). However, since most of the studies on musical features are based on expert-selected samples (e.g., Tan et al., 2012), it is still underexplored how these results transfer to self-selected samples.

Aims of the Study

1) Identify musical attributes that best differentiate relaxing from non-relaxing music.
2) Identify mechanisms perceived as most impacting for these effects
3) Explore the lyrics' sentiment content and its contribution

Additionally, an underlying motivation of this study was to test the usability of the data provided by Spotify and genius.com through their Application Programming Interfaces (APIs) in the context of music research.

Method

Participants

The participants were recruited from the population of registered students and staff of Linköping University, Sweden. One hundred and sixty participants answered the survey, from which 121 provided valid and complete answers (48.8% women, 49.9% men, 1.7% selected 'other'). Ages ranged from 18 to 36 (M = 23.3, SD = 3.4). The sample can be characterized as highly engage in music: 79.3% reported listening to music six or more times per week and only 9.2% reported listening less than 5 times per week. Seventy percent of the participants have played some instrument or sang, and from these 28 percent still does. Most of the participants had music classes in school (44.6% up to secondary education), and only three participants had musical training at a conservatory or university levels. As an incentive, the participants were given the chance of entering a raffle for 15 prizes of 100 SEK (approximately 9.60 EUR/10.75 USD).

Procedure

The data were collected through an online survey in Qualtrics (12.2016, Provo, UT). Besides the demographic questions, participants were asked to provide examples of music tracks under the following scenario: "Imagine you are feeling anxious, stressed or nervous, but you need to calm down in order to be able to focus on your work. Whilst in this situation, you decide to listen to some music to help you relax. Which would be good examples of music pieces that would work for you in this kind of situation? Please think of three music pieces that you have used in the past to calm down. Write down the title and artist. And which music pieces you are familiar with and you like but would not work well in this stressful situation, with the same goal of calming down (they can be useful for other situations)? Please think of three examples that would not work for you. Write down the title and artist”. The data from participants that provided at least one musical example were kept for further analyses. In total, 618 musical examples were collected (351 relaxing musical pieces and 267 non-relaxing).

Contributing musical mechanisms. For each example that they provided, the participants were asked to rate a list of musical mechanisms in regards to their contribution to the relaxing/non-relaxing effect by using a continuous slider from “No contribution” to “Very strong contribution”. The list of mechanisms was based on previous studies (Baltazar & Saarikallio, 2016, 2019) and was presented as a) Lyrics, b) Rhythm/ pace, c) Music’s genre/ my preference, d) Identification with the artist, e) Familiarity with the music, f) Memories, g) Beauty/ aesthetic value/ performer’s high skill, h) Emotion/ mood expressed, i) Visual images induced by the music, j) Acoustic features (e.g., timbre, sounds, instruments, roughness/softness, etc.).

All the 618 examples were rated in terms of contributing mechanisms.

Musical features. In terms of audio descriptors, the data were pulled from Spotify’s application programming interface (API) by using the R package *spotifyr*, version 1.1.0 (Thompson, Parry, Phipps, & Wolff, 2017). After providing the tracks’ titles and artists’ names, *spotifyr* returns the audio features and other metrics that Spotify has computed for each track. The audio features compiled for this study and corresponding descriptions can be consulted in Table 1. The duration of the tracks was also extracted in order to calculate the lyrics’ word density. The

Table 1. Audio features and corresponding descriptions provided by Spotify’s API.

Audio Features	Description
Energy	Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy.
Valence	A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry).
Danceability	Danceability describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 0.0 is least danceable and 1.0 is most danceable.
Acousticness	A confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.
Instrumentalness	Predicts whether a track contains no vocals. “Ooh” and “aah” sounds are treated as instrumental in this context. Rap or spoken word tracks are clearly “vocal”. The closer the instrumentalness value is to 1.0, the greater the likelihood the track contains no vocal content.
Liveness	Detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live.
Loudness	The overall loudness of a track in decibels. Loudness values are averaged across the entire track. Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). Values typical range between -60 and 0.
Speechiness	Speechiness detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g., talk show, audiobook, poetry), the closer to 1.0 the attribute value.
Tempo	The overall estimated tempo of a track in beats per minute.

Retrieved and adapted from https://developer.spotify.com/documentation/web-api/reference/tracks/get-audio-features/

features of 65 tracks were not successfully extracted (due to incorrect writing of title/artist by participants or by its unavailability in Spotify's services).

Lyrics. Data were extracted from the API of a lyrics' web database (Genius) by using the functions from the R package *genius* (Parry & Barr, 2019) that are integrated into the package *spotifyr*. The lyrics were pre-processed with *tidytext* version 0.2.0 (Silge & Robinson, 2016). Then, the emotional content of the lyrics was explored through two approaches: categorical and dimensional. The categorical approach was effectuated through the function get_sentiments from *tidytext*, using the *nrc l*exicon (Mohammad & Turney, 2013). For each track, a score was obtained for the emotions sadness, joy, anger, trust, and fear. As for the dimensional approach, the sentiment polarity offered by the package *sentimentr*, version 2.7.1 (Rinker, 2019) was used. This parameter is equivalent to valence, ranging from negative to positive. The function pulls the words' sentiment ratings from polarized dictionaries while taking into account valence shifters (e.g., 'not', 'really', 'very', 'but', etc.). Finally, lyrical density was calculated by dividing the number of words in the lyrics by the duration of the track.

Lyrics were found for around 63% of the cases. Amongst the tracks with lyrics pulled from the database, 95.6% received a complete description in terms of categorical and dimensional sentiment scores (a small percentage had lyrics in other languages than English and, therefore, could not be compared with the polarized dictionary).

Statistical Analyses

Discriminant function analysis (DFA) was chosen to assess the contribution of each independent variable to the categorization of musical examples as relaxing or non-relaxing. DFA is a multivariate test of the difference between groups for a categorical dependent variable and interval independent variables. This analysis provides an indication of how much the two groups of music differ (via the group centroids) and what are the variables that best discriminate between groups (via discriminant loadings). Pairwise comparisons (univariate ANOVAs) were performed to detect systematic mean differences between relaxing and non-relaxing music. Finally, the performance of the DFA functions was assessed through the percentage accuracy in classifying cases into two groups.

Results

The analyses occurred in two steps: first, the whole sample was analyzed in terms of perceived mechanisms and audio features, and then the subsample with lyrics was analyzed in terms of all the discriminating variables. Due to a statistically significant Box *M* test, which indicates that covariances are not equal across groups, the discriminant analyses were conducted using separate covariance matrices. For the same reason, discriminant loadings were preferred over standardized coefficients because the former are not affected by collinearity.

The first DFA was derived for two groups (relaxing and non-relaxing music) using the discriminating variables related to self-perceived musical mechanisms, Spotify's audio features, and lyric density (tracks with no lyrics were scored as zero). The discriminant function was statistically significant (canonical R = .62, Wilks' Λ = .61, $\chi^2(20)$ = 257.572, p < .001) and the highly divergent group centroids indicate that the groups were successfully discriminated by the function (relaxing music: .686, non-relaxing music: -.924). Table 2 presents the descriptive statistics of the discriminating variables, the structure matrix from the discriminant function, and the mean comparisons between groups (relaxing v non-relaxing).

The discriminant loadings in the structure matrix indicate the correlations between the discriminant variables and the function, which are a reflex of the contribution of each variable to the final model. Values equal or higher than .20 denote strong discriminant power. In Table 2, the variables with high discriminant loadings are marked in darker grey shading. The highest loading variables were the self-perceived mechanisms *aesthetic value*, *genre/preference*, *familiarity*, the musical features *energy*, and *loudness*.

Table 2. Descriptive statistics and discriminant function for total sample.

Discriminating variables (a)	Type of variables	Relaxing music (n = 307)		Non-relaxing music (n = 228)		Structure matrix	Mean comparisons	
		M	*SD*	*M*	*SD*	dl	$F(1, 533)$	
Aesthetic value	mechanism	59.443	33.587	27.136	31.596	0.613	127.287	***
Genre/ Preference	mechanism	61.420	29.260	33.763	30.723	0.575	112.001	***
Familiarity	mechanism	52.857	32.355	28.022	29.392	0.496	83.281	***
Energy	audio	0.514	0.264	0.686	0.239	-0.422	60.265	***
Loudness	audio	-10.309	6.191	-6.789	3.550	-0.418	59.244	***
Acoustic features	mechanism	67.153	28.117	49.496	33.960	0.357	43.165	***
Valence	audio	0.346	0.229	0.463	0.241	-0.311	32.879	***
Acousticness	audio	0.379	0.370	0.219	0.297	0.291	28.719	***
Instrumentalness	audio	0.230	0.354	0.098	0.243	0.263	23.518	***
Word density	lyrics	0.073	0.068	0.101	0.084	-0.227	17.474	***
Speechiness	audio	0.060	0.059	0.085	0.084	-0.215	15.656	***
Rhythm	mechanism	73.283	25.855	63.263	33.081	0.213	15.457	***
Identification	mechanism	30.358	31.828	21.096	28.193	0.19	12.197	***
Danceability	audio	0.494	0.173	0.542	0.174	-0.172	9.997	**
Liveness	audio	0.174	0.155	0.200	0.186	-0.097	3.219	
Tempo	audio	121.031	31.582	125.274	28.862	-0.087	2.54	
Contagion	mechanism	69.980	28.077	66.053	31.984	0.082	2.272	
Visual imagery	mechanism	42.831	35.870	40.132	35.107	0.047	0.754	
Memories	mechanism	37.997	34.795	36.794	36.520	0.021	0.117	
Lyrics	mechanism	52.010	37.238	50.895	37.287	0.019		

Note. dl = discriminant loadings (i.e., correlations between discriminating variables and standardized canonical discriminant function)
(a) Ordered in descending order by size of correlation with function
* $p < .05$; ** $p < .01$; *** $p < .001$

In lighter shading, one can see the variables that fell short from the cut-off point score but still achieved statistical significance in the mean comparisons between groups. These include *identification with artist or song* and *danceability*. Looking at the sign of the discriminant loadings and at the group centroids (relaxing music: .686, non-relaxing music: -.924), one can determine to which group each variable is the closest[1].

The accuracy of the function was assessed by the ability to categorize each musical track as either relaxing or non-relaxing. The first DFA achieved an overall classification accuracy of 80.4% (81.1% for relaxing music, and 79.4% for non-relaxing music), which is much higher than the expected accuracy by change (50%).

The second discriminant DFA was derived for the same groups (relaxing and non-relaxing music) using all the discriminating variables (perceived musical mechanisms, audio features, and lyrics data – density and sentiment scores). The discriminant function was statistically sig-

[1] For example, the positive value of the discriminant loading for *aesthetic value* makes it closer to the centroid attributed to relaxing music. Therefore, a high rating in aesthetic value positively predicts the categorization of that example as relaxing music. On the other hand, high *energy* predicts the group of non-relaxing music (while the opposite is also true: low energy is more likely observed in the relaxing music).

nificant (canonical $R = .67$, Wilks' $\Lambda = .56$, $\chi^2(26) = 202.801$, $p < .001$) and the group centroids were highly divergent (relaxing music: .815, non-relaxing music: -.980). See Table 3 for descriptive statistics, structure matrix, and mean comparisons between groups. The shading follows the same coding used in Table 2. The strongest discriminant variables in this subsample were the mechanisms *aesthetic value*, *genre/preference*, and *familiarity*, and the audio features *loudness*

Table 3. Descriptive statistics and discriminant function for subsample with lyrics.

Discriminating variables (a)	Type of variables	Relaxing music (n= 196)		Non-relaxing music (n = 163)		Structure matrix	Mean comparisons	
		M	*SD*	*M*	*SD*	dl	$F(1, 357)$	
Aesthetic value	mechanism	59.005	33.609	25.951	31.299	0.565	91.597	***
Genre/ Preference	mechanism	62.776	28.612	33.534	30.617	0.552	87.210	***
Familiarity	mechanism	54.760	30.932	27.669	29.520	0.498	71.144	***
Acoustic features	mechanism	66.189	28.239	47.110	33.762	0.344	33.995	***
Loudness	audio	-9.017	4.300	-6.624	3.482	-0.338	32.396	***
Energy	audio	0.539	0.237	0.683	0.242	-0.336	32.396	***
Valence	audio	0.368	0.223	0.473	0.246	-0.250	17.923	***
Word density	lyrics	0.112	0.054	0.138	0.069	-0.242	16.724	***
Identification	mechanism	32.250	31.913	20.595	28.793	0.213	12.964	***
Rhythm	mechanism	72.628	25.148	61.779	33.593	0.206	12.213	***
Acousticness	audio	0.327	0.338	0.222	0.297	0.183	9.581	**
Lyrics	mechanism	62.546	31.994	52.110	36.958	0.169	8.220	**
Speechiness	audio	0.064	0.069	0.085	0.087	-0.155	6.924	**
Anger	lyrics	0.045	0.050	0.061	0.071	-0.140	5.603	*
Instrumentalness	audio	0.103	0.240	0.065	0.195	0.096	2.645	
Danceability	audio	0.523	0.157	0.546	0.159	-0.083	1.957	
Sadness	lyrics	0.067	0.060	0.076	0.084	-0.073	1.533	
Visual imagery	mechanism	43.403	34.010	40.227	34.732	0.052	0.761	
Joy	lyrics	0.088	0.093	0.096	0.103	-0.046	0.618	
Polarity	lyrics	0.038	0.163	0.024	0.188	0.044	0.555	
Trust	lyrics	0.073	0.074	0.079	0.084	-0.038	0.414	
Liveness	audio	0.174	0.146	0.181	0.149	-0.029	0.237	
Memories	mechanism	37.908	35.232	36.233	36.888	0.026	0.193	
Contagion	mechanism	68.153	28.686	66.933	30.714	0.023	0.151	
Tempo	audio	123.928	31.647	124.765	28.811	-0.015	0.067	
Fear	lyrics	0.070	0.068	0.071	0.081	-0.008	0.020	

Note. dl = discriminant loadings (i.e., correlations between discriminating variables and standardized canonical discriminant function)

(a) Ordered in descending order by size of correlation with function

* $p < .05$; ** $p < .01$; *** $p < .001$

and *energy.* In comparison to the first function, some differences were observed in this subsample of pieces with lyrics. Namely, the perceived mechanisms *acoustic features*, *identification with artist/song*, and *lyrics* increased their contribution. The audio features *acousticness* and *speechiness*, in turn, decreased their contribution to the function, while *instrumentalness* and *danceability* dropped to non-significant. In terms of lyrics-related variables, word density remained a strong contributor and anger emerged as a weak contributor to the function. The remaining lyric-related variables did not contribute to the function.

This second function was equally successful in classifying group membership (83.6% of the cases and, more specifically, 82.7% for relaxing music and 84.7% for non-relaxing music).

Discussion

This study reached its aims successfully: musical features, contributing mechanisms, and lyrics-related variables discriminated with high accuracy between relaxing and non-relaxing music. As far as we know, this is the first music research study based on data scraped from the APIs of Spotify and genius[2].

Overall, relaxing music was characterized by high scores in *aesthetic value*, *genre/preference*, *familiarity*, *acoustic features*, *acousticness*, *instrumentalness*, *rhythm*, and *identification with artist or song*. On the other hand, non-relaxing music was characterized by high scores in *energy*, *loudness*, *valence*, *word density*, *speechiness*, and *danceability*.

One innovative aspect of this study was the inclusion of three distinct types of data: self-report (perception of the contribution of each musical mechanism), audio features (provided by Spotify), and lyrics-related variables (word density and sentiment content). Although significant variables emerged from all the three categories, lyrics were the least successful category in discriminating relaxing music. Amongst the lyrics-related variables, word density was the most prominent one. Non-relaxing music revealed a higher density than relaxing music, which was a tendency supported by *speechiness* and *instrumentalness*: non-relaxing music had a higher presence of spoken and sang words. This does not mean that relaxing music did not have lyrics – on the contrary, almost two-thirds of relaxing music did have lyrics (196 tracks out of 307), which contrasts with previous research that has found that relaxing music tends not to have lyrics nor vocalizations (Tan et al., 2012). This difference might be partly accounted for by the source of music: our study analyzed music that participants reported listening in daily life, whereas most of the previous research used expert-selected music based on classical repertoire.

Regarding the sentiment of the lyrics, *anger* emerged as a contributing (albeit weak) variable in the distinction between relaxing and non-relaxing, with non-relaxing music showing a higher presence of this emotion. Research on musical choices has been showing two clear patterns: people tend to select music that matches their mood or that helps them reach the desired state. Given the goal to relax, anger would not be an instrumental emotion and the need for self-regulation would direct them away from negative stimuli. There is an overall lack of studies on how lyrics inform this kind of decisions, but the results obtained by Ali and Peynircioğlu (2006) suggest that calm and happy music might be particularly affected when negative lyrics are present.

No similar patterns were found regarding the other sentiment variables (polarity, sadness, joy, trust, fear). The adopted approach of sentiment extraction from lyrics is limited and produces a rather coarse description of the emotional content of the lyrics. Different approaches should be adopted in future studies for comparison (e.g., rating of the overall mood of each piece by experts or by participants; inclusion of other elements of language in the analyses). An alternative explanation is that lyrics themselves do not differ greatly between relaxing and non-relaxing music. That could be expected from relaxing

2 Some exploratory work has been done with the package *spotifyr* and published in the form of blog posts. We acknowledge such material as an inspiration and guide in the early stages of this study (e.g., Elvers, 2018; Thompson, 2017).

music, which is often described in the literature as not having lyrics (Tan et al., 2012). Besides, previous studies suggest that lyrics have a lower impact in the perception of emotions than melodies (Ali & Peynircioğlu, 2006) and that individuals tend to rely more on the expectations towards certain types of music (calm, relaxing, in this case) than on their lyrics (Susino & Schubert, 2019). In fact, looking at the subsample with lyrics, the perceived contribution of this mechanism by the participants to the relaxation effect had a rather weak discriminant loading.

The self-reported contribution of musical mechanisms and audio features were both strongly represented by discriminant variables. The former was present in the top three contributions to the discriminant function for the total sample (*aesthetic value*, *genre/preference*, and *familiarity*) and in the top four in the subsample with lyrics (*aesthetic value, genre/preference*, *familiarity*, and *acoustic features*). Such a significant contribution from self-reported mechanisms highlights the value of adopting a combination of approaches (self-report and computational). The kind of musical mechanisms identified as significantly varying in the function of the music (relaxing or non-relaxing) could have not to be derived from computational methods alone since they are so-called individual-related mechanisms (Baltazar & Saarikallio, 2019).

Despite the role of preferences and familiarity, some patterns tended to be shared by the participants, as seen by the audio features that contributed to the discriminant function. Loudness, energy, valence, acousticness, instrumentalness, speechiness, and danceability successfully differentiated relaxing from non-relaxing music, independently of individual factors. Overall, non-relaxing music was louder, more energetic, more positively valent, higher in spoken words, and more danceable, whereas relaxing music tended to be acoustic and instrumental. According to the model by Baltazar and Saarikallio (2019), audio features increase in significance for goals such as relaxation (categorized as repair- or pleasure-focused), whereas individual-dependent aspects (such as aesthetic appreciation, memories, identification with artist/song…) are more central to affect- or cognition-focused self-regulation. It could be hypothesized that if the participants had been instructed to think of a scenario where they were trying to cope with a problematic situation, there would have been fewer audio features emerging as a discriminant.

The role of aesthetic appreciation is particularly interesting since its contrast between groups was the highest contributor to the discriminant functions. Aesthetic value is identified by Brattico, Bogert, and Jacobsen (2013) as one of the components of musical aesthetic experiences. Considering that participants chose only music they appreciated, it is more likely that the disparate scores stem from the pleasant sensations related to aesthetic experiences rather than from judgments of liking. According to the work of Brattico and Varankait (2019), musical aesthetic experiences are empowering given their contributions to mood, cognitive functions, happiness and quality of life. This phenomenon can also be understood from the angle of musical pleasure, whose strongest emotional constituent seems to be relaxation (Saarikallio, Maksimainen, & Randall, 2019). The present results suggest that participants capitalize on aesthetic and pleasurable experiences as a protective factor against stress.

In terms of absolute rating of contributing mechanisms, the *rhythm/pace of the music* received the highest score from the participants in the relaxing examples and the second highest in the non-relaxing examples. Surprisingly, tempo did not significantly differ between groups and did not fall in the *slow* category typical of relaxing music. It seems thus that the participants' perception might be informed by the rhythm's structure or accentuation (Levitin, Grahn, & London, 2018).

Contagion, the mechanism through which individuals feel the emotion/mood expressed by the music (Juslin & Västfjäll, 2008), was highly rated by the participants independently of the group. Even though we cannot ascertain which emotions were induced by contagion, we can hypothesize that participants felt different emotions in the function of the group and recognized their favorable/unfavorable impact as relatively equal.

Some changes were observed in the discriminating power of the independent variables when looking only at the songs with lyrics. Understandably, the mechanism *identification with the artist/song* increased its discriminant loading, as this effect relies greatly on the message and values transmitted by the lyrics (Lippman & Greenwood, 2012; Van den Tol & Edwards, 2013). As expected, identification processes were especially beneficial for relaxing music. The increase observed in the mechanism *acoustic features* is intriguing, as it does not provide many answers regarding what sonic attributes might have become more relevant when lyrics are present. One hypothesis is that participants valued characteristics specific to the vocals (Demetriou, Jansson, Kumar, & Bittner, 2018).

Conclusion

The present study observed known principles of emotion induction through music in self-chosen samples. Besides confirming that individuals are skillful in selecting appropriate music to relax and that there are transversal features for relaxing music, the results highlight the role of individual-dependent mechanisms such as aesthetic appreciation and familiarity. We propose a stronger focus on participant-selected music and perceived musical mechanisms in future studies, as well as a holistic approach in terms of data sources.

The audio features provided by Spotify's API revealed to be useful and reliable, yielding similar results as previous feature extraction studies. In terms of lyrics' extraction, the results obtained – whilst not proliferous – are promising for future research with more sophisticated sentiment analyses.

References

Ali, S., & Peynircioglu, Z. (2006). Songs and emotions: Are lyrics and melodies equal partners? *Psychology of Music*, *34*(4), 511–534.

Baltazar, M., & Saarikallio, S. (2016). Toward a better understanding and conceptualization of affect self-regulation through music: A critical, integrative literature review. *Psychology of Music*, *44*(6), 1500–1521.

Baltazar, M., & Saarikallio, S. (2019). Strategies and mechanisms in musical affect self-regulation: A new model. *Musicae Scientiae*, *23*(2), 177–195.

Baltazar, M., Västfjäll, D., Asutay, E., Koppel, L., & Saarikallio, S. (2019). Is it me or the music? Stress reduction and the role of regulation strategies and music. *Music* & *Science*, *2*, 1–16.

Brattico, E., Bogert, B. & Jacobsen, T. (2013). Toward a neural chronometry for the aesthetic experience of music. *Frontiers in Psychology: Hypothesis and Theory*, *4*: 206. doi:10.3389/fpsyg.2013.00206

Brattico, E., & Varankait, U. (2019). Aesthetic empowerment through music. *Musicae Scientiae*, *23*(3), 285–303.

Demetriou, A., Jansson, A., Kumar, A., & Bittner, R. M. (2018). Vocals in music matter: The relevance of vocals in the minds of listeners. In E. Gómez, X. Hu, E. Humphrey, & E. Benetos (Eds.), *Proceedings of the 19th International Society for Music Information Retrieval Conference* (pp. 514–520). Paris, France. doi:10.5281/zenodo.1492465

DeNora, T. (1999). Music as a technology of the self. *Poetics*, *27*(1), 31–56.

Elvers, P. (2018). *Sentiment analysis of musical taste: A cross-European comparison*. Retrieved from http://paulelvers.com/post/emotionsineuropean-music/

Getz, L. M., Marks, S. & Roy, M. (2014). The influence of stress, optimism, and music training on music uses and preferences. *Psychology of Music*, *42*(1), 71–85.

Groarke, J., Groarke, A., Hogan, M., Costello, L. & Lynch, D. (2019). Does listening to music regulate negative affect in a stressful situation? Examining the effects of self-selected and researcher-selected music using both silent and active controls. *Applied Psychology: Health and Well-Being*. Advance online publication. doi:10.1111/aphw.12185

Juslin, P. & Västfjäll, D. (2008). Emotional responses to music: The need to consider underlying mechanisms. *The Behavioral and Brain Sciences*, *31*(5), 559–575.

Levitin, D., Grahn, J. & London, J. (2018). The psychology of music: Rhythm and movement. *Annual Review of Psychology*, *69*(1), 51–75.

Liljeström, S., Juslin, P. N. & Västfjäll, D. (2012). Experimental evidence of the roles of music choice, social context, and listener personality in emotional reactions to music. *Psychology of Music*, *41*(5), 579–599.

Lippman, J. R. & Greenwood, D. N. (2012). A song to remember: Emerging adults recall memorable music. *Journal of Adolescent Research*, *27*(6), 751–774.

Mohammad, M. S. & Turney, P. D. (2013). Crowdsourcing a word-emotion association lexicon. *Computational Intelligence*, *29*(3), 436–465.

Parry, J. & Barr, N. (2019). Genius: Easily access song lyrics from genius.com (R package version 2.2.0). Retrieved from https://github.com/josiahparry/genius

Pelletier, C. (2004). The effect of music on decreasing arousal due to stress: A meta-analysis. *Journal of Music Therapy*, *41*(3), 192–214.

Rinker, T. (2019). sentimentr: Calculate text polarity sentiment (Version 2.7.1). Retrieved from http://github.com/trinker/sentimentr

Saarikallio, S., Baltazar, M. & Västfjäll, D. (2017). Adolescents' musical relaxation: Understanding the related affective processing. *Nordic Journal of Music Therapy*, *26*(4), 376–389.

Saarikallio, S., Maksimainen, J. & Randall, W. M. (2019). Relaxed and connected: Insights into the emotional-motivational constituents of musical pleasure. *Psychology of Music*, *47*(5), 644–662.

Silge, J. & Robinson, D. (2016). tidytext: Text mining and analysis using tidy data principles in R. *Journal of Open Source Software*, *3*(1), 37.

Spotify (n.d.). *Get audio features for a track*. Retrieved from https://developer.spotify.com/documentation/web-api/reference/tracks/get-audio-features/

Susino, M. & Schubert, E. (2019). Negative emotion responses to heavy metal and hip-hop music with positive lyrics. *Empirical Musicology Review*, *14*(1–2). doi:10.18061/emr.v14i1-2.6376

Tan, X., Yowler, C., Super, D. & Fratianne, R. (2012). The interplay of preference, familiarity and psychophysical properties in defining relaxation music. *Journal of Music Therapy*, *49*(2), 150–179.

Thayer, R., Newman, J. & McClain, T. (1994). Self-regulation of mood: Strategies for changing a bad mood, raising energy, and reducing tension. *Journal of Personality and Social Psychology*, *67*(5), 910–925.

Thompson, C. (2017, February 12). *FitteR happieR: Finding the most depressing Radiohead song with R, using the Spotify and Genius lyrics APIs*. Retrieved from https://www.rcharlie.com/post/fitter-happier/

Thompson, C., Parry, J., Phipps, D. & Wolff, T. (2017). spotifyr: R wrapper for the 'Spotify' Web API (R package version 1.1.0). Retrieved from http://github.com/charlie86/spotifyr

Van den Tol, A. J. M. & Edwards, J. (2013). Exploring a rationale for choosing to listen to sad music when feeling sad. *Psychology of Music*, *41*(4), 440–465.

Van Goethem, A. & Sloboda, J. (2011). The functions of music for affect regulation. *Musicae Scientiae*, *15*(2), 208–228.

Västfjäll, D. (2002). Emotion induction through music: A review of the musical mood induction procedure. *Musicae Scientiae*, *5*(1 suppl), 173–211.