GUIDING MUSIC GUIDING SLEEP: AN INVESTIGATION OF SUBJECTIVE AND OBJECTIVE PROPERTIES OF MUSIC THAT FACILITATES SLEEP INDUCTION

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Abstract

This thesis presents three papers advancing a systematic approach to understanding what music helps with sleep. The first reveals the distinctiveness of sleep music by examining playlists from the music streaming service Spotify, using their vast public data source to study the features of music in sleep playlists. The second paper adds to this assessment of musical properties by considering listener perspectives, revealing the relative importance of subjective and objective facets in predicting what makes music sleep inducing. The final paper tests the efficacy of music listening at night-time, finding that listening to music led to a significant improvement in sleep behaviours that was not directly associated with music type, nor the participants' preferred choice of music. Together, these studies provide specific clarifications and recommendations to the field. Our results support previous descriptions of sleep music as acoustic, instrumental, and having little rhythmic activity or dynamic variation, and bring new emphasis to the importance of timbre. Subjectively, a sense of comfort and familiarity were significant factors that were repeatedly revealed by participants' feedback, however the latter had opposing connotations between individuals. Notions of attention or distraction also appear to be important, but require better contextualisation. Future studies on the use of music to promote sleep should consider the subtle variabilities that can have a significant impact on its efficacy, and probe into other factors that contribute to its effect for an individual. Overall, we have shown that music can help with sleep, and suggest a path to optimising its potential.

Keywords: Sleep, music, relaxation, musical features, Spotify

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Dedication

I would like to dedicate this thesis to my family, especially my parents and my siblings. I deeply love you all.

Declaration

I, the author, confirm that this thesis is my own work. I am aware of the University's Guidance on the Use of Unfair Means. This work has not previously been presented for an award at this, or any other, university.

List of publications by candidate

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For the study in Chapter 2, see:

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Kirk, R., Panoutsos, G., van de Werken, M., & Timmers, R. *Positive Effects of Music on Sleep Exist but Relate to Neither Musical Properties nor Preferences.* [Manuscript in preparation]. Department of Music, University of Sheffield.

CONTENTS

1. INTRODUCTION

Background and context

Music is often used as a tool for affecting or controlling our mental and physical states; our emotions, our moods, our activities. An abundance of research has been devoted to studying this phenomenon. A challenge throughout is that of the complexities and idiosyncrasies that define an individual's interactions with music, and the effects music listening can have. The case of using music to help with sleep is no exception. Often conceptualised in relation to relaxation (Blanaru et al., 2012; Cordi et al., 2019; Kräuchi, 2007), sleep, and using music for sleep, might be seen as an extension of relaxation behaviours. This raises important questions; does using music for the purpose of relaxation extend to promoting sleep, or are the requirements of falling asleep unique or more specific? Can the effects of music on sleep be attributed primarily to intrinsic properties of the music? What can we learn from listeners' self-reported experiences and use of music to inform the application of music in focused therapies? To what extent is it generalisable? This thesis intends to expand notions of sleep music by particularly probing listeners' idiosyncrasies with a view to better understanding how music can be used as a potential sleep aid.

What is sleep?

Sleep is an altered state of consciousness that is characterised by a reduction in mental and physical activity compared to wakefulness. During sleep, the body enters a restorative state, repairing or bolstering our skeletal, neural, muscular, and immune systems, a process that we cannot live without (Walker, 2017). Disrupted sleep has been linked with increasing risk of multiple degenerative physiological and neurological conditions, including cardiovascular disease, diabetes, and dementia (Bassetti et al., 2015; Nagai et al., 2010; Someren et al., 2015). On a day-to-day basis, a lack of sleep can affect not just our mood and energy but also cognitive abilities such as problem solving and decision-making (Satterfield & Killgore, 2019). Although we still have much to learn about sleep, its importance for our health and wellbeing are drastically clear.

Getting to sleep

The process of transitioning from fully awake to asleep is known as the sleep onset process (SOP). During the SOP, we go through stages of reducing arousal and alertness until entering total sleep. As many will know, however, this can be far from a succinct process; delays to sleep onset can come in many forms, but even the transition itself is imprecise. In a seminal early investigation of the different stages of sleep onset, measured in brain wave activity, Hori et al. (1994) found that more than 50% of participants still reported that they were "awake" when aroused as they entered the final of nine identified stages of sleep onset. This ninth stage of the SOP as defined by Hori et al. (1994) is considered by other measures as standard Stage 2 sleep, in other words, already sleeping. Although "awake" responses did decrease through the stages, this difference in awareness highlights the blurred lines of consciousness people experience between awake and asleep states.

The ease with which one transitions through the SOP is an important part of sleep health. The time it takes to fall asleep, or sleep onset latency (SOL), is a key measure and considered to be closely affected by mental activity. To fall asleep, the body and mind must first enter a "sleep ready state"; this is partly mediated by physiological conditions (sleep pressure or tiredness built up during wakefulness and circadian cycles) but also psychological states. At sleep readiness, the body appears to be given implicit "permission" to fall asleep by a cognitive signal referred to as the "lights out" effect (Kräuchi & Wirz-Justice, 2001). In healthy sleepers, this is observed as a rapid transition through the SOP at the point of lights out, hence the name; this simple act of acknowledging that now is the time to go to sleep is enough to trigger this process. Individuals with sleep problems however commonly find it difficult to reach this ready state and experience a delayed sleep onset. Barriers may include environmental factors or physical discomfort, but psychological distress is one of the most common complaints (Morin et al., 2006). Negative stressors are particularly problematic, but any excitative, arousing mental activity can contribute to an inability to switch off at night.

Accordingly, sleep problems are sometimes referred to as a disorder of hyperarousal, a heightened affective, cognitive, or physiologic state (Levenson et al., 2015). Understanding sleep issues in this sense encapsulates the combinations of physical and mental arousal that can impede sleep onset. Healthy sleep on the other hand has been conceptualised as a “very relaxed behavioural state” (Kräuchi, 2007, p.241). Relaxation is “the mental and physical freedom from tension or stress” (Titlebaum, 1998, p.123), an antithesis to hyperarousal. Thus, considering sleep in relation to relaxation offers one route to contextualising the promotion of sleep behaviours, albeit as an extension given the very particular goal of falling asleep.

Measuring sleep

The gold standard for objectively measuring sleep quality is by polysomnography, a combination of electroencephalography (EEG) for measuring brain waves and other physiological markers that is used to define the progression of sleep stages. Other behavioural and physiological indicators are used; reaction times (e.g., when responding to an auditory stimuli with a button press) are commonly measured in sleep and napping studies, and changes in skin temperature are a reliable predictor of when a person transitions to sleep (Kräuchi, 2007; Ogilvie, 2001). Subjectively, the Pittsburgh Sleep Quality Index (PSQI, Buysse et al., 1989) is a comprehensive questionnaire that is used to assess overall sleep health based on an individual’s own reporting of various aspects of their sleep, such as timings, awakenings during the night, and perceived sleep quality. Sleep diaries are also commonly used to assessing sleep behaviours on a night-to-night basis. However, these different measures do not always agree (e.g., Lazic & Ogilvie, 2007) and there are some contentions as to our ability to reliably measure a good night's sleep. Subjective accounts are vulnerable to self-reporting biases but can provide insights that neurophysiological indicators may not reveal. As we have discussed, psychological factors are strong mediators of the physiological process of falling asleep and how an individual perceives their sleep health can itself impede or reinforce sleep behaviours. While objective physiological indicators are important, personal accounts are extremely valuable particularly considering the important role of psychological factors in promoting sleep and can offer better insights into the effectiveness of treatments that focus on this aspect.

Sleep problems, and sleep music

Reports on the prevalence of insomnia vary depending on sources and methodology, but most reports suggest 5-15% of people suffer from insomnia disorder, while 30-40% of individuals report at least one night-time insomnia symptom (Levenson et al., 2015). Various treatments exist, from medical to behavioural therapies. Pharmacological interventions are not always sufficient and can have serious risks (Degenhardt et al., 2002; Lemmer, 2007), and limited access or availability of health services necessitates the study and promotion of alternative ways of dealing with sleep issues.

Music provides one such alternative. The relationship between music and sleep has a longstanding significance, evident in the universal phenomenon of lullabies. Parents singing to their infants to sooth them to sleep is an activity ubiquitous across cultures, not just in its practice but in the commonalities in the types of musical vocalisations parents use (Mehr et al., 2019; Trehub et al., 1993). This cultural and human significance may explain why using music to help with sleep is so popular in the general adult population. Surveys suggest between 14% and 51.9% of people use music, or believe that music is useful, in helping to get to sleep (Aritake-Okada et al., 2009; Furihata et al., 2011; Huang et al., 2018; Morin et al., 2006; Urponen et al., 1988). Although this prevalence is not necessarily an indicator of its efficacy, it is still a testament towards music's popularity and its availability, accessibility, and preference as a non-pharmacological sleep aid.

With the boon of technological advancement in recent decades and the capabilities and access to digital devices, digital applications for wellbeing in general have become extremely abundant. The exact number of mental health-related apps is unknown but thought to be in the tens of thousands (Clay, 2021), and the digital therapeutics industry worth billions (Weir, 2021). There is clearly a public appetite and a commercial market for these types of interventions, and a growing body of research to go with it. With the use of music, researchers are building on a history of music psychological research relating music's effects on moods and emotions (for an overview, see e.g., Swaminathan & Schellenberg, 2015) to develop targeted, personalised programs that tailor music to an individual to support their wellbeing (e.g., Coutinho et al., 2021; Janssen et al., 2012; Williams et al., 2019). Similar applications of music specifically for sleep are as yet relatively few, but this is an area for clear study and development.

The efficacy of music for sleep

Considerable research has been invested in the study of using music to help with sleep (e.g., Blanaru et al., 2012; Bloch et al., 2010; Chan et al., 2010; Chen et al., 2013; Cordi et al., 2019; Gao et al., 2020; Hernández-Ruiz, 2005; Jespersen et al., 2019; Jespersen & Vuust, 2012; Oxtoby et al., 2013). Although there is some disagreement with regards to its efficacy (e.g., Lazic & Ogilvie, 2007), contentions may be largely due to methodological discrepancies. Regardless, there remains strong interest among researchers in this field and positive support for music's value as a sleep aid (Jespersen et al., 2022).

Different mechanisms have been proposed for how music might help with sleep, with particular focus on music's effect on physiological arousal, the ability to influence emotions, and how it can act as a focal point creating a distraction from disruptive thoughts (Jespersen

& Vuust, 2012). These mechanisms address the physical and psychological effects music can have on listeners that may be routes to tackling the physical and psychological barriers that can impede falling to sleep. Regulating arousal and mood are key functions of music listening generally (T. Schäfer et al., 2013), with relaxation a common goal or concurrent activity (Greasley & Lamont, 2011; Juslin et al., 2008), making music an apt tool for sleep. The psychological effects of music have particular significance given the cognitive factor in sleep initiation (Kräuchi & Wirz-Justice, 2001) and the blurred transitions in consciousness that occur during the sleep onset process (Hori et al., 1994). The temporal and unfolding nature of music further make it a suitable accompaniment to moderate these transitions.

An additional avenue worth considering is that of the prosocial effects of listening to music. Music may have beneficial effects for wellbeing by acting as a social surrogate, providing a sense of accompaniment or interaction in the absence of others (K. Schäfer et al., 2020; K. Schäfer & Eerola, 2018). In this way, listening to music may help to promote a sense of comfort or safety. This could have similar significance for sleep; in much the same way that singing lullabies to an infant may reinforce feelings of safety through the act of parental nurturing, adults may find a sense of comfort when listening to music at night-time. Other aspects of our sleep are thought to have evolved in line with prosocial behaviours, such as the observed phenomenon of chronotypes (an individual's naturally preferred sleep pattern; whether you're a morning lark or a night owl), which is hypothesised to have evolved as a safety mechanism; staggered sleeping patterns reduces the amount of time where a group is most vulnerable, ensuring group safety by effectively sharing vigilance responsibilities during the night (Samson et al., 2017). Lullabies could play into this by indicating the still awake and thus protective presence of a parent. Other evidence suggests that the human thermoregulatory system, a key component in the sleep-wake cycle (Kräuchi, 2007), is sensitive to social behaviours (IJzerman et al., 2012, 2015), further highlighting a potential link between prosocial activity and sleep. These elements of comfort and safety may play a role in other mechanisms, such as relating to emotions, but could be valuable to consider more explicitly to appreciate the nuances of music's potential contribution to promoting sleep.

Studies often select music for sleep with respects to its type or characteristics. This has some intuitive foundation; indeed, a fascinating element of the lullaby phenomenon is not only its ubiquitousness but its cross-cultural recognisability (Trehub et al., 1993). However, adult music listening for sleep is extremely varied with reports revealing a variety of listening preferences (Dickson & Schubert, 2020a; Trahan et al., 2018). Naturally, the cognitive predispositions or requirements of adults may differ to those of infants when it comes to sleep. However, there may still be grounds for a generalisable basis from which to build personal variability. As we will discuss in more detail later in this thesis (see esp. Chapter 2), a more systematic approach to evaluating the properties of music used for sleep is needed.

There are other practical aspects to consider with regards to the application or efficacy of music for sleep. Most studies prescribe listening to music in bed as the listener falls asleep. Two studies (that we are aware of) asked participants to listen to music earlier in the evening (Kuula et al., 2020; Oxtoby et al., 2013), others assessed the effects of music before an afternoon nap (Cordi et al., 2019; Iwaki et al., 2003) and others still ran listening sessions in the afternoon but measured night-time sleep outcomes (Shum et al., 2014). Rather than taking as general support for the use of music to help with sleep, positive outcomes in these different circumstances may point to multiple mechanisms through which music may help with sleep. These could be deterministic of the particular music that is most suited to help with sleep when used in a particular context, or be something that is personally optimisable (i.e., some individuals may benefit more from listening to music at different times or in certain settings). Assessing each of these perspectives is beyond the scope of this thesis, but it illustrates the level of complexity and nuance that could be considered when investigating how music can be used to help with sleep.

Questions and discrepancies – building a framework for studying music and sleep

The prevalence and indeed the ubiquitousness of music generally make it a favourable tool for therapeutic applications. However, there are many challenges for research in this regard. As we will return to throughout this thesis, there are key discrepancies in the literature with regards to the use of music to help with sleep, namely with respects to what type or types of music are best for helping with sleep, what researchers suggest compared with what users select, and the key concepts or mechanisms are that are important for an individual listener and why. Considering what we have discussed above, our line of research will endeavour to clarify these issues and in particular lean towards understanding the psychological perspectives of listeners. Although there needs to be more clarification of the types and characteristics of music most optimal for sleep, we believe there is still grounds for a foundation in a musical approach. However, this needs to be done in tandem with a respect for listener perspectives and alternatives carefully tested in situ. Therefore, this research will focus on i) contributing to music-features comparisons, attempting to elaborate on existing assertions, ii) take a perceptual approach and attempt to identify key subjective factors from listeners, and iii) test findings on sleep at night-time. Our focus is on the use of music during sleep onset, during this transitional phase of consciousness where music may tap into arousal functions and promote relaxation most relevant for transitioning to sleep.

Methodologically, we first aim to expand on the musical notions proposed in the literature by using the latest tools and large online datasets to evaluate this. We then try to tie this music-focused approach with listener perspectives to gain an insight into relevant perceptual values, thus transitioning to a more listener-focused view. Finally, we compare listening to different music at night-time to test for effects in situ, presenting music playlists constructed from a features-oriented perspective but contextualising outcomes with considered reference to the listeners experience. Outcomes will provide firmer grounding for considering how the use of music can be optimised for sleep, both in terms of recommendations to individuals and the development of therapeutic applications.

As this thesis is presented in a format for publication, each chapter is intended as a stand-alone article and therefore many points will be reiterated throughout. This introduction is intended to provide a summary and overall context on which this research is built.

Research questions

This thesis aims to address key challenges of research into music for sleep by focusing on the following questions:

1) What are the features of music that are best for promoting sleep?

2) What are the subjective qualities that are most important for music that is considered sleep inducing?

3) What is the respective contribution of personal perceptions and intrinsic musical properties in aiding sleep?

Linkage of papers

Paper One - Sleep Music: Exploring features of Spotify playlists

This first paper (Chapter 2) presents the results of our first study, an initial foray into understanding the types of musical features associated with music considered suitable for the purpose of sleep. Using the vast body of data available in the Spotify Data Catalogue, we analysed the features of tracks included in Spotify playlists intended for sleep, as indicated by their titles or descriptions, and compared these with music from playlists intended for relaxing or energising, such as dance or workout playlists. In line with our interest in contextualising sleep with respects to relaxation, we give particular attention to the differences between music in sleep playlists compared to music in playlists presented as for relaxing more generally. Using a combination of linear and non-linear analyses we show that sleep playlists are indeed distinct from playlists of music for other purposes, in terms of the musical features available in the Spotify Data Catalogue. Spectral brightness is the most defining feature distinguishing music from sleep playlists from those more generally for relaxing. While this supports a notion of sleep music as something distinct, there was considerable variability in the types of music making up the sleep playlists. We also found a prominent presence of nature sounds and discuss the value and reliability of the features provided by Spotify. Crucially, an analysis of public playlists such as this and the discussion of objective features of sleep music needs to be complemented by probing valuable insight from subjective evaluations of listeners.

Paper Two - The relative contribution of subjective and musical factors in music for sleep

The paper presented in Chapter 3 consists of an empirical study that aimed to address some of the limitations of the previous study by incorporating listener perceptions of sleep music. A listening study was conducted through an online survey that included musical excerpts sampled from the Spotify dataset analysed in the previous study. Additional samples created a varied dataset to explore listener perceptions of music for the purposes of sleep, relaxation, and energising. Primary data was gathered in the form of ratings from participants, which was supplemented by a musical analysis of the tracks allowing us to investigate the relative contribution of a range of subjective factors and musical properties towards what makes a piece of music sleep inducing. Our results suggested that notions of comfort, liking, and freeing of the mind were most important for music perceived as sleep inducing. Our analysis of musical features indicated properties that largely conformed with notions from the wider literature, such as that sleep music should have little rhythmic and dynamic variation (Jespersen et al., 2022), but also advanced our findings that spectral brightness is a key property. However, crucially, we found that the musical properties were overshadowed by the subjective factors in predicting what music was perceived to be most sleep inducing. This music was on average of a similar type, namely soft, minimal, piano-based solo instrumentals, however the individual variability was such that it suggests a necessity for optimising approaches to how music is selected in research beyond acoustic properties. Comments left by participants further revealed the intersubjective variability, with contradicting notions of the role of personal associations and familiarity. A key caveat is that these results are based on perceptions in a listening study that need to be tested in the context of real sleep at night-time. It is possible that daytime perceptions do not necessarily translate to real efficacy when in the intended context of sleep.

Paper Three - Positive effects of music on sleep exist but relate to neither musical properties nor preferences

The final study presented in this thesis (Chapter 4) presents the results of an experimental study intended to examine the effects of different selections of music on sleep at night-time and the role of personal preferences. Using models developed in the previous study (Chapter 3), we identified two streams for selecting potentially optimal sleep music to create two music playlists for this study. Over consecutive nights participants listened to either one of the two playlists or silence and completed short questionnaires in the evening and sleep diaries each morning. Feedback from participants after the study allowed us to compare the effects of the music on the basis of personal preference. We found that listening to music significantly improved some measures of sleep behaviours, however this was not related to the type of music listened to nor the participants' preference for a particular playlist. One third of our participants slept better with music they said they were less likely to choose to go to sleep with. Some participants commented that they were surprised at their experiences generally or with respect to the specific playlists. The suggestion that participants can be naive to the effects of music on their sleep could help to understand the discrepancies we see between what researchers suggest and listeners select for music for sleep (Dickson & Schubert, 2020a; Trahan et al., 2018), and indeed emphasise the role researchers can have in advising the use of music as an aid for sleep.

Research aim and objectives

Together these studies aim to enhance understanding of the properties of music that can best help with sleep and explore the subjective factors that contribute to individual variability. It examines generalisability of musical choices as evidenced in playlists with those based on subjective evaluations during daytime and actual effects at night, and to what extent subjective facets interact with explicit musical effects in the particular context of music for sleep.

2. SLEEP MUSIC: EXPLORING FEATURES OF SPOTIFY PLAYLISTS

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Kirk, R., & Timmers, R. (in press). Sleep Music: Exploring Features of Spotify Playlists. *Musicae Scientiae*.

Chapter 2 is presented in its current form in the process of being published.

Statement of Contribution of Joint Authorship

Kirk, R. - (Candidate)

Conceptualisation of the study, data collection and analysis, writing and compilation of manuscript, preparation of tables and figures.

Timmers, R. - (Principal Supervisor)

Supervised and assisted with research design, advised on data analysis, interpretation of results, and reviewing and editing of manuscript.

Linkage of Paper to Research Methodology and Development

The study presented in the following paper set out to address a fundamental question for this project: what is sleep music? This was an initial step to tackling our first primary research question of what are the features of music that are best for promoting sleep. Using resources provided by Spotify we looked at distinctions and patterns among and between music playlists drawing from a vast source of public data. In line with our aims, we drew comparisons between playlists for sleep with those intended for relaxation. Differences between music in these categories may support the notion of a distinct purpose of music listening for sleep that is apart from that for relaxation. Results revealed distinct qualities of sleep music and established a foundation of points that fed into the remaining thesis and provided a dataset of reference for further probing and sampling of stimuli in the later studies.

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 that is considered more generally for relaxing by comparing features of playlists on the music streaming service Spotify. Ninety playlists to facilitate sleep, to relax, and, for comparison, to energise were gathered, based on titles and descriptions. Our analysis found significant differences between the playlist categories for many of the features, 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, and slower, quieter, and with less energy compared to the other playlists, conforming with previous work (e.g., Jespersen et al., 2015; Scarratt et al., 2021). Our results emphasise the importance of timbral qualities in music for sleep and confirm sleep music as something distinct compared to music for relaxation. The results can be used to guide the selection of music to support sleep, including transitioning 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 optimising 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 variety of music for sleep that does not necessarily fit the typical description of sedative music (Dickson & Schubert, 2020a; Trahan et al., 2018). For example, Dickson & Schubert (2020) 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 contained 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 (e.g., 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 the opposite purpose, that is, of energising. The analyses focused on distinctions and overlaps between features of music for different purposes. Understanding the distinctions between them could help to refine and optimise 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 (e.g., Huang et al., 2016, 2017); Korean pop music (e.g., Lee et al., 2019); classical music (e.g., Harmat et al., 2008; Oxtoby et al., 2013; Tan, 2004); Western (including new age, electric, popular oldies, classical, and slow jazz) and Chinese music (e.g., Lai & Good, 2005); Chinese, Czech and Taiwanese music (e.g., Chang et al., 2012) Indian music (e.g., Deshmukh et al., 2009); Enya (e.g., Tan, 2004); commercial sleep or meditative music (e.g., Cordi et al., 2019; Jespersen & Vuust, 2012; Lazic & Ogilvie, 2007; Picard et al., 2014); and music that is unspecified but described as soothing, relaxing, etc. (e.g., 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 (e.g., 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 (e.g., 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 bpm (Jespersen et al., 2015; Tan, 2004), with a frequent use of tempi around 60-80 bpm (e.g., Chen et al., 2013; Huang et al., 2016, 2017; Shum et al., 2014; Su et al., 2013). A comparison of studies describing relaxing and energising music respectively reported tempi around 60-100 bpm for relaxing music (e.g., Elliott et al., 2011; Nilsson, 2011; X. Tan et al., 2012) and around 100-133 bpm for energising music (e.g., 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 & Schubert (2020) 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 feature of music for sleep. Scarratt et al. (2021) reported that sleep music in Spotify playlists tends to be quieter than music in general, while Cordi et al. (2019) played music at levels between 45 and 50dB to participants in their study. Nilsson (2008) suggested that soothing music used therapeutically should be played at a maximum level of 60dB.

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 & Schubert (2020) 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 & Schubert (2020) 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 (e.g., 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, Timmers et al.'s (2019) analysis 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 (e.g., 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—energising.

To do this, we analysed 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. It provides a wealth of data on the features of the music in its catalogue through its

Web API (Application Program Interface). An API is a software intermediary which some web applications provide as a means of accessing data related to their content. Through the Spotify API, it is possible to gather data on the musical features of all the tracks in its catalogue such as their tempo, energy, or duration. This provides a valuable resource for researchers wishing to analyse music used in different ways (e.g., Barone et al., 2017).

Methods

Data collection

Data were collected from the Spotify Data Catalogue (SDC) using its Web API and the Spotipy library in Python. Two of Spotify's tools 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]

Table 1

List and descriptions of Spotify features extracted for this study.

Source	Feature	Description

[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 capitalised will refer specifically to the data extracted from Spotify.

Audio Features	Acousticness	A confidence measure from .0 to 1 of whether the track is acoustic. 1 represents high confidence the track is acoustic.
	Danceability	Danceability describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 0.0 is least danceable and 1.0 is most danceable.
	Duration	The duration of the track in milliseconds.
	Energy	Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy.
	Instrumentalness	Detects whether a track contains vocals. The closer the instrumentalness value is to 1, the greater likelihood the track contains no vocal context. Values above .5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.
	Liveness	Detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live. A value above 0.8 provides strong likelihood that the track is live.
	Loudness	The overall loudness of a track in decibels (dB). Loudness values are averaged across the entire track and are useful for comparing relative loudness of tracks. Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). Values typical range between -60 and 0dB.
	Mode	Mode indicates whether the track is major or minor, the type of scale from which its melodic content is derived. Major is represented by 1 and minor by 0.

	Speechiness	Detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g. talk show, audio book, poetry), the closer to 1 the attribute value. Values above 0.66 describe tracks that are probably made entirely of spoken words. Values between .33 and .66 describe tracks that may contain both music and speech, either in sections or layered, including such cases as rap music. Values below .33 most likely represent music and other non-speech-like tracks.
	Tempo	The overall estimated tempo of a track in beats per minute (BPM). In musical terminology, tempo is the speed or pace of a given piece and is related to the speed of the pulse or musical beat.
	Valence	A measure from .0 to 1 describing the musical positivity conveyed by a track. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry).
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.

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

A list of Spotify playlists and their corresponding IDs were gathered manually using the search function in the Spotify web player.[3] Playlists for sleep and relaxing were gathered

[3] Every track, album, or playlist on Spotify has a unique ID. This ID is what we need to make requests for 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.

using the search terms *sleep** and *relax** respectively. Playlists for energising were gathered using the search terms *energi** (to accommodate different spellings and variations, e.g., energise/energize, energising, 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 this theme. Playlists name, creator, and ID 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 Energising playlists), by order of appearance in each search. This resulted in a set of 90 playlists consisting of a total of 17,274 tracks [see Appendix A for a complete list of the playlists included]. Playlists titles suggested 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 feature values across the three categories of playlist. Next, we used Principal Component Analysis (PCA) to investigate linear relationships between features and group features according to their shared components. Finally, nonlinear data-driven modelling was used to test the ability of features to accurately predict the playlist category of tracks and to assess the importance of each feature in this prediction. Nonlinear modelling was conducted using the Statistics and Machine Learning Toolbox in MATLAB. All other statistical analyses were performed using SPSS, and Laerd Statistics (https://statistics.laerd.com/) was used for guidance on procedure and reporting. Prior to analysis, all continuous data were normalised to values between 0 and 1.

Results

Univariate tests

Figure 1 shows violin plots of the distribution of features of tracks split per music category. Inspection of medians and distributions shows that several of the features depicted a general trend, typically descending from Energising to Relaxing to Sleep. For example, with this sequence of categories, the music became slower, quieter, and less bright. For other features, such as Acousticness and Energy, the Sleep and Relaxing playlists had overlapping characteristics while being strongly distinct from Energising playlists. There were no clear distinctions between the three categories in Duration, Liveness, and Speechiness: most music in all three categories were under 4 minutes in length, contained little spoken word and tended not to be live.

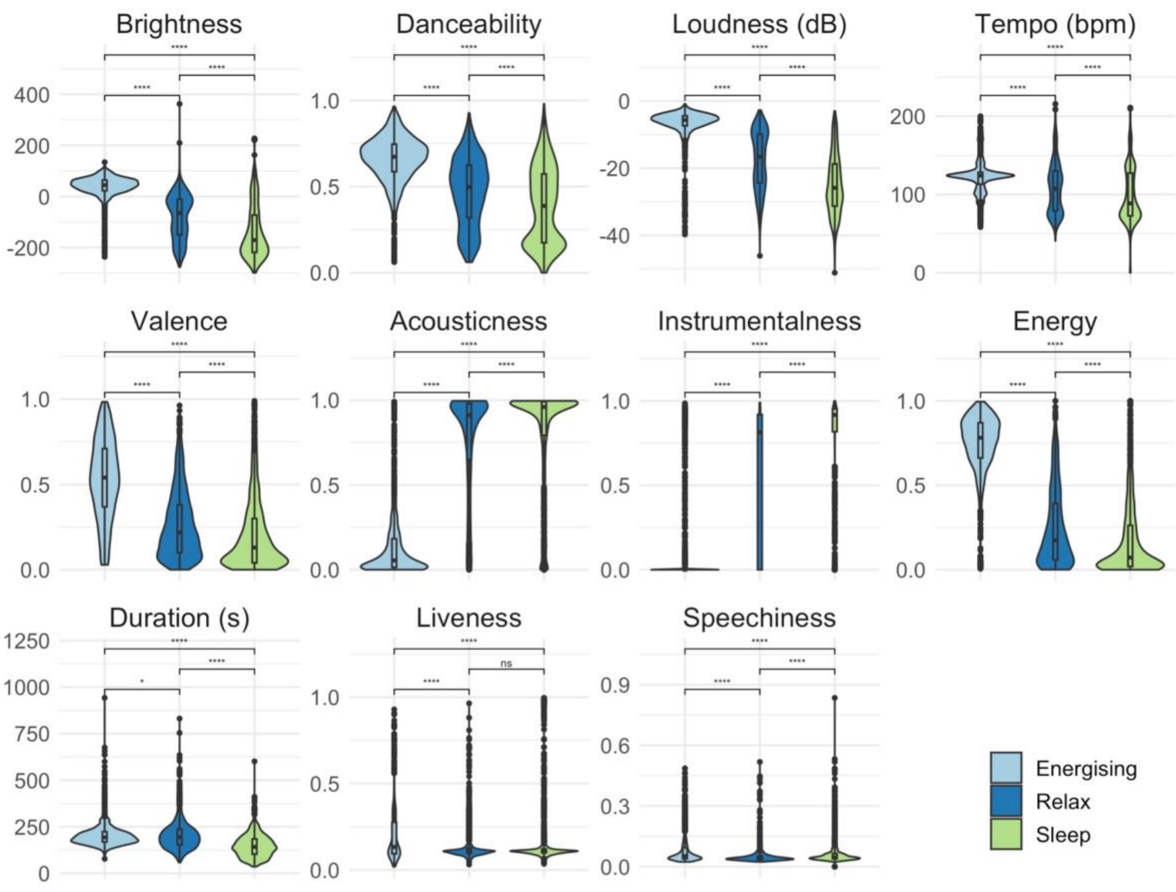
Assumptions of normality of distribution were not satisfied for many features, as assessed by visual inspection of histograms and confirmed by z-score calculations of skewness and kurtosis. Therefore, non-parametric tests were used to compare features across categories.

As a dichotomous dependent variable, Mode was analysed using the chi-squared test of homogeneity to determine differences between proportions in the three playlists. A total of 716 tracks (47.7%) in the Energising playlists were in a minor key, compared to 494 (32.9%) in the Relaxing playlists and 391 (26.1%) in the Sleep playlists, a statistically significant difference, $p = <.001$. Post hoc analysis involved pairwise comparisons using the z-test of two proportions with a Bonferroni correction. All pairwise comparisons were statistically significant.

For all other features, Kruskal-Wallis H tests were used to compare feature values across the three playlist categories. The results showed all features to have significant differences between the playlist categories. Pairwise comparisons were performed using Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons, confirming that all but one of the pairwise comparisons were statistically significant, the exception being the difference in Liveness between Sleep and Relaxing playlists (see Figure 1). Overall, music in Sleep playlists tended to be acoustic and instrumental, and lower in all other features compared to Relaxing and Energising playlists, particularly Brightness, Danceability, Energy, Loudness, Tempo, and Valence. To enhance insight into the groupings of features in differentiating music categories, further analysis was carried out.

Figure 1

Violin plots of features by playlist category, original values (ex. Duration converted to seconds).



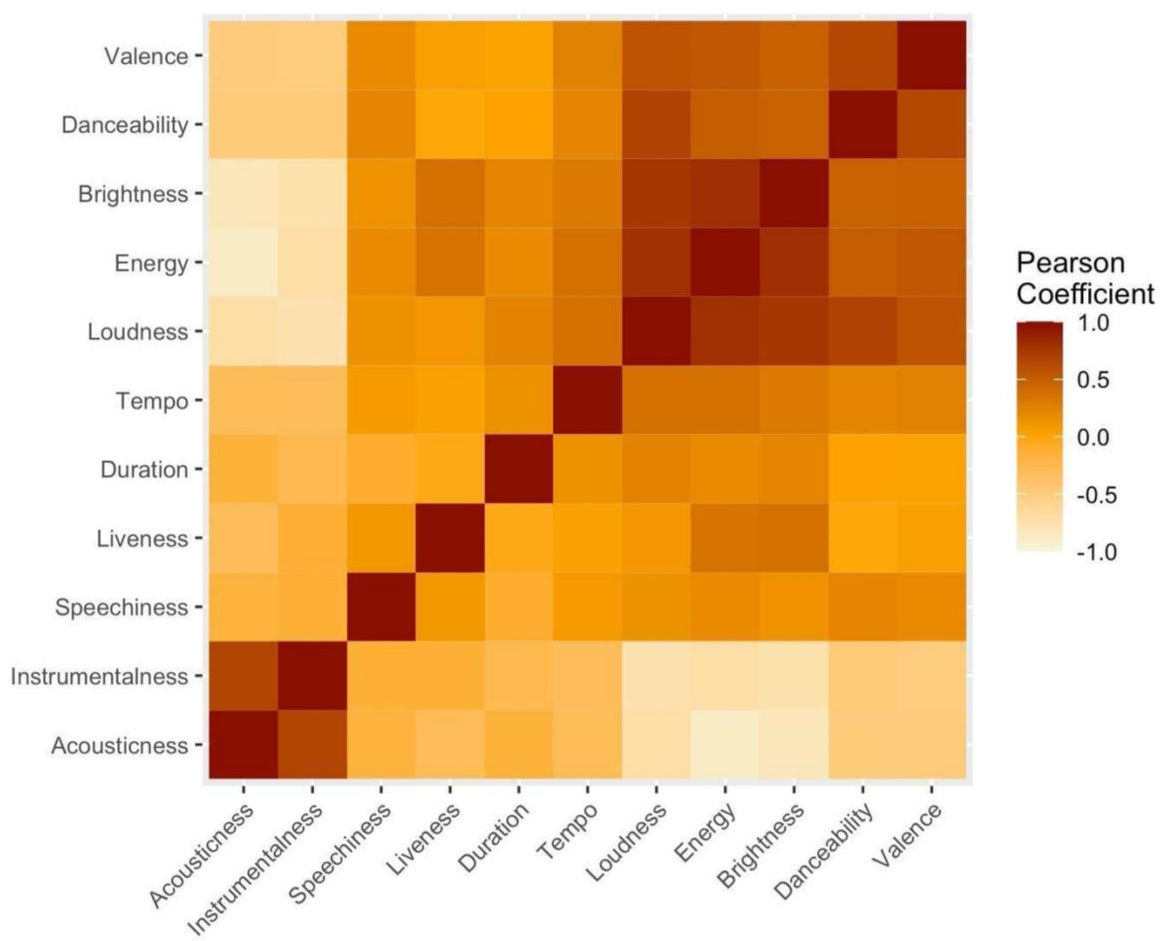
All pairwise comparisons significant except Liveness between Sleep and Relaxing playlists, *$p < .05$. **$p < .01$. ***$p < .001$.

Principal Component Analysis (PCA)

Musical features are more likely to vary together than independently, serving similar functions. Principal Component Analysis (PCA) is a method of reducing a set of variables (in this case musical features) to its main underlying components, in a way to reveal underlying patterns in the data. We omitted Mode from this analysis because as a dichotomous variable it is not suitable for inclusion. We assessed the suitability of all other features to be included in the PCA by inspecting the matrix of correlations between them (see Figure 2).

Figure 2

Heatmap of correlations between features, clustered hierarchically.



Absolute correlation coefficients for Duration and Speechiness with all other features were less than .3, which is too low for inclusion. We therefore ran the PCA omitting these features. The overall Kaiser-Meyer-Olkin (KMO) measure for this analysis 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 factorisable.

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.

Table 2

PCA matrix, rotated solution. Variables with coefficients <.3 are suppressed.

Feature	**Component 1 (56.6%)**	**Component 2 (13.5%)**
Loudness	0.871	
Danceability	0.819	
Valence	0.788	
Instrumentalness	-0.741	-0.373
Energy	0.735	0.573
Acousticness	-0.683	-0.584
Brightness	0.680	0.618
Tempo	0.444	
Liveness		0.861

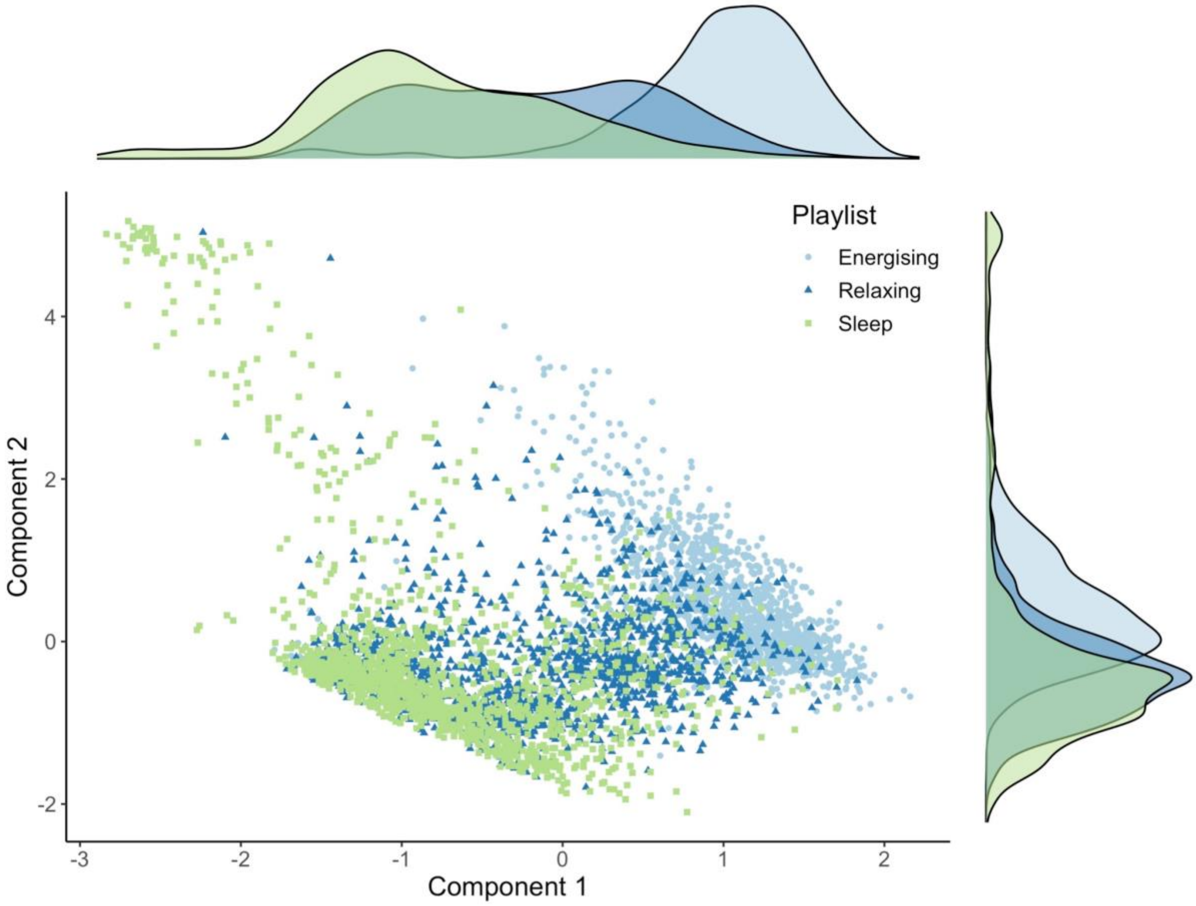
Extraction Method: Principal Component Analysis

Rotation Method: Varimax with Kaiser Normalisation

Component scores were calculated for each track by SPSS using regression weightings based on the retained two-component solution. A visualisation of these scores can be seen in Figure 3. We can see both overlap and separation of distributions between the different categories, where music in Sleep playlists seems to be more extreme and opposite to Energising than Relaxing playlists. There is a distinguished tail separating some of the Sleep tracks from the rest of the data, particularly along the second component. Inspection of the music in this section found it to contain exclusively tracks of nature sounds, typically sounds of rain or waves, which had high values for Liveness. The Liveness measure is supposed to detect the presence of an audience; it is possible that the audio analysis method used by Spotify has mistaken these nature sounds as that of an audience. These nature sounds seem to have been particularly present in the Sleep playlists, which otherwise contained tracks with lower scores for Component 2, giving rise to a binomial distribution.

Figure 3

Scatter plot of the PCA component scores for each track by playlist category, with density plots along each axis showing the distributions of the respective scores in each component.



To examine the effect of the nature sounds, three playlists containing 150 tracks that consisted entirely, in the case of two, and predominantly in the case of the third, of nature sounds were identified and removed from the dataset, and PCA was rerun.[4] Again, Duration and Speechiness did not meet requirements and were excluded. 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 the first component of our original analysis, with only the addition of Liveness, which returned

[4] Univariate tests were also re-run, but the results did not differ.

the lowest value. A forced two component extraction increased overall explained variance to 69.8%, with Liveness again taking prominence of the second component (Eigenvalue = .910).

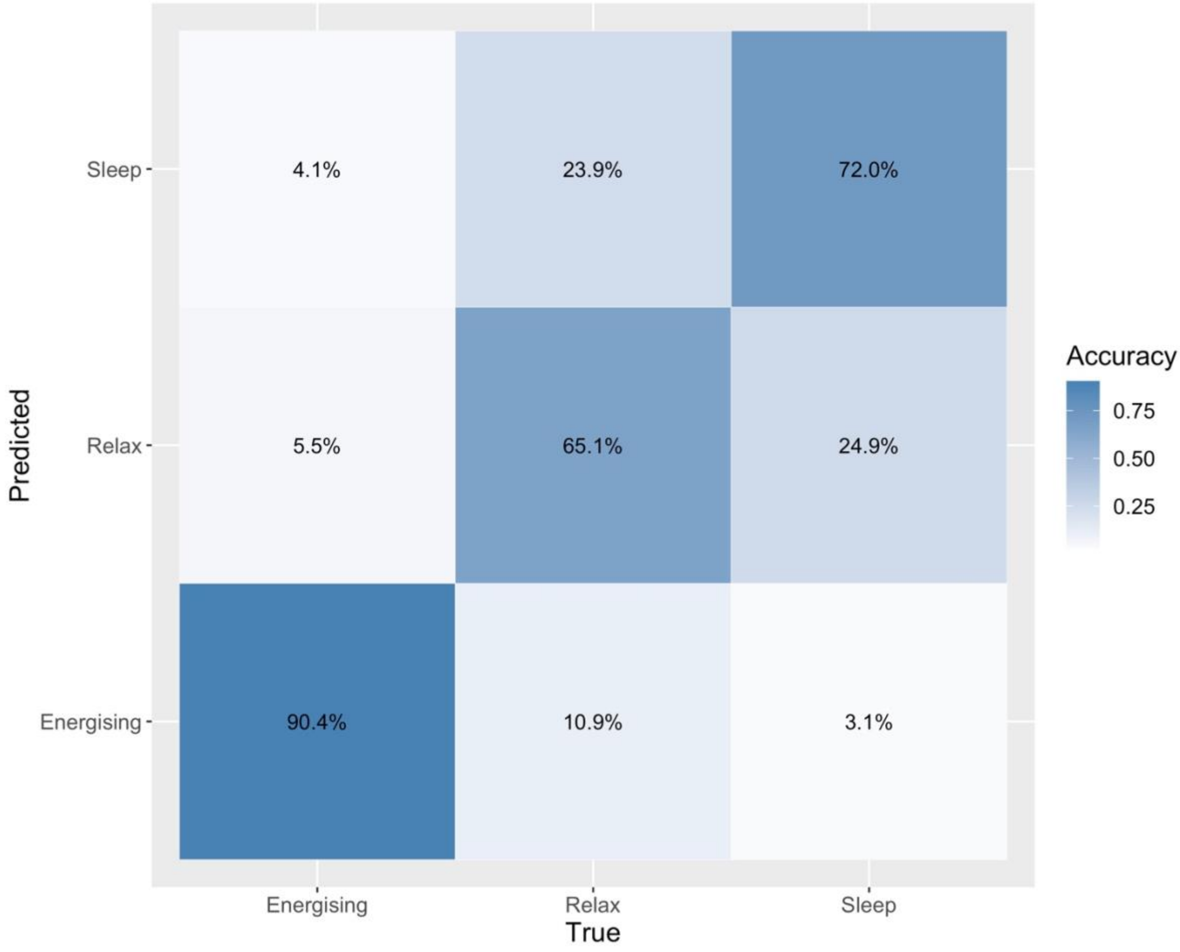
Nonlinear models

Finally, classification models were used to assess the predictability of the playlist category of each track based on their features. Classification models attempt to discern how well a given set of classes (in this case playlist categories) can be identified based on a given set of predictors (in this case musical features). The selection of features was carried over from the PCA (i.e., omitting Duration and Speechiness), with the reintroduction of 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 considerably better for the Energising playlists (90.4% overall prediction rate) and poorest for the Relaxing playlists (65.1%). Tracks from the Sleep playlists were correctly classified in 72.0% of cases.

Figure 4

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

[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 is 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.

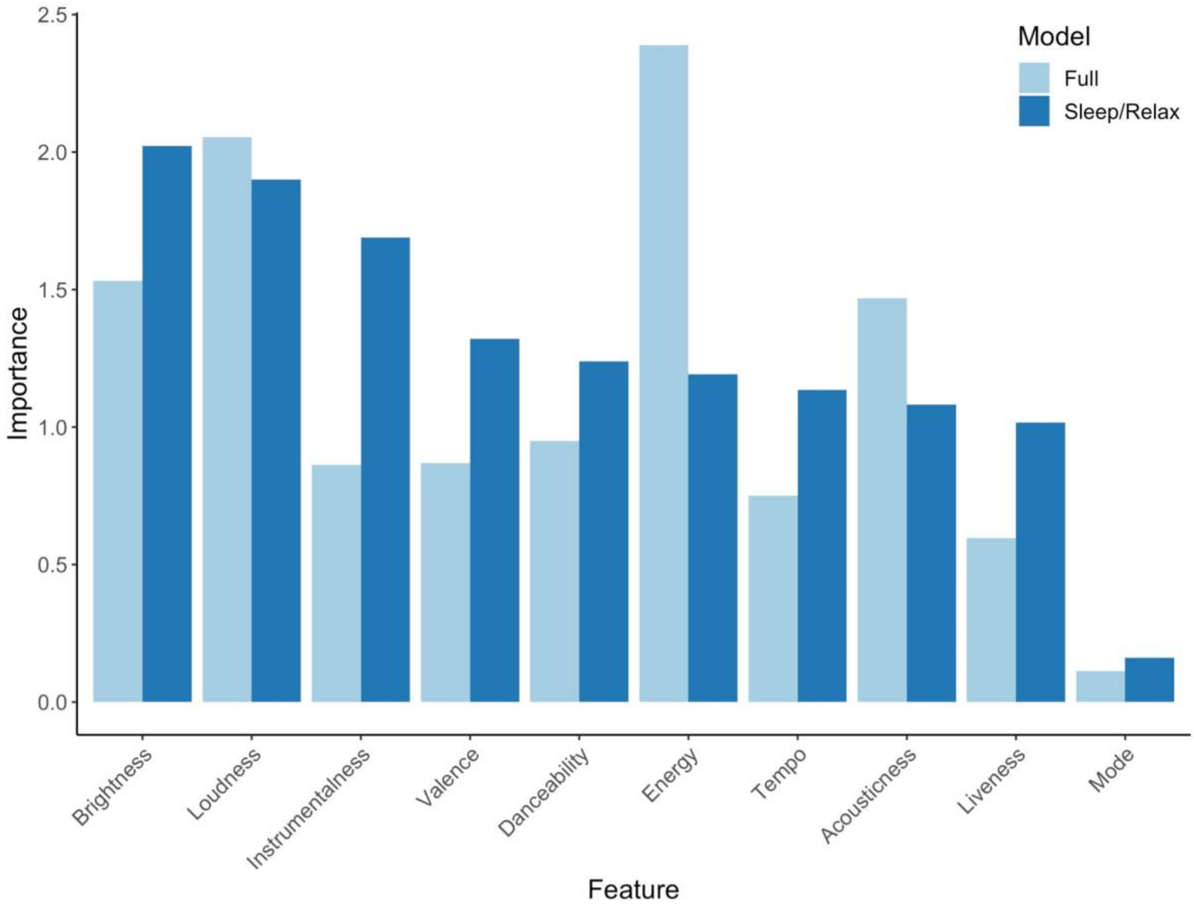


Identifying the weightings of individual predictors in a model can tell us more about the distinctions between each class and the relevance of the predictors. Predictor weight was investigated using the MATLAB predictorImportance function for decision trees and calculated for each fold of the model before averaged. Energy appeared as the strongest predictor, followed by Loudness, Brightness, and Acousticness. Given the clear distinctiveness of the Energising playlists in several features, such as Energy and Acousticness (see Figure 1), it was likely that these features would strongly influence the model. To better assess the differences between the Sleep and Relaxing playlists, the analysis was rerun omitting the Energising playlists to produce a Sleep/Relaxing model. As predicted, this greatly reduced the importance of Energy, with Brightness coming to the fore as the strongest predictor, followed by Loudness, Instrumentalness, and Valence (see Figure 5). This model improved validation accuracy to 74.7% and 72.9% for the Sleep and Relaxing playlists, respectively.

Removing the nature sounds subset from the data only slightly altered the results. Overall classification accuracy of the full model reduced by 0.9% to 74.9%. There were more noticeable differences in the accuracy rates for the Sleep playlists, reducing to 69.4% and 69.3% for the full and Sleep/Relaxing models respectively. Brightness remained the strongest predictor for the Sleep/Relaxing model and overtook Loudness to become the second strongest predictor in the full model. The only other noticeable difference was for Valence, which decreased in importance in both models.

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.



Discussion

The presented research helps to refine the understanding of music for sleep by investigating how it is distinguished from music for other purposes, in particular from music for relaxing. This assessment is restricted to the musical features data available from Spotify, however we may still glean several useful insights from our results.

The importance of brightness

Our finding that sleep music is low in brightness is in line with previous work (Dickson & Schubert, 2020a; Timmers et al., 2019). As the strongest predictor for distinguishing sleep music from relaxing music more generally, our analysis emphasises 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 playlists 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 characterised 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 Energising playlists on the other hand were dominated by pop and dance tunes, with a heavy emphasis on electric or synthesised instruments. These included tracks like 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 which included birds chirping. 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 relevant 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 centre of the spectrogram) is perceived as softer. In turn, music producers may take this into consideration when mixing audio and may turn down high frequencies when intending to achieve a softer, calmer sound. Loudness was the second most important predictor in our classification model distinguishing Sleep and Relaxing playlists.

Manipulating the brightness of a piece of music explicitly in future research may be a way to investigate whether it is features such as intensity feeding into brightness or purely timbral brightness that is of relevance here (e.g., Bannister, 2020).

Nature sounds

Timmers et al. (2019) found that sleep music playlists regularly include music that contains a significant amount of non-musical acoustic sounds such as nature sounds, and we have similarly found a considerable presence of these sounds in Spotify Sleep playlists. Apart from the playlists identified in our PCA analysis that contained exclusively natural sounds, naturalness had a notable presence in other playlists in the Sleep category. For example, the playlist Relaxing Spa Music – Perfect Bliss, Water Sounds Massage contains music that is dominated by sounds of waves and rippling water, overlayed with ambient drones. The Sleep Lullabies playlist consists of piano renditions of classic lullabies accompanied by ocean sounds, and several other playlists include tracks that contain elements of nature sounds in their composition.

The relevance of these nature sounds in music for sleep is unknown. In an experimental study, Jespersen & Vuust (2012) used music that included natural sounds such as waves and birdsong. However, they do not test whether it contributed any explicit value. Sounds of nature may help to encourage psychological and physiological relaxation (Alvarsson et al., 2010; Annerstedt et al., 2013; Ghezeljeh et al., 2017; Jo et al., 2019). Applications of this can be found in the incorporation and manipulation of nature sounds in relaxation protocols of auditory feedback devices (e.g., Yu et al., 2017, 2018). In a study on the effectiveness of music for stress reduction, Thoma et al. (2013) found that cortisol levels were lowest in their group that listened to sounds of rippling water, not music. Participants rated the rippling water as equally preferred and equally relaxing as music.

Tempo and mode

Sleep music is typically described as slow in tempo. Unfortunately, measures of tempo in automated feature extraction can be problematic. Computational calculations of tempo are less reliable than many of the other measures due to the difficulty in finding the relevant beat level to extract, prompting some researchers to use alternative methods for discerning tempo (e.g., Egermann et al., 2015). In our results, tempo values in the Sleep playlists cover a vast range (0-211 bpm) that is unlikely to be reliable. Inspection of the tempo distributions shows two peaks in the Sleep playlists and (to a lesser degree) the Relaxing playlists (see Figure 1), which could be evidence of a doubling error in the calculation. This can happen when there is no clear pulse for the feature extraction process to accurately calculate tempo (e.g., music at 60 bpm is miscalculated as 120 bpm).

Reports in the literature for mode offer a mixed picture for sleep music. Some studies used music with minor tonalities for sleep (Chang et al., 2012; Huang et al., 2016, 2017; Su et al., 2013). However, Timmers et al. (2019) saw a clear preference for major modes in an assessment of sleep music playlists from YouTube, Spotify, and Apple, perhaps highlighting a difference in what researchers might prescribe compared to what users select. Major modes might intuitively comply with encouraging positive moods, which have been indicated to be more conducive towards sleep (Jespersen & Vuust, 2012). In our study, the difference in the balance between major and minor modes was striking and appeared to follow a trend, with a roughly equal split for tracks in Energising playlists compared to a 67.1% and 73.9% majority of major modes in Relaxing and Sleep playlists, respectively. Few studies have indicated or analysed the tonal modality of sleep music or have explicitly investigated the relevance of positive mood as a mediator of the effect of music on sleep, making this is an important avenue for further investigation.

Limitations of Spotify features

The vast data source made accessible by the Spotify Web API is an extremely useful tool for researchers. However, due to their proprietary nature, we do not have access to the underlying feature extraction methods, and calculation details are scarce in the documentation. This makes it very difficult to reliably interpret some of the results. As we found, the Liveness measure returned some curious outcomes, and the Tempo values may not be reliable due to computational issues with this feature. The fact that these were two of the weakest features in our analysis could simply be an unfortunate consequence of their unreliability, rather than an indication that tempo for example is not an important factor in music used for sleep.

Valence is another of the Spotify features that raises some questions. Valence is a complex measure and a core component of affective research (Kuppens et al., 2013), making it an interesting aspect to observe. Although middling in classification importance, the feature was relatively distinctive between the categories. It appeared that music in Sleep and Relaxing playlists are more negatively valenced than in Energising playlists, with Sleep music even more so than Relaxing music. This seems to contradict the prominence of major modes that we have seen, and indeed would challenge the notion that positive emotions are best for music for sleep (Jespersen & Vuust, 2012), although pleasure can still be derived from music with seemingly negative emotional content (Sachs et al., 2015). This finding may be linked to how Spotify's Valence feature is calculated; it is common for positive valence to be associated with high energy and brightness. Since the music in the Sleep playlists are low in both, it can be expected to be associated with low values for Valence as well. A more sophisticated definition of Valence may be required to analyse Valence in slow and soft music correctly.

Musical features not provided by Spotify could be very relevant for music for sleep and provide further insights, such as more detailed sonic analysis (e.g., McAdams et al., 2017) and qualitative assessments (e.g., Dickson & Schubert, 2020). While it is possible to add such analyses, they are computationally and time demanding on such large datasets and not feasible within the scope of this study. Through the Spotify API it is possible to obtain 30 second mp3 preview clips of any track which could be used for such additional analysis. A limitation of this is that 30 seconds may not provide a reliable representation of an entire piece of music.

There is also a wider issue with regards to using global features of whole tracks, where only single values are given to represent entire pieces of music. Music can be extremely variable, consisting of structural, tonal, dynamic, and other changes that may be integral to the affective qualities of music (Coutinho & Cangelosi, 2011). The Audio Analysis tool available from the Spotify API allows for more refined evaluation of tracks, providing values for attributes broken up into time-segments (see description in Methods, Data collection). However, the tool has a limited number of features and does not include many of the features from the Audio Features tool that we have investigated here.

Limitations of Spotify playlists

We have studied playlists that are labelled for particular purposes, however their suitability for those purposes is taken only from what has been determined by their creators. Our selection of 30 playlists in each category is a reasonable sample that may represent a variety of perceptions and opinions, and indeed the variability that we see in our results across the playlists could be some testament to the diversity of the sample. However, it should be noted that 37 playlists (41%) credit Spotify as the creator (11 Energising, 12

Relaxing, 14 Sleep). Regardless, this music has not been empirically tested and verified as suiting the purported playlist purposes. We should therefore be cautious about asserting that they represent music that explicitly e.g., aids sleep.

Listener perspectives

The variability of the values of features found here reflects the diversity of sleep music found in other studies (e.g., Dickson & Schubert, 2020; Scarratt et al., 2021; Trahan et al., 2018). Some of these studies consider music reported by listeners which, like public playlists, may represent a diversity of individual preferences. Sleep music may only be partially distinct by its characteristics, while further distinctiveness comes from the way individuals use music or playlists to help with their sleep. There seems to be an implicit assumption that music is listened to at bedtime while an individual is falling asleep, a protocol used in most empirical studies of sleep music. However, Oxtoby et al. (2013) found a benefit of music when participants were asked to listen to provided music for at least 20 minutes after 6pm during their “normal night-time activities” (p. 9). It is possible that individuals who report listening to music to help with sleep take a broader view of their evening routine that may involve listening to music, for example, as they fall asleep, throughout the night, or just in the evening as a wind-down towards bedtime. All of these may still have a beneficial impact on the sleep of these individuals. Music may also be used simply as a masking tool, such as for individuals living in a noisy neighbourhood, rather than for any psychological effects. Other factors, such as musical preferences or changes with age could also play a role in what music works (Lee-Harris et al., 2018) and contribute to the habits and behaviours of individuals that differentiates not only what music, but also how, and why they might use music to help with sleep.

Conclusion

We analysed a subset of Spotify playlists dedicated to sleep, relaxing, and energising, totalling 4,500 tracks, and statistically compared them on the basis of twelve musical features selected from the Spotify API. We found that while similar in many ways to playlists described more generally as relaxing, music from sleep playlists were still distinctive, showing more extreme feature characteristics than music for relaxation and being separable using non-linear classification models. Specifically, we found that brightness was the most important predictor in distinguishing music from sleep and relaxing playlists, emphasising the relevance of timbral qualities not often discussed in the sleep music literature. We also found a considerable contribution of tracks comprising nature sounds and being in major mode. Other features tended to conform with prior descriptions of sleep music (Jespersen et al., 2015; Scarratt et al., 2021), which describe this music to be acoustic, instrumental, and low in energy, loudness, and tempo.

Our results are based on categorisations of mostly commercial playlists from an online streaming platform, and although this provides a valuable perspective into the types of music that are considered suitable for sleep, it does not serve as support for real efficacy. It can nonetheless serve as an informative basis for making selections in future research and posits potential avenues for further study. Specifically, this study provides an important step in the definition of a musical feature space associated with different energy levels as well as an orthogonal dimension of liveness or naturalness of sounds associated with sleep music per se.

3. THE RELATIVE CONTRIBUTION OF SUBJECTIVE AND MUSICAL FACTORS IN MUSIC FOR SLEEP

Forthcoming:

Kirk, R., Panoutsos, G., van de Werken, M., & Timmers, R. *The Relative Contributions of Subjective and Musical Factors in Music for Sleep.* [Manuscript in preparation]. Department of Music, University of Sheffield.

Chapter 2 is presented in a format suitable for submission to a journal.

Statement of Contribution of Joint Authorship

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Conceptualisation of the study, research design and methodology, data collection and analysis, writing and compilation of manuscript, preparation of tables and figures.

Panoutsos, G. - (Secondary Supervisor)

Assisted with guidance on analyses procedures, interpretation of results, and editing of manuscript.

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Linkage of Paper to Research Methodology and Development

The purpose of this study was to address one of the key limitations of the first study (Chapter 2) and expand our perspective on sleep music by considering the subjective qualities valued by listeners. An online listening study gathered ratings from participants on a selection of musical stimuli to explore the perceptual qualities listeners associated with music perceived to be helpful for sleep, i.e., what makes a piece of music sleep inducing. An analysis of musical features expanded our findings from the previous study and allowed us to examine the relative contribution of these factors to the perception of the propensity for music to induce sleep. By using the MIR Toolbox for MATLAB (Lartillot et al., 2008; Lartillot & Toiviainen, 2007), we were able to investigate more detailed musical features than those available from Spotify, such as more specific rhythmic properties as pulse clarity and event density, made practical by focusing on the smaller number of musical excerpts used in this study. Combining this with subjective ratings gives a more nuanced understanding of the affordances of music as relates particularly to the use for sleep, shifting focus from the musical to the perceptual in understanding what makes music sleep inducing.

Abstract

Previous research into music for sleep has focused on describing the types of musical characteristics associated with such music (Kirk & Timmers, in press [this thesis, Chapter 2]; Scarratt et al., 2023). This study expanded 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 conformed with previous research (Jespersen et al., 2022), with additional emphasis on brightness (Kirk & Timmers, in press [this thesis, Chapter 2]), however the subjective ratings overshadowed the musical features in predicting what music was most sleep inducing. Our findings have implications for how music is selected for future sleep studies and highlight the importance of personalisation.

Keywords: Sleep, music information retrieval, valence, arousal, comfort.

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 are 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, 2020a; 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 this has been the case, leaving possible speculation as to the real validity of their selections. This is not to discredit findings; 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 properly 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 best 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, work requirements, lifestyle, genetics, and 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 (Hernandez-Ruiz et al., 2018), 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, 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 [this thesis, Chapter 2]). 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 properly 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 (2020b) found that distraction was both a reason for and against using music for sleep, for some “providing a blockage to […] negative thoughts” (Dickson & Schubert, 2020b, 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, 2020b, 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 on 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 considered 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 [this thesis, Chapter 2]), 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, and 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 [this thesis, Chapter 2]). [6] The original analysis concerned 4,500 tracks from Spotify playlists that were collected using search terms related to sleeping, relaxing, and energising [see Appendix B1.1 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, including

[6] 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.

Erik Satie's Gymnopédie No.1, performed by Ron Adelaar in this instance. This piece has been used in several studies as an example of relaxing music (e.g., Iwanaga et al., 2005; Rickard, 2004; Siragusa et al., 2020) and was specifically mentioned by participants in a survey as a piece of music they used to help with sleep (Trahan et al., 2018).

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. A further eight tracks were selected comprising music 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 B1.2]. 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 (2020a) 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 [this thesis, Chapter 2]). 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 (2020a), 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 from 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 study took approximately 20-40 minutes to complete.

Analysis

First, we compare differences in ratings and musical features between the music categories. Due to non-normal distribution of the data within music categories, as assessed by visual inspection of histograms and confirmed by Shapiro-Wilks tests, we used nonparametric statistical tests. For the ratings, due to their repeated measures Friedmans tests were used with pairwise comparisons using Wilcoxon signed-ranks tests with Bonferroni corrections for multiple testing. The musical features were compared using Kruskal-Wallis H tests with pairwise comparisons using Dunn's (1964) procedure with a Bonferroni adjustment. Next, for 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.

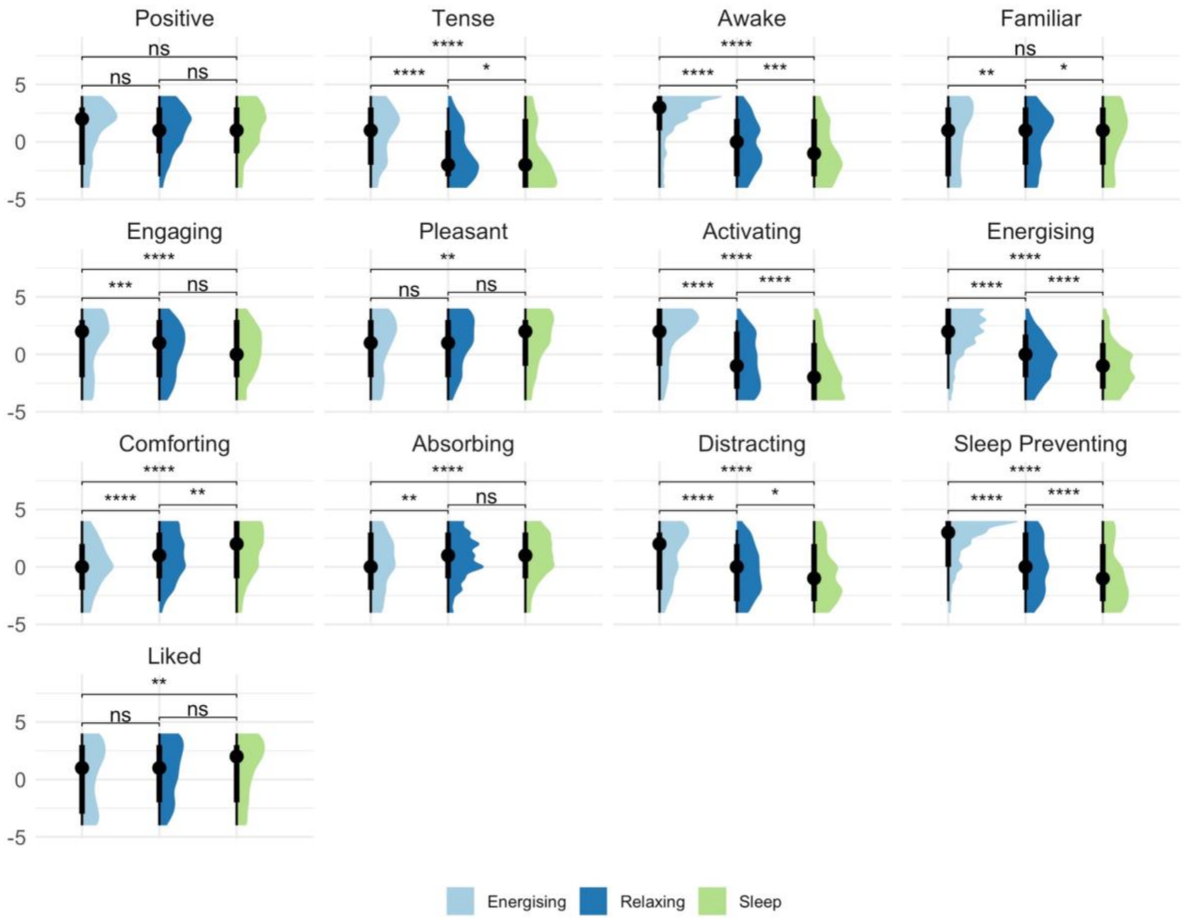
Results

Overview of ratings and features

The final dataset consisted of 1512 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 Wilcoxon signed-ranks tests with Bonferroni corrections for multiple testing are shown.



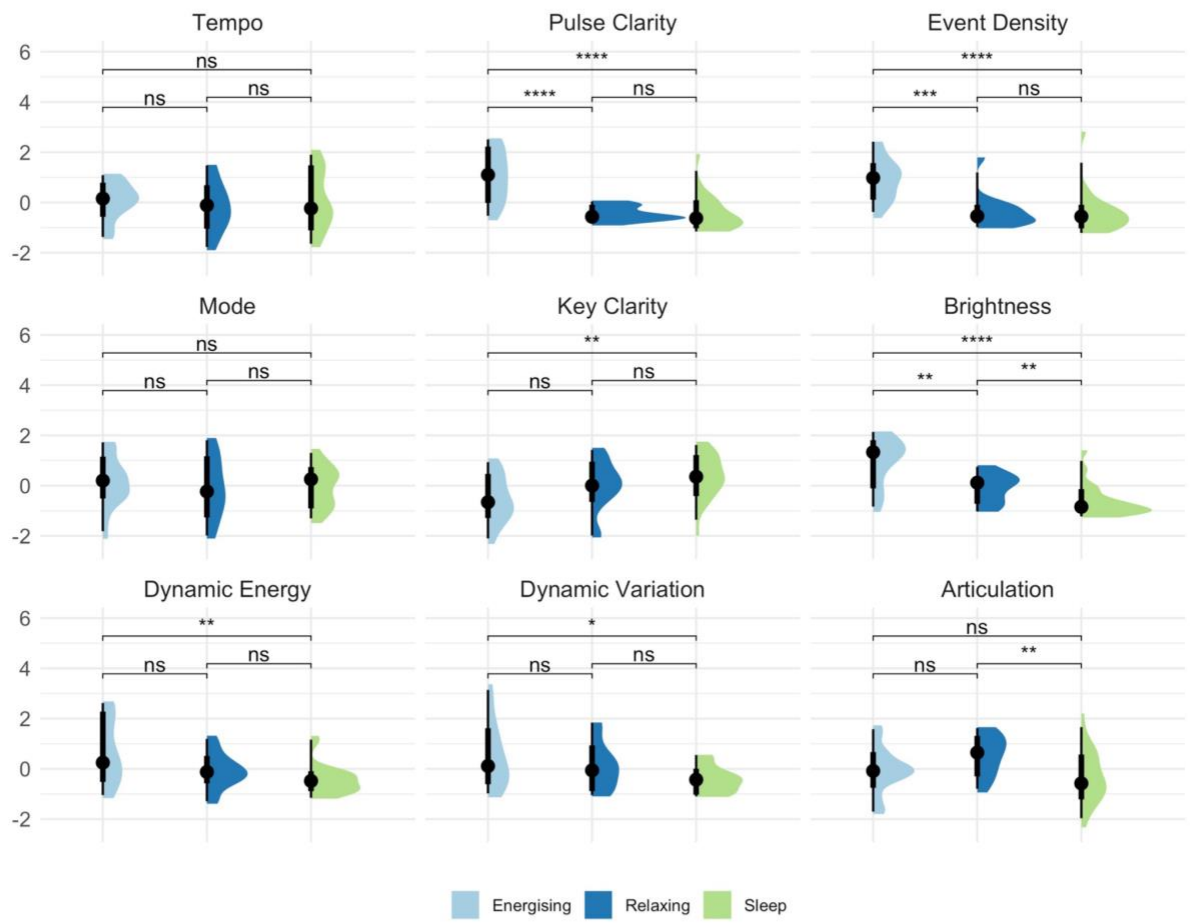
*p <.05. **p <.01. ***p <.001.

Friedman tests revealed significant differences between the categories for all of the ratings except Positivity, 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 relaxed, sleepy, calming, sedating, comforting, freeing of the mind, and sleep inducing than relaxing music, and additionally more pleasant, liked, and absorbing, but not engaging, 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 most of 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 Kruskal-Wallis H tests are shown.



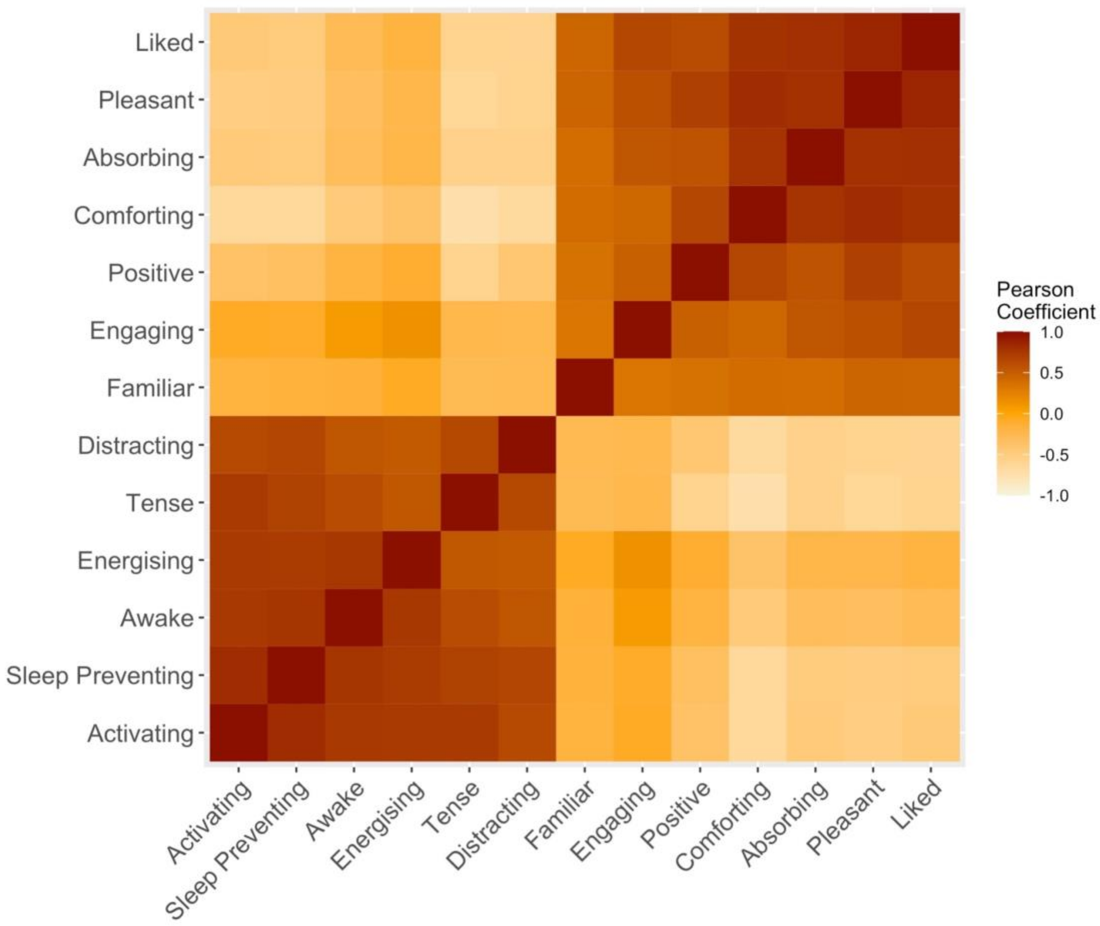
**p* <.05. ***p* <.01. ****p* <.001.

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

Ratings 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).[7] 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	
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

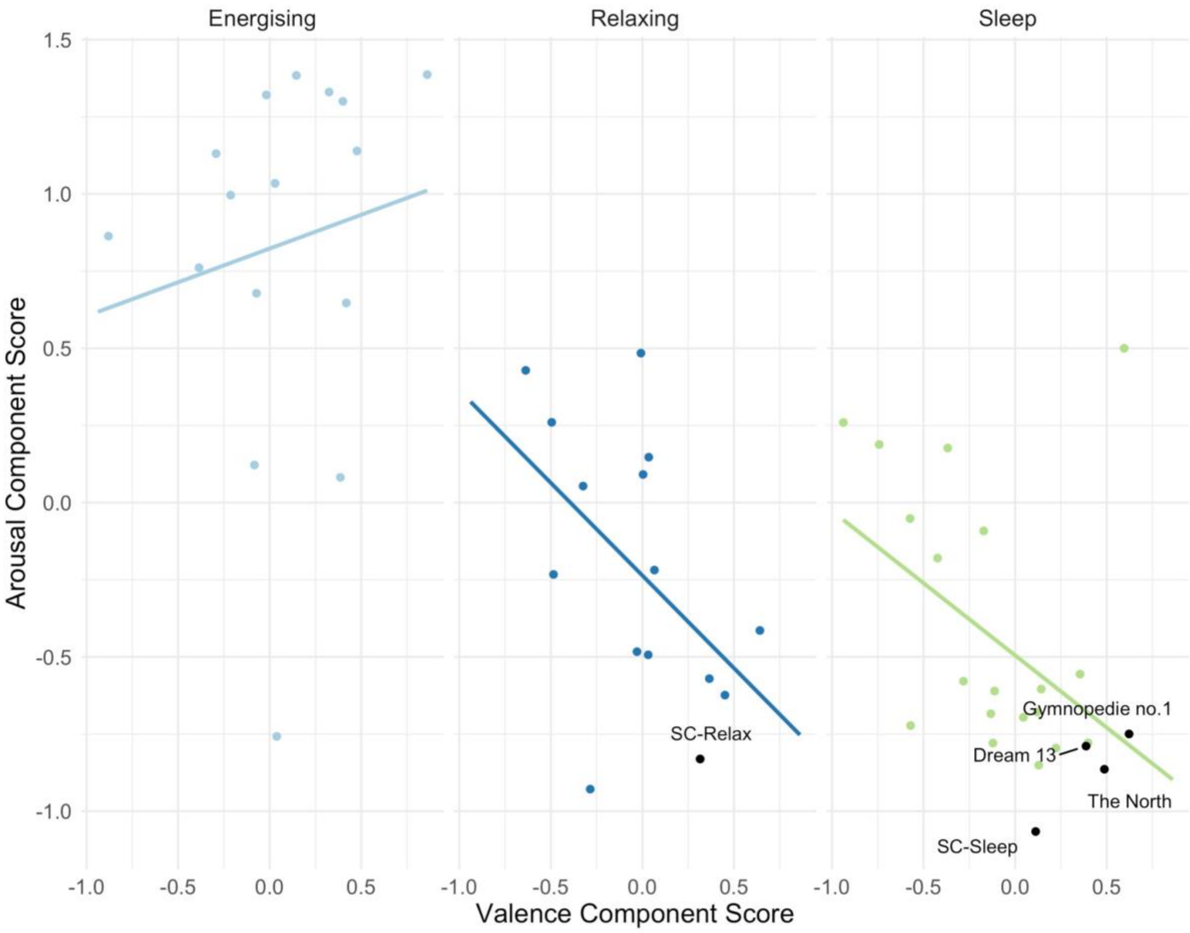
Component scores were used to explore the dimensional structure of the music selection. Average component scores were calculated for each track and are presented in Figure 4,

[7] 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.

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 (2020a). 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).[8]

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 (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**	***R²***	***ΔR²***
		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

[8] 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, ΔR^2 = .691. This is not surprising given that averaging the ratings removes the individual variability in the data.

Table 4

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

(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		
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		

Table 4

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

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.[9] 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 (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.

[9] A list of the ten most sleep inducing pieces can be found in Appendix B2.

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

> When quarantine started[10] 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

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

> 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 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 Distracting-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 dissecting.

Familiarity

Familiarity is often considered influential in the context of music listening for mood regulation and emotional affect (X. 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, 2020b; 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 [this thesis, Chapter 2]) indicating an important feature that is often overlooked in discussions around sleep music. It confirms findings of Dickson & Schubert (2020a) 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).[11] 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 B1.1]. Given the extreme variety found in Spotify sleep playlists (Scarratt et al., 2023), our selection may be limited and is not guaranteed to 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

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

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 properly 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.

4. POSITIVE EFFECTS OF MUSIC ON SLEEP RELATE TO NEITHER MUSICAL PROPERTIES NOR PREFERENCES

Forthcoming:

Kirk, R., Panoutsos, G., van de Werken, M., & Timmers, R. *Positive Effects of Music on Sleep Exist but Relate to Neither Musical Properties nor Preferences.* [Manuscript in preparation]. Department of Music, University of Sheffield.

Chapter 2 is presented in a format suitable for submission to a journal.

Statement of Contribution of Joint Authorship

Kirk, R. - (Candidate)

Conceptualisation of the study, research design and methodology, data collection and analysis, writing and compilation of manuscript, preparation of tables and figures.

Panoutsos, G. - (Secondary Supervisor)

Supervised and assisted with the conceptualisation of the study and research design.

van de Werken, M. - (Secondary Supervisor)

Supervised and assisted with the conceptualisation of the study and research design.

Timmers, R. - (Principal Supervisor)

Supervised and assisted with the conceptualisation of the study, research design, analysis procedures, interpretation of results, and reviewing and editing of manuscript.

Linkage of Paper to Research Methodology and Development

This final study extends findings in the previous two studies by testing the effects of music listening on sleep at night-time. After establishing a theoretical basis for the relevant contribution of subjective and musical features in determining what music is best for sleep, this study put those ideas to the test in the intended context to study real efficacy. Participants listened to one of two music playlists or no music (silence) on consecutive nights and completed sleep diaries each morning. The music playlists were curated using models developed in the second study (Chapter 3) to sample tracks from the Spotify dataset extracted in the first (Chapter 2). We used sleep diaries to record self-report measures of sleep behaviours in keeping with our emphasis on listener perspectives and our interest in the psychological component of falling asleep. The PSQI (Buysse et al., 1989) was also used to measure general sleep health before and after the study, however we were particularly interested in understanding the night-to-night experiences of our participants. Further qualitative information was sought by providing opportunities for participants to give feedback in the form of comments throughout all stages of the study. We also provided some participants with sensors to measure skin temperature as an objective measure of sleep (results of which are not reported in this paper), which we will use in future research to study the relationship between temperature changes and sleep with music and how this corresponds with the self-reported experiences of listeners.

Abstract

Understanding the interplay between musical and subjective factors is an opportunity for predicting what music may work best to support sleep. In a night-time study we tested the effects of different music playlists compared with no music on three outcomes of sleep behaviours. Two playlists were created by selecting music based on previously developed models for predicting optimal music for sleep on the basis of subjective ratings and musical features. After a baseline measure, 30 participants listened to one playlist or the other or silence when going to sleep for three nights each in the comfort of their own home. Sleep diaries completed each morning provided measures of self-reported sleep onset latency, sleep quality, and sleep efficiency. A follow up survey ascertained which playlist each participant would most likely choose to listen to for sleep. We found no significant difference between the music conditions and between either music condition and silence for any sleep outcomes when compared outright or by participant preferred choice. There was an improvement in sleep behaviours when the music was more preferred, however for one third of participants this choice was the less successful of the two playlists at improving sleep. When compared on the basis of sleep behaviour outcomes, there were significant differences between conditions and music that was more successful at improving sleep significantly improved sleep efficiency and sleep quality compared with silence. Feedback from participants indicated positive experiences of using music with sleep and surprise at how they responded to the different playlists. These results suggest neither the type of music nor individual preference is an outright reliable guide for selecting music for sleep, and listeners may be naive to the beneficial effects music can have on their sleep.

Keywords: Music, sleep efficiency, sleep quality, sleep onset latency.

Music is a popular tool used for helping with sleep with potential benefits as an aid for insomnia (Jespersen et al., 2022). Both sleep behaviours and musical tastes are highly idiosyncratic and therefore any therapeutic intervention is likely to require careful consideration of the possible requirements for personalisation. Existing research is unclear with respect to the subjective and personal factors that may influence good musical choices for individuals to support their sleep and there are discrepancies between what researchers typically select for studies or interventions compared with what listeners themselves report using (Dickson & Schubert, 2020a; Trahan et al., 2018). Researchers typically select music for studies on the basis of particular features, whereas the reasons for individual users’ selections are hugely varied and range from improving mood and relaxation, creating a distraction away from negative thoughts, or for simply masking other sounds that would otherwise disturb sleep (Dickson & Schubert, 2020b; Trahan et al., 2018). Sleep studies suggest the use of very specific music to help with sleep, while listener reports open the scope to all types of music. It is possible that what an individual listener chooses to listen to for sleep is not transferable to others and may not necessarily be what is most optimal for them; selections may be made based on convenience, habituation, or only from what is already familiar, and the alternative options are near limitless. They may simply be naive to what is most effective, and yet personal requirements or preference are still likely to be important. A better understanding of this issue and the relevant contribution of intrinsic musical effects and subjective associations is paramount for understanding how to best prescribe the use of music to help with sleep.

Preference and familiarity

Preference and familiarity are often discussed as important factors in the emotional experience of music, however there is some uncertainty around their relative role and influence. For example, Jiang et al. (2016) found that liking was the most important factor in reducing stress, but not familiarity, whereas Tan et al. (2012) found that familiarity significantly correlated with the degree of relaxation reported by participants. Similarly, van den Bosch et al. (2013) found that familiarity had a mediating effect on the experience of emotional arousal in response to music. While these studies refer to stress, relaxation, and arousal, all factors relevant for sleep, there may be differences in the types of music that are best suited to these elements depending on the particular circumstances. Although sleep may be considered a “very relaxed behavioural state” (Kräuchi, 2007, p. 241), as a particular outcome the music that is effective in that context may be different to other forms of relaxation. Indeed, listening preferences appear to change with the time of day (Heggli et al., 2021), which may correspond to changes in mood and alertness that fluctuate naturally and influence listening behaviours. Likewise, familiarity may have differing degrees of relevance for sleep compared with other relaxation-focused listening activities depending on the listener. In a recent listening study, unfamiliarity significantly predicted ratings for how sleep inducing a piece of music was perceived to be, while comments left by participants indicated that familiarity could be either a benefit or a detriment; for some, familiarity played an important role in creating a sense of comfort, but for others prevented dissociation required for falling asleep (Kirk et al., in prep [this thesis, Chapter 3). Whether or not familiarity still influenced a sense of relaxation (as in Tan et al., 2012), for those participants it was not conducive to the specific goal of falling asleep. Liking or preference may be a better indicator of what music is more effective at helping sleep more generally, although familiarity either at initiation or through habituation may still be an important aspect for some.

Understanding music for sleep

To further understand listeners' values with regards to using music for sleep, recent research examined the subjective qualities of music that listeners perceived as sleep inducing. Participants' subjective ratings were found to be stronger predictors than musical features of how sleep inducing a piece of music was perceived to be, suggesting the relevance of personal appraisals over intrinsic musical properties for inducing sleep (Kirk et al., in prep [this thesis, Chapter 3]). Potential for sleep induction was significantly predicted by ratings for comfort, liking, and arousal-related factors (calming, sedating, and sleepy). Musical factors were still important, with event density, pulse clarity, dynamic variation, and brightness also significant, but statistical models including only musical features performed relatively poorly.

This listening study was not carried out at night in a real sleep context and faces a key limitation that what listeners may perceive or assume to be sleep inducing may be different to what truly works in the intended context. It is possible that there isn't such a discrepancy; the generally positive results of studies where music is selected ad hoc by researchers suggests it is possible to make intuitive judgements about effective music for sleep. Nonetheless, personal tastes and requirements when it comes to sleep are still important to understand, if not for total efficacy but potentially as a way of optimising selections given in interventions. In the study described above, despite the strength of the models ratings for different pieces received a full range of responses, with all except one showing considerable intersubjective variability to both extremes of sleep preventing and sleep inducing (Kirk et al., in prep [this thesis, Chapter 3]).

Some studies have given listeners the option to choose the music they listen to in their intervention, either bringing in their own music or choosing from a selection provided by the researchers (e.g., Chang et al., 2012; Iwaki et al., 2003; Shum et al., 2014), but these are few. The beneficial effects of the agency of choice has been shown in other musical interventions (Howlin & Rooney, 2021), and may be similarly important in this case. While researchers' selections may benefit from closer consideration of listener preferences and values, the understandings of researchers may also be informative for finding good solutions for an individual.

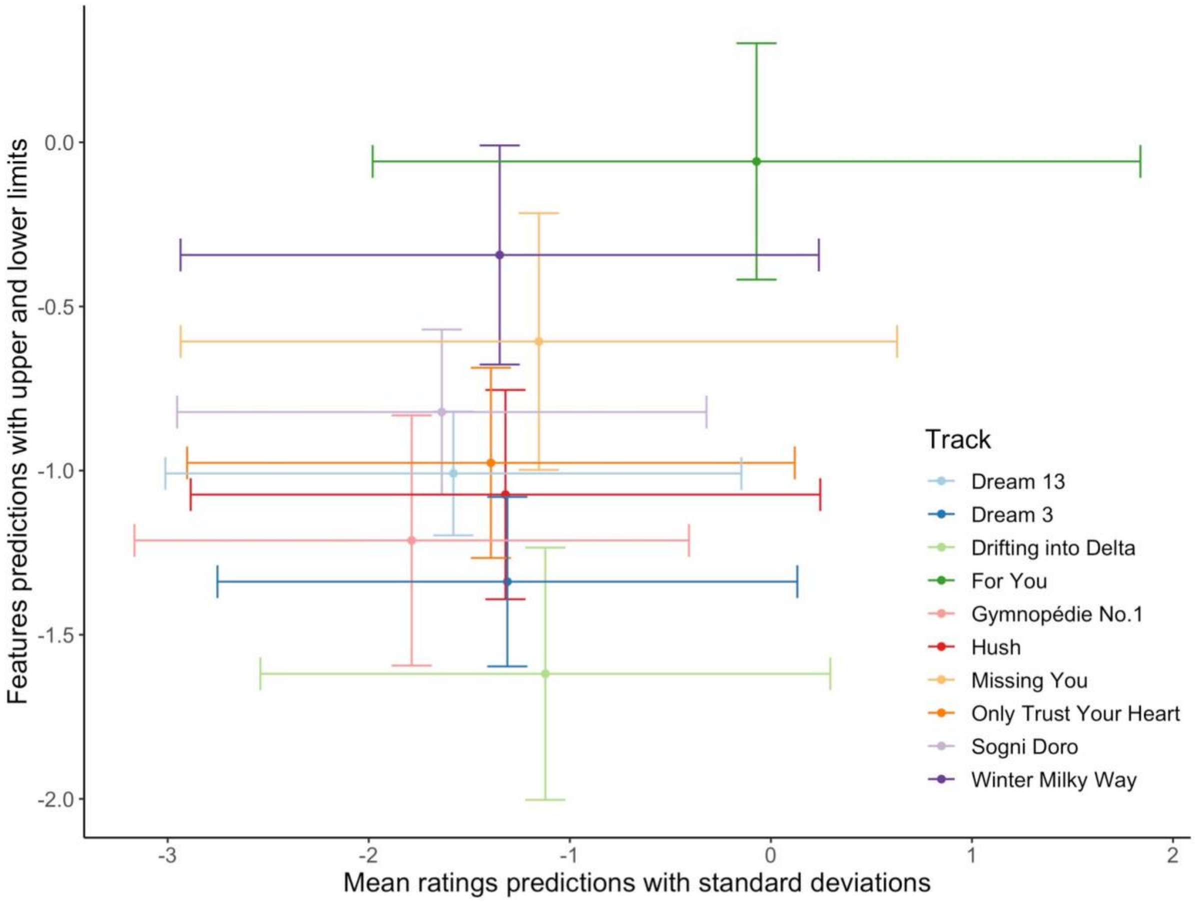
Modelling music for sleep

Previous work developed models for predicting the propensity of pieces of music to induce sleep based on their musical features or subjective ratings (Kirk et al., in prep [this thesis, Chapter 3]). The models were weakly correlated, emphasising the difference in directions to identifying music optimal for sleep induction (model predictions for a subset of these pieces can be seen in Figure 1). Overall, the subjective models outperformed the features models, and yet the feature distinctions for both were in line with common notions of what makes music sleep-inducing (Dickson & Schubert, 2020a; Jespersen et al., 2022).

Indeed, although responses were varied, the pieces rated as most sleep-inducing on average were typically slow, with soft attack and little rhythmic or dynamic variation. These results could be seen to support a general notion of what types of music can help with sleep, but reveal how subjectivity should be considered to address individual variability.

Figure 1

Model predictions for sleep propensity.



The ten tracks depicted here were selected from a set of 56 pieces used in a previous study (Kirk et al., in prep [this thesis, Chapter 3). Negative values indicate sleep inducing. The predictions based on musical features are specific to the individual tracks and are plotted with the upper and lower limits of the model predictions. The predictions based on participant ratings were calculated on the responses for each track by multiple individual participants in the study, therefore the plot depicts the average prediction for each track with error bars depicting the standard deviation in the sample.

Current study

In this study we examine the extent to which musical features and personal preference affect the efficacy of music to help with sleep. We compared music selected as optimal for sleep on the basis of musical properties alone with music associated with subjective perceptions of listeners as predicted using models developed previously (Kirk et al., in prep [this thesis, Chapter 3). Feedback from participants allows us to examine the influence of personal preference on sleep induction. We test the following hypotheses:

H1: Listening to music at bedtime will improve sleep compared with no music (silence).

H2: Music that is predicted to be more optimal for sleep on the basis of musical features will be more successful at improving sleep.

H3: Music that is more preferred by listeners for the purpose of sleep will be more successful at improving sleep.

Methods

Ethics statement

This study received ethical approval from the University of Sheffield (application reference No. 052445) and informed consent was obtained from all participants prior to the study commencement.

Overview

A within subjects study was conducted to test the effect of music listening on sleep outcomes. Three main conditions (two music playlists and silence) were randomised in blocks of three nights each with orders counterbalanced between participants. An initial one week baseline period served to assess the reliability of the silent condition as representative of normal sleep behaviours. Three measures of sleep outcomes were gathered using sleep diaries: sleep onset latency (SOL), sleep quality (SQ), and sleep efficiency (SE). A group of participants were also asked to wear sensors to measure skin temperature during sleep for a pilot investigation that will be reported separately as it falls outside the scope of this paper. A pre-screening survey was implemented prior to participating in the main study.

Participants

Participants were recruited through the University of Sheffield student volunteers list. A recruitment message gave an overview of the study and a link to the pre-screening survey which included full information and a consent form. Inclusion criteria included having a regular sleeping pattern (no night shift work), some sleep onset latency (taking at least 20 minutes to fall asleep), that participants did not currently listen to music to fall asleep (but were open to it) or use other methods that could conflict with listening to music, and were available for a period of time to complete the study that did not involve travelling across time zones. For the course of the study participants were asked to maintain a regular sleeping schedule and limit going out late, limit caffeine, have no alcohol on the nights they participate, and be honest and precise in their responses to the questionnaires. Additionally, they were asked if they had a room or bed partner and to discuss the study with them before agreeing to take part. Where applicable, bed partners were also asked to provide consent before the study went ahead. Participants were offered a £75 Amazon gift voucher as compensation for their time and commitment.

Responses to the pre-screening survey were assessed for compliance with eligibility criteria for the second phase, and eligible participants were subsequently invited to take part in the main study. We received 69 complete responses to the survey. 58 met all inclusion criteria and were contacted for the main study. 38 participants were subsequently recruited and after dropouts 30 participants (18 female, 17 aged 21-29) completed the study in its entirety.

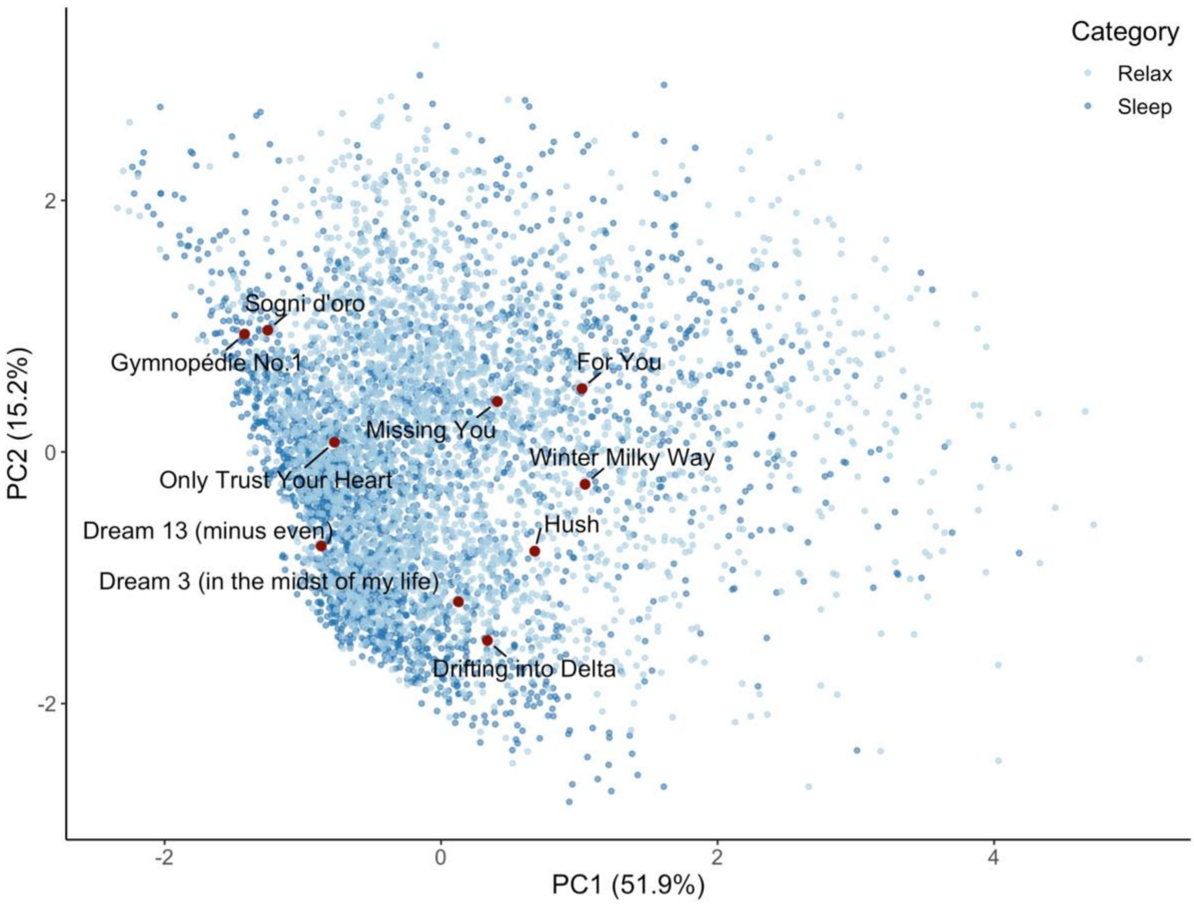
Stimuli

Preparation

Principal Component Analysis (PCA) was used previously to extract components based on musical features provided by the Spotify Data Catalogue to create a feature space for comparison (Kirk & Timmers, in press [this thesis, Chapter 2]). Using the same dataset, and following a similar process, we mapped the ten tracks presented in Figure 1 onto this dataset to explore how they differ on a larger feature space. The original dataset consisted of tracks taken from playlists intended for the purpose of sleeping, relaxing, and energising (e.g., dance and workout playlists) (N = 17,274). We first focused our selection by removing all energising playlists and filtering the dataset to include only instrumental tracks and tracks greater than two minutes in duration. A further subset of playlists that consisted entirely of nature sounds were also removed. After filtering, we ran a PCA on the features for the remaining tracks (N = 5,637). A plot of the resulting component scores of this dataset can be seen in Figure 2.

Figure 2

Plot of component scores resulting from a PCA of features from the Spotify Data Catalogue on playlists categorised as for relaxation or sleep. Two components were extracted explaining 67.1% of the variation in the data [full details of this analysis can be found in Appendix C].



The ten focus tracks cover a reasonable spread across this feature space. Crucially, we can see that the pieces predicted by the previous models as most optimal based on features and ratings (Figure 1) occupy the extreme ends of the bottom and top-left areas, respectively. The pieces at the extreme top-left (Gymnopédie No.1, Sogni d'oro) are among the most sleep-inducing as predicted by the ratings, but not the features, and the extreme bottom (Dream 3, Drifting into Delta) are the most sleep-inducing as predicted by the features, but not the ratings (Figure 1). The second component (PC2, vertical axis in Figure 2) comprises features associated with rhythmic properties, whereas the first component (PC1) is associated with instrumentation along with brightness and energy. Thus, as well as being distinct in terms of their optimisation prediction we can also differentiate these pieces along a musical features-based gradient to sample music for comparative study.

Selection

Two playlists of roughly 30 minutes were sought for the study. 30 minutes is comparable to the length of music used in other studies (e.g., Huang et al., 2017; Kuula et al., 2020). To construct these playlists, we sampled pieces from the larger dataset of Spotify playlists using component scores produced by the above PCA analysis. Mean scores were calculated for each component for the pieces at the two poles in Figure 2 (Gymnopedie No.1/Sogni D'oro, Dream 3/Drifting into Delta). After some fine-tuning, a threshold of +/- .3 on both dimensions was used to sample from the dataset to create an initial selection for each playlist. A final aural assessment whittled down the selection to nine tracks of similar duration totalling around 31-32 minutes for each playlist. The final tracklist can be seen in Table 1. The first playlist (A) represents music predicted as more optimal for sleep based on associations with subjective evaluations, and are typically solo piano pieces, minimal and with a clear pulse and rhythm. The second playlist (B) represents music predicted as more optimal for sleep based on musical features and tracks are typically ambient pieces with limited instrumentation, no clear pulse and little or no discernible rhythmic properties.

Table 1

Track list for both playlists.

Playlist	**Track**	**Artist**	**Album**	**Duration**
A	Reset	Arata Rin	Reset	3:26
	A Moment of Clarity	Tiny Rhino	Ma Belle	3:04
	Evenings	Miso Miso	My Miracle	4:19
	Todoroki	Edo Vibes	Edo Vibes	3:07
	John Brown's Song	Gregory Oberle	Yankee Doodle	3:05
	All is well	Fraire Jaques	Bonne Nuit	3:11

	Lullaby	Milo Stavos	Lullaby	3:53
	Sentinel	Geir Gudmundson	Sentinel	4:16
	Solitude	Fabrizio Paterlini	Life	3:02
Total				**31:26**
B	Contemplation	Spirit Minds	Drifting Ocean	3:20
	Colors	Ashtanga	Colors	3:11
	Steps into a dream	Caelando	Steps into a dream	3:45
	Threads	Ebb & Flod	Moonrise	3:12
	Curves	Norrona	Curves	3:14
	Airborne	Crow City	Airborne	3:54
	Cardboard Gadgets	Georg Valeks	Cardboard Gadgets	3:35
	The Poet	Low Moon	The Poet	3:19
	Country Chimes	Coconut Calm	Country Chimes	4:21
Total				**31:55**

For music playback in the study, we used Spotify and Apple Music. Inquiry during the recruitment phase revealed the vast majority of our participants used one of these applications and the remaining reported that they were happy to trial a service for the purpose of this study. We therefore created each playlist as a public playlist in Spotify and Apple Music and provided links for the respective conditions in the evening questionnaire for the study (see Materials below). During the study, participants were instructed to ensure that they turned off autoplay and did not shuffle the playlists. This ensured that track order was the same for all participants.

Materials

Pre-screening questionnaire

All questionnaires were published on the Qualtrics survey platform. During pre-screening, participants were asked to provide general demographic information (age, gender), musical behaviours, and sleep health and habits using the Pittsburgh Sleep Quality Index (PSQI, Buysse et al., 1989). A selection of musical excerpts was also presented for participants to rate, assessment of which will not be included in this analysis.

Evening and morning questionnaires

Two questionnaires were used for the main data collection. The evening questionnaire was completed when participants went to sleep. Participants were first asked to confirm if they were using temperature sensors and subsequently rate their current state of mood (positive-negative and tense-relaxed on 9-point scales) and alertness using the Karolinska Sleepiness Scale (Åkerstedt & Gillberg, 1990). They then indicated the condition for that evening (Baseline, Silence, Music A, Music B) following their personalised schedule (see Procedure) and the time that they were going to sleep. When indicated, a final page presented participants with a link to the appropriate playlist for the selected music condition.

The morning questionnaire was to be completed as soon as the participants got out of bed and consisted of the Core version of the Consensus Sleep Diary (Carney et al., 2012). If the evening's trial was a music condition, they were asked to confirm that they indeed played the music, if there were any issues with playback, and finally asked to provide details about their experiences of the music in an open response question. Participants were told to be as accurate and honest as possible in their responses and encouraged to provide as much detail as they wished about their thoughts and experience of the music. This final question was left deliberately open so as not to bias remarks and allow participants to share whatever they felt was relevant to them.

Both questionnaires were distributed as personalised links through Qualtrics to email addresses provided by participants in the pre-screening survey. The links were set up to allow multiple entries, meaning that participants could use the same links repeatedly to fill in the relevant questionnaire when required throughout the study.

Closing survey

After completing the night study, participants were asked to fill in a final questionnaire, first asking them to repeat the PSQI (Buysse et al., 1989) with respect to the period of the study. They were then asked to provide ratings on the two study playlists along a series of bi-polar scales, the final asking, 'If you were to choose music to go to sleep with, how likely would you choose this music?'. A 90 second excerpt, comprising 10 second clips of each track from each playlist, was provided as a reminder. Space for open comments were also provided. Finally, they were asked to reflect on their experience of the study more generally with a series of agree/disagree statements. The survey ended with a debrief explaining the basis and aims of the study.

Procedure

Participants completed the study in the comfort of their own homes over 16 nights (one week baseline followed by three nights of each of the main conditions). Each participant was provided with a personalised schedule showing their condition permutation and were asked to refer to this each night when completing the evening questionnaire (see Materials). They were told to complete the evening questionnaire before going to sleep and the morning questionnaire when they got out of bed throughout the entire period of the study. Participants were asked to keep to their regular bedtime behaviours, other than adhering to the requirements of the study.

Participants used their own digital devices to complete the questionnaires and manage the music playback. For consistency, all participants were asked to use headphones or earphones to listen to the music. Two participants reported that this was uncomfortable when trying to sleep and were permitted to use speakers instead. Due to the already limited control that comes with an at-home study, we allowed this on the basis of ensuring participant sleep comfort and acknowledge it as a possible limitation given the effects that headphone listening may have in contributing to a sense of space and comfort (Downs, 2021) that may be important for sleep (Kirk et al., in prep [this thesis, Chapter 3]).

Analysis

Data provided in the sleep diaries were used to extract three measures; sleep onset latency (SOL, the reported time in took to fall asleep, in minutes), sleep quality (SQ, as rated on a five-point scale from very poor to very good), and sleep efficiency (SE, the time spent asleep as a percentage of the time spent in bed). Each measure was averaged within conditions for each participant. Differences between the conditions outright (Silence vs. Music A vs. Music B) were first analysed, addressing hypotheses 1 and 2. Next, we looked at differences based on which music was more or less preferred by each participant (as indicated by responses in the closing survey - see Results for more details) to test our third hypothesis. As a final exploratory analysis, we examined differences between playlists on an individual basis based on which music was more or less successful in actuality at improving sleep (as determined by sleep diary responses - see Results for more details).

Exclusion of data was only done in the case of response errors or missing data from participant surveys. Due to non-normal distribution of the sleep diary responses, as determined by inspection of histograms, non-parametric tests were used for all analyses. Friedman tests were used to compare differences between conditions for each sleep outcome and Wilcoxon signed-rank tests were used for all pairwise comparisons. All analyses were performed using R.

Results

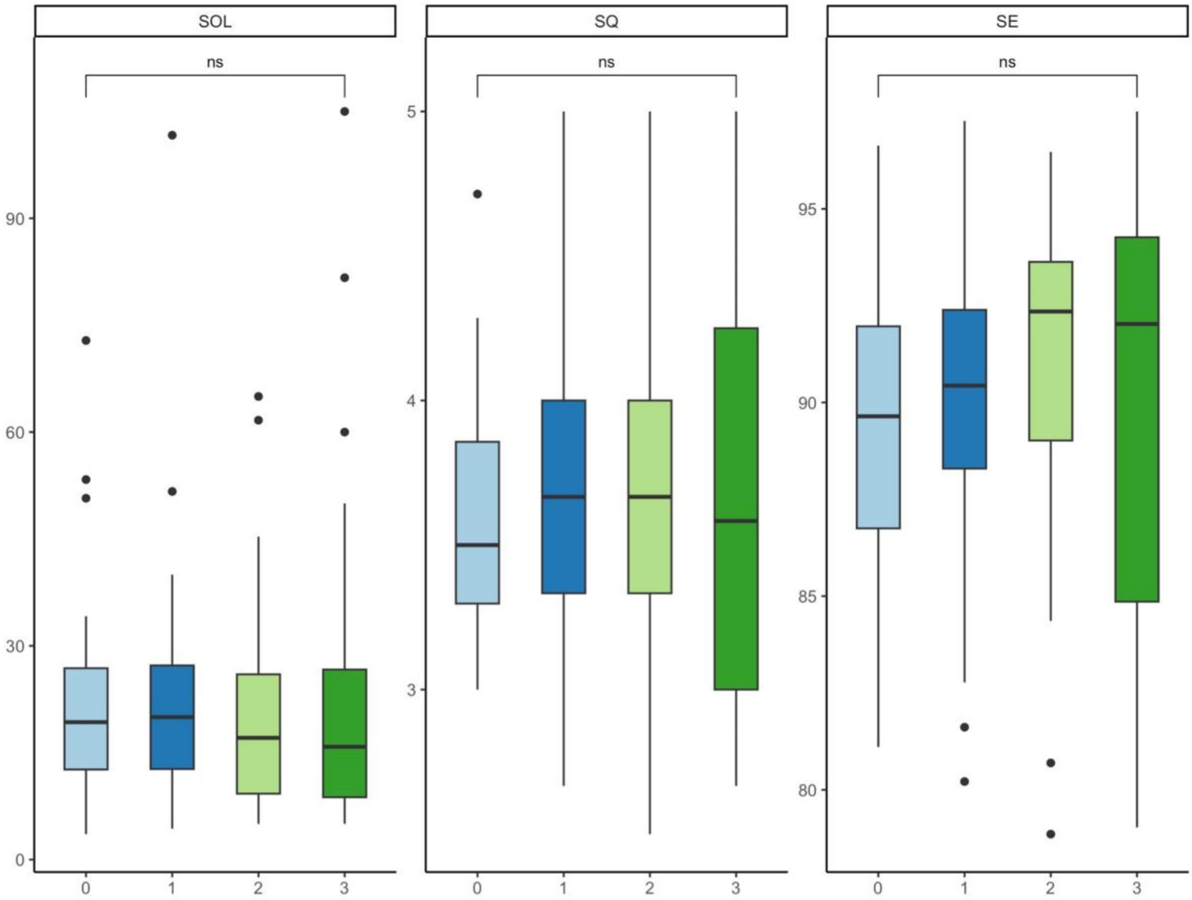
Baseline and order effects

We first assessed the validity of the Silence condition by comparing all measures against the Baseline. There were no significant differences between the Baseline and Silence conditions for SQ, SOL, or SE ($p > .05$).

To examine the possibility of any transfer effects, we compared differences between conditions by order of presentation in the study. There were no significant differences between the conditions for any of the measures ($p > .05$). Visualising the data we can see a slight trend in SE improving throughout the study, possibly beginning to plateau towards the end (Figure 3). In a final check, Spearman tests further showed no significant correlation between SE and order ($p > .05$).

Figure 3

Boxplots of conditions arranged in chronological order during study, regardless of actual condition (music or not), starting from Baseline (0).



Impact of mood and alertness

To see if mood and alertness had an impact on the sleep outcomes, we checked to see if these ratings correlated with the sleep outcomes. Spearman tests revealed significant correlations between Alertness and SOL and SE, and between SQ and Positivity and Tension (see Table 2). Only the correlation between Alertness and SOL had a coefficient greater than .3, and this was the most significant result. It will therefore be considered for potential as a confounding factor later in our analysis.

Table 2

Correlations between mood and alertness ratings and sleep outcomes.

	SQ	SOL	SE

Positivity	.248**	-.016	.100
Tension	.200*	-.054	.160
Alertness	-.071	.504***	-.275**

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

Main outcomes

To address our first two hypotheses, we examined the effects of the conditions on each outcome measure. Friedman tests revealed no statistically significant differences for any of the outcome measures between the three conditions. Neither music condition was associated with better sleep compared to silence, nor were the music conditions significantly different from each other (Figure 3, Main Conditions). Inspection of individual responses did suggest differing trends between participants, however.

To test our third hypothesis, we used responses from the closing survey to the question ‘If you were to choose music to go to sleep with, how likely would you choose this music?’, with responses on a 9-point scale from ‘Very unlikely’ to ‘Very likely’, to categorise the music conditions and determine which was more or less preferred for each participant. This categorisation produced more noticeable trends in sleep outcomes, however there were still no significant differences between the conditions, although SQ was approaching significance ($\chi^2(2) = 5.391$, $p = .068$) (Figure 3, Preferred).

Additional findings

As a further exploratory investigation, we examined the correspondence of participants’ choice of preferred playlist with differences in sleep outcomes between the music conditions. Each playlist was scored for each participant against the desired outcome in each sleep measure (i.e., lower SOL, greater SE, better SQ) to indicate which was most successful for each participant. Music B was the most successful for 16 participants compared to 14 for

Music A, whereas Music A was more preferred by 18 participants compared to 12 for Music B. The preferred matched the most successful playlist for 20 participants, compared with 10 where it did not. In other words, one third of participants said they were more likely to choose the music that was less successful at helping them sleep, to go to sleep with.

Analysis after recategorising the music based on successful outcome revealed statistically significant differences for SOL ($\chi^2(2) = 11.375$, $p < .005$), SE ($\chi^2(2) = 25.400$, $p < .005$), and SQ ($\chi^2(2) = 9.657$, $p < .05$) between the three conditions (Figure 3, Successful). Pairwise tests revealed statistically significant differences between the music conditions for all measures ($p < .05$) and both SQ and SE were also significantly greater for the more successful music compared to silence ($p < .05$).

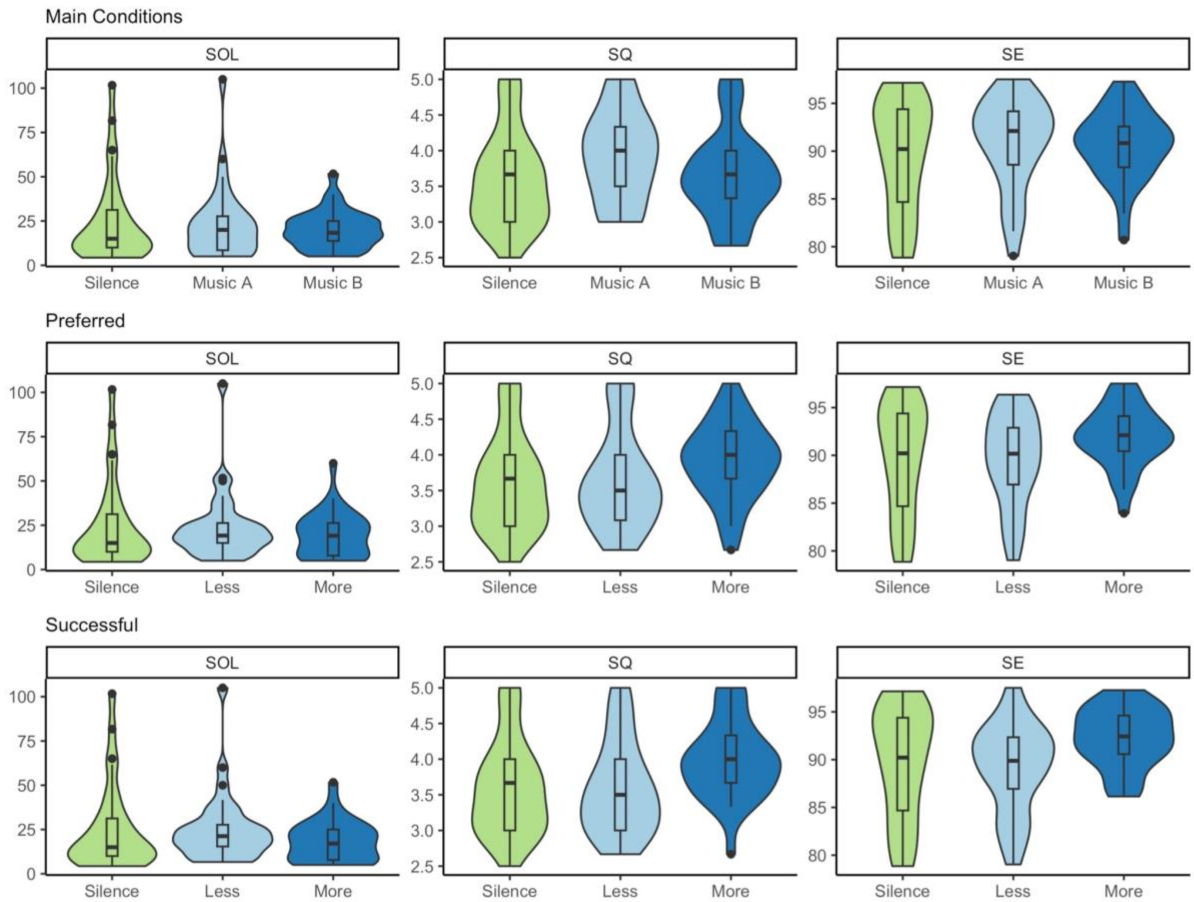
Table 3

Summary statistics of the self-report measures by comparison and condition.

Measure		Condition			Preferred		Successful	
		Silence	**Music A**	**Music B**	**Less**	**More**	**Less**	**More**
SOL	Median	15.000	20.000	18.333	19.167	19.083	21.250	17.083
	Mean	25.161	23.517	20.406	24.333	19.589	25.622	18.300
	SD	24.218	20.684	10.686	19.295	12.770	19.664	11.516
SE	Median	90.212	92.103	90.837	90.170	92.103	89.878	92.431
	Mean	89.643	90.806	90.594	89.512	91.888	89.142	92.258
	SD	5.765	4.749	3.658	4.797	3.166	4.642	3.063
SQ	Median	3.667	4.000	3.667	3.500	4.000	3.500	4.000
	Mean	3.606	3.922	3.650	3.661	3.911	3.594	3.978
	SD	0.676	0.622	0.621	0.700	0.537	0.662	0.544

Figure 4

Violin plots of sleep measures for all comparisons.



Alertness

To assess the relative impact of Alertness on SOL outcomes, we used regression models with SOL as a dependent variable and Alertness, Condition, and Order as independent variables in a standard multiple linear regression. SOL was first log transformed due to the heavy skew in the distribution. We ran models for all three condition categorisations (Main Conditions, Preferred, Successful). All prerequisite assumptions for the analyses were satisfied.

All three models with each of the musical categorisations were significant. Alertness was the only significant predictor in each (Table 4). All adjusted R^2 values were small (< .2). These results suggest that SOL is better predicted by levels of alertness at bedtime than the music conditions. The same regression models for SE showed only the model for the Successful music comparison to be significant, $F(3,86) = 2.840$, $p < .05$, adj. $R^2 = .058$). Alertness did not significantly contribute to the model, albeit marginally ($p = .057$). Condition was the only significant predictor ($p < .05$), in line with the results of the nonparametric analyses. Finally, regression models for SQ with Positivity or Tension were also examined, but none were significant. Order did not contribute significantly to any of the models.

Table 4

Multiple regression results for SOL.

Sleep Onset Latency	***B***	**95% CI for *B***		***SE B***	***ß***	***p***	***R²***	***ΔR²***
		LL	***UL***					
Main Conditions							.204	.177
(Constant)	3.131	2.729	3.534	.202		<.001		
Alertness	.222	.128	.316	.047	.456	<.001		
Condition	-.017	-.181	.147	.083	-.020	.835		
Order	.026	-.140	.191	.083	.030	.759		
Preferred							.212	.185
(Constant)	3.203	2.800	3.606	.203		<.001		
Alertness	.224	.131	.318	.047	.461	<.001		
Condition	-.079	-.242	.085	-.082	-.092	.342		
Order	.022	-.143	.187	.083	.025	.793		
Successful							.221	.194
(Constant)	3.228	2.836	3.620	.197		<.001		
Alertness	.227	.134	.321	.047	.467	<.001		
Condition	-.113	-.276	.050	.082	-.132	.172		
Order	.028	-.136	.191	.082	.032	.736		

Table 4

Multiple regression results for SOL.

Note. B unstandardised regression coefficient; *CI* = confidence interval; *LL* = lower limit; *UL* = upper limit; *SE B* = standard error of the coefficient; *ß* = standardised coefficient; *p* = significance probability; R^2 = coefficient of determination; ΔR^2 = adjusted R^2.

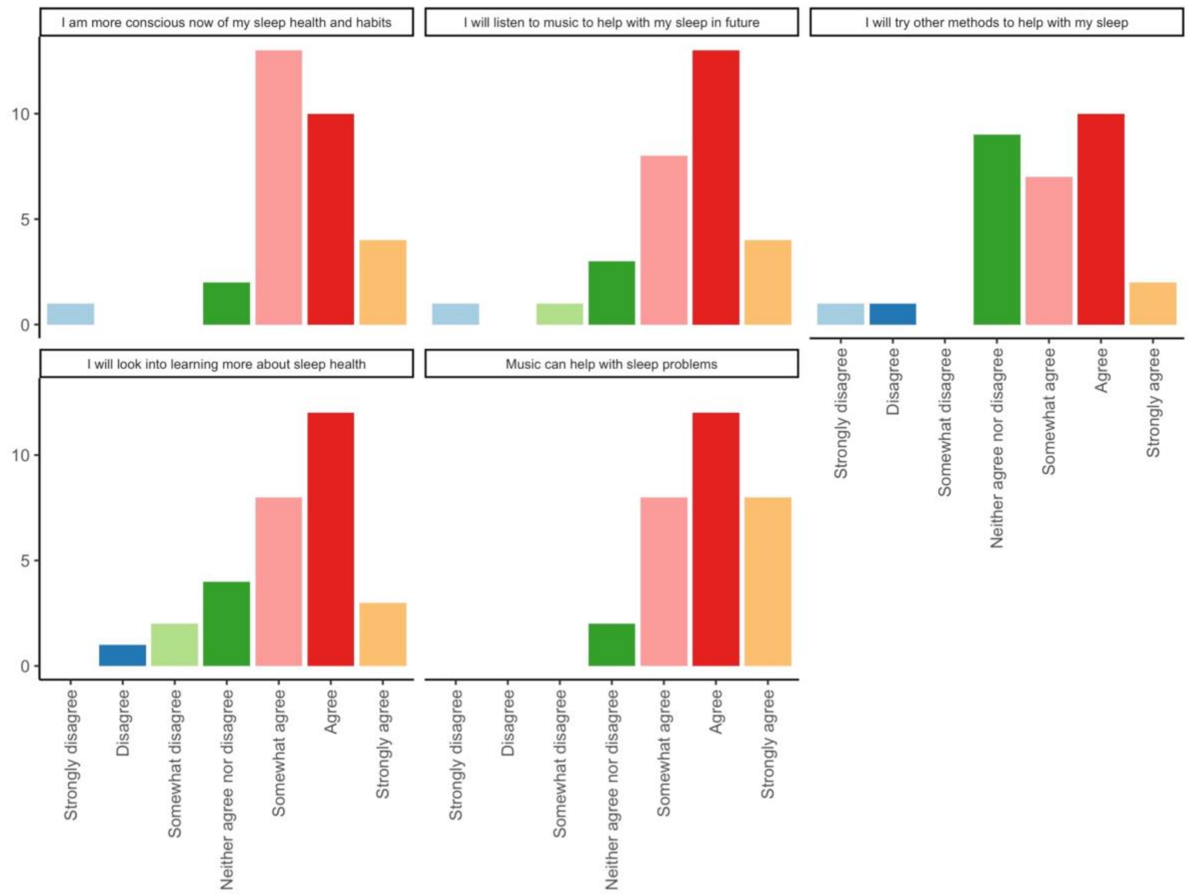
Closing survey outcomes - PSQI differences and attitudes towards sleep health and habits

Changes in participants PSQI scores from the pre-screening and closing surveys were examined to see if there was any change during the course of the study. Data were approximately normally distributed, as determined by visual inspection of histograms and Shapiro-Wilk tests, therefore a paired samples t-test was used for this comparison. PSQI scores from the closing survey were significantly lower than scores from the pre-screening survey ($t(27) = 3.617$, $p <.005$, $d = .684$), indicating that participants' sleep health during the study was better than in the period when they first signed up.

Participants may have become more conscious of their sleep health and habits through the course of the study. To query attitudes towards sleep, and general attitudes around the use of music specifically, we included five agree/disagree statements at the end of the closing survey; 'I am more conscious of my sleep health and habits', 'I will listen to music to help with my sleep in future', 'I will try other methods to help with my sleep', 'I will look in to learning more about sleep health', 'Music can help with sleep problems'. Participants tended to agree with all items, which were statistically significant ($p < .05$ according to one-sample Wilcoxon signed-rank tests compared to the midpoint), suggesting that participating in the study had an influence on their attitudes towards sleep and using music for sleep (Figure 5).

Figure 5

Post-study attitudes towards sleep health and habits.



Discussion

Our results support our first hypothesis, that listening to music would lead to better sleep outcomes compared with silence, although not in the way we expected. Music did not improve sleep compared with silence when compared by music type nor the preference of participants, opposing our second and third hypotheses. There were, however, improvements in sleep that were independent of these categorisations that when analysed did reveal significant outcomes. An overall improvement in PSQI scores also suggests that the study had a positive effect on the sleep health of our participants.

Sleep outcomes

SOL was only significantly different between music conditions when compared on the basis of their success at helping sleep and not significantly different for any music compared with silence. In fact, median SOL times were greater for both music conditions compared to silence in all comparisons (Table 2). This may have been because participants actively listened to the music. One participant commented; “It took longer to fall asleep because I was listening to the music” (P43). Yet despite participants seemingly taking longer to fall asleep, there were improvements in both SQ and SE. The clearest trends were in SE, which was greater compared to silence overall for nearly all comparisons, and statistically significant when the music was more successful at promoting sleep. Previous studies have also found an effect of music on sleep efficiency over other measures (e.g., Gao et al., 2020). SE is affected by awakenings during the night, which appeared to be reduced during the music conditions in our study. Our data is limited to only three trials for each condition, however, and should therefore be interpreted with some caution. Yet, this effect of the music was explicitly acknowledged by one participant, who stated, “Music helped me to sleep and was first time I hadn’t woken up in the night” (P07). Night-time awakenings may be caused by various factors; listening to music may have helped alleviate some psychological stressors at bedtime that had a lasting effect on sleep through the night. The relaxing effects of the music generally were commented on by participants, for example, “Although I didn’t fall asleep during the music it calmed and relaxed me and meant that when the music stopped I was more relaxed than when it started” (P17). The influence of music on mood is seen as an important factor in its ability to help with sleep (Jespersen & Vuust, 2012), and comments such as these add evidence to this case.

Another factor in improving sleep outcomes could be the introduction of a routine. One of our recruitment criteria was that participants did not currently listen to music to sleep and by introducing music listening as an activity at bedtime the study itself may have encouraged a type of routine, something that is often recommended for improving sleep (Chaput et al., 2020; Mindell & Williamson, 2018; Zisberg et al., 2010). That being said, we found significant differences between our two music conditions for some of the sleep outcomes, which suggests that there is indeed an effect of the condition itself and not simply an effect of the intervention as a whole. This is further supported by our evaluation of order effects that did not suggest a significant factor of time in improving sleep outcomes through the course of the study (Figure 3). Further, while data in most conditions were quite varied, sleep behaviours in the more successful and preferred conditions were more consistent and consolidated (see Figure 4). The differences in variability between the conditions could be an effect of outliers; we have been reluctant to remove outliers given the size of our sample, only excluding trials where there were errors or missing data in participant responses. Nonetheless, more consistent results for the more preferred or successful music conditions could be a further sign of an improved routine that may have been encouraged by the study generally, that was made more successful by particular musical conditions. A longer study with a greater number of trials in each condition would help to tease this out.

Expectations

The findings suggest that what participants believe works for them, or are more likely to choose, may not necessarily align with what is most effective. In some cases, participants appeared to be aware of such challenges to their preconceptions; “Thought it would keep me awake longer but was actually very relaxing and made me sleep quicker” (P07). Others reflected more deeply:

> I definitely preferred B to A, which I find funny as before the study I'd have almost certainly picked A over B as I'd much prefer piano music to those sort of relaxing sound pieces, but then again maybe my interest towards the piano pieces are part of the reason they're maybe not for me for sleeping as I find them too interesting to listen to. (P49)

This participant has reflected on the experience of listening to music as it pertains to the particular purpose of sleeping, finding it not to be as they expected. Similar experiences for others had negative outcomes, as one remarked; “I was surprised to find that I didn't like this music and I found it annoying to try to fall asleep to especially on the first night I listened to it” (P35).

These comments reveal how listeners may have expectations about music and its effects with respect to sleep (and indeed possibly other therapeutic applications) that may have consequences in practice. There is not only an importance for researchers to understand what may help that they may guide participants but also for individuals to understand the possibilities and be open to reassessing their expectations.

Familiarity, habituation, and long term effects

Another theme that emerged from comments left by participants were the effects of repeated nights of music listening. One participant commented, “I found it a bit more soothing and relaxing now that I'm more used to it” (P35). Again, other participants offered more detailed reflections:

> I found it quite relaxing last night as it sounded more just like background noise. Although I didn’t have the best nights sleep, I definitely found the music more comforting to fall asleep to this time as I have the past 2 times because I’m getting more familiar with it. (P29)

Although we found no effects for continuity of the study overall, there may have been some effect of habituation within the conditions. With only three nights for each condition, it is difficult to properly assess this possibility. Previous studies have suggested that increased exposure to music increases relaxation (e.g., Iwanaga et al., 1996), however again this may have different implications in the context of sleep with positive or negative effects as previously found (Kirk et al., in prep [this thesis, Chapter 3]). For some participants, continued listening did appear to have positive connotations; “I think if I was to continue listening to the playlist and get used to it I’d start falling asleep faster each time” (P29).

We did find a significant difference in PSQI scores between the pre-screening and post-study surveys. The former was completed at the recruitment phase, with varying time delays before participants completed the main study, which could have been a factor. There may have been some recency bias in the responses to the PSQI in the closing survey, that may corroborate with the improving (if not significant) trend we saw in sleep diary responses towards the end of the study (Figure 3). The latter part of the study contained more nights of music (6) than silence (3), and indeed many participants commented positively about their experience of the music on their sleep. Participants also seemed to be more aware of sleep health and habits after the study (Figure 5).

Limitations

We have highlighted several key limitations, in particular controlling the music playback and the small number of trials in the study. The latter could be shrouding key effects, such as that for familiarity or habituation, including that resulting from forming a routine. Previous music and sleep studies have varied durations, with many consisting of only a single trial for each condition tested (e.g., Chen et al., 2013; Iwaki et al., 2003; Kuula et al., 2020). These were typically lab-based studies. Others consisted of interventions lasting three weeks or longer (e.g., Deshmukh et al., 2009; Harmat et al., 2008; Jespersen & Vuust, 2012). The comments we received from participants in this study strongly suggest that important findings could be had from more long-term investigations.

Our results are based on self-report from sleep diaries and could be further supplemented by additional sleep measures that might provide objective data on sleep behaviours. The typical caveats of cost and availability of equipment certainly apply in this case. Personal devices were considered, and participants were asked if they owned any devices that included physiological measures or actigraphy (e.g. smartwatches, fitbits) that they would be willing to share data from, but concerns over lack of consistency and the ability to extract adequately detailed data deterred their inclusion in our study. Further, the use of mobile applications for measuring sleep was rejected over concerns of reliability (Fino et al., 2020; Ong & Gillespie, 2016; Patel et al., 2017). A group of our participants (N=20) did wear sensors for measuring skin temperature, which is strongly associated with sleep patterns (Te Lindert & Van Someren, 2018) and, to our knowledge, has never been used in a sleep study with music. Analysis of the outcomes of this measure will be reported on separately.

Conclusion

The complexities of the effects of music on sleep have been further highlighted in this study. Our results support the use of music to help with sleep but indicate not only that the type of music is not strictly determinate of sleep outcomes, but participants themselves may have conflicting notions of what they should use to help with their sleep. Listening to music may improve sleep quality and sleep efficiency but appears to have less of an effect on sleep onset latency. These effects may change over time with continued listening and habituation. Overall sleep health is a combination of several factors, and music may tap into mechanisms that improve particular aspects that in turn have positive overall effects on sleep.

5. SUMMARY, DISCUSSION, AND CONCLUSION

The focus of this thesis has been to enhance understanding of the properties of music that can best help with sleep and explore the objective and subjective factors that promote sleep and reveal individual variability. In particular, our intention was to shift focus from the music to the perceptual values of listeners, tapping into the specific affordances of music that are especially relevant for sleep, and how this differs from relaxation. The following questions were central to the research:

1) What are the features of music that are best for promoting sleep?
2) What are the subjective qualities that are most important for music that is considered sleep inducing?
3) What is the respective contribution of personal perceptions and intrinsic musical properties in aiding sleep?

In Chapter 2 we showed that music for sleep is distinct from music that is otherwise used for the more general purpose of relaxation, with sleep music characterised as more acoustic, instrumental, quieter, and less bright (RQ1). The study in Chapter 3 further found brightness to be a key factor and music with fewer events, a less clear pulse, and less dynamic variation was perceived as more sleep inducing. Subjective accounts however were more nuanced. Listener ratings were significantly better at predicting what music was perceived as sleep inducing, in particular factors strongly related to arousal, but we also saw a significant impact of liking, familiarity, freeing of the mind, and comfort (RQ2). Each of these concepts was mentioned in comments by participants. In the case of familiarity, this seemed to have opposing implications for different individuals, supporting or hindering the music's suitability for sleep.

Following these findings our final study (Chapter 4) tested the respective contribution of personal perceptions and intrinsic features of music in a night-time study (RQ3), and found that neither stood out as the most reliable indicator for music to improve sleep. Participants were split in terms of which playlist led to the greatest improvement in sleep, and for one third of participants the selection that was most successful was not the playlist they reported that they were more likely to choose themselves. The music we provided was selected on the basis of findings in our second study; both playlists were constructed on different premises but predicted to be optimal for supporting sleep in some way. Musically speaking, both playlists were relatively low in terms of activating features and similar to music used or suggested by other sleep studies (Cordi et al., 2019; Kuula et al., 2020; Trahan et al., 2018). Despite both our selections converging on prior work, the fact that we saw significant differences in sleep outcomes between the playlists shows just how crucial the music selection can be.

Our findings reflect the interindividual variability that is an intrinsic aspect of many musical experiences but has received less empirical investigation in the context of listening to music for sleep. Using music to help with sleep is a very specific goal that has important potential health implications, therefore this research has vital importance. We have shown the impact relatively small differences in musical characteristics may have, even if in general the music can be broadly conceived as sleep music. This opens further scope for exploring the underlying factors that may contribute to effective uses of music for sleep. Below, we consider possible avenues for further research.

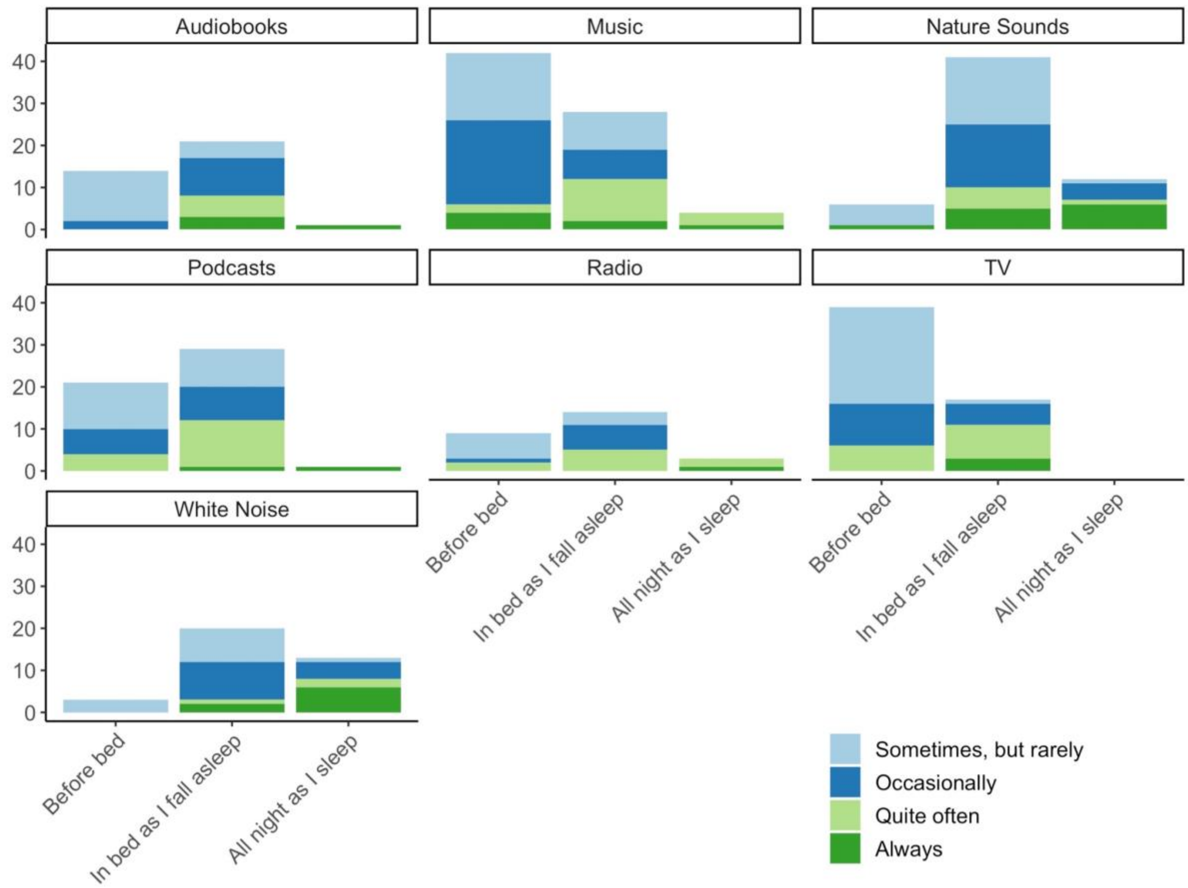
Different ways of using of music

The study presented in Chapter 4 required participants to listen to music in bed as they were going to sleep. This follows the typical paradigm employed in many music and sleep studies, however as we raised in our Introduction and touch upon in Chapter 2 individuals may take a broader view of their night-time routine that may include listening to music at different times. The survey conducted in the second study (Chapter 3) included background questions on sleep habits that delved into this very question, not reported in that paper. Participants were asked to indicate what methods, if any, they used to help with sleep, from a list of items collated from previous surveys (Furihata et al., 2011; Huang et al., 2018; Morin et al., 2006; Urponen et al., 1988) with some additions including listening to audiobooks and podcasts. Participants were asked to indicate how often they used those methods along a five-point scale (Never – Sometimes, but rarely – Occasionally – Quite often – Always). A follow up question asked participants for more detail on specific items that could be used continuously in the evening or throughout the night (e.g., listening to music) by indicating how they used this method (In the evening, before I go to bed – In bed, as I fall asleep – All night, as I sleep). The crossover of responses to these questions can be seen in Figure 1 below. Different methods were more popularly used at different times of the evening or night, with music noticeably more often used before going to bed. This changed depending on how often music was used, with more participants who listened to music "quite often" doing so in bed, as they fell asleep, but not those who said they "always" used music to help with their sleep. This highlights an important consideration for how we consider the use of music to help with sleep more generally that may at the very least give context to the discrepancies we see in surveys of the choices of music individuals listen to to go to sleep (e.g., Dickson & Schubert, 2020a; Trahan et al., 2018). There could be differences in the type of music that is most suitable for helping with sleep depending on when it is used in a night-time context.

Similarly, different subjective values may play a greater or lesser role, and this could bridge the gap between perceptions or preconceptions listeners may have and the real effectiveness at bedtime, such as we saw in our second and third studies (Chapters 3 and 4). The purpose of music perhaps changes to one that is more similar to relaxation when it is used earlier in the evening, and in this context personal preferences may be more important. Listening to music at bedtime, on the other hand, requires something more subjectively neutral where perhaps the specific musical properties play a greater role. Comments made by one participant during our third study support this suggestion (Chapter 4, p. 97). Either way of using music could be beneficial; other studies employing different protocols including listening to music in the evening before bedtime or even during the day have also shown positive effects on sleep (Kuula et al., 2020; Oxtoby et al., 2013; Shum et al., 2014).

Figure 1

Frequency and use of methods indicated as used for helping with sleep.



Reasons why, and the effects of distraction, habituation, and familiarity

Other work has delved into the reasons why people use music to help with their sleep. Trahan et al. (2018) found that their participants used music to help physically and mentally relax, and as a distraction. Dickson & Schubert (2020b) similarly found that the greatest influence for using music to help with sleep was for relaxation and distraction. Comments from our participants in the third study (Chapter 4) support these points, in particular mental relaxation; "The music was great. It smoothed my mind which was so tensed due to the personal reasons" (P04). One participant was very aware of physical as well as psychological effects while listening to the music; "It immediately made my eyes, arms, and torso feel really heavy, and concentrating on the music calmed my thoughts down a lot" (P08). Nevertheless, it is not the case that sleep music is equivalent to music for relaxation as shown in our first and second studies (Chapters 2 and 3), even though they do overlap. The purpose of using music for sleep may be related to relaxation, but the music most suited in this context and the degree of specific affordances are distinct.

Another reason for using music for sleep, as a distraction, seemed to have mixed connotations. One participant in our third study (Chapter 4) commented positively on getting used to the music and found that by the third night of one condition "... the music wasn't distracting at all, and it was the first time I fell asleep before the music finished" (P08). Other participants picked up on the lack of distraction as a positive; "The music itself is ignorable in a good way, you can listen to it without much attention" (P49). We discuss in Chapter 3 the different connotations distraction may have, and the difficulty of assessing listeners' attitudes towards it. Here we see what distraction means to different participants; for one listener, concentrating on the music provided a way to calm thoughts, and for others being able to ignore the music was seen as a positive. The concepts of attention or dissociation are clearly important; in Chapter 3, our listening study found that freeing the mind was a significant factor in predicting how sleep inducing a piece of music was perceived to be. We attempted to further clarify this concept by considering the notions of absorption and engagement, however neither factor proved informative in our results. Improving the way distraction and related notions are conceptualised in the context of music and sleep should be a goal for future research.

Several participants highlighted a habituation effect as familiarity with the music increased:

> The music was more relaxing and easier to fall asleep to now that I had already heard it the night before as it was less of a surprise. I was able to not focus on it quite as much which allowed me to fall asleep faster than the night before. (P35)

One participant appeared to foresee a negative effect of familiarisation; “I listened through all the songs which I can see becoming too familiar if I listened to them on a regular basis” (P45). This difference of opinion continues the theme we saw in Chapter 3, although the majority of responses we received in the study in Chapter 4 suggested a perceived positive longer-term impact. The extent to which habituation and familiarity has a real impact warrants further research to establish if indeed there is an improvement in sleep behaviours or other changes in the experiences of listeners over longer interventions, especially the interaction between familiarity and distraction.

More qualitative studies would offer a fruitful way of delving into these themes and further understanding the impacts of music on sleep. This might also include investigating the impact on next day moods or behaviours, also alluded to by some participants in our third study; “I've noticed my mind feels less fatigued in the morning” (P12). Day-time behaviours are important indicators of overall sleep health (Morin et al., 2006; Schutte-Rodin et al., 2008) and would be useful to consider in this context (Jespersen et al., 2022). The participants in our study were not current users of music for sleep, and their perspectives may be interesting to compare with those who do regularly use music to help with their sleep (e.g., Dickson & Schubert, 2020b; Trahan et al., 2018).

Understanding individual differences, and why music?

The scale of our studies was not sufficient to make strong judgments about specific individual differences that may have influenced our results. There may be key measurable factors that could shed light on our findings. Age has previously been found to correspond with differences in perceptions of relaxation (Lee-Harris et al., 2018). Musicality might also be a factor; Trahan et al. (2018) found that young people with higher musical engagement were more likely to use music to help with their sleep. More generally, personality has been associated with musical preferences (Liljeström et al., 2013; T. Schäfer & Mehlhorn, 2017) and musical preferences have been linked to cognitive predispositions (Greenberg et al., 2015). Considering the latter may offer some intriguing insights in the context of using music for sleep; different cognitive predispositions may correspond to different psychological requirements when it comes to music, let alone sleep, that may help to explain differences in the experiences reported in our studies. One example might be whether music is required to create a distraction and what qualifies as distracting enough for an individual. It may be possible to relate personal "sweet spots" to particular levels of certain musical features, or choices of music to particular goals and needs of a listener.

Listening to music is not the only method people use to help with their sleep at night. Reading is a similarly if not more popular activity for getting ready for sleep (Furihata et al., 2011; Huang et al., 2018; Morin et al., 2006). Other continuous auditory stimuli are also popular, such as listening to the radio, audiobooks, or white noise. A 2019 survey on podcast listening found that just over half of respondents listened to podcasts while relaxing before going to sleep (Beniamini, 2019). It is intriguing to consider what different stimuli can offer, and why some may be preferred over others for helping with sleep. Cognitively speaking, listening to the human voice requires different attentional demands compared with music (Akça et al., 2023) that may make audiobooks or podcasts for example more suitable for certain individuals.

Considering music against other methods may help reveal what or who it is that music is best suited for. Previous sleep studies that have compared music with other methods often use other relaxation techniques or physical exercises (e.g., Blanaru et al., 2012; Deshmukh et al., 2009; Kuula et al., 2020). Harmat et al. (2008) compared music with listening to audio books and found that audiobooks did not significantly improve sleep, unlike music. Away from sleep research, sounds of nature may promote relaxation (Alvarsson et al., 2010; Annerstedt et al., 2013; Jo et al., 2019). Other empirical evidence on the efficacy of audiobooks, podcasts, or other auditory stimuli that could be used as methods to help with sleep is, to our knowledge, limited. By understanding other methods and how music fits in we may learn more about who music is effective for and why.

Applicable usages

Despite the individual variability, music can indeed help people, and the crucial value of this research is that it may inform health applications. The application of music is studied in several other health settings such as Parkinsons and Dementia (Machado Sotomayor et al., 2021; Russo et al., 2023) and there is a clear research interest in the use of music for wellbeing applications (e.g., Janssen et al., 2012; Yu et al., 2018). Some existing approaches for developing music-based therapeutic applications use machine learning techniques to generate music to target emotional states (e.g., Williams et al., 2020), while other applications work with a user's existing music collection as a basis for selecting music to suit a desired emotional outcome (e.g., Coutinho et al., 2021). These approaches may have different advantages and disadvantages in the context of sleep; although we have not compared music provided by participants in our research, our evidence might suggest that basing a therapy purely on listeners' personal music tastes may not be the most effective. However, this is a further comparative route worth pursuing. Finding a balance between personal music tastes and research-led recommendations is likely to be beneficial. A generative music approach, on the other hand, might need to consider the potential for habituation effects that could either positively or negatively influence how it is received.

Generative or manipulative approaches might present other possibilities. The act of falling asleep is a dynamic process of changing cognitive states; a more dynamic approach to a musical sleep therapy may be a way of optimising its application, for example transitioning music from waking to sleeping states in a way similar to the ISO principle used in music therapy (Altshuler, 1954). This is a concept central to the sleep app developed by Sheffield based company, SleepCogni.[12] Other apps utilise a similar transitional paradigm, such as the POLYHYMNIA Mood app developed by Coutinho et al. (2021), where playlists are generated to guide a user from their current state to a desired mood, which they found can significantly reduce depression symptoms in users.

Sleep onset is also accompanied by changing physiological states that could be used as guiding signals for such applications. Biofeedback systems have been developed using music for relaxation and health purposes (e.g., Ho & Chen, 2011; Lorenzoni et al., 2019; Yu et al., 2018), and there is clear potential for similar approaches to be applied in sleep therapies. We also measured skin temperature in our third study; processing of this data fell outside of the scope of this thesis and is planned for future research. We intend to assess if there are meaningful changes in skin temperature between the two music and the silence conditions. This may indicate the potential for using skin temperature as a signal to guide a musical stimulus, similar to other work using for example skin conductance as a marker of arousal to guide a musical closed-loop biofeedback system (Williams et al., 2020).

Practicalities of studying music for sleep

We have employed a mixed methodology in this thesis to study music for sleep from different perspectives, including an analysis of a large public dataset (Chapter 2), a listening study carried out in an online survey (Chapter 3), and an extended in situ sleep study (Chapter 4). With each feeding into the next we have demonstrated a step-by-step systematic approach to investigating this complex topic. By utilising the tools and data provided by Spotify, we were able to reveal prevailing trends in music playlists containing thousands of tracks and sample stimuli for use in the ensuing research. The online survey allowed us to gain listener perspectives on an array of musical stimuli with a broad reach and take a first

[12] https://www.sleepcogni.com

look at combining subjective perspectives with objective assessments. Finally, the night-time study allowed us to validate and develop our previous findings in an ecologically valid setting. Because an extended sleep study requires considerable time and commitment from participants, it was essential to carry out as much groundwork as possible to focus the research aims and methods, just as it was important to put the findings from our earlier studies to the test at night-time.

As we have indicated, additional approaches would help to further elaborate the findings, such as more qualitative study and the inclusion of objective measures of sleep behaviours (Chapter 4). The literature on music and sleep includes a mix of lab and at home studies, each affording different possibilities. Lab studies allow for more control of experimental conditions and the inclusion of equipment for measuring sleep activity, such as polysomnography (e.g., Cordi et al., 2019; Iwaki et al., 2003; Lazic & Ogilvie, 2007). However, these require additional resources and access to facilities and such studies are often considerably shorter with few if any trial repetitions. At-home studies on the other hand lose certain controls and limit the use of additional measures but can be less resource-intensive and tend to be much longer; some previous studies lasted several weeks (e.g., Blanaru et al., 2012; Picard et al., 2014; Shum et al., 2014). Longer studies are beneficial not least for establishing reliable results but also for exploring potential interrelated factors such as familiarity and distraction, as discussed above. More importantly, at home studies allow participants to sleep in their own bed in an environment they are most comfortable with. As technologies improve, future research will benefit from advances in wearable devices that can reliably track sleep behaviours (Hof Zum Berge et al., 2020; Svensson et al., 2019) bringing the benefits of lab and at-home studies closer together.

Novelty

Recent work has delved into the musical properties of sleep music (Dickson & Schubert, 2020a; Scarratt et al., 2023). Work on listeners' perspectives has otherwise focused primarily on the reasons people use music to help with sleep (Dickson & Schubert, 2020b; Trahan et al., 2018). We have adopted a more perceptual approach for the first time, and compared sleep outcomes between different types of music, as well as comparisons against silence. Most studies only compare music against a silent control or an alternative method, such as breathing exercises (e.g., Kuula et al., 2020), muscle relaxation techniques (e.g., Blanaru et al., 2012), or audiobooks (e.g., Harmat et al., 2008). Lee et al. (2019) compared music by certain features but focused on pop songs. By comparing different musical playlists both of which were constructed on a systematic basis and predicted to be optimal for helping with sleep, we were able to demonstrate the complexities in this topic, to the extent that we found significant differences in sleep outcomes depending on the music conditions with only one associated with a significant improvement in sleep outcomes compared to silence. We hope that future studies will take care to reflect on the nuances that can have important impact on how music is effective for sleep.

Conclusion

Music offers a potentially valuable alternative therapy for helping with sleep problems. The research presented in this thesis has revealed nuances and complexities in the use of music for sleep and pointed towards particular aspects for consideration for future research. First and foremost, we have shown that music for sleep is recognised as a separate category and that this can be effective in improving sleep. What music works best for an individual may correspond to different factors. We found that brightness is an important musical feature seldom discussed in previous studies. Subjectively the notion of comfort is important in music that is perceived to be sleep inducing. Familiarity and attention or dissociation are also key, but the implications differ between individuals. When tested in situ, neither objective musical features nor subjective appraisals outright determine what music works best for an individual, and listeners may be naive to the effects music will have on their sleep.

There are further potentially influential factors worth exploring. For music to work as an intervention, consideration of individual factors, such as age, musicality, and cognitive predispositions, could shed further light on the differences in experiences that could determine what types or choices of music may best help an individual. By using multiple methodological approaches, combining subjective and objective evaluations of music, in-situ testing and different sleep measures, we can systematically probe into the facets that influence how and why music can help with sleep.

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APPENDICES

Appendix A - Playlists in Spotify study, Chapter 2

Playlist	Creator	ID	Likes	Tracks
Energising				
Energising 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	Spotify	37i9dQZF1DX5EY8JFBuaLS	41,459	122
Energizing Music	chaj1	7yKgnCJZQDlqOLFSr2HC56	1,510	231
Energiser	nutatiahh	2BIu9x9P6wXjrtsQtGepfg	197	69
Pura Energía	Spotify	37i9dQZF1DWYp5sAHdz27Y	249,228	100
Energia positiva	salamander_05	1xyGdY1GuPHaQyvikZglmB	3,994	298
Alta Vibración 432 Hz & Energía Positiva	Jordi Sanz	1Upphcq8Euc3IpsIhuCnkw	24,877	126
Energia 97FM 2021	hotvibesnetwork	4ttPvH5KXUbAKpR6ucYD6R	1,638	113
Dance Hits	Spotify	37i9dQZF1DX0BcQWzuB7ZO	3,362,538	100
DANCE 2021 Party Summer Electro Pop Só Tracks Hits Beach Tropical House Electrônicas Dua Lipa	Victor Oliveira	0tLyGnQZ5T8wlu0tydvQU3	60,005	131
Dance Anthems 2021	Double J Music	0qiyp96nNBGdRLApUAmMtG	32,563	112
Dancehall 2021 [new]	DJ Fabi Benz	1AKuDAKQOUSbQ8KKJkrlMi	36,150	200
Massive Dance Classics	Spotify	37i9dQZF1DWYtg7TV07mgz	1,009,545	50

Dance Party! Best Dance Hits	Lost Records	5oKz4DsTP8zbL97UIPbqp4	171,329	435
Dance Workout	Filtr UK	7wBpRbIoatquCDVcxybHEk	397,867	74
Dance Pop	Spotify	37i9dQZF1DWZQaaqNMbbXa	228,814	150
Dance Nation | Ministry of Sound	Ministry of Sound	7FUhHHA0zXAPVsJdDrNxNs	259,416	60
DANCE MUSIC 2021 Best Dance 2021 & EDM Hits 2021	Filtr Éxitos	6g40a9GjWBkX8ewR0vF9C2	242,718	198
Workout Music 2021, Gym Music, Treino, Cardio Music, Training Music, Fitness Motivation, Bass Music	BLACK DOT	190wZ2oVo7MTrBvNlPiub2	570,992	100
Workout	Spotify	37i9dQZF1DX70RN3TfWWJh	4,497,825	100
Adrenaline Workout	Spotify	37i9dQZF1DXe6bgV3TmZOL	1,309,302	120
The Rock Workout	Spotify	37i9dQZF1DX6hvx9KDaW4s	458,038	50
Workout Beats	Spotify	37i9dQZF1DWUSyphfcc6aL	1,004,616	70
Workout Motivation 2021	Slagelhag Workout	2237sMNMlXS4wWLgdQ1UuV	578,369	275
Workout Playlist 2021	metr	7AiuMp1D8Hli18nyTbriZ9	253,131	91
Workout Bhangra	Spotify	37i9dQZF1DX8To1hlfhp7U	16,529	74
Workout Beats 2021	Selected	4XIEV4NaByrujFUjFoG32v	183,777	98
80s Workout	Spotify	37i9dQZF1DWZY6U3N4Hq7n	273,024	80
Relaxing				
Relax & Unwind	Spotify	37i9dQZF1DWU0ScTcjJBdj	3,669,078	114
Relaxing Massage	Spotify	37i9dQZF1DXebxttQCq0zA	537,966	206
Relaxing Music 2020	Lofi Infini	0Ie5X3JS6BrLSWKrRm310H	47,509	85

Ambient Relaxation	Spotify	37i9dQZF1DX3Ogo9pFvBkY	1,113,286	298
Pop Relax	Spotify	37i9dQZF1DX3SQwW1JbaFt	137,327	60
Relaxing Classical	Filtr UK	1ZJpJahEFst7u8njXeGFyv	322,721	80
Relaxing Piano	Double J Music	0OOZzfr4olaGarfeaydGZf	75,646	400
Relaxing Piano : soft & calming piano music for relaxation	Dream Relaxation	2ODMZHnO9zcajVJ54Rlhz7	503,440	157
lofi hip hop music - beats to relax/study to	ChilledCow	0vvXsWCC9xrXsKd4FyS8kM	5,818,585	300
Jazz Relax	Spotify	37i9dQZF1DXbOVU4mpMJjh	696,372	50
Relaxing Guitar Music	Florecilla Records	6wFWKXnsBFQxWQjSug7ory	12,531	392
Relaxing Jazz Background Music	jazz_jazz_jazz75	71tQFRd9OWYWWSQdxLQccn	19,221	818
Hanging Out and Relaxing	Spotify	37i9dQZF1DXci7j0DJQgGp	1,789,929	145
Relax in the Bath	Matt Johnson	5sMfgeII8qGOwcgxfqqDaM	26,056	130
Relaxing Songs	lyssastreiner	4D3hxAbOjVu5jaC5Bnlmky	72,516	100
Soothing Relaxation	Soothing Relaxation	4AyG5SW1hu3toT9kd9PSXR	94,253	135
Relaxing Reading	Spotify	37i9dQZF1DX3DZBe6wPMXo	90,184	50
Relaxing acoustic	samkeane-gb	4rdl06oulIdgDNjJts2rmp	1,908	99
Relaxing Pop	Mindy Moss Shaffer	3LNyeJ7KMVZvNp9zClWCW3	9,512	171
Relaxing Spanish Guitar	Spotify	37i9dQZF1DX6BbeVFYBeZs	67,534	84
Relaxing Spa Music - Perfect Bliss, Water Sounds Massage	zenmeditationplanet	0pUKEVfbKICpYx35RozAk7	3,826	200
Deep House Relax	Spotify	37i9dQZF1DX2TRYkJECvfC	2,271,019	200
Relaxing Playlist	Pie	0B1cW8x7Mopg6Du5BJ4spM	2,066	134
Piano Relaxation	Piano Relaxation	04Bx6c3eZmYdWZRkQrLB7l	73,787	153

Bach Relax	Spotify	37i9dQZF1DWU1JctQodQRj	49,978	73
Relaxing & Chill House 2021 The Good Life Radio	Sensual Musique	75XrS5HXOmVYMgdXlaQTwO	181,269	323
Relax Tayo	Spotify	37i9dQZF1DWU96w4Gh7vJe	490,976	50
Meditação e Relaxamento	Spotify	37i9dQZF1DXaKgOqDv3HpW	715,406	119
Mindfulness - Focus/Relax	1165 Recordings	2ozb9cgwMcl2SDWK4SLRp8	78,561	346
Relaxing Music	Pryve	1r4hnyOWexSvylLokn2hUa	96,662	228
Sleep				
Sleep	Spotify	37i9dQZF1DWZd79rJ6a7lp	4,272,769	163
Deep Sleep	Spotify	37i9dQZF1DWYcDQ1hSjOpY	1,421,084	214
Sleep Piano Music	Pryve	7xhcF9ddiyF8Skbd1tenro	109,579	347
Baby Sleep	Spotify	37i9dQZF1DX0DxcHtn4Hwo	499,645	292
Songs For Sleeping	Spotify	37i9dQZF1DWStLt4f1zJ6I	466,696	99
Sleep, Baby Sleep	Spotify	37i9dQZF1DXdJ5OFSzWeCS	171,083	336
Sleepy Piano	Spotify	37i9dQZF1DX03b46zi3S82	227,909	187
Jazz for Sleep	Spotify	37i9dQZF1DXa1rZf8gLhyz	899,517	105
Sleep Piano	Ron Adelaar	1Ty8JKNLTI5C7DKE65jvb9	82,802	355
LoFi Sleep	James Gilsdorf	3DP5Khm13rl3I9mQkgX6fx	11,250	375
Sleep Tight	Spotify	37i9dQZF1DWSUFOo47GEsI	570,733	190
Classical Sleep	Spotify	37i9dQZF1DX8Sz1gsYZdwj	397,436	54
Sleep Sounds	Filtr	6k6C04ObdWs3RjsabtRUQa	124,240	1,159
Sleep Lullabies	gkyla	30oR4iBzmouadY8aawVODx	1,988	187
Sleep: Into the Ocean	Spotify	37i9dQZF1DXabJG3i5q2yk	1,445	59
Soothing Strings For Sleeping Babies	Spotify	37i9dQZF1DX2C8CFEPyYmg	111,828	205
Lo-Fi Beats	Spotify	37i9dQZF1DWWQRwui0ExPn	4,263,935	650

SLEEPY TIME	macyleeeeedavis22	68JXTKfqFZEWO1DQRdVndh	82,874	192
Sleeping Songs	megan21	5OajoGDWc6pK101SCqH1R7	52,014	180
Sleepy Music	Sleepy Times	1u9NkEi4uwvlKu1Nlhx5T7	6,955	348
Baby Sleep Aid: White Noise	Spotify	37i9dQZF1DXby8tlLbzqaH	205,908	168
Lullabies for Sleep	Double J Music	25wThb57sSId0kPwhgSgaO	64,078	144
Lofi Fruits Music lofi hip hop music to chill, relax, study, sleep to - lofi beats, chillhop	Strange Fruits	3LFIBdP7eZXJKqf3guepZ1	7,392,030	347
Relaxing Rain Sleep Sounds	Filtr Sweden	7f24KaDrATReBg45esAgX8	11,348	1,027
Sleep Noise	Spotify	37i9dQZF1DWSW4ppn40bal	48,645	134
432 Hz Sleep Music	Miracle Tones	4wavvfiVFxWmGgjkR5w0Fh	34,171	260
Calming Sleep Music	gery07	6X7wz4cCUBR6p68mzM7mZ4	37,851	458
Sleeping Music	TheGoodVibe	7mVeHiaEmixl8tKak7UwQT	57,945	109
Sleep Music	LoudKult	21wbvqMl5HNxhfi2cNqsdZ	213,568	301
lofi sleep, lofi rain	colours in the dark	35xI4hSJ8MdO1xkXwsd56a	189,033	100

NB: This information was gathered after submission at the reviewing stage. Playlists titles, creator names, and content are liable to change.

Appendix B - Music for listening study, Chapter 3

1. Music Selection

1.1. 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. In the table below, 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.

1.2. 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

2. 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

Appendix C - Music selection PCA for night study, Chapter 4

PCA was run on a dataset of 11 features describing 5,637 tracks extracted from Spotify. The features were Acousticness, Danceability, Duration, Energy, Instrumentalness, Liveness, Loudness, Speechiness, Tempo, and Valence from Spotify's Audio Features tool and Brightness extracted from the Audio Analysis tool on Spotify's API (for more details, see). Suitability of PCA was first assessed. Inspection of a correlation matrix revealed Duration, Liveness, Speechiness, and Tempo had no coefficients greater than .3, therefore PCA was run omitting these variables. The overall Kaiser-Meyer-Olkin (KMO) measure was .752 with individual KMO measures > .7 except Valence (.689), 'middling' according to Kaiser (1974). Bartlett's test of sphericity was significant ($p < .001$) indicating that the data was likely factorisable. PCA revealed two components explaining 51.9% and 15.2% of the variance, respectively. The Varimax rotated solution did not reveal a simple structure, with three variables loading on two components.

Feature	Component 1 (51.9%)	Component 2 (15.2%)
Acousticness	-.788	
Energy	.767	.411
Brightness	.732	.396
Instrumentalness	-.661	
Loudness	.583	.563
Danceability		.857
Valence		.810

Extraction Method: Principal Component Analysis

Rotation Method: Varimax with Kaiser Normalisation.