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Characterizing music for sleep: A comparison of Spotify playlists

Rory Kirk
University of Sheffield, UK

Renee Timmers
University of Sheffield, UK

Abstract

There is widespread interest in the use of music to help with sleep, although there is little clear understanding of the features that distinguish music for sleep from music for other purposes. We asked if music intended to facilitate sleep is distinct from music more generally considered as relaxing by comparing the features of tracks comprising three types of playlist on the music streaming service Spotify. Ninety playlists to facilitate sleep, relaxation and, for comparison, energy were gathered, based on titles and descriptions. Our analysis found significant differences between many of the features of the tracks in the three playlist categories, and nature sounds were prominent in sleep music playlists. A nonlinear classification model correctly classified music from sleep playlists with an accuracy rate of 72%, with brightness being the strongest predictor in distinguishing music from sleep and relaxing playlists. Music from sleep playlists could generally be described as acoustic, instrumental, slower, quieter, and with less energy compared to the other playlists, conforming with previous work. Our results emphasize the importance of timbral qualities in music for sleep and confirm sleep music to be distinct from music for relaxation. The results can be used to guide the selection of music for sleep, and the transition from relaxation to sleep.

Keywords

relaxation, music classification, music information retrieval, brightness, nature sounds

Music continues to attract strong research attention for its potential as a non-pharmacological aid for sleep (Kakar et al., 2021; Wang et al., 2021). To this end, one of the keys to optimizing its use is an understanding of the types and characteristics of music that are most suitable for promoting sleep. Many studies use music with similar characteristics such as slow tempo and little rhythmic or dynamic variation (Jespersen et al., 2015), often referring to recommendations put forward by Gaston (1951, 1968) and Nilsson (2011) for selecting so-called sedative or soothing music. However, researchers have found that survey respondents report using a

Corresponding author:
Rory Kirk, Music Mind Machine, Department of Music, University of Sheffield, Jessop Building, 34 Leavygreave Road, Sheffield S3 7RD, UK.
Email: r.kirk@sheffield.ac.uk

variety of music for sleep that does not necessarily fit the typical description of sedative music (Dickson & Schubert, 2022; Trahan et al., 2018). For example, Dickson and Schubert (2022) found that 59% of songs chosen by respondents had lyrics, contradicting the typical preference for instrumental music in sleep studies. In an analysis of Spotify playlists, Scarratt et al. (2021) profiled sleep music playlists against the Music Streaming Sessions Dataset (Brost et al., 2020) and found that while sleep music generally fits the assumptions of most researchers (instrumental, acoustic, low in energy), playlists demonstrate considerable variability and a wide range of styles.

There seems to be a close association in the literature between music for relaxation and music to induce sleep, and indeed the notion of relaxation is informally used as a basis for selecting music in sleep studies without this relationship having been explicitly investigated (Huang et al., 2016, 2017; Lai & Good, 2005). Considering that sleep can be seen as a "very relaxed behavioural state" (Kräuchi, 2007, p. 241), linking music for sleep with relaxation seems apt, suggesting that winding down and relaxing may be important contributing factors for music to help with falling asleep.

To investigate this relationship, we examined the overlap and distinctions between music for relaxation and music for sleep as defined commercially and by consumers in Spotify playlists. We asked if there is a difference between music for relaxation and music for sleep, or if music for sleep overlaps to a large degree with music for relaxation, albeit in a more extreme form. To facilitate comparison, we compared playlists for the purposes of relaxing and sleeping with playlists for an opposite purpose, that is, of energizing. The analyses focused on distinctions and overlaps between features of music for these purposes. Understanding the differences between them could help to refine and optimize our understanding of the music associated with sleep induction.

Sleep music: Selections and characteristics

Studies investigating the effects of music on sleep have used stimuli in a variety of genres, including Buddhist music (Huang et al., 2016, 2017); Korean pop music (Lee et al., 2019); classical music (Harmat et al., 2008; Oxtoby et al., 2013; L. P. Tan, 2004); Western (including new age, electric, popular oldies, classical, and slow jazz) and Chinese music (Lai & Good, 2005); Chinese, Czech, and Taiwanese music (Chang et al., 2012); Indian music (Deshmukh et al., 2009); Enya (L. P. Tan, 2004); commercial sleep or meditative music (Cordi et al., 2019; Jespersen & Vuust, 2012; Lazic & Ogilvie, 2007; Picard et al., 2014); and music that is otherwise unspecified but described as soothing, relaxing, or similar (Iwaki et al., 2003; Johnson, 2003; Shum et al., 2014). Some studies have used music composed by the researchers themselves or specifically for the study by another composer (Bloch et al., 2010; Chen et al., 2013), while others have allowed participants to bring their own music or choose from a selection of researcher-chosen music (Chang et al., 2012; Iwaki et al., 2003; Johnson, 2003; Shum et al., 2014).

Music is often selected on the grounds that it has particular features, although detailed accounts of these features tend to be sparse, which makes it hard to present selection criteria systematically. The feature reported most often is tempo, typically within the range of 48 to 85 beats per minute (bpm; Jespersen et al., 2015; L. P. Tan, 2004), with a frequent use of tempi around 60–80 bpm (Chen et al., 2013; Huang et al., 2016, 2017; Shum et al., 2014; Su et al., 2013). A comparison of studies describing relaxing and energizing music, respectively, reported tempi around 60–100 bpm for relaxing music (Elliott et al., 2011; Nilsson, 2011; X. Tan et al., 2012) and around 100–133 bpm for energizing music (Etani et al., 2018; Moelants, 2002, 2003, 2008; van Noorden & Moelants, 1999).

As for dynamics, it is often suggested that music for sleep should have a "stable dynamic structure" (Jespersen et al., 2015, p. 15) and "no dramatic changes" (Chang et al., 2012, p. 923). Dickson and Schubert (2022) compared the features of music that survey respondents reported as having been used successfully and unsuccessfully for sleep, using the MIR Toolbox (Lartillot et al., 2008; Lartillot & Toiviainen, 2007) to calculate dynamic variation measured by the standard deviation from the root mean square (RMS) amplitude. There was no difference between the two categories of music in terms of dynamic variation but the music used successfully for sleep tended to be more legato.

Softness is another suggested feature of music for sleep. Scarratt et al. (2021) reported that sleep music in Spotify playlists tends to be quieter than other music, while Cordi et al. (2019) played music at levels between 45 and 50 dB to participants in their study. Nilsson (2011) suggested that soothing music used therapeutically should be played at a maximum level of 60 dB.

Music for sleep has been reported to have "no strong rhythmic accentuation" (Jespersen et al., 2015, p. 15). Indeed, Timmers et al. (2019) found clear differences between the music in sleep playlists and UK Top 40 songs in terms of event density and pulse clarity, while Dickson and Schubert (2022) found that music used successfully for sleep had low-to-medium rhythmic activity.

Some researchers have investigated the spectral features of sleep music compared to other music. Music in sleep playlists was found to have less bright timbres compared to UK Top 40 songs (Timmers et al., 2019), and Dickson and Schubert (2022) found that music used successfully for sleep had a lower main frequency register. Spectral features are not typically described in studies of sleep music, but these results suggest that they should be. Brightness is linked with intensity and perceived energy (Gomez & Danuser, 2007), and has been shown to affect perceived emotion (Eerola et al., 2012, 2013). Spectral centroid, used as a measure of brightness, has been found to correlate with emotional arousal (McAdams et al., 2017; Sievers et al., 2019).

Finally, the analysis by Timmers et al. (2019) showed that sleep music and UK Top 40 songs differ in terms of mode; while Top 40 songs can be major or minor, sleep music was overwhelmingly in the major mode. This suggests that it is important for sleep music to be positively valenced. This has also been found to be the case with music for relaxation, where relaxation is interpreted as having positive valence and offering release from negative tension, not just low activation as may be inferred from the other features discussed so far (Lee-Harris et al., 2018).

In this brief overview, we have identified parallels between the features of sleep music and the features of music that has been found to elicit emotional responses, particularly arousal (Chuen et al., 2016; Coutinho & Cangelosi, 2011; Kim et al., 2019; van der Zwaag et al., 2011), including its rhythmic, dynamic, spectral, and tonal features. The extent to which music for sleep resembles music intended to promote relaxation is as yet unknown, and our study was designed to fill this gap. Furthermore, while some features of music have been reported relatively often, others have not. Accordingly, we aimed to carry out a systematic analysis of a set of features, including brightness and mode, and compare their occurrence in music for sleeping, relaxing, and—for contrast—energizing.

To do this, we analyzed the features of music in Spotify playlists. With around 286 million monthly active users (Iqbal, 2020), Spotify is one of the most popular online streaming platforms. The Spotify Data Catalog (SDC) contains a wealth of data including features of the music on the platform, which can be accessed through its Web API (Application Program Interface). An API is a software intermediary that some web applications provide as a means of accessing data related to their content. Through the Spotify API, it is possible to extract data on the musical features of all the tracks in the SDC, such as their tempo, energy, or duration. This provides a valuable resource for researchers wishing to analyze music used in different ways (Barone et al., 2017).

Methods

Data collection

Data were collected from the SDC using the Spotify Web API and the Spotipy library in Python. Two of the tools available in the Web API were used to extract musical features: Audio Features, which provides global values for a selection of musical features for each track; and Audio Analysis, which returns additional features for individual tracks according to tatums,[1] beats, bars, segments, and sections. We included part of the timbre object provided by the segments breakdown. This returns a vector with 12 values per segment that represent different aspects of the spectrogram. The first four values correspond to loudness, brightness, flatness, and attack. To include brightness in our analysis, we averaged values across segments to obtain an overall brightness value for each track. Table 1 presents the full list of features included in our analysis, and their descriptions.[2]

A list of Spotify playlists and their corresponding IDs were gathered using the search function in the Spotify web player.[3] Playlists for sleeping and relaxing were gathered using the search terms *sleep** and *relax**, respectively. Playlists for energizing were gathered using the search terms *energi** (to accommodate different spellings and variations, e.g., energise/energize, energizing, etc.), *dance*, and *workout*. The latter were included as *energi** proved to be a relatively limited search term. Other search terms were considered but these three were deemed sufficient to capture the energizing theme. Playlist names, creators, and IDs were logged for input into the Spotipy script.

In order to balance the selection, 30 playlists of at least 50 tracks each were collected in each category (hereafter referred to as Sleep, Relaxing, and Energizing playlists), by order of search appearance. This resulted in a set of 90 playlists consisting of a total of 17,274 tracks (see Appendix 1 for a complete list of the playlists included). Titles of playlists indicated themes such as Jazz for Sleep and Relaxing Guitar Music and the number of tracks in each playlist varied considerably, from 50 to 1,159 tracks in a single playlist. To reduce potential bias from this imbalance, we took a random sample of 50 tracks from each playlist. This resulted in a total of 4,500 tracks (1,500 in each category) for the analysis.

Analysis

The analysis consisted of three phases. First, we compared the values of the Spotify features (see Table 1) in each track across the three categories of playlist (Sleep, Relaxing, and Energizing). Next, we used principal component analysis (PCA) to investigate linear relationships between features and groups of features according to their shared components. Finally, we used nonlinear data-driven modeling to test the ability of features to predict the category of playlist in which the tracks could be found accurately and assess the extent to which each feature contributed to this prediction. We conducted nonlinear modeling using the Statistics and Machine Learning Toolbox in MATLAB. We performed all other statistical analyses in SPSS. We used Laerd Statistics (https://statistics.laerd.com/) for guidance on procedure and reporting. We normalized all continuous data to values between 0 and 1 prior to analysis.

Table 1. List and descriptions of Spotify features extracted for this study.

Source	Feature	Description
Audio features	Acousticness	A confidence measure from 0 (low) to 1 (high) of whether a track is acoustic
	Danceability	Describes how suitable a track is for dancing from 0 (low) to (high) 1 based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity
	Duration	The duration of a track in milliseconds
	Energy	A perceptual measure of intensity and activity, measured from 0 (low) to 1 (high). Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy
	Instrumentalness	A measure indicating the likelihood that a track contains vocals, from 0 to 1, where values closer to 1 indicate a greater likelihood the track contains no vocal content
	Liveness	Indicates a probability that a track was performed live, from 0 to 1. A value above .8 suggests a strong likelihood that a track is live
	Loudness	The overall loudness of a track in decibels (dB)
	Mode	A binary indication of whether a track is major or minor. Major is represented by 1 and minor by 0
	Speechiness	Detects the presence of spoken words in a track, from 0 to 1, with values closer to 1 suggesting a recording is more exclusively speech-like (e.g., talk show, audio book, poetry)
	Tempo	The overall estimated tempo of a track in beats per minute (bpm)
	Valence	A measure from 0 (low) to 1 (high) describing the musical positivity conveyed by a track
Audio analysis	Brightness	A measure of levels of upper-mid- and high-frequency content. The value from Spotify is one of twelve measures related to the spectrum of a track that make up their timbre object

Source: Descriptions are adapted from the Spotify documentation. The full documentation on the available features can be found online: https://developer.spotify.com/documentation/web-api/reference/#/operations/get-audio-features, accessed 06/11/2023.

Results

Univariate tests

The violin plots in Figure 1 show the distribution of the values for the Spotify features of the tracks in each playlist category. The medians and distributions of these values suggest a trend typically decreasing from Energizing to Relaxing to Sleep. For example, tracks in these three playlist categories became progressively slower, quieter, and less bright. Other features such as the Acousticness and Energy of the tracks in the Sleep and Relaxing playlists had similar values, which were distinct from the tracks in the Energizing playlists. Tracks in the three playlists had similar values for Duration, Liveness, and Speechiness, as they were all mostly less than 4 min long, recorded in studios rather than live, and rarely included spoken words.

Many of the features failed to meet the assumptions of normality of distribution, as assessed by visual inspection of histograms and confirmed by z-score calculations of skewness and

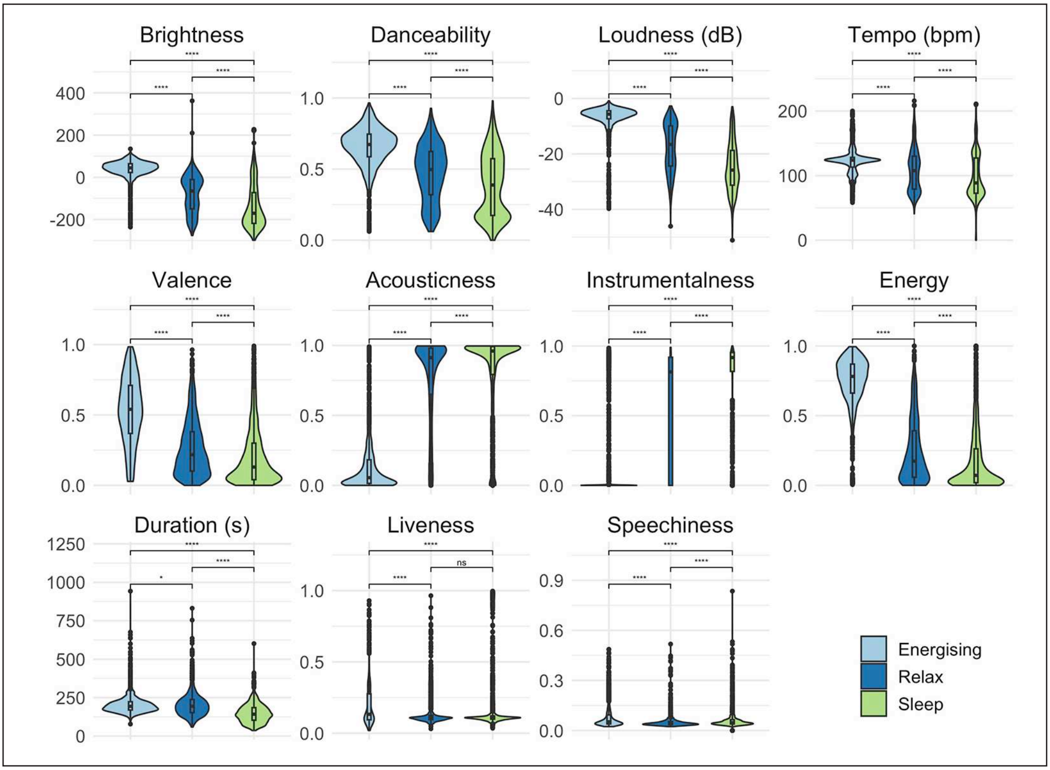

Figure 1. Violin plots of features by playlist category, original values (duration converted to seconds).
Note: All pairwise comparisons significant except Liveness between Sleep and Relaxing playlists.
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

kurtosis. We therefore used non-parametric tests to compare the features of the tracks in each playlist category.

Because Mode is a dichotomous dependent variable, we used a chi-squared test of homogeneity, and post hoc pairwise comparisons using the *z*-test of two proportions with a Bonferroni correction, to identify potential differences between the proportions of tracks in the minor mode in the three playlist categories. The chi-squared test was statistically significant ($p = .001$), as were all pairwise comparisons: 47.7% (716) of the tracks in the Energizing playlists were in the minor mode, compared to 32.9% (494) in the Relaxing playlists and 26.1% (391) in the Sleep playlists.

We used Kruskal–Wallis H tests, and pairwise comparisons using Dunn's (1964) procedure with a Bonferroni correction, to compare the values for all the other Spotify features of the tracks in each playlist category. With one exception (Liveness in the Sleep and Relaxing playlists, as shown in Figure 1), the pairwise comparisons were all statistically significant. The tracks in the Sleep playlists tended to be acoustic and instrumental, with lower values for all the other features in the tracks in the Relaxing and Energizing playlists, particularly Brightness, Danceability, Energy, Loudness, Tempo, and Valence.

We then went on to conduct a PCA to provide insight into how groups of features, rather than individual features, may contribute to the differentiation between playlist categories.

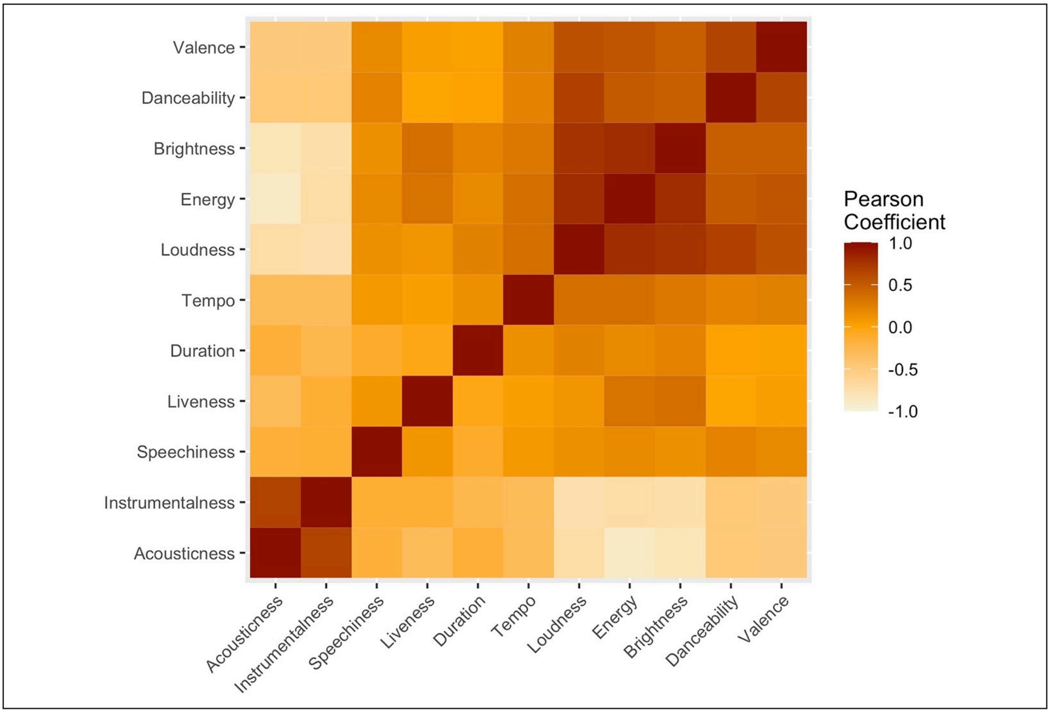

Figure 2. Heatmap of correlations between features, clustered hierarchically.

Principal component analysis

Musical features serving similar functions are more likely to vary together than independently. PCA enables a set of variables (in this case musical features) to be reduced to its main components, and can reveal patterns in the data. We omitted Mode from this analysis because, as a dichotomous variable, it was not suitable for inclusion. We assessed the suitability of all other features to be included in the PCA by calculating correlations between them and inspecting the matrix of correlations illustrated in Figure 2.

We omitted Duration and Speechiness from the PCA because their correlations with all other features were less than $r = .3$. The overall Kaiser–Meyer–Olkin (KMO) measure for the PCA was .846, or meritorious, according to Kaiser's (1974) classification. All individual KMO measures were greater than .7 except for Liveness (.572). Bartlett's Test of Sphericity was statistically significant ($p < .0005$), indicating that the data were likely to be factorizable.

PCA revealed two components with Eigenvalues greater than 1, explaining 70.1% of the variance. The Varimax rotation revealed a complex structure, with several of the features loading on both components (see Table 2). The features with the highest values loading on to Component 1 were Loudness, Danceability, and Valence. The strongest contributor to Component 2 was Liveness, which was the only feature that did not load on Component 1.

We used SPSS to calculate component scores for each track with regression weightings based on the retained two-component solution. Figure 3 represents a visualization of these scores. This shows the distribution of scores across the three playlist categories to be both separate and overlapping, such that the scores for the components of the Sleep tracks are more extreme than those of the Energizing and Relaxing tracks. The Sleep tracks have a long tail, particularly on

Table 2. PCA matrix, rotated solution.

Feature	Component 1 (56.6%)	Component 2 (13.5%)
Loudness	.871	
Danceability	.819	
Valence	.788	
Instrumentalness	–.741	–.373
Energy	.735	.573
Acousticness	–.683	–.584
Brightness	.680	.618
Tempo	.444	
Liveness		.861

Note: Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Variables with coefficients < .3 are suppressed.

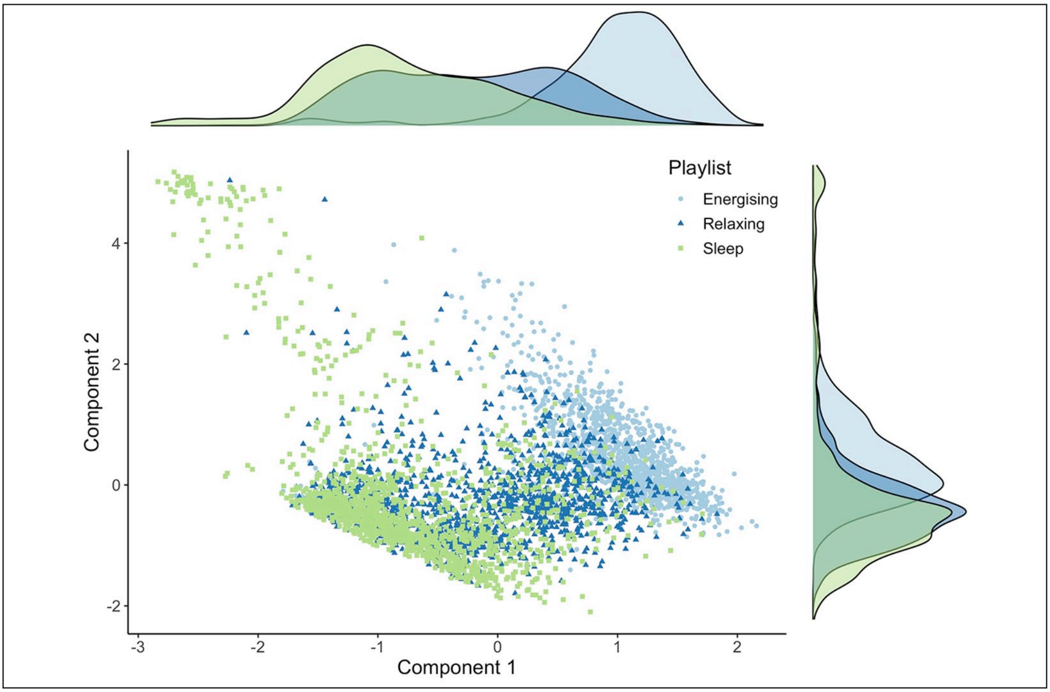

Figure 3. Scatter plot of the PCA component scores for each track by playlist category with density plots along each axis showing the distribution of component scores.

Component 2, distinguishing them from the tracks in the other playlists. This is because many of these Sleep tracks consisted of sounds of nature such as rain or waves, which scored high for Liveness. We assume that the audio analysis methods used by Spotify mistook nature sounds for those of an audience, producing the binomial distribution illustrated in Figure 3.

We therefore conducted the PCA again having identified and removed 150 tracks in two playlists consisting entirely, and one playlist consisting predominantly, of nature sounds;[4] as

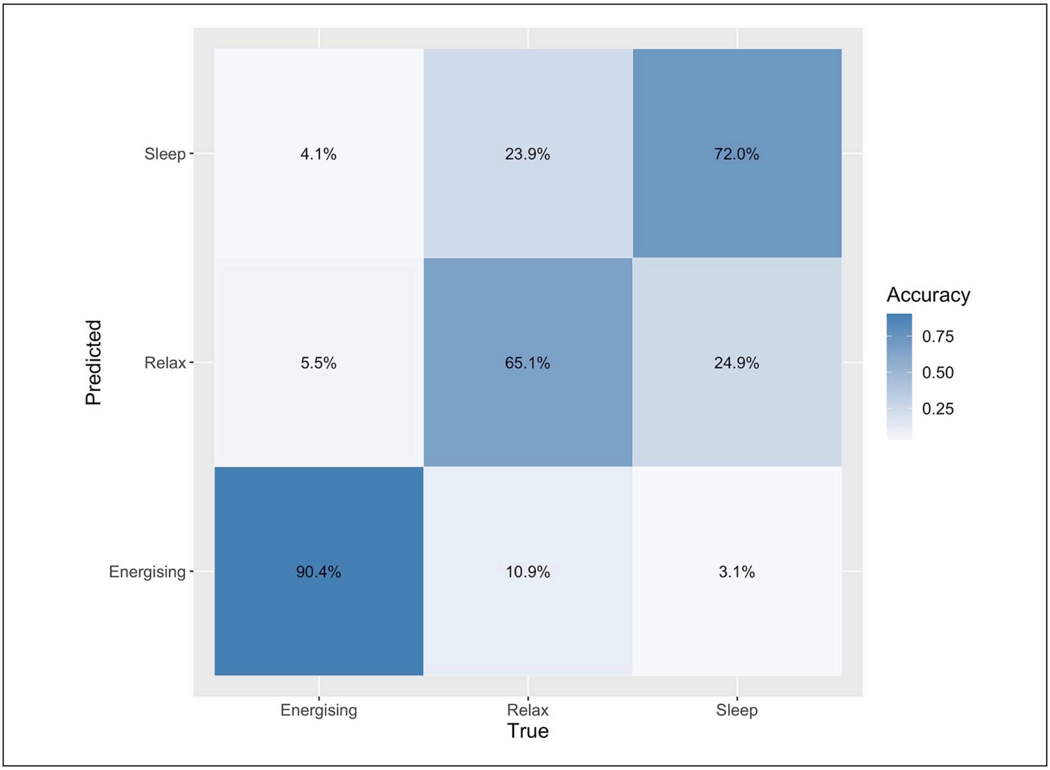

Figure 4. Confusion matrix showing the distribution of predictions for each track in each playlist category.

before, we excluded Duration and Speechiness. The resulting KMO was .877, an improvement on the first model, while all individual KMOs were above .8, including Liveness (.947). Bartlett's Test of Sphericity was again statistically significant ($p < .0005$). This solution produced a single component with an Eigenvalue greater than 1, which explained 59.7% of the variance. The resulting solution showed very similar loadings as Component 1 in our original analysis, with only the addition of Liveness, which returned the lowest value. A forced two-component extraction increased the overall explained variance to 69.8%, with Liveness once again prominent in Component 2 (Eigenvalue = .910).

Nonlinear models

Finally, we used classification models to assess how well the Spotify features of each track predicted the category of playlist in which it could be found. Classification models attempt to discern how well a given set of classes (in this case, playlist categories) can be identified from a given set of predictors (in this case, the features). We used the same features as in the PCA (i.e., omitting Duration and Speechiness) and reintroduced Mode. We used classification decision trees, which can accommodate both continuous and categorical variables (James et al., 2013). A bag ensemble tree was fit using 10-fold cross validation,[5] which returned an overall validation accuracy of 75.8%. Performance varied for each category (see Figure 4), with the model performing best for the Energizing playlists (90.4% overall prediction rate) and worst for the

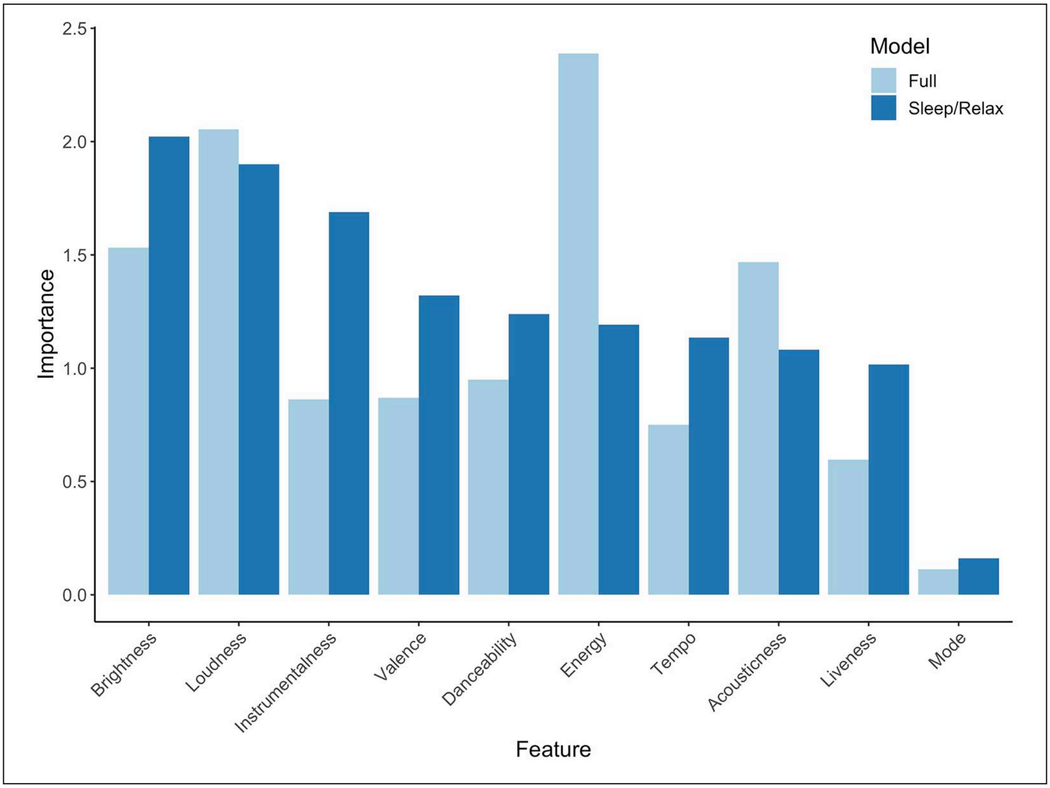

Figure 5. Weight or importance of each predictor presented for the model trained on the full dataset and the model trained on the sleep and relaxing playlists only. Predictors are sorted by importance in the sleep/relaxing model.

Relaxing playlists (65.1%). Tracks from the Sleep playlists were correctly classified in 72.0% of cases.

Identifying the weightings of individual predictors in a model can tell us more about the distinctions between each class and the relevance of the predictors. Predictor weight was investigated using the MATLAB predictorImportance function for decision trees and calculated for each fold of the model before being averaged. Energy was the strongest predictor, followed by Loudness, Brightness, and Acousticness. The model was likely to have been strongly influenced by several distinguishing features of the tracks in the Energizing playlists, such as Energy and Acousticness (see Figure 1). We therefore conducted the analysis again excluding the Energizing playlists to produce a Sleep/Relaxing model enabling us to differentiate between these two types of playlist. With the influence of Energy much reduced, Brightness was the strongest predictor, followed by Loudness, Instrumentalness, and Valence (see Figure 5). The validation accuracy of this model increased to 74.7% for the Sleep and 72.9% for the Relaxing playlists, respectively.

Removing the tracks consisting entirely or predominantly of nature sounds from the dataset altered the results only slightly. The overall validation accuracy of the full model was reduced by 0.9% to 74.9%, with a greater reduction for the Sleep playlists (69.4%), while the validation accuracy of the Sleep/Relaxing model was reduced to 69.3%. Brightness was a stronger predictor than Loudness, and therefore the second strongest predictor, in the full model, and remained the strongest predictor in the Sleep/Relaxing model. Finally, the importance of Valence decreased in both models.

Discussion

In this study, we aimed to increase our understanding of music for sleep by investigating how it may be distinguished from music for other purposes, especially relaxation, using the features of tracks on playlists available in, and as defined by, Spotify.

The importance of brightness

Our finding that sleep music is low in Brightness is in line with previous work (Dickson & Schubert, 2022; Timmers et al., 2019). As the strongest predictor for distinguishing sleep music from relaxing music more generally, our analysis emphasizes the importance of this sonic feature that is typically less reported in the sleep music literature. The relevance of Brightness could relate to its effect on emotional arousal (Bannister, 2020; Eerola et al., 2013; McAdams et al., 2017) as one mechanism by which music aids sleep (Jespersen & Vuust, 2012).

Brightness could be a reflection of other facets, such as instrumentation, recording quality, and pitch. Sleep music in these types of playlist tended to be acoustic and instrumental, and while there were many ambient and electronic music playlists, around half consisted of solo piano music or piano with ambient drones. Of the remaining Sleep playlists, several contained lo-fi music, which is characterized by having little high-frequency information. Some Sleep playlists contained tracks of white or brown noise, and it was these that exhibited the lowest Brightness values. Other low Brightness tracks included ambient pieces such as Crystal Glass by Uffe Jörgensen, Dromen by Bedtijd (Dutch for bedtime; the song title means dreams or dreaming), and Wanderstar by Amel Scott, and solo piano music such as Morning Ditty by Tiffany Royce and Afternoon with Auntie by Jenna Schwartz. Most of the Energizing playlists, on the contrary were dominated by pop and dance tunes, with a heavy emphasis on electric or synthesized instruments. These included tracks such as Freed from Desire by Gala and Venus by Bananarama, which had some of the highest Brightness values. Relaxing playlists were more varied, with some consisting of acoustic folk/rock/pop music (e.g., I See Fire by Ed Sheeran and I Guess I Just Feel Like by John Mayer) and others including more ambient instrumental music. Interestingly, the tracks with the highest Brightness values were also found in Sleep playlists in the form of nature sounds, specifically forest sounds including the chirping of birds. These were contained in one of the playlists omitted in the reanalysis without the nature sounds, perhaps explaining the improved KMO values in the resultant PCA and the improvement of Brightness as a predictor in our classification models.

Loudness was correlated with Brightness. The combination of Loudness and Brightness could be related to equal-loudness contours, or the Fletcher Munson Curve (Fletcher & Munson, 1933), which describes how listeners perceive different frequencies at different volumes and predicts that lower Brightness or centroid (pitch center of the spectrogram) is perceived as softer. In turn, music producers may take this into consideration when mixing audio and may reduce high frequencies when they want to achieve a softer, calmer sound. Correlations between Loudness and spectral centroid have been observed in music production, although whether this is deliberate or an unconscious product of the phenomenon is unclear (Deruty et al., 2014). Loudness was the second most important predictor in our classification model distinguishing Sleep from Relaxing playlists.

Explicitly manipulating the Brightness of a piece of music in future research may be a way to investigate whether intensity or timbre is the more important contributor to Brightness (Bannister, 2020).

Nature sounds

Timmers et al. (2019) found that sleep music playlists regularly include music containing a large proportion of non-musical acoustic sounds such as nature sounds, and we too have found these extensively in Spotify Sleep playlists. Other than the three playlists specifically identified in our PCA analysis as consisting exclusively or predominantly of nature sounds, nature was notably present in other playlists in the Sleep category. For example, the playlist Relaxing Spa Music—Perfect Bliss, Water Sounds Massage contains music dominated by sounds of waves and rippling water with an overlay of ambient drones. The Sleep Lullabies playlist consists of piano renditions of classic lullabies accompanied by ocean sounds, and several other playlists include compositions including elements of nature sounds.

The relevance of these nature sounds to music for sleep is unknown. In an experimental study, Jespersen and Vuust (2012) used music including natural sounds such as waves and birdsong but did not explicitly test the effect of these sounds on sleep. They may encourage psychological and physiological relaxation (Alvarsson et al., 2010; Annerstedt et al., 2013; Ghezeljeh et al., 2017; Jo et al., 2019), however, and applications of this suggestion can be found in the incorporation and manipulation of nature sounds in biofeedback relaxation protocols (Yu et al., 2017, 2018). Participants who listened to the sound of rippling water in a study of the effectiveness of music for stress reduction (Thoma et al., 2013) had lower cortisol levels than those who listened to music, liked it as much, and found it equally relaxing.

Tempo and mode

Sleep music is typically described as slow in tempo. It is harder to measure tempo using automated feature extraction methods than some other features, because beats can be extracted at more than one level, particularly when the music has no clear pulse (e.g., 60 bpm is reported as 120 bpm). For this reason, alternative methods have been developed (Egermann et al., 2015). The tempo values we report are probably unreliable as they vary from 0 to 211 bpm. The tempo distributions illustrated in Figure 1 show two peaks in both the Sleep and, albeit to a lesser degree, the Relaxing playlists, which may indicate a doubling error in the calculation.

The literature on the role of mode in sleep music presents a mixed picture. Music in the minor mode was used in some studies (Chang et al., 2012; Huang et al., 2016, 2017; Su et al., 2013). However, in their investigation of YouTube, Spotify, and Apple sleep playlists, Timmers et al. (2019) found a clear preference for music in the major mode, perhaps highlighting a difference between the features that are prescribed by researchers and those preferred by users. Positive mood is conducive of sleep (Jespersen & Vuust, 2012) and the major mode may be thought of as promoting positive mood. In our study, we found striking differences between the three types of playlist in terms of the balance of tracks in major and minor modes, with a clear trend; the proportions were approximately equal in the Energizing playlists but majorities of major-mode tracks in the Relaxing (67.1%) and Sleep (73.9%) playlists. This is an important avenue for further investigation as few studies of mode in sleep music or positive mood as a mediator of the effect of music on sleep have been reported.

Limitations of Spotify features

As a large repository of data, the Spotify Data Catalog is an extremely useful resource for researchers. Spotify's feature extraction methods are not accessible to them, however, because of their proprietary nature, and its documentation does not provide full details of calculations. Our results are, therefore, not as reliable as we would like, particularly those relating to values for Liveness and Tempo. Unreliability may explain why they were two of the weakest features in our analysis rather than suggesting, for example, that Tempo is not an important factor in music used for sleep.

Another questionable Spotify feature is Valence, a complex measure worth exploring because it is a core component of affective responses (Kuppens et al., 2013). Although Valence was only of medium importance in our classification model, it was nevertheless useful for distinguishing between the types of playlist. Sleep and Relaxing playlist tracks are more negatively valenced than those in the Energizing playlists, with Sleep music more negatively valenced than Relaxing music. This would appear to contradict the predominance of major-mode tracks in all three types of playlists and even the suggestion that music for sleep should promote positive emotions (Jespersen & Vuust, 2012), although pleasure can still be derived from music with apparently negative emotional content (Sachs et al., 2015). This finding may be linked to the way Spotify determines the presence of positive or negative Valence, typically associating the former with high values for energy and brightness. Since Sleep playlist tracks have low values for both, they can also be expected to have low values for Valence. To explore the role of Valence in slow and soft music more effectively, it may require a more sophisticated definition.

Examination of features other than those provided by Spotify could provide further relevant insights into music for sleep. These could be obtained from more detailed sonic analyses (McAdams et al., 2017) and qualitative assessments (Dickson & Schubert, 2022) of the Spotify dataset, although these would not have been feasible within the scope of this study given their computational demands and the constraints of time. It would be possible to carry out such analyses using the 30-s preview clips of tracks available in the form of MP3 files from the Spotify API, although these might be too short to provide a reliable representation of the whole track.

A wider issue with using the global features of entire tracks as data is that they are represented by single values. Music is inherently variable, involving structural, tonal, dynamic, and other changes that may be integral to the affective qualities of music (Coutinho & Cangelosi, 2011). It is possible to carry out a more refined evaluation of specific time-segments of a track using the Audio Analysis tool available from the Spotify API (see Data collection, above), but its features are limited, such that many of those we included in our analysis using the Audio Features tool are not present.

Limitations of Spotify playlists

While we studied playlists labeled as serving particular purposes, their suitability for those purposes was determined by their creators and not on the basis of empirical evidence. In choosing 30 playlists in each of three categories of playlists, we aimed to identify a sample representing a variety of creators' perceptions and opinions, and this was reflected in the variability of our results. Of the 90 selected playlists, a total of 37 (41%) are credited to Spotify itself (11 Energizing, 12 Relaxing, 14 Sleep) but we have no way of knowing if the tracks in these playlists actually serve the purpose, respectively, of energizing or relaxing listeners, or helping them sleep.

Listeners' perspectives

The variability of our results, in terms of Spotify feature values, reflects the diversity of sleep music as reported in other studies (Dickson & Schubert, 2022; Scarratt et al., 2021; Trahan et al., 2018). Some consider tracks chosen by their participants which, like Spotify and other publicly available playlists, reflect individual preferences. Music for sleep may differ from music for other purposes only partly because of characteristics such as those represented by Spotify features; it may also differ from music for other purposes because of the way it is used by listeners. It is typically assumed that they listen to it while they are falling asleep in bed, the protocol most commonly used in empirical studies of sleep music. Participants in a study by Oxtoby et al. (2013) who listened to researcher-provided music for sleep for at least 20 min after 6 pm during their "normal night time activities" (p. 9), however, experienced positive impacts (although not on their measured sleep quality). People who find music conducive for sleep in the real world may listen to it as they wind down toward bedtime, as they fall asleep, or throughout the night. Rather than seeking psychological effects, they may use it to mask a noisy environment (Dickson & Schubert, 2020). Music may help people sleep because they like it, although preferences can change over time (Lee-Harris et al., 2018), or simply because listening to music is habitual. In short, many factors underlie individuals' choice of music for sleep and how they use it.

Conclusion

We analyzed 30 Spotify playlists in each of three categories (Sleep, Relaxing, and Energizing), comprising 4,500 tracks in all. We extracted the values for 12 Spotify features of each track and compared the types of playlist using statistical methods. While sleep and relaxing music are similar in many ways, the features of sleep music are more extreme, and the two categories can be distinguished using nonlinear classification models. Specifically, sleep and relaxing music are distinguished, above all, by their brightness, thus highlighting the relevance of timbral qualities not often discussed in the sleep music literature. Also, music for sleep is likely to be in the major mode and/or incorporate nature sounds. Otherwise, its characteristics conform to those already described in literature (Jespersen et al., 2015; Scarratt et al., 2021): acoustic; instrumental; and low in energy, loudness, and tempo.

While our analysis of a dataset drawn from playlists available on a commercial streaming platform provides valuable insights into the characteristics of music that is considered suitable for helping people to sleep, they do not necessarily do so. Nevertheless, our results can inform the selection of music to be used in future research and suggest avenues for further study. Finally, they are helpful for identifying the orthogonal dimensions of a sleep-music feature space, namely energy and the liveness or naturalness of sounds.

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ORCID iD

Rory Kirk https://orcid.org/0000-0001-5499-0271

Notes

1. A tatum represents the lowest regular pulse train that a listener intuitively infers from the timing of perceived musical events. The term was defined by Jeffrey Bilmes in their MA thesis (Bilmes, 1993).
2. For the remaining sections, feature names that are capitalized will refer specifically to the data extracted from Spotify.
3. Every track, album, or playlist on Spotify has a unique ID. This ID is used to request information on that track/album/playlist from the API. In the Spotify web player (https://open.spotify.com), the ID is the string of letters and numbers at the end of the URL. For example, the URL of the playlist Relaxing Music is https://open.spotify.com/playlist/1r4hnyOWexSvylLokn2hUa; the ID for this playlist is 1r4hnyOWexSvylLokn2hUa.
4. Univariate tests were also re-run, but the overall results did not differ.
5. This procedure follows a common approach to building classification models whereby the dataset is split into training and test sets. A model is trained, or fit, with the training set while the test set is used to evaluate the model. A *k*-fold cross-validation is a method of resampling a dataset to reduce bias that may occur when splitting the dataset. In this process, the data are randomly split into a specified number of groups (*k*; in our case, $k = 10$), and each in turn is treated as the test set, effectively resulting in *k* models being fit. The final validation accuracy is the average of the evaluations of those *k* models.

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Appendix 1

Full list of playlists and their description (where provided), creator, ID, and number of likes and tracks. Playlists titles, creator names, and content are liable to change.

Playlist	Description	Creator	ID	Likes	Tracks
Energizing					
Energizing music	—	louisep!	76YdW0YY1aEYUwAUQPv2kr	840	249
Gym Playlist Energie	—	Energie Fitness	4qJhnePHLlfgWqnvEAGnVH	7,051	220
Energizing Study Music—No Lyrics	—	smd82408	4axJH5T0SzA0G91NeszOws	1,608	118
Enfoque con Energia	Trap y electrónica instrumental para enfoque (en: Trap and instrumental electronics for focus)	Spotify	37i9dQZF1DX5EY8JFBuaLS	41,459	122
Energizing Music	—	chaj1	7yKgnCJZQDlqOLFSr2HC56	1,510	231
Energiser	—	nutatiahh	2BIu9x9P6wXjrtsQtGepfg	197	69
Pura Energía	El subidón musical que necesitas (en: The musical high you need)	Spotify	37i9dQZF1DWYp5sAHdz27Y	249,228	100
Energia positiva	—	salamander_05	1xyGdY1GuPHaQyvikZglmB	3,994	298
Alta Vibración 432 Hz & Energía Positiva	Música de alta frecuencia vibracional y aumento de energía positiva (en: High vibrational frequency music and increase of positive energy)	Jordi Sanz	1Upphcq8Euc3IpsIhuCnkw	24,877	126
Energia 97FM 2021	Energia 97 FM 2021 📻 Radio Energia 97 FM Top 40—Brasil Hits—Best Radio Brasil—a melhor música 2021—Best Brasil Music	hotvibesnetwork	4ttPvH5KXUbAKpR6ucYD6R	1,638	113
Dance Hits	All the big ones with deadmau5 & Kaskade	Spotify	37i9dQZF1DX0BcQWzuB7ZO	3,362,538	100
DANCE 2021 Party Summer Electro Pop Só Tracks Hits Beach Tropical House Electrônicas Dua Lipa	cover: @mahdi_chf by Unsplash—Dua Lipa, Sunset Hits Beach Party Ibiza Night Club Dance Music Hot Pop Beats Good Vibes Chill Deep House Progressive New Eletro Hits Novas Eletrônicas Músicas Lançamentos	Victor Oliveira	0tLyGnQZ5T8wlu0tydvQU3	60,005	131

(Continued)

Appendix 1. (Continued)

Playlist	Description	Creator	ID	Likes	Tracks
Dance Anthems 2021	Dance music now. Club hits + remixes from Sigala (Wish You Well), Joel Corry (Sorry, I Wish), ATB (Your Love 9PM), Topic (Breaking Me). Playlist updated regularly—FOLLOW () for updates! Get the IBIZA 2022 album here! 💿🏝 Double J Music [2022 description]	Double J Music	0qiyp96nNBGdRLApUAmMtG	32,563	112
Dancehall 2021 [new]	New Dancehall music trending in 2022. Follow now! Independently selected by DJ Fabi Benz. Cover: Mehkadon	DJ Fabi Benz	1AKuDAKQOUSbQ8KKJkrlMi	36,150	200
Massive Dance Classics	Floorfillers galore from the 90s and 00s.	Spotify	37i9dQZF1DWYtg7TV07mgz	1,009,545	50
Dance Party! Best Dance Hits	The best dance party songs of all time. Party hard with our selection of guaranteed floorfillers that will get everyone on the dancefloor! We can't guarantee your dance moves will be great. . .but surely, the music will be!—Picture © Free	Lost Records	5oKz4DsTP8zbL97UIPbqp4	171,329	435
Dance Workout	Dive into the biggest Dance and Electronic throwback summer hits. Songs for sunny days, happy mornings, afternoon sunsets, UK summer, Bank Holiday Bangers, Heatwaves, Barbecue, Pool party, BBQ tunes. Cover: Calvin Harris	Filtr UK	7wBpRbIoatquCDVcxybHEk	397,867	74
Dance Pop	Hit the dance floor with your favorite bops!	Spotify	37i9dQZF1DWZQaaqNMbbXa	228,814	150

(Continued)

Appendix 1. (Continued)

Playlist	Description	Creator	ID	Likes	Tracks
Dance Nation—Ministry of Sound	It's going off! Expect the biggest club anthems and floor fillers to get you on the dancefloor. Featuring hits from Regard, Sigala, Majestic, Oden & Fatzo, Joel Corry and many more. . .	Ministry of Sound	7FUhHHA0zXAPVsJdDrNxNs	259,416	60
DANCE MUSIC 2021 Best Dance 2021 & EDM Hits 2021	Best dance music right now! Discover the latest dance and EDM hits & 2022 top Dance Music.	Filtr Éxitos	6g40a9GjWBkX8ewR0vF9C2	242,718	198
Workout Music 2021, Gym Music, Treino, Cardio Music, Training Music, Fitness Motivation, Bass Music	Workout Music 2022, Workout Playlist 2022, Gym Music, Treino, Cardio Music, Training Music, Fitness Motivation, Bass Music Mix. Trening, Formazione, Formacion	BLACK DOT	190wZ2oVo7MTrBvNlPiub2	570,992	100
Workout	Pop hits to keep your workout fresh.	Spotify	37i9dQZF1DX70RN3TfWWJh	4,497,825	100
Adrenaline Workout	If your workout doubles as an outlet for your aggression, this is the playlist for you.	Spotify	37i9dQZF1DXe6bgV3TmZOL	1,309,302	120
The Rock Workout	For when only raw rock will do . . .	Spotify	37i9dQZF1DX6hvx9KDaW4s	458,038	50
Workout Beats	Need to break a sweat? Turn these jams up and stay motivated!	Spotify	37i9dQZF1DWUSyphfcc6aL	1,004,616	70
Workout Motivation 2021	These songs will get you motivated! The best playlist on Spotify for your Workouts (at home). Follow and get motivated🏆	Slagelhag Workout	2237sMNMlXS4wWLgdQ1UuV	578,369	275
Workout Playlist 2021	My favorite Workout bangers 2021. Mostly Rap, mixed with some edm tracks:)	metr	7AiuMp1D8Hli18nyTbriZ9	253,131	91
Workout Bhangra	Get ready for a full-body workout	Spotify	37i9dQZF1DX8To1hlfhp7U	16,529	74

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Appendix 1. (Continued)

Playlist	Description	Creator	ID	Likes	Tracks
Workout Beats 2021	Get fit with the best workout & gym beats out there. Workout Music 2021, Workout Songs, Gym Music, Fitness Motivation, Home Workout, Training Music, Dance Workout, Bass Music, Cardio Music, Treino, Crossfit Beats, Fitness Motivation, Workout Motivation, Running Songs	Selected	4XIEV4NaByrujFUjFoG32v	183,777	98
80s Workout	Grab your leg warmers and spandex: let's get physical!	Spotify	37i9dQZF1DWZY6U3N4Hq7n	273,024	80
Relaxing					
Relax & Unwind	Let your worries and cares slip away . . .	Spotify	37i9dQZF1DWU0ScTcjJBdj	3,669,078	114
Relaxing Massage	Soothing drones, ambient piano and new age music	Spotify	37i9dQZF1DXebxttQCq0zA	537,966	206
Relaxing Music 2020	Relaxing Songs 2020—Relaxing Music 2020—Meditation Music—Relax—Chill Music—Calm Songs—Calm Music	Lofi Infini	0Ie5X3JS6BrLSWKrRm310H	47,509	85
Ambient Relaxation	Relax and unwind with chill, ambient music	Spotify	37i9dQZF1DX3Ogo9pFvBkY	1,113,286	298
Pop Relax	La musica giusta per la massima spensieratezza (en: The right music for carefree/light-heartedness)	Spotify	37i9dQZF1DX3SQwW1JbaFt	137,327	60
Relaxing Classical	Relax, unwind and chill to the world's greatest composers. Perfect background music for sleep and study	Filtr UK	1ZJpJahEFst7u8njXeGFyv	322,721	80

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Appendix 1. (Continued)

Playlist	Description	Creator	ID	Likes	Tracks
Relaxing Piano	Beautiful solo classical songs. Ludovico Einaudi (Una Mattina), Yann Tiersen, Max Richter, Erik Satie, Yiruma and more. Follow New Music Friday Classical Double J Music	Double J Music	0OOZzfr4olaGarfeaydGZf	75,646	400
Relaxing Piano: soft & calming piano music for relaxation	The sounds of soothing piano music to make you feel cozy and relaxed. Come for updates to the playlist and enjoy—by @dream.relaxation	Dream Relaxation	2ODMZHnO9zcajVJ54Rlhz7	503,440	157
lofi hip hop music—beats to relax/study to	A daily selection of chill beats—perfect to help you relax & study 📚	ChilledCow	0vvXsWCC9xrXsKd4FyS8kM	5,818,585	300
Jazz Relax	Relax to vocal and instrumental jazz	Spotify	37i9dQZF1DXbOVU4mpMJjh	696,372	50
Relaxing Guitar Music	Soothing modern classical guitar music, perfect to unwind and enjoy calm and quiet moments. Enjoy and please follow the playlist if you like it	Florecilla Records	6wFWKXnsBFQxWQjSug7ory	12,531	392
Relaxing Jazz Background Music	—	jazz_jazz_jazz75	71tQFRd9OWYWWSQdxLQccn	19,221	818
Hanging Out and Relaxing	The perfect playlist to just sit back and chill out with	Spotify	37i9dQZF1DXci7j0DJQgGp	1,789,929	145
Relax in the Bath	Release the tension and soak up this playlist of super relaxing songs	Matt Johnson	5sMfgeII8qGOwcgxfqqDaM	26,056	130
Relaxing Songs	—	lyssastreiner	4D3hxAbOjVu5jaC5Bnlmky	72,516	100
Soothing Relaxation	—	Soothing Relaxation	4AyG5SW1hu3toT9kd9PSXR	94,253	135
Relaxing Reading	Gentle instrumental music to help you relax while you read	Spotify	37i9dQZF1DX3DZBe6wPMXo	90,184	50

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Appendix I. (Continued)

Playlist	Description	Creator	ID	Likes	Tracks
Relaxing acoustic	—	samkeane-gb	4rdl06oulIdgDNjJts2rmp	1,908	99
Relaxing Pop	—	Mindy Moss Shaffer	3LNyeJ7KMVZvNp9zClWCW3	9,512	171
Relaxing Spanish Guitar	The beautiful sound of the Spanish guitar to help you wind down	Spotify	37i9dQZF1DX6BbeVFYBeZs	67,534	84
Relaxing Spa Music—Perfect Bliss, Water Sounds Massage	Zen Meditation Planet offers Perfect Bliss in music playlist . . .	zenmeditationplanet	0pUKEVfbKICpYx35RozAk7	3,826	200
Deep House Relax	Forget it and disappear with chill house	Spotify	37i9dQZF1DX2TRYkJECvfC	2,271,019	200
Relaxing Playlist	—	Pie	0B1cW8x7Mopg6Du5BJ4spM	2,066	134
Piano Relaxation	The perfect selection of relaxing, calm piano music to help you relax, sleep or focus. Classical piano pieces inspired by the old masters	Piano Relaxation	04Bx6c3eZmYdWZRkQrLB7l	73,787	153
Bach Relax	Let the daily stresses of the world melt away with this peaceful playlist, filled with the warm, comforting melodies of JS Bach	Spotify	37i9dQZF1DWU1JctQodQRj	49,978	73
Relaxing & Chill House 2021 The Good Life Radio	My favorite songs from the genres: Chill House, Deep House, Tropical House, Chillout, Lounge, Ambient 2022 and basically anything that you want to listen to when you are relaxing in a lounge or at the beach:)—Relax, Relaxing House Music	Sensual Musique	75XrS5HXOmVYMgdXlaQTwO	181,269	323
Relax Tayo	Sit back and relax to our favorite local indie and R&B sounds	Spotify	37i9dQZF1DWU96w4Gh7vJe	490,976	50
Meditação e Relaxamento	Respira, inspira. . . Uma seleção musical ideal para você relaxar. (en: Breathe, inspire. . . An ideal musical selection for you to relax)	Spotify	37i9dQZF1DXaKgOqDv3HpW	715,406	119

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Appendix 1. (Continued)

Playlist	Description	Creator	ID	Likes	Tracks
Mindfulness—Focus/Relax	Peaceful instrumental music for meditation and relaxation	1165 Recordings	2ozb9cgwMcl2SDWK4SLRp8	78,561	346
Relaxing Music	Relaxing ambient music to calm down to. Hit play and unwind with these chill songs	Pryve	1r4hnyOWexSvylLokn2hUa	96,662	228
Sleep					
Sleep	Gentle ambient piano to help you fall asleep	Spotify	37i9dQZF1DWZd79rJ6a7lp	4,272,769	163
Deep Sleep	Soothing, minimalist ambient for deep sleep	Spotify	37i9dQZF1DWYcDQ1hSjOpY	1,421,084	214
Sleep Piano Music	Relaxing piano music to help you fall asleep. Calming piano music for background listening and sleeping	Pryve	7xhcF9ddiyF8Skbd1tenro	109,579	347
Baby Sleep	Soothing instrumental music for sleepy babies	Spotify	37i9dQZF1DX0DxcHtn4Hwo	499,645	292
Songs For Sleeping	A series of soothing sounds to softly send you to sweet, sweet slumber	Spotify	37i9dQZF1DWStLt4f1zJ6I	466,696	99
Sleep, Baby Sleep	Soft music for sleepy babies	Spotify	37i9dQZF1DXdJ5OFSzWeCS	171,083	336
Sleepy Piano	Calm piano music for sleeping	Spotify	37i9dQZF1DX03b46zi3S82	227,909	187
Jazz for Sleep	Let these jazz tracks lull you to sleep	Spotify	37i9dQZF1DXa1rZf8gLhyz	899,517	105
Sleep Piano	Bedtime. Relax and indulge with some profoundly beautiful piano pieces—Background Piano—Classical Piano—Easy Piano—Peaceful—Sleep—Sleepy—Study—Flight—Airplane—Nightmode—Night—Night Shift ☽	Ron Adelaar	1Ty8JKNLTI5C7DKE65jvb9	82,802	355

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Appendix 1. (Continued)

Playlist	Description	Creator	ID	Likes	Tracks
LoFi Sleep	LoFi Sleep Rain zzz | HOURLY—Updated Hourly—Last Update was on 13 May 2022 at 7:01 a.m. in New York.—Instagram and Twitter: @lofipandajams—LoFiPandaJams.com	James Gilsdorf	3DP5Khm13rl3I9mQkgX6fx	11,250	375
Sleep Tight	Music to reduce insomnia and help you relax	Spotify	37i9dQZF1DWSUFOo47GEsI	570,733	190
Classical Sleep	Drift off to these peaceful classical melodies	Spotify	37i9dQZF1DX8Sz1gsYZdwj	397,436	54
Sleep Sounds	Bedtime ASMR sounds, relaxing soundscapes, calming thunderstorms and ambient vibes. Ease in to a night of sound sleep and sweet dreams	Filtr	6k6C04ObdWs3RjsabtRUQa	124,240	1,159
Sleep Lullabies	—	gkyla	30oR4iBzmouadY8aawVODx	1,988	187
Sleep: Into the Ocean	Drift off with these peaceful ocean sounds	Spotify	37i9dQZF1DXabJG3i5q2yk	1,445	59
Soothing Strings For Sleeping Babies	Soothing strings for our sleepy little ones	Spotify	37i9dQZF1DX2C8CFEPyYmg	111,828	205
Lo-Fi Beats	Let yourself be sunkissed with beats to chill, relax, study, code, focus, skate, and roll . . .	Spotify	37i9dQZF1DWWQRwui0ExPn	4,263,935	650
SLEEPY TIME	The perfect playlist to sleep through your alarm to lol	macyleeeeedavis22	68JXTKfqFZEWO1DQRdVndh	82,874	192
Sleeping Songs	—	megan21	5OajoGDWc6pK101SCqH1R7	52,014	180
Sleepy Music	Sleep music	Sleepy Times	1u9NkEi4uwvlKu1Nlhx5T7	6,955	348
Baby Sleep Aid: White Noise	White noise to help babies fall asleep	Spotify	37i9dQZF1DXby8tlLbzqaH	205,908	168

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Appendix 1. (Continued)

Playlist	Description	Creator	ID	Likes	Tracks
Lullabies for Sleep	Sleep baby, sleep. A relaxing playlist of peaceful piano songs and nursery rhymes, for babies and adults alike. Browse all playlists here doublejmusic.com or at Double J Music	Double J Music	25wThb57sSId0kPwhgSgaO	64,078	144
Lofi Fruits Music lofi hip hop music to chill, relax, study, sleep to—lofi beats, chillhop	Lofi Fruits Music 🍉 Try Jazz Fruits, Rain Fruits & Piano Fruits Strange Fruits	Strange Fruits	3LFIBdP7eZXJKqf3guepZ1	7,392,030	347
Relaxing Rain Sleep Sounds	Stressful times? Breathe in, breathe out. Take a nap, wind down or fall asleep to soothing, rainy thunder storms for calming mindfulness	Filtr Sweden	7f24KaDrATReBg45esAgX8	11,348	1,027
Sleep Noise	Colored noise to help you sleep	Spotify	37i9dQZF1DWSW4ppn40bal	48,645	134
432 Hz Sleep Music	432hz healing frequency for sleep meditation, anxiety relief, DNA repair, and inner peace. Helps resist insomnia and to balance body and mind	Miracle Tones	4wavvfiVFxWmGgjkR5w0Fh	34,171	260
Calming Sleep Music	Music to help you fall asleep, and relax, sleep well! ❤	gery07	6X7wz4cCUBR6p68mzM7mZ4	37,851	458
Sleeping Music	Listen to this as you fall asleep and you will have amazing dreams	TheGoodVibe	7mVeHiaEmixl8tKak7UwQT	57,945	109
Sleep Music	Ambient Sleep Music, Musica para dormir, Music to sleep, Piano, Ambient, Orchestral, Sweet dreams, Relax, Meditation, Sov Gott, Calming music, New Music Every Friday	LoudKult	21wbvqMl5HNxhfi2cNqsdZ	213,568	301
lofi sleep, lofi rain	Weekly selection of the best peaceful & quiet lo-fi beats for a perfect sleepy night zzz	Colors in the dark	35xI4hSJ8MdO1xkXwsd56a	189,033	100