The relative contributions of subjective and musical factors in music for sleep

Rory Kirk[1], George Panoutsos[2], Maan van de Werken[3] & Renee Timmers[1,4]

[1]Music, Mind, Machine, Department of Music, University of Sheffield, UK; [2]Department of Automatic Control and Systems Engineering, University of Sheffield, UK; [3]SleepCogni, BrainTrain2020 Ltd., Sheffield, UK; [4]Healthy Lifespan Institute, University of Sheffield, UK

Author note

Correspondence concerning this article should be addressed to Rory Kirk.

Email r.kirk@sheffield.ac.uk

Abstract

Previous research into music for sleep has focused on describing the types of musical characteristics associated with such music (Kirk & Timmers, in press; Scarratt et al., 2023). The current study aimed to increase understanding of sleep music by investigating subjective perceptions of listeners associated with music that is considered sleep inducing, including conceptualisations related to arousal, emotions, and distraction (Jespersen & Vuust, 2012). Musical features of the stimuli presented were extracted to compare the relative contribution of subjective and objective aspects. Our results reveal differing but important roles for valence and arousal, and highlight notions of comfort, liking, and dissociation that attribute to music that is most sleep inducing. The musical properties of sleep music conformed with previous research (Jespersen et al., 2022), with an additional emphasis on brightness (Kirk & Timmers, in press), however the subjective ratings overshadowed the musical features in predicting what music was most sleep inducing. Our findings have implications for how music used to facilitate sleep is selected and highlight the importance of personalisation.

There has been a growing awareness of the proliferation of sleep problems in modern society and their profound impact on health and wellbeing (Grandner, 2017), garnering efforts to improve conscious maintenance of individual sleep health and understand methods for alleviating sleep issues (Walker, 2017). As one such method, the use of music to help with sleep has created a considerable amount of research attention, with studies exploring the efficacy of music as a sleep aid generally as well as in clinical settings (see Kakar et al., 2021; Wang et al., 2021). Thus, continued efforts are being made to better understand how music can be used to help with sleep and optimise its potential for therapeutic application.

One such area that requires better understanding is the properties and qualities of music that can best promote sleep. In experimental studies researchers typically choose music that is described as relaxing, soothing, or sedative, with a slow tempo and little rhythmic or dynamic variation (Jespersen et al., 2022). Many cite guidelines given by Gaston for so-called sedative music (Gaston, 1951, 1968), and Nilsson's recommendations for the types of music suited for clinical settings (Nilsson, 2008, 2011). However, individuals who report listening to music to help with their sleep describe a considerably more varied selection of music (Dickson & Schubert, 2020; Trahan et al., 2018). For example, Dickson & Schubert (2020) found that music their participants identified as successful at aiding sleep was characterised by medium tempo, legato articulation, major mode, and the presence of lyrics, which they concluded did not conform to the usual sedative, instrumental music recommendations. Tempo was 107 bpm on average, compared to 52-85 bpm typically seen in sleep studies (Jespersen et al., 2022). In an analysis of Spotify playlists, Scarratt et al. (2023) found the most popular track across 989 playlists that were intended for sleep (i.e., had sleep in the title or description, a total of 225,927 songs) was Dynamite by Korean pop group BTS, an upbeat track filled with syncopation and a busy rhythm section. Their dataset overall leaned towards ambient and instrumental music, but was nonetheless distinctly diverse, highlighting the individual variation in the choice of music used to facilitate sleep (Scarratt et al., 2023).

These findings raise questions for how experimental research studies choose music for the purposes of aiding sleep. Indeed, the music used often comes from a range of sources or different selection processes, including music specifically composed for sleep (e.g., Cordi et al., 2019; Lazic & Ogilvie, 2007), music chosen based on levels of relaxation (e.g., Huang et al., 2016, 2017; Lai & Good, 2005), or music selected by the participants themselves (e.g., Iwaki et al., 2003; Johnson, 2003). Some studies carry out preliminary work to validate their selections (e.g., Cordi et al., 2019; Jespersen & Vuust, 2012), however most do not report if any such preliminary work was conducted, which could mean the music selected is not in fact optimal. However, most studies tend to support the use of music as a sleep aid, possibly suggesting that music works as a more general intervention and requirements may not be so specific. Nonetheless, to assess the therapeutic and even clinical application of music requires a systematic understanding of the factors that contribute.

A promising avenue of investigation is to better understand the sleep-related affordances that music may offer to individuals and how these interact with acoustical and musical properties. We expand assessments of sleep music by investigating listeners' perceptions and explore how music that is considered sleep inducing is conceptualised along a number of subjective dimensions by participants, including themes relating to valence, arousal, absorption, comfort, and liking. We also conduct a musical features analysis to complement our assessment and tie together the acoustical and perceptual properties of music for sleep. It is the interaction between musical features and individual factors that is hypothesised to be predictive of music's effect. By exploring listener perceptions in combination with musical attributes we provide an improved insight into what music is suited to facilitate sleep.

Psychological factors influencing sleep, and the potential of music

Sleep is a vitally important part of everyday life, yet a reported 30-40% of individuals suffer from at least one night-time insomnia symptom (Levenson et al., 2015). A range of factors can affect the quality of an individual's sleep, including environmental factors, such as work requirements and lifestyle, or biological factors such genetics and overall health (Grandner, 2017). Some are external factors, while others relate to internal physiological and psychological mechanisms. Psychological factors play a particular role in the sleep-wake cycle; sleep onset is seemingly moderated by a cognitive signal that gives the body implicit 'permission' to relax and fall asleep, referred to as the 'lights out' effect (Kräuchi & Wirz-Justice, 2001).

This psychological switch can be difficult to control. Negative thoughts or other day-to-day physical and psychological stressors can prevent the body from reaching a sleep-ready state. Sleep problems are sometimes seen as a disorder of hyperarousal, described by Levenson et al. (2015) as heightened physiologic, affective, or cognitive activity. Regulating arousal and mood is considered to be one of the key functions of music listening generally (T. Schäfer et al., 2013), commonly used to relax and alleviate stress, thus music listening seems a suited method to help alleviate these psychophysiological barriers and promote sleep onset.

In light of the above, Jespersen & Vuust (2012) have proposed three mechanisms by which music can help with sleep. These relate to music's effects on physiological arousal, emotional effects, and as a means of distraction. Music that finds a balance between positive emotions, promoting mood and relaxation, and causes a decrease in sympathetic activity and an increase in parasympathetic activity would be expected to promote sleep. Further, music can act as a focal point of attention that distracts a listener from stressful thoughts (Hernández-Ruiz, 2005), a suggestion that is supported by reports from individuals as a reason they use music to help with sleep (Trahan et al., 2018).

These mechanisms overlap with general conceptions around the functions of music listening. Further to regulating arousal and mood, T. Schäfer et al. (2013) suggest that people listen to music to achieve self-awareness, and as an expression of social relatedness. Each factor could be important for facilitating sleep; achieving self-awareness may be relevant for certain individuals as a way of helping arousal and mood regulation, for example by way of introspective contemplation (e.g., meditation). The sense of social relatedness may also be valuable; some theories suggest that music may act as a social surrogate, improving wellbeing by providing a sense of belonging and connectedness in the absence of social interaction (K. Schäfer et al., 2020; K. Schäfer & Eerola, 2018). These associations may help to evoke a sense of comfort and security conducive to sleep. Indeed, the human thermoregulatory system, key to the sleep-wake cycle (Kräuchi, 2007), is thought to be affected by feelings of social bonding whereby changes in body temperature are associated with feelings of social connectedness, possibly linked to evolutionary developments that reinforced social behaviours in early humans (IJzerman et al., 2012, 2015). Thermoregulation is key to the extent that temperature changes may have a causal effect on sleep by affecting particular neuronal activity that triggers sleep onset (Kräuchi, 2007).

More broadly, the concepts of arousal and valence are central to the study of emotional affect. In sleep music studies, much of the arousal component is generally assumed, with sleep music typically expected to be lower in energy. Valence implications are arguably equally important for sleep music, however surprisingly few studies investigate this systematically and if analysed the picture is complex. Scarratt et al. (2023) found that valence as given by Spotify in their Data Catalogue was significantly lower, i.e., more negative, for tracks in sleep playlists compared to music from the Music Streaming Sessions Dataset (MSSD), a publicly available dataset released by Spotify (Brost et al., 2020) considered to represent 'general' music. This finding appears to contradict the suggestions by Jespersen &

Vuust (2012) that sleep music should be positive. However, this result is difficult to interpret given the proprietary nature of the features in Spotify's Data Catalogue and the lack of details published regarding their underlying mechanics, and could be due to the interpretation of certain features such as lower pitch and subdued brightness as negative in valence (Kirk & Timmers, in press). In our current study, we can assess valence more directly from participants' ratings. We expect the valence factor to be relevant for positive promotion of sleep, countering the potential for depressive states also associated with low arousal.

Other affordances may also be relevant for music as a sleep aid. One such element is the notion that music can be used as a distraction (Jespersen & Vuust, 2012), however this is difficult to qualify. Distractions can have negative consequences that prevent dissociation required for sleep; music could help to relieve certain distractions, or be the cause of negative distraction itself. Indeed, Dickson & Schubert (2020a) found that distraction was both a reason for and against using music for sleep, for some "providing a blockage to […] negative thoughts" (Dickson & Schubert, 2020a, p. 191) but for others stimulating too much concentration or triggering emotions that would hinder their sleep. For one participant, simply "any form of noise would distract me and keep me awake" (Dickson & Schubert, 2020a, p. 191).

In this light, we may benefit from also considering the concepts of absorption and engagement. The terms are often conceptualised with relation to each other and associated with dissociation, but having different connotations with respects to consciousness in experience (Herbert, 2012, 2013). Similar to distraction, absorption and engagement may operate in complex and nuanced ways. Herbert (2012) suggests that music "affords multiple entry points to involvement" (Herbert, 2012, p. 57), including multiple potentially effective processes to sooth, relax and wind down, and facilitates an "altered relationship to self and environment" (Herbert, 2013, p. 372). If the intention is to free the mind of stressful thoughts, more than create a strong focal point, there may be a sweet spot where music can achieve this and facilitate sleep.

Advancing existing research

The theoretical framework suggested by Jespersen & Vuust (2012) provides a basis for empirical validation, namely for the effects on arousal, emotion, and distraction. In addition, we propose further concepts that are relevant for music listening and may play a role in sleep, such as comfort, engagement, and absorption. Given the overlap with music listening functions generally, it is important to consider how these conceptualisations relate to sleep music more specifically by contrasting with music for other purposes. Such a comparison risks however comparing very contrasting types of music, observing more differences than required. To address this, we solicited the involvement of composers to create music specifically for the purpose of this study in addition to comparing features and conceptualisations of commercially available music.

Current study

An experimental study was conducted to empirically investigate the subjective conceptualisations of sleep music. Specifically, we aimed to investigate what subjective qualities are associated with music that is considered most supportive of sleep and what the relative contribution is of subjective qualities and objective musical features in the assessment of music as sleep inducing. An online listening study was designed to gather ratings from listeners in response to a wide selection of musical pieces. To characterise responses to sleep music in relation to other forms of music listening, we included music suited for the purpose of sleep with music for relaxing and energising, as categorised by our selection process (see Methods section for details). Participants were asked to evaluate the music along 13 bipolar dimensions capturing subjective responses related to valence, arousal, comfort, engagement, absorption, and distraction. An assessment of musical features of the stimuli was carried out using the MIR Toolbox for MATLAB (Lartillot et al., 2008; Lartillot & Toiviainen, 2007). Participants were also invited to leave comments during the study to provide further qualitative data.

Methods

Ethics Statement

This study received ethical approval from the University of Sheffield (application reference No. 036383) and informed consent was obtained from all participants at the commencement of the survey.

Participants

We received 108 complete responses (69 female (63%), 45% aged 21-29). Most participants were from Europe (N=79, 18 Asia, 11 other). 78 participants (72%) reported that they played or had played a musical instrument. Given the skew of these demographics, they will not be compared in the analysis and only serve to describe our sample.

Stimuli

Stimuli consisted of 56 one-minute excerpts. Following a previous study of Spotify playlists (Kirk & Timmers, in press), music was selected on the basis of falling into three categories; music for the purpose of sleep, music for relaxing, and music for energising. This included commercial music sampled from Spotify playlists, music gathered from previous sleep studies, and novel compositions created for the purposes of this study (see below for details). The intention was to create a diverse set of stimuli to draw sufficient comparisons. The new compositions were commissioned to gather material that has stylistic uniformity (is comparable across pieces from a single composer) whilst serving different purposes. This study serves a double purpose for investigating the suitability of these pieces amongst a comparison of commercial music intended for these purposes.

Novel compositions

MA students in Composition at the University of Sheffield were set the task of creating a set of three pieces of music one minute in length suitable for the purposes of energising, relaxing, or sleep induction. They were asked to compose excerpts that were closely related to each other, i.e., following a similar theme or base material, but varied in characteristics to differentiate between the different purposes. Eight composers returned a total of 24 pieces, including a variety of interpretations and stylistic contrasts (e.g., solo instrumentals and larger arrangements; acoustical pieces and electronic compositions).

Selection from Spotify

A matched number of tracks were selected from Spotify playlists that had been analysed in a previous investigation (Kirk & Timmers, in press). [1] The original analysis concerned 4,500 tracks from Spotify playlists that were collected using search terms related to sleeping, relaxing, and energising. See Appendix Aa for details on the selection process for this study. The resulting 24 tracks consisted of mainly pop and dance songs in the energising playlists, all of which contained vocals, while most songs in the relaxing playlists were from the chill-hop genre, with only two songs in this set containing vocals. The sleep selection was entirely instrumental, consisting of mainly solo piano pieces.

Commercial sleep music

A third set of sleep music was added to the musical materials to represent music purposefully composed to facilitate sleep rather than music selected for this purpose by users as recorded in Spotify playlists. For this a further eight tracks were selected comprising music

[1] The final submitted paper for this investigation was based on a resampling of the dataset after this selection was made, which was a random sampling from over 17k tracks. Therefore, they are not technically identical datasets, however the initial playlist selection criteria were the same.

taken from commercial recordings marketed specifically for sleep or deep relaxation, and music that had been used in previous research. This track list and respective citations can be found in Appendix Ab. These will hereby be referred to as commercial sleep music (CSM).

Sound file preparation

Files for all 56 tracks were cut to the first minute with a three second fade out and exported as uncompressed 24-bit WAV files. We used YouTube to host the audio files online for embedding into the survey. Videos were created for each sample, set to a plain black background and exported to Standard Definition 480p .mov files. All uploads were set as Unlisted videos on new purpose-created channels linked to the first author's University Google account, simply titled by numbers from 1-56.

Questionnaire items

Background and mood questions

Several background questions were presented in this survey, assessing musical engagement, personality, and sleep habits. The analysis of these is outside the scope of the current article, which will focus on the analysis of the music and subjective ratings in relation to evaluations of sleep induction.

Participants were asked to rate their mood, alertness, and tension before the listening phase along three 9-point bipolar scales intended to indicate valence, energy, and tension: Negative-Positive, Extremely Alert-Extremely Sleepy, Tense-Relaxed. These questions showed moderate mood levels for all participants and are not investigated further.

Subjective responses to music

For each musical excerpt, listeners were asked to rate the music along 13 dimensions using 9-point bipolar scales. These were presented as ratings for describing the music and describing the effects of the music on the listener, including a rating for how sleep inducing or preventing a piece was, and a like/dislike question (see Table 1). Items were considered associated with emotional valence, energy and tension arousal, taking the three-dimensional model of affect into consideration (Ilie & Thompson, 2006; Schimmack & Grob, 2000), comfort, engagement, absorption, and distraction. Because distraction could be differently construed, it was presented with “freeing the mind” as its antithesis to convey the notion of dissociation. Finally, an open comment box was provided for additional feedback.

Table 1

Listening phase ratings questions. Participants were asked to indicate in one direction or another along a 9-point scale.

I would describe the music as:		
	Negative	Positive
	Tense	Relaxed
	Sleepy	Awake
	Familiar	Unfamiliar
	Boring, unappealing	Engaging
The effect of the music on me can be described as:		
	Pleasant	Unpleasant
	Calming	Activating
	Energising	Sedating
	Comforting	Distressing
	Absorbing	Repelling
	Distracting	Freeing the mind
	Sleep inducing	Sleep preventing
How much do you like/dislike the music?		
	Like	Dislike

Musical features

A selection of musical features was extracted using the MIR Toolbox for MATLAB (Lartillot et al., 2008; Lartillot & Toiviainen, 2007). Our choice of features largely followed Dickson & Schubert (2020) for comparison, but with some additions to provide a more detailed analysis. As well as a measure of dynamic variation, we extracted the total dynamic energy of each track. Instead of an aural assessment of rhythmic activity, we included measures of event density and pulse clarity. As well as rhythmic and dynamic variation, we assessed modal variability by extracting key clarity. Brightness was also included following previous work that found this measure to be the strongest predictor for distinguishing sleep and relaxing playlists from Spotify (Kirk & Timmers, in press). The full list of features and their descriptions can be seen in Table 2.

Table 2

Musical features included in our analysis. Includes features assessed by Dickson & Schubert, 2020, hereby referred to as D&S.

Feature	Description	Type of analysis
Articulation	Mean ratio of the decay in amplitude over time.	MIR Toolbox using the Decay Slope Mean, following D&S.
Brightness	Level of upper mid and high frequency content.	MIR Toolbox using the mirbrightness function. D&S measured the mean frequency spectrum centroid (Hertz), which they compare to brightness.
Dynamic energy	Global energy of the signal using the root mean square (RMS) amplitude.	MIR Toolbox using the mirrms command.
Dynamic variation	Standard Deviation of the root mean square (RMS) amplitude.	MIR Toolbox using the mirrms command, following D&S.
Event density	Average frequency of events per second.	MIR Toolbox using the mireventdensity command.
Key clarity	The key strength associated with the best estimation of the tonal centre.	MIR Toolbox using the mirkey command.
Mode	Major vs minor.	MIR Toolbox using mirmode function, which returns a value between +/-1 to indicate the degree of major/minor mode. D&S used aural analysis (Major/Minor).
Pulse clarity	Estimates the rhythmic clarity, indicating the strength of the beats.	MIR Toolbox using mirpulseclarity command (Lartillot, Eerola, et al., 2008).

Tempo	Calculation of beats per minute (bpm)	MIR Toolbox using the mirtempo command. D&S chose manual tempo tapping (Tap BPM).

Procedure

The survey was conducted online using the Smart Survey platform and disseminated through University of Sheffield mailing lists and other online platforms, including Facebook, Reddit, and Twitter. No specific demographic was targeted, and the only requirement was that participants had no hearing impairments. Full information on the study and a consent form was provided at the beginning of the questionnaire. Each participant was presented with a random subset of 14 examples from the 56-piece selection, balanced across each category (i.e., two excerpts from each category (sleeping, relaxing, energising) and source (Spotify, novel compositions) combination plus an additional two CSM pieces).

Participants were asked to carry out the listening portion in the evening, as appropriate for the topic of the study taking circadian effects into account that may affect mood and alertness (Romeijn & Van Someren, 2011). However, due to the inconvenience of requiring participants to organise the time to complete the survey this requirement was reconsidered and instead only recommended at the final stages of data collection to make it easier to gather extra participants. To provide a reflective assessment of the adherence to the evening completion request, we used the finish times recorded by Smart Survey as a proxy. Participants who's finish times were at least 30 mins after 6pm in their respective time-zone were considered to have completed the listening phase in the evening. This assessment suggested that 62 (57%) of the participants did complete the study in the evening. As this is only a portion of the sample, this requirement was not met, and we will instead consider this a limitation of our study. A debriefing page was included at the end of the survey with an open comment box for participants to provide extra feedback. According to the timings recorded by Smart Survey, the survey took approximately 20-40 minutes to complete.

Analysis

First, we compare differences in ratings and musical features between the music categories. To compare ratings between the music categories, ratings were first averaged within each category by participant. Data within each category were approximately normally distributed, as assessed by visual inspection of histograms and confirmed by Shapiro-Wilks tests, therefore the ratings categories were compared using one-way repeated measures ANOVAs and paired samples t-test for pairwise comparisons. The musical features were not normally distributed, therefore Kruskal-Wallis H tests were used with pairwise comparisons performed using Wilcoxon signed-rank tests. Next, for the ratings data across music categories which met normality of distribution assumptions, Principal Component Analysis (PCA) was used to explore underlying patterns in the ratings by reducing the variables to their fundamental components. Finally, multiple linear regression investigated the contribution of combinations of all our variables to predict what makes a piece of music sleep inducing.

All statistical analysis was carried out using SPSS, and Laerd Statistics (https://statistics.laerd.com/) was used for guidance on procedure and reporting.

Results

Overview of ratings and features

The final dataset consisted of 1,512 entries (108 participants x 14 tracks each). Each track received 15-43 responses (*M* = 27, *SD* = 5.41). Distribution of ratings by music categories can be seen in Figure 1. For consistency and to aid interpretation, we have ordered each rating along its relative positive-negative valence or high-low arousal directionality. For example, Sleep Preventing is considered the high end as an arousal dimension, whereas Sleep

Inducing is low. All figure and table labels correspond to the positive- or high- directed adjective of each dimension.

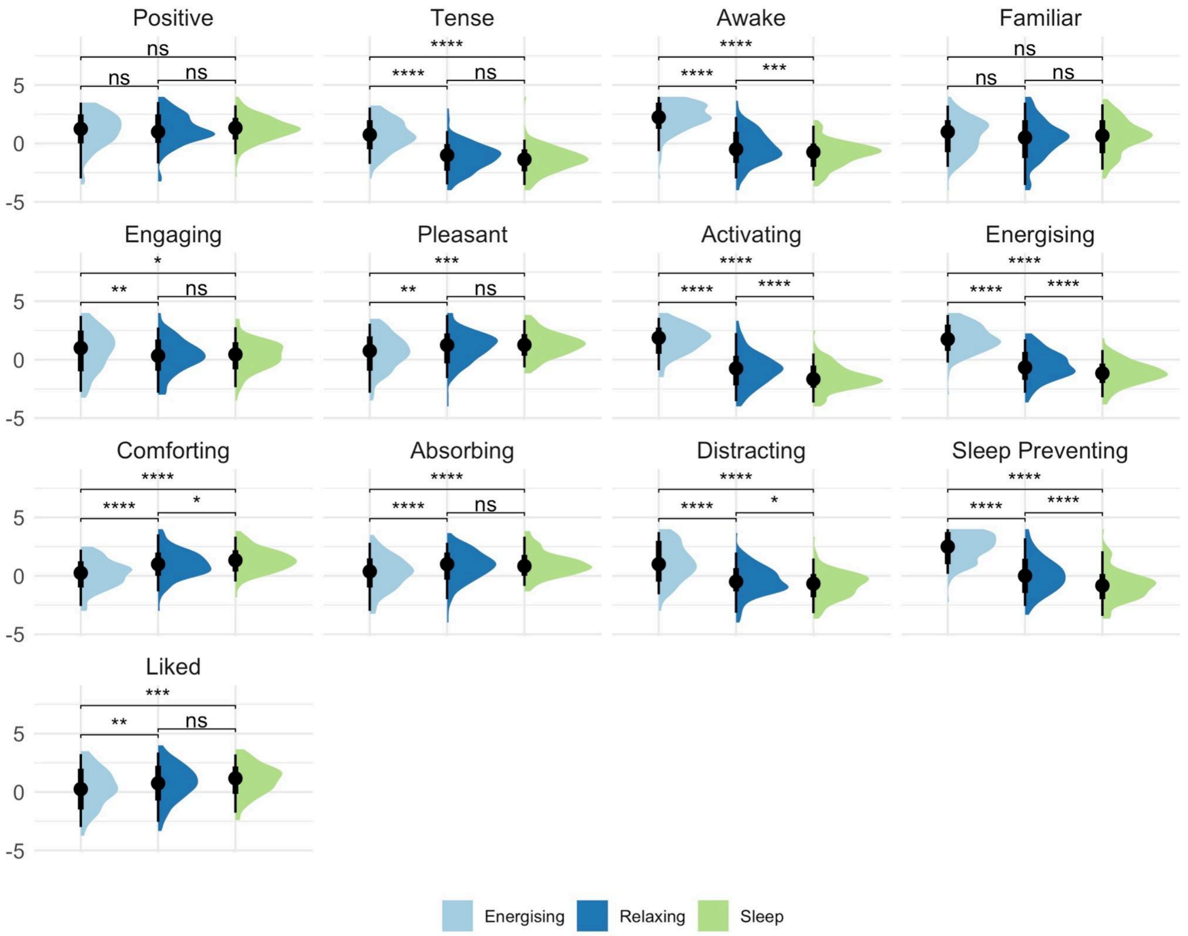

Figure 1

Plots of all ratings by music category. Results of paired samples t-tests are shown. ns = not significant. *p <.05. **p <.01. ***p <.001.

Repeated measures ANOVAs revealed significant differences between the categories for all of the ratings except Positivity and Familiarity, yet not all pairwise comparisons were significant (see Figure 1). The categories themselves were not uniform; for example, tracks in the Relaxing category were split for Sleep Preventing ratings. Ratings for individual tracks were likewise extremely varied. Overall, music in the sleep category was rated significantly more sleepy, calming, sedating, comforting, freeing of the mind, and sleep inducing than relaxing music, and additionally more relaxed, pleasant, absorbing, and liked than energising music.

Musical feature distributions per music category can be seen in Figure 2. Kruskal-Wallis H tests revealed significant differences for all features except Tempo and Mode. For the remaining features, pairwise comparisons found significant differences between Energising and Sleep music for all but Articulation, which was significant between the Sleep and Relaxing music. Brightness was the only other feature significantly different between Sleep and Relaxing music.

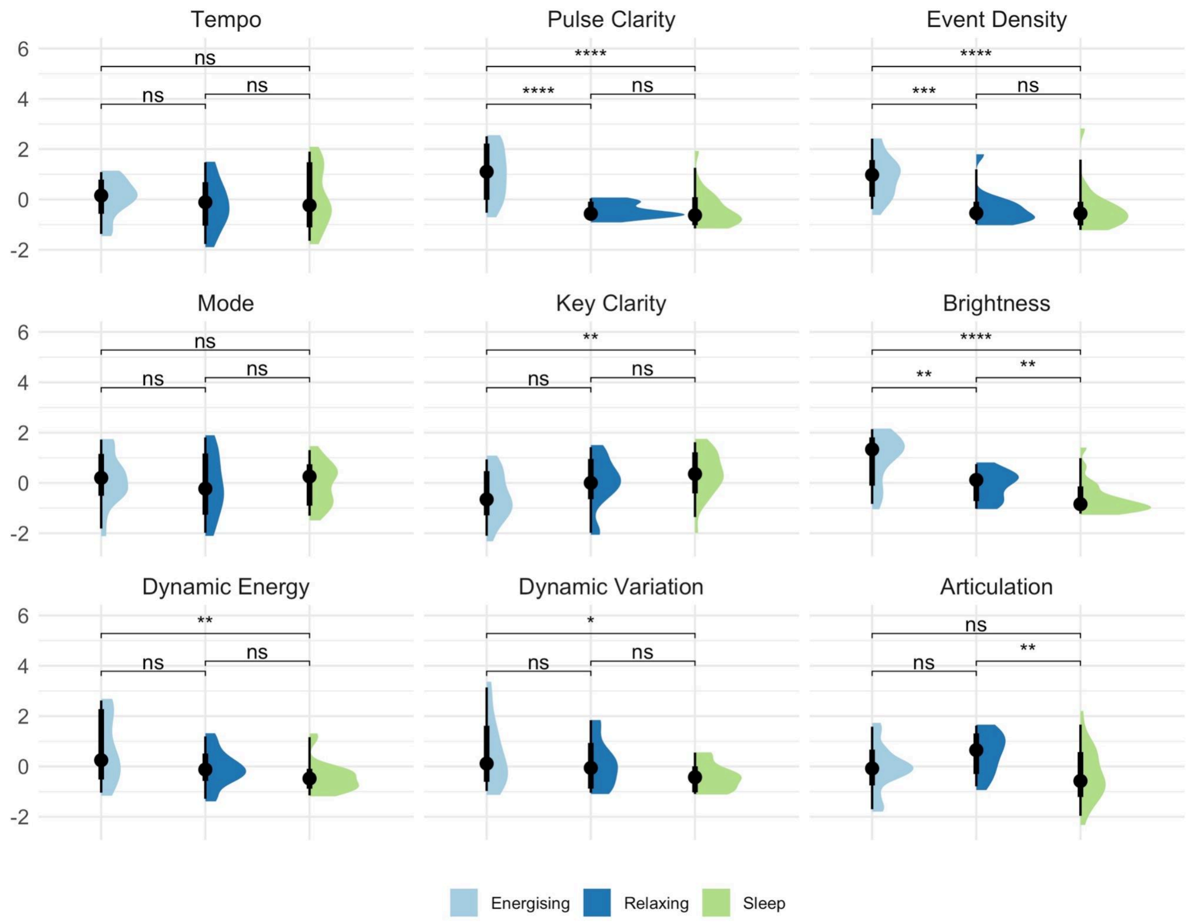

Figure 2

Plots of musical features, excluding artifacts revealed during the analysis (see Results). All values are standardised. Results of Wilcoxon signed-ranks tests are shown. ns = not significant. **p* <.05. ***p* <.01. ****p* <.001.

Interrelations between subjective ratings

Linear analysis was run to investigate relationships between the different subjective dimensions. Overall ratings (i.e., not separated by playlist category) were close to normally distributed, as assessed by visual inspection of histograms and Normal Q-Q plots without strong outliers. Pearson correlation results are depicted in the heatmap shown in Figure 1. Many variables were highly linearly correlated. Correlations showed a clustering of variables into two distinct groups akin to positive-negative valence and high-low arousal, respectively.

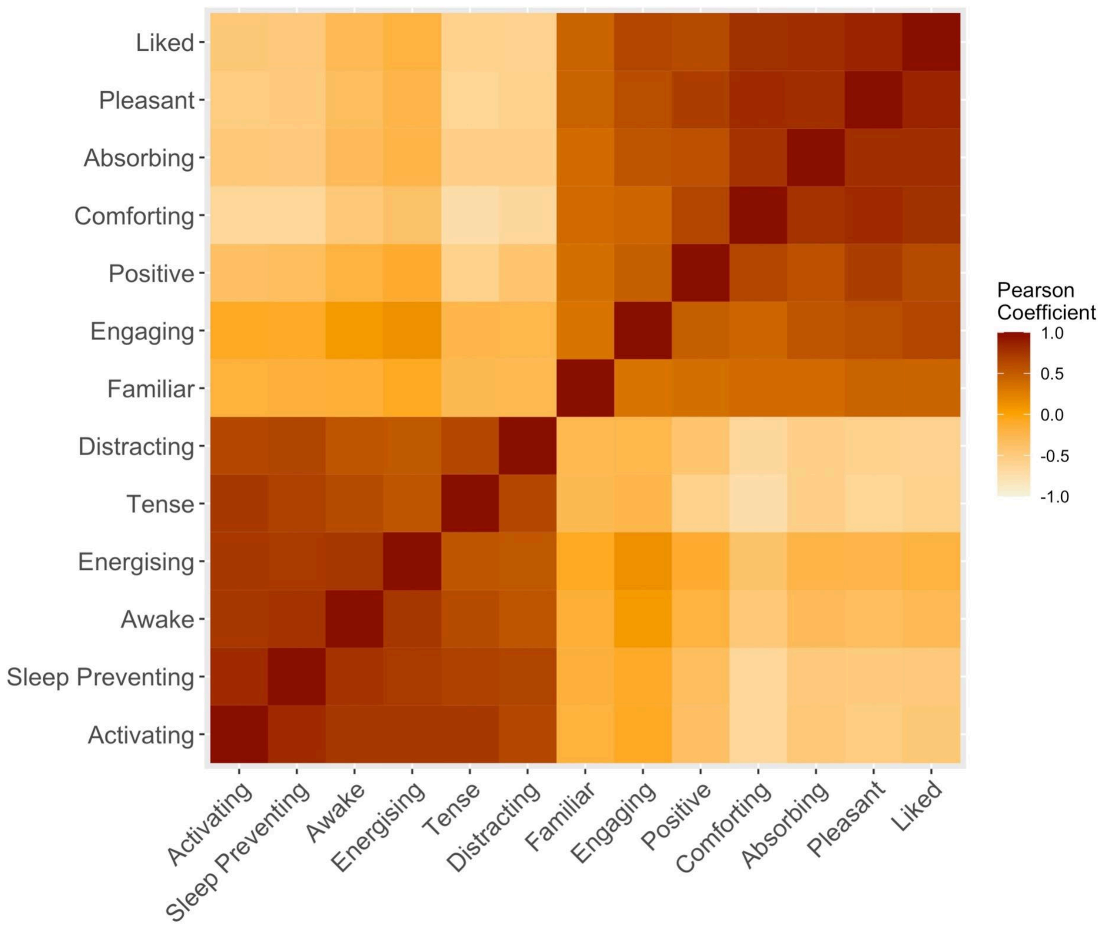

Figure 3

Correlations heatmap showing correlation coefficients between pairs of evaluative dimensions ordered with hierarchical clustering.

Principal Component Analysis (PCA) was used to further examine this clustering. Suitability for PCA was first assessed by inspection of the correlation matrix. All variables returned correlation coefficients greater than .3, and most were greater than .6 except Familiar-Unfamiliar (greatest .443). Familiar-Unfamiliar was also the only variable with a Communality coefficient less than .5 (.297). As a middling factor that did not fit as strongly with the other variables, we decided to rerun the analysis excluding Familiar-Unfamiliar. The resultant analysis gave an overall Kaiser-Meyer-Olkin (KMO) measure of .932, or "marvellous" according to Kaiser's classifications (Kaiser, 1974). Bartlett's Test of Sphericity was significant ($p < .0005$), indicating that the data was likely factorisable. The PCA revealed two components with Eigenvalues greater than 1 explaining 77.2% of the total variance. Varimax rotation (Table 3) revealed a close to simple solution, with most factors loading exclusively on one component. The first component contained variables which might relate to a listener's positive experience of the music, whereas the second contained activation factors, befitting a valence-arousal distinction. From that perspective, we can also see a possible tension arousal overlap with Tense-Relaxed and Comforting-Distressing falling into both components, reminiscent of a three-factor model (Ilie & Thompson, 2006; Schimmack & Grob, 2000).[2] We will hereafter refer to these components as the Valence component and the Arousal component. The Valence component accounted for a larger proportion of the variance in responses (57%) than the Arousal component (20%).

Table 3

Varimax rotated component matrix, final solution. Coefficients <.3 are suppressed.

Rating	Valence Component (56.9%)	Arousal Component (20.3%)
Liked	0.888	

[2] A forced three-component extraction did not reveal a tension dimension, instead resulting in a more complex solution with no logical interpretation of the components.

Pleasant	0.878	
Absorbing	0.829	
Engaging	0.802	
Comforting	0.764	-0.509
Positive	0.760	
Energising		0.897
Awake		0.895
Activating		0.868
Sleep Preventing		0.867
Tense	-0.503	0.697
Distracting	-0.466	0.650

Method: Principal Component Analysis
Rotation: Varimax with Kaiser Normalisation

Component scores were used to explore the dimensional structure of the music selection. Average component scores were calculated for each track and are presented in Figure 4, separated by the three categories (Sleep, Relaxing, Energising). There is some separation of each category, with the Sleep and Relaxing music occupying a similar space lower than the Energising music on the arousal scale. There appear to be linear trends in different directions between the Sleep and Relaxing music compared to the Energising music. For Sleep and Relaxing music, Arousal values decrease with increased Valence, while the opposite is the case for Energising music.

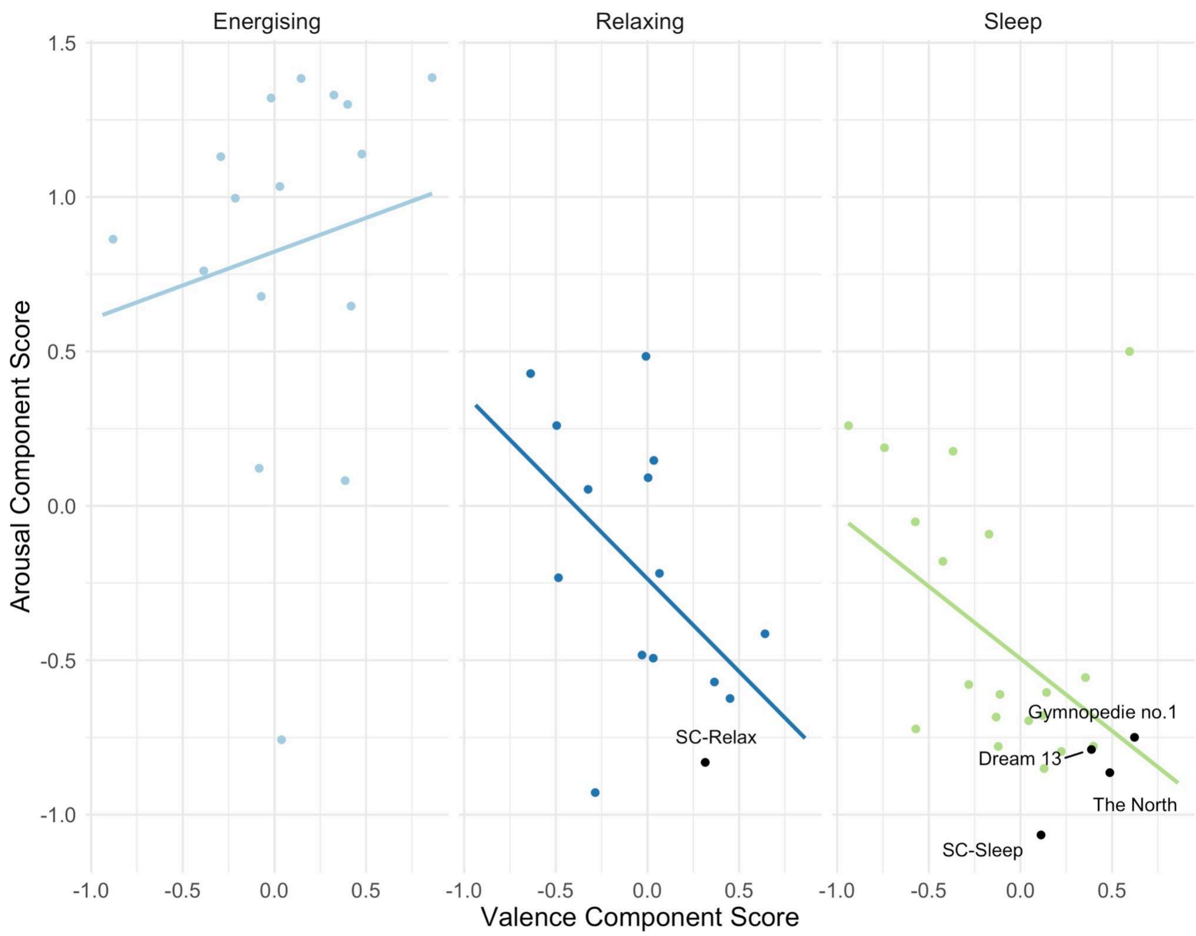

Figure 4

Average component scores for each track by playlist category with trend lines between Valence (x-axis) and Arousal (y-axis) component score. The five tracks with the lowest average Sleep Preventing ratings (i.e., were rated as highly sleep inducing) are labelled. These concern two tracks by one composer at the University of Sheffield, labelled as SC, Dream 13 (minus even) by Max Richter, The North by Niels Eje, and Gynopédie No. 1 by Eric Satie.

Predicting sleep induction - subjective ratings and musical features

To assess which qualities correspond to how sleep inducing a piece of music is perceived to be, we used the Sleep Preventing-Sleep Inducing rating as a dependent measure in regression models of the ratings and acoustic features.

Analysis of the ratings revealed potential collinearity issues based on an assessment of Variance Inflation Factors (VIF). Pleasant-Unpleasant, Comforting-Distressing, and

Like-Dislike each had VIF values >5. Pleasant was the only variable with correlation coefficients >.8, with both Comforting-Distressing and Like-Dislike, so this was removed. Comforting-Distressing still had a marginally high VIF value (5.151) in the subsequent analysis, so we will review this outcome with some caution. All other assumptions were satisfied. This model statistically significantly predicted the sleep induction ratings, $F(11, 1435) = 443.955$, $p < .001$, adj. $R^2 = .771$, and several of the ratings added statistically significantly to the prediction (see Table 4, Model A). The highest coefficients were returned for the variables associated with Arousal. Of the Valence variables, Comforting-Distressing had the highest value, above liking, freeing of the mind, and familiarity. None of the other Valence-associated variables significantly contributed to the model.

Next, we looked at how well the musical features predicted the Sleep Preventing-Sleep Inducing rating. The first analysis found collinearity issues with the two RMS outputs (Dynamic Energy and Variation); therefore, the analysis was rerun with only Dynamic Variation, keeping in step with Dickson & Schubert (2020). In the second attempt, two tracks returned Leverage values greater than .5, and these were subsequently removed. The final model statistically significantly predicted the sleep induction ratings, $F(8, 1438) = 89.110$, $p < .001$, adj. $R^2 = .328$, and Brightness, Event Density, and Pulse Clarity added statistically significantly to the prediction (see Table 4, Model B).[3]

Finally, a combined analysis was carried out including all of the variables above. The model statistically significantly predicted the sleep induction ratings, $F(19, 1427) = 258.981$, $p < .001$, adj. $R^2 = .772$ (Table 4, Model C). The same subjective variables were significant as in Model A. Fewer musical features were significant: Brightness ($p = .859$) and Pulse Clarity

[3] Using average Sleep Preventing-Sleep Inducing ratings gave much the same results but improved the overall model fit, $F(8,45) = 15.791$, $p<.001$, $\Delta R^2 = .691$. This is not surprising given that averaging the ratings removes the individual variability in the data.

(*p* = .598), were no longer statistically significant; instead, Dynamic Variation was found to significantly predict sleep induction ratings (*p* = .026) in addition to Event Density (*p* = .045).

Table 4

Multiple regression results for sleep induction by ratings and musical features separately, then together.

Sleep Induction	*B*	95% CI for *B*		*SE B*	*ß*	R^2	ΔR^2
		LL	*UL*				
Model A						.773	.771
(Constant)	.656***	.577	.735	.04			
Activating	.298***	.247	.349	.026	.293***		
Awake	.266***	.222	.311	.023	.26***		
Energising	.204***	.153	.254	.026	.178***		
Comforting	-.202***	-.271	-.134	.035	-.166***		
Liked	-.106***	-.161	-.051	.028	-.101***		
Distracting	.1***	.058	.141	.021	.09***		
Familiar	.061***	.031	.09	.015	.057***		
Positive	.035	-.01	.08	.023	.028		
Engaging	.028	-.013	.069	.021	.024		
Tense	.012	-.037	.06	.025	.011		
Absorbing	-.006	-.063	.05	.029	-.005		
Model B						.331	.328
(Constant)	-1.316*	-2.546	-.085	.627			
Brightness	3.523***	2.572	4.473	.485	.271***		
Event Density	.784***	.594	.975	.097	.265***		
Pulse Clarity	1.574***	.914	2.234	.336	.139***		
Articulation	.058	-.005	.12	.032	.042		
Mode	-.639	-1.643	.366	.512	-.029		
KeyClarity	-.709	-2.322	.903	.822	-.023		
Tempo	0	-.003	.003	.002	-.003		

Table 4

Multiple regression results for sleep induction by ratings and musical features separately, then together.

Dynamic Variation	-.204	-4.981	4.573	2.435	-.002		
Model C						.775	.772
(Constant)	.558	-.169	1.284	.37			
Activating	.281***	.228	.333	.027	.276***		
Awake	.263***	.217	.308	.023	.257***		
Comforting	-.212***	-.28	-.144	.035	-.174***		
Energising	.195***	.145	.246	.026	.171***		
Liked	-.111***	-.167	-.056	.028	-.106***		
Distracting	.096***	.055	.138	.021	.087***		
Familiar	.057***	.027	.087	.015	.054***		
Event Density	.118*	.003	.233	.059	.04*		
Dynamic Variation	3.223*	.379	6.067	1.45	.035*		
Engaging	.032	-.01	.073	.021	.028		
Mode	.576	-.02	1.172	.304	.026		
Tempo	-.002	-.004	0	.001	-.025		
Positive	.026	-.02	.071	.023	.021		
Tense	.01	-.04	.059	.025	.009		
Pulse Clarity	-.106	-.501	.288	.201	-.009		
Articulation	.007	-.029	.044	.019	.005		
Brightness	-.052	-.628	.524	.294	-.004		
Absorbing	-.001	-.057	.055	.029	-.001		
Key Clarity	.013	-.935	.962	.484	0		

Note. Model = "Enter" method in SPSS Statistics; *B* unstandardised regression coefficient; *CI* = confidence interval; *LL* = lower limit; *UL* = upper limit; *SE B* = standard error of the coefficient; *ß* = standardised coefficient; R^2 = coefficient of determination; ΔR^2 = adjusted R^2.

**p* <.05. ***p* <.01. ****p* <.001.

A closer look at the most sleep-inducing pieces

To tie together our analyses and help interpret the results, we take a closer look at the five most sleep-inducing tracks, as determined by mean ratings, previously highlighted in Figure 4.[4] Two of these tracks were written by a composer studying at the University of Sheffield. Of the remaining three, two were from commercial recordings that had been used in previous sleep studies, specifically selections from the albums Sleep by Max Richter (Kuula et al., 2020) and MusiCure by Niels Eje (Jespersen & Vuust, 2012). The final piece is a recording of Erik Satie's Gymnopédie No. 1, a piece that appears in several studies as an example of relaxing music or reported by listeners as a piece used for sleep (e.g., Iwanaga et al., 2005; Rickard, 2004; Siragusa et al., 2020; Trahan et al., 2018). This track was the most familiar, which could correspond to its greater average values for liking, pleasantness, comfort, absorption, and engagement, culminating in the highest Valence score of this selection. By contrast, the most sleep-inducing piece had the lowest Valence score of these five, but also the lowest Arousal score, and indeed the lowest scores for most of the variables that contributed to this component (Awake-Sleepy, Energising-Sedating, Sleep Preventing-Sleep Inducing). The musical features of this most sleep-inducing piece were indeed maximally associated with lower activation; this piece had lower values for Articulation, Dynamic Energy and Variation, Event Density, and no clear pulse compared to the other five. Conversely, the track was more minor in Mode, and had the highest Brightness values of the five.

Most of these pieces received very little in the way of comments from participants. Many other pieces received plenty of commentary, predominantly critical, personal, or expressions of enthusiasm in the case of the Energising pieces. The exception of these five was Gymnopédie No. 1, again perhaps due to its familiarity. One participant exclaimed, "Erik Satie is one of my favourite composers :)" (P72), another stated that the piece was one of

[4] A list of the ten most sleep inducing pieces can be found in Appendix B.

their “favourite pieces of music” (P82). Another discussed listening to the piece to help with their sleep:

> When quarantine started[5] I barely slept due to stress and anxiety and I used this piece to fall asleep for a month straight, it's more than comforting that song just feels like home. (P71)

The theme of comfort is echoed by another participant who described the piece as “very melancholic and comforting, it's like a cuddle for your soul” (P115). For others, however, the familiarity was not conducive to sleep, with one participant stating, “I love Satie, so this would keep me awake as I tried to remember the fingering!” (P85), and for another, “Individual notes are too distinct and the melody too familiar, would not allow me to disassociate” (P108). One participant elaborated further:

> It only doesn't "free my mind" completely because I recognize the tune and as a musician I was predicting what came next while I listened. (This is why I can't listen to music to fall asleep!) Otherwise the piece itself, the same dynamic, the single timbre, and steady tempo... all were very relaxing. (P77)

Discussion

In this study, we incorporated subjective indications with musical features to assess what makes music ‘sleep inducing’. We used music from three sources (Spotify playlists, commercial sleep music, and novel compositions) that fell into three categories (Sleep, Relaxing, and Energising) to give a broad selection. The results showed that the experience of

[5] This study took place in the year 2021 during the SARS-CoV-2 pandemic.

music as sleep inducing was dependent on an appropriate combination of valence and arousal evaluations with greater valence and lower arousal corresponding with highest sleep induction. Reflecting this combination, we found a prominent role for notions of comfort, which significantly predicted ratings towards sleep induction along with liking and freeing the mind and was highlighted in participants' comments. Brightness, Event Density, Pulse Clarity, and Dynamic Variation were significant musical characteristics, however their relative contributions were small and differed between analyses. Overall our results indicate that subjective appraisals are strong predictors of evaluations of music as sleep inducing, overshadowing musical attributes in predictive ability, and accounting for a high proportion of variance. In the following we discuss these results in more detail.

Arousal and valence distinctions

Sleep Prevention was better predicted by variables associated with arousal, whereas valence was less prominent in our regression models. This could be a reflection of the music selection; although no variables were explicitly manipulated, the categorical selection (from Energising to Relaxing to Sleep) itself connotes a dimension of arousal. However, the divergent trends seen in our PCA analysis still offer some intrigue. Higher Valence component scores seem to correspond to lower Arousal component scores for Sleep and Relaxing music, whereas Arousal scores were higher with increasing Valence for Energising music (see Figure 4). The orthogonal relationship (or possible lack thereof) between valence and arousal is complex (Kuppens et al., 2013); the divergence seen here could indicate an interaction that differs depending on the goals of the music. For Energising music, the perception of greater arousal is enhanced when the music is enjoyed or deemed positive, whereas for Relaxing and Sleep music, where the intention is to reduce arousal, this is also better achieved when the music is seen as more positive. Crucially, we saw that the pieces rated as the most sleep inducing on average occupied the extreme end of the right lower quadrant of this space (low arousal, positive valence).

Our valence interpretation should remain loose; these patterns could also be a factor of the dimensions that feed into the component scores, such as engagement, absorption, and tension, which could have different relevance for Energising music compared to the other categories. Likewise, this could explain their lack of significance in our regression analysis. Explicitly manipulating valence would expand on these results. Nonetheless, we find support for the suggestion that positive valence is important for sleep music, and may vary in association with arousal, both contributing towards the potential for sleep induction. This gives empirical support to the suggestions put forward by Jespersen & Vuust (2012), that music best for sleep should be positive and low in arousal.

Comfort and freeing the mind

As predicted, comfort was a significant factor for sleep induction, both predicting ratings and specifically referred to by participants in comments. Supporting feelings of comfort and safety may be important avenues by which music benefits wellbeing, possibly by acting as a social surrogate (K. Schäfer et al., 2020; K. Schäfer & Eerola, 2018), and this may be another avenue by which music helps sleep. Although we haven’t explicitly studied what makes a piece of music comforting this would be a fruitful avenue of further investigation.

Distraction is the third mechanism suggested by Jespersen & Vuust (2012), and this was more difficult to distinguish. The Distraction-Freeing the mind rating significantly predicted sleep induction ratings, however absorption and engagement did not offer any further insight, in contrast to our expectations. Neither were significant predictors in our regression analysis, possibly again due to having different relevance for the different categories. Our comparisons of the music categories found that music in the Sleep and Relaxing categories was significantly less Engaging but significantly more Absorbing than Energising music (see

Figure 1). The significance of Freeing the mind nonetheless suggests that dissociation is an important factor in music for sleep and needs further dissection.

Familiarity

Familiarity is often considered influential in the context of music listening for mood regulation and emotional affect (Tan et al., 2012; van den Bosch et al., 2013). Previous surveys have highlighted the importance of familiarity for the listener when it comes to choosing music for sleep (Dickson & Schubert, 2020; Trahan et al., 2018), and in our study participant comments highlighted both positive and negative aspects of familiarity. In some cases, the desire to predict or remember a piece as it unfolds was described as a hindrance. Indeed, familiarity was significantly negatively associated with sleep induction, according to our regression analysis. It is difficult to consolidate familiarity and the effect of predictability in this sense; for some, increased predictability might reduce attentional demand, and therefore cognitive effort, whereas the anticipation in listening to something novel might have the opposite effect and prevent dissociation. Our results offer both positive and negative associations with familiarity, with specific reference to predictability by participants, suggesting that this is a more complex relationship. It is possible that personal differences play a role; individuals may have different requirements when it comes to their sleep and different cognitive approaches to music listening that place a variable role on familiarity and predictability. Musicality may also be a factor, with some participants' comments suggesting an influence of their instrumental musicianship. Clearly an important issue, a more explicit testing of familiarity will benefit future research on sleep music, and could explore potential implications for distraction, as well as the relationship with comfort, safety, and liking.

Subjective vs. musical properties

Brightness was a significant predictor in one of our analyses, corroborating with previous work (Kirk & Timmers, in press) indicating an important feature that is often overlooked in discussions around sleep music. It confirms findings of Dickson & Schubert (2020) that music their participants reported as successful in helping with sleep was associated with lower main frequency register compared to unsuccessful music. Brightness can reflect different factors such as instrumentation, recording quality, or pitch, so it only provides a general indication of the timbral qualities of a track. However, these results suggest that this is an important factor to be considered.

Other significant features, Pulse Clarity, Event Density, and Dynamic Variation, point to rhythmic and dynamic aspects that are more commonly discussed in the sleep music literature, with our results aligning with the general assumptions of researchers (Jespersen et al., 2022). Other indications further align with prior notions of the types and characteristics of sleep music; many of the most sleep inducing pieces, based on average responses, were piano based, soft, calm, and minimal.

Overall, our regression models indicate a greater importance of subjective evaluations for predicting what music was perceived as most sleep inducing. Not only were the subjective factors more significant in the combined model (Table 4, Model C) but the accuracy of both Models A (ΔR^2 = .771) and C (ΔR^2 = .772) was considerably greater than the features only Model B (ΔR^2 = .328).[6] Although there were general trends in the musical characteristics of the most sleep inducing pieces, there was considerable individual variability that the features alone could not account for.

Limitations and implications

The musical selection process included music from Spotify playlists that were selected based on a best fit approach (see Appendix Aa). Given the extreme variety found in Spotify sleep playlists (Scarratt et al., 2023), our selection may be limited and is not guaranteed to

[6] The features model predicting average sleep induction ratings was also weaker than the models with subjective ratings (ΔR^2 = .691).

represent what might be best for sleep. The CSM selection offered some expansion and allowed comparisons between purpose-composed commercial music and general Spotify playlist selections, but results for the category may still be limited. Potential music choices could be near inexhaustible, and a practical assessment requires that such selective processes are made. Nevertheless, an expansion of this work could look to further selections of different music, potentially explicitly manipulating certain parameters such as valence, arousal, or musical properties.

Our study used convenience sampling and our sample demographic was notably skewed. As a result we have not factored any participant background information into our analysis. Our focus was to explore general perceptions of a musical selection, but given the individual variability in responses a consideration of personal differences would be extremely valuable. For example, Lee-Harris et al. (2018) found that for younger people relaxation was most strongly associated with levels of arousal, while for older people it was more associated with valence.

Only a sample of our participants completed the study in the evening. Because our primary interest is music that can be used for sleep, this is a limitation, as time of day can affect not only mood but also attention and vigilance (Romeijn et al., 2012), and potentially participants' experience of the music. Furthermore, our results are indications of perceptions in a listening study and not in the context of real sleep at night time. The translation of these factors to the real efficacy of music for sleep remains to be tested.

Conclusion

The subjective nature of musical experiences is routinely discussed in music psychology research. Our results establish this with respect to music for sleep where previously emphasis has focused on music type. Musical features are still prominent, but there is clear potential for subjective optimisation that may improve how music is used in sleep therapies. We have provided a conceptual foundation and a basic ranking of pieces considered to be sleep inducing, as rated by 108 participants, supporting the selection of specific pieces used in previous studies (e.g., Jespersen & Vuust, 2012; Kuula et al., 2020). The results provide valuable insight into the types of subjective evaluations relevant for sleep music and a foundation for more specific probing. In particular, notions of comfort and freeing of the mind are important for music that might promote sleep.

Data availability

The full dataset can be accessed at https://doi.org/10.15131/shef.data.25442095.v1.

Author contributions

RK contributed to conceptualisation, study design, data collection and analysis, interpretation of results, writing and editing. GP contributed to analyses, interpretation of results, writing and editing. MvdW contributed to conceptualisation, study design, interpretation of results, writing and editing. RT contributed to conceptualisation, study design, analysis, interpretation of results, writing and editing.

Funding

This research was supported by a Doctoral Training Partnership Scholarship from the UK Engineering and Physical Sciences Research Council (EPSRC).

References

Brost, B., Mehrotra, R., & Jehan, T. (2020). The Music Streaming Sessions Dataset. *arXiv:1901.09851 [Cs]*. http://arxiv.org/abs/1901.09851

Cordi, M. J., Ackermann, S., & Rasch, B. (2019). Effects of relaxing music on healthy sleep. *Scientific Reports*, *9*(1), 1–9. https://doi.org/10.1038/s41598-019-45608-y

Dickson, G. T., & Schubert, E. (2020). Musical features that aid sleep. *Musicae Scientiae*, 1029864920972161. https://doi.org/10.1177/1029864920972161

Gaston, E. T. (1951). Dynamic music factors in mood change. *Music Educators Journal*, *37*(4), 42–44. JSTOR. https://doi.org/10.2307/3387360

Gaston, E. T. (1968). *Music in therapy*. Macmillan.

Grandner, M. A. (2017). Sleep, health, and society. *Sleep Medicine Clinics*, *12*(1), 1–22. https://doi.org/10.1016/j.jsmc.2016.10.012

Herbert, R. (2012). Musical and non-musical involvement in daily life: The case of absorption. *Musicae Scientiae*, *16*(1), 41–66. https://doi.org/10.1177/1029864911423161

Herbert, R. (2013). An empirical study of normative dissociation in musical and non-musical everyday life experiences. *Psychology of Music*, *41*(3), 372–394. https://doi.org/10.1177/0305735611430080

Hernández-Ruiz, E. (2005). Effect of music therapy on the anxiety levels and sleep patterns of abused women in shelters. *Journal of Music Therapy*, *42*(2), 140–158. https://doi.org/10.1093/jmt/42.2.140

Huang, C.-Y., Chang, E.-T., Hsieh, Y.-M., & Lai, H.-L. (2017). Effects of music and music video interventions on sleep quality: A randomized controlled trial in adults with sleep disturbances. *Complementary Therapies in Medicine*, *34*, 116–122. https://doi.org/10.1016/j.ctim.2017.08.015

Huang, C.-Y., Chang, E.-T., & Lai, H.-L. (2016). Comparing the effects of music and exercise with music for older adults with insomnia. *Applied Nursing Research*, *32*, 104–110. https://doi.org/10.1016/j.apnr.2016.06.009

IJzerman, H., Coan, J. A., Wagemans, F. M. A., Missler, M. A., Beest, I. van, Lindenberg, S., & Tops, M. (2015). A theory of social thermoregulation in human primates. *Frontiers in Psychology*, *6*. https://doi.org/10.3389/fpsyg.2015.00464

IJzerman, H., Gallucci, M., Pouw, W. T. J. L., Weiβgerber, S. C., Van Doesum, N. J., & Williams, K. D. (2012). Cold-blooded loneliness: Social exclusion leads to lower skin temperatures. *Acta Psychologica*, *140*(3), 283–288. https://doi.org/10.1016/j.actpsy.2012.05.002

Ilie, G., & Thompson, W. F. (2006). A comparison of acoustic cues in music and speech for three dimensions of affect. *Music Perception*, *23*(4), 319–329. https://doi.org/10.1525/mp.2006.23.4.319

Iwaki, T., Tanaka, H., & Hori, T. (2003). The effects of preferred familiar music on falling asleep. *Journal of Music Therapy*, *40*(1), 15–26. https://doi.org/10.1093/jmt/40.1.15

Iwanaga, M., Kobayashi, A., & Kawasaki, C. (2005). Heart rate variability with repetitive exposure to music. *Biological Psychology*, *70*(1), 61–66. https://doi.org/10.1016/j.biopsycho.2004.11.015

Jespersen, K. V., Pando-Naude, V., Koenig, J., Jennum, P., & Vuust, P. (2022). Listening to music for insomnia in adults. *Cochrane Database of Systematic Reviews*, *8*. https://doi.org/10.1002/14651858.CD010459.pub3

Jespersen, K. V., & Vuust, P. (2012). The effect of relaxation music listening on sleep quality in traumatized refugees: A pilot study. *Journal of Music Therapy*, *49*(2), 205–229. https://doi.org/10.1093/jmt/49.2.205

Johnson, J. E. (2003). The use of music to promote sleep in older women. *Journal of*

Community Health Nursing, *20*(1), 27–35. JSTOR.

Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika*, *39*(1), 31–36. https://doi.org/10.1007/BF02291575

Kakar, E., Venema, E., Jeekel, J., Klimek, M., & Jagt, M. van der. (2021). Music intervention for sleep quality in critically ill and surgical patients: A meta-analysis. *BMJ Open*, *11*(5), e042510. https://doi.org/10.1136/bmjopen-2020-042510

Kräuchi, K. (2007). The human sleep–wake cycle reconsidered from a thermoregulatory point of view. *Physiology & Behavior*, *90*(2), 236–245. https://doi.org/10.1016/j.physbeh.2006.09.005

Kräuchi, K., & Wirz-Justice, A. (2001). Circadian clues to sleep onset mechanisms. *Neuropsychopharmacology*, *25*(1), S92–S96. https://doi.org/10.1016/S0893-133X(01)00315-3

Kuppens, P., Tuerlinckx, F., Russell, J. A., & Barrett, L. F. (2013). The relation between valence and arousal in subjective experience. *Psychological Bulletin*, *139*(4), 917–940. https://doi.org/10.1037/a0030811

Kuula, L., Halonen, R., Kajanto, K., Lipsanen, J., Makkonen, T., Peltonen, M., & Pesonen, A.-K. (2020). The effects of presleep slow breathing and music listening on polysomnographic sleep measures – a pilot trial. *Scientific Reports*, *10*(1), Article 1. https://doi.org/10.1038/s41598-020-64218-7

Lai, H.-L., & Good, M. (2005). Music improves sleep quality in older adults. *Journal of Advanced Nursing*, *49*(3), 234–244. https://doi.org/10.1111/j.1365-2648.2004.03281.x

Lartillot, O., & Toiviainen, P. (2007). *A Matlab toolbox for musical feature extraction from audio*. International Conference on Digital Audio Effects, Bordeaux, France. /paper/A-Matlab-Toolbox-for-Musical-Feature-Extraction-Lartillot-Toiviainen/cd7380a34bf43bb0a14177d8daf30ceaab2ef80a

Lartillot, O., Toiviainen, P., & Eerola, T. (2008). A Matlab toolbox for music information retrieval. In *Data Analysis, Machine Learning and Applications* (pp. 261–268). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-78246-9_31

Lazic, S. E., & Ogilvie, R. D. (2007). Lack of efficacy of music to improve sleep: A polysomnographic and quantitative EEG analysis. *International Journal of Psychophysiology*, *63*(3), 232–239. https://doi.org/10.1016/j.ijpsycho.2006.10.004

Lee-Harris, G., Timmers, R., Humberstone, N., & Blackburn, D. (2018). Music for relaxation: A comparison across two age groups. *Journal of Music Therapy*, *55*(4), 439–462. https://doi.org/10.1093/jmt/thy016

Levenson, J. C., Kay, D. B., & Buysse, D. J. (2015). The pathophysiology of insomnia. *Chest*, *147*(4), 1179–1192. https://doi.org/10.1378/chest.14-1617

Leys, C., Ley, C., Klein, O., Bernard, P., & Licata, L. (2013). Detecting outliers: Do not use standard deviation around the mean, use absolute deviation around the median. *Journal of Experimental Social Psychology*, *49*(4), 764–766. https://doi.org/10.1016/j.jesp.2013.03.013

Nilsson, U. (2008). The anxiety- and pain-reducing effects of music interventions: A systematic review. *AORN Journal*, *87*(4), 780–807. https://doi.org/10.1016/j.aorn.2007.09.013

Nilsson, U. (2011). Music: A nursing intervention. *European Journal of Cardiovascular Nursing*. https://doi.org/10.1016/j.ejcnurse.2010.06.004

Rickard, N. S. (2004). Intense emotional responses to music: A test of the physiological arousal hypothesis. *Psychology of Music*, *32*(4), 371–388. https://doi.org/10.1177/0305735604046096

Romeijn, N., Raymann, R. J. E. M., Møst, E., Te Lindert, B., Van Der Meijden, W. P., Fronczek, R., Gomez-Herrero, G., & Van Someren, E. J. W. (2012). Sleep, vigilance, and thermosensitivity. *Pflugers Archiv*, *463*(1), 169–176. https://doi.org/10.1007/s00424-011-1042-2

Romeijn, N., & Van Someren, E. J. W. (2011). Correlated fluctuations of daytime skin temperature and vigilance. *Journal of Biological Rhythms*, *26*(1), 68–77. https://doi.org/10.1177/0748730410391894

Scarratt, R. J., Heggli, O. A., Vuust, P., & Jespersen, K. V. (2023). The audio features of sleep music: Universal and subgroup characteristics. *PLOS ONE*, *18*(1), e0278813. https://doi.org/10.1371/journal.pone.0278813

Schäfer, K., & Eerola, T. (2018). How listening to music and engagement with other media provide a sense of belonging: An exploratory study of social surrogacy: *Psychology of Music*. https://doi.org/10.1177/0305735618795036

Schäfer, K., Saarikallio, S., & Eerola, T. (2020). Music may reduce loneliness and act as social surrogate for a friend: Evidence from an experimental listening study. *Music & Science*, *3*. https://doi.org/10.1177/2059204320935709

Schäfer, T., Sedlmeier, P., Städtler, C., & Huron, D. (2013). The psychological functions of music listening. *Frontiers in Psychology*, *4*, 511. https://doi.org/10.3389/fpsyg.2013.00511

Schimmack, U., & Grob, A. (2000). Dimensional models of core affect: A quantitative comparison by means of structural equation modeling. *European Journal of Personality*, *14*(4), 325–345. https://doi.org/10.1002/1099-0984(200007/08)14:4<325::AID-PER380>3.0.CO;2-I

Siragusa, M. A., Brizard, B., Dujardin, P.-A., Réméniéras, J.-P., Patat, F., Gissot, V., Camus, V., Belzung, C., El-Hage, W., Wosch, T., & Desmidt, T. (2020). When classical music relaxes the brain: An experimental study using Ultrasound Brain Tissue Pulsatility Imaging. *International Journal of Psychophysiology*, *150*, 29–36.

https://doi.org/10.1016/j.ijpsycho.2020.01.007

Tan, X., Yowler, C. J., Super, D. M., & Fratianne, R. B. (2012). The interplay of preference, familiarity and psychophysical properties in defining relaxation music. *Journal of Music Therapy*, *49*(2), 150–179. https://doi.org/10.1093/jmt/49.2.150

Trahan, T., Durrant, S. J., Müllensiefen, D., & Williamson, V. J. (2018). The music that helps people sleep and the reasons they believe it works: A mixed methods analysis of online survey reports. *PLoS ONE*, *13*(11). https://doi.org/10.1371/journal.pone.0206531

van den Bosch, I., Salimpoor, V. N., & Zatorre, R. J. (2013). Familiarity mediates the relationship between emotional arousal and pleasure during music listening. *Frontiers in Human Neuroscience*, *7*. https://doi.org/10.3389/fnhum.2013.00534

Walker, M. (2017). *Why we sleep: Unlocking the power of sleep and dreams*. Simon and Schuster.

Wang, C., Li, G., Zheng, L., Meng, X., Meng, Q., Wang, S., Yin, H., Chu, J., & Chen, L. (2021). Effects of music intervention on sleep quality of older adults: A systematic review and meta-analysis. *Complementary Therapies in Medicine*, *59*, 102719. https://doi.org/10.1016/j.ctim.2021.102719

Appendix

A. Music selection

a. Spotify

Category	Artist	Album	Track
Energising	*Clean Bandit*	*Tick Tock (feat. 24kGoldn)*	*Tick Tock (feat. 24kGoldn)*
	Bad Bunny	**LAS QUE NO IBAN A SALIR**	**PA' ROMPERLA**
	Spillage Village	Baptize (with JID & EARTHGANG feat. Ant Clemons)	Baptize (with JID & EARTHGANG feat. Ant Clemons)
	220 KID	Too Many Nights	Too Many Nights
	Shawn Mendes	Shawn Mendes	In My Blood
	The Weeknd	After Hours	Blinding Lights
	Janet Jackson	Rhythm Nation 1814	Rhythm Nation
	Avicii	Stories	Waiting For Love
	THAT KIND	Lights Go Down	Lights Go Down
Relaxing	Band of Horses	Acoustic at The Ryman (Live)	The Funeral - Live Acoustic
	Nothingtosay	Introspective	For You
	Healing Sounds for Deep Sleep and Relaxation	Spiritual Shamanic Music – 15 Ambient Songs Perfect for Deep Meditation and Sleep	Ethnic Session
	xander.	Cabin Fever	Don't Let Her Go
	No Spirit	Memories We Made	Some Alone Time
	Ryohei Shimoyama	Winter Milky Way	Winter Milky Way
	Sitting Duck	Wonderland Chapter 1	Slow Mornings
	S N U G	Moonglow	Missing You
Sleep	*Alice ASMR*	*ASMR Trigger Sounds*	*Blow Torch ASMR*

	Dan Evans-Parker	*Hush*	*Hush*
	Max Huber	When You Love Someone (Piano Version)	When You Love Someone - Piano Version
	Bud Hollister	The Stillness Within	The Stillness Within
	Pacific Ocean Samples	Beach Waves	White Noise Waves
	Luana Dias Araujo	**Polly Wolly Doodle**	**Polly Wolly Doodle**
	Steve Devon	Only Trust Your Heart	Only Trust Your Heart
	ThePianoPlayer	Sonnambula	Sogni d'oro
	Carla Moses	**I Will Say Goodbye**	**smoke gets in your eyes**
	Serge Charlesbois	**Hot Cross Buns**	**Rub-A-Dub Dub Three Men In A Tub**
	Ron Adelaar	*Gymnopédie No.1*	*Gymnopédie No.1*

To generate the selection of music, twelve audio features provided by the Spotify API were extracted and a principal component analysis (PCA) reduced the variables to two components. Component scores were then used to characterise each track. After calculating scores, the dataset was re-divided into the different categories. Modified z-scores using Median Absolute Deviation (MAD) (Leys et al., 2013) against the median within each category were calculated on each component score to re-centre these values within their respective groups. Using the explained variance percentages from the PCA for each component, weighted averages were calculated to give a single score for each track. The eight tracks nearest to 0 (positive and negative, four either side) in each group were selected on the assumption that they should be generally representative of each category. Three tracks in the Sleep category were only available for streaming on Spotify and thus could not be purchased for download, and one track had to be excluded at a later stage due to copyright restrictions when implementing in the online study. All tracks were purchased for download from iTunes or Amazon. Tracks in bold were omitted either due to being unavailable for purchase or were blocked from YouTube on the grounds of copyright issues; tracks in italics are the replacements. Further results in the Sleep playlist not being available outside of Spotify streaming resulted in a slight skew towards the negative side of 0 in this selection, but this was kept in the interest of remaining closer to 0 rather than simply having an equal number of results either side of 0.

b. Commercial sleep music

Artist	Album	Track	Used in previous study
Dr. Jeffrey Thompson	Delta Sleep System	Delta Sleep System, Part 1	Lazic & Ogilvie, 2007

Dr. Lee Bartel / SonicAid	Music to Promote Sleep	Drifting into Delta	Cordi et al., 2019; Picard et al., 2014
Marconi Union	The Ambient Zone Just Music Café, Vol. 4	Weightless	Radox Spa/Mischief PR, n.d.
Max Richter	From Sleep	Dream 3 (in the midst of my life) Dream 13 (minus Even)	Kuula et al., 2020 – used the longer 'Sleep' album.
Niels Eje	MusiCure	The North Legend Northern Light	Jespersen & Vuust, 2012

B. Ten most sleep-inducing pieces

Piece	Source	Category	Description	Tempo	Tonality
1. SC-8	Composers	Sleep	Solo piano, minimal classical, open ringing notes and chords	V. slow/ free time	Maj
2. Max Richter – Dream 13 (minus even)	CSM	Sleep	Piano and cello, classical	Med	Maj
3. Niels Eje – The North	CSM	Sleep	Wave sounds, harp and piano, New Age	Med	Maj
4. SC-13	Composers	Relaxing	Solo piano, continuous melody	Slow	Min
5. Erik Satie – Gymnopedie no.1 (Ron Adelaar)	Spotify	Sleep	Solo piano, classical	Slow	Maj
6. Steve Devon – Only Trust Your Heart	Spotify	Sleep	Solo piano, slow jazz, continuous melody	Slow	Maj/7ths /dom
7. Dan Evans-Parker – Hush	Spotify	Sleep	Piano and brushed snare, chord based	Slow	Min
8. SC-14	Composers	Relaxing	Cello, piano, clarinet, slow melody	Slow	Maj

9.	Max Richter – Dream 3 (in the midst of my life)	CSM	Sleep	Solo piano, chord based	Slow	Min
10.	Ryohei Shimoyama – Winter Milky Way	Spotify	Relaxing	Solo fingerstyle guitar	Slow	Min