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Patients choose music with high energy, danceability, and lyrics in analgesic music listening interventions

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Abstract

Self-selected music is the best predictor of a successful outcome in music interventions, but the reasons behind this are unclear. One suggestion is that patients choose different types of music compared to experimenters. To explore this suggestion, the current study identified specific pieces of music that were used in previous studies for pain management using a scoping review, and analyzed each track in terms of the Spotify audio features of energy, danceability, instrumentalness, valence, and tempo. Music was categorized depending on whether it was chosen by the patient from an unlimited choice (PUC), a limited choice (LC), or chosen by the experimenter (EC), so that comparisons could be made between groups. One-way analyses of variance (ANOVAs) identified that PUC music was significantly higher in energy and danceability, and lower in instrumentalness, compared to LC or EC music. A logit ordinal regression demonstrated that as people are given more freedom to choose music to reduce their pain, they increasingly choose music that is higher in energy and danceability, and more likely to contain lyrics. This study also demonstrates the impact of allowing patients to choose music from an unlimited range compared to choosing from a limited range of music.

Keywords

music therapy, music features, pain, choice, music listening

Listening to pre-recorded music is being widely introduced as an analgesic treatment in a range of clinical pain management settings (Robb et al., 2018), including cancer pain, procedural pain, labor pain, and even surgical recovery (Lee, 2016). In 2008, a systematic review of 42 studies indicated positive outcomes in 59% of music intervention studies for pain (Nilsson, 2008). Since 2008, subsequent systematic reviews based on 97 studies (Lee, 2016) and

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14 studies (Garza-Villarreal, Pando, Vuust, & Parsons, 2017) were able to identify an even greater impact of music interventions and conclude that there is a statistically significant small to moderate effect of music interventions for pain management. Music listening can effectively reduce both opioid and non-opioid analgesic requirements (Lee, 2016) and reduce subjective measures of perceived pain, and pain unpleasantness (Garza-Villarreal et al., 2017). In addition, some evidence indicates that music listening in clinical contexts also lowers heart rate, systolic blood pressure, and respiration (Lee, 2016), and may decrease cortisol levels indicating a reduction in the biological stress response (Finn & Fancourt, 2018). However, despite these encouraging effects, it is important to note that there is a great degree of inconsistency in music intervention studies in terms of how they are delivered and subsequently the degree to which they are effective (Bradt, Dileo, Grocke, & Magill, 2016; Lunde, Vuust, Garza-Villarreal, & Vase, 2019). For example, Clark et al., (2006) asked patients to listen to a personalized tape whenever they felt like it, which ultimately led to some patients not listening to the music, making evaluation impossible. Accordingly, several authors have identified the need for a greater understanding of the patient–music interaction that mediates analgesic benefits in music listening interventions (Fancourt, Ockelford, & Belai, 2014; Keenan & Keithley, 2015; Krishnaswamy & Nair, 2016; Lee, 2016). Unlike music therapy, music listening interventions do not involve discussing or creating music or rely on a patient–therapist interaction (Bradt, 2012; Robb et al., 2018). Instead music listening interventions rely on direct engagement with the musical pieces and can involve listening to pre-recorded or live music, and may be delivered by the bedside or in more public hospital spaces (Bradt, 2012; Finn & Fancourt, 2018).

Many music listening interventions use non-lyrical, instrumental, low tempo music with about 60–80 bpm (beats per minute) (Björkman, Karlsson, Lundberg, & Frisman, 2013; Ovayolu et al., 2006; Soo et al., 2016), as this type of music was found to be beneficial in aiding after elective surgery (Nilsson, 2008). This recommendation is in line with models of entrainment, based on the idea that a slow musical tempo would lead to slower respiration and subsequent relaxation coupled with a reduction in perceived pain (Allred, Byers, & Sole, 2010; Labbé & Grandjean, 2014). However, when this model has been explicitly examined using pain ratings, randomized controlled trials demonstrate that the relationship is not so simple (Allred et al., 2010; Hsieh et al., 2014). Individual responses to music are idiosyncratic, and people do not experience a universal response to a given piece of music. This means that different people can respond very differently both physiologically and psychologically to the same piece of music. For example, music with a fast tempo can sometimes lead to an increase in heart rate, but other time people actually demonstrate a reduction in heart rate in response to high tempo music (Thaut, 2016), which undermines the entrainment hypothesis (Allred et al., 2010; Labbé & Grandjean, 2014). In addition, while some people may find low tempo music relaxing, other people associate low tempo music with sadness, boredom, longing, or disgust (Gabrielsson & Lindström, 2010). At the same time, it has also been shown that high tempo music is more likely to be perceived as more positive in terms of emotion (Gabrielsson & Lindström, 2010), which may be beneficial in facilitating positive effects in some music interventions (Mitchell & MacDonald, 2012). Qualitative studies have previously identified that patients find music beneficial in chronic pain contexts because it *energizes* them (Gold & Clare, 2013). Similarly, in a lab study using heat stimuli, participants reported that they chose music that was upbeat and energizing, because they thought it would be more distracting (Hsieh et al., 2014).

Rather than focusing on musical features in isolation, the person's own choice of music is considered fundamental to the success of a music intervention (Horden, 2016; Hsieh et al., 2014; Mitchell & MacDonald, 2012). In fact, several meta-analyses demonstrate that patients' own choice in music, is the best predictor of a successful music intervention, regardless of who

Table 1. Descriptions of Spotify audio features.

Energy	Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. For example, death metal has high energy, while a Bach prelude scores low on the scale. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy.
Instrumentalness	Predicts whether a track contains no vocals. "Ooh" and "aah" sounds are treated as instrumental in this context. Rap or spoken word tracks are clearly "vocal." The closer the instrumentalness value is to 1.0, the greater likelihood the track contains no vocal content. Values above 0.5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.0.
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.
Valence	A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g., happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g., sad, depressed, angry).
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 derives directly from the average beat duration.

For additional information on audio features, including typical distribution profiles, see the Spotify for Developers documentation (Spotify, 2019).

delivers the intervention (Garza-Villarreal et al., 2017; Lee, 2016; Tsai et al., 2014). The reason for the enhanced effectiveness of self-selected music is still unclear, yet different pieces of music become functionally equivalent, in their ability to reduce the experience of pain (Swaminathan & Schellenberg, 2015). Questions arise whether it is the act of making a choice, or whether people choose music with different features, compared to music chosen by experimenters, that ultimately enhances effectiveness. The act of making a choice has been related to enhancing the individual's locus of control within the health care environment, which is related to increases in well-being (Hsieh et al., 2014; Linnemann et al., 2015). Another potential mechanism is the enhanced emotional response that people have to self-chosen music (Lunde et al., 2019), leading to greater enjoyment responses (Howlin & Rooney, in press). When patients are asked, they emphasize the energizing and motivating effect of music (Gold & Clare, 2012; Hsieh et al., 2014), particularly in the context of chronic pain (Gold & Clare, 2012). This corresponds with the "Cognitive Vitality Model" of music interventions for pain management, which emphasizes that the benefits of music listening is derived through enhanced motivation and cognitive vitalization (Howlin & Rooney, in press). Another apparent discrepancy in the literature is that while instrumental music is advocated in many music listening studies (Björkman et al., 2013; Ovayolu et al., 2006; Soo et al., 2016), patients declare that they often find song lyrics useful in mediating analgesic benefits (Garza-Villarreal et al., 2015; Mitchell, MacDonald, & Knussen, 2008; Mitchell, MacDonald, Knussen, & Serpell, 2007).

To date there has been no comparison of the musical features within music chosen by patients compared to music chosen by experimenters. This is partly due to poor reporting standards in music intervention studies, with only 15% of studies giving details of the specific music used, which has usually been limited to the reporting of tempo (Robb et al., 2018). But it is now possible to examine additional musical features on a large scale by extracting quantitative audio features based on Spotify Developer analyses (see Table 1), which are being increasingly adopted in academic research (Park, Thom, Mennicken, Cramer, & Macy, 2019). Spotify audio features use a combination of lower level features to give a more complete picture about the overall gestalt of the music. In order to quantify the difference between participant-chosen music and experimenter-chosen music, this study aims to characterize the audio features found in patient-selected music and compare them to the audio features found in experimenter-chosen music. Specifically, this study will examine the levels of energy, instrumentalness, valence, and tempo (see Table 1) since these features have been emphasized in the literature as core components of music interventions (Allred et al., 2010). If people are choosing music that facilitates motivational and cognitive vitalizing processes more readily, it seems plausible that patients may in fact be choosing music that is higher in energy. Similarly, it seems useful to examine patterns of danceability, since it is based on rhythmic patterns which have previously been considered as the bridge between music listening and pain reduction (Spintge, 1996).

The aim of this study was to focus on the decision making of patients and experimenters in music interventions, and characterize the different types of music that arise as a result of these choices. The primary research question is to explore the degree to which audio features in music chosen for pain relief can be predicted by the person choosing the music, and will be addressed in two parts;

RQ1a: What type of music do patients choose for pain management?

RQ1b: Are there any differences in the pattern of audio features, between self-chosen music from an unlimited range, compared to self-chosen music from a limited range or music chosen by an experimenter?

By addressing this, we can identify patterns of music chosen by patients, and gain greater insights into the differences between experimenter-chosen music and patient-chosen music.

Method

Study design and methodology

This study was conducted in two stages. Stage 1 consisted of a systematic literature review that was conducted to identify pieces of music that were previously used in pain management settings. Stage 2 involved classifying how the music was chosen, and analyzing each corpus of songs in terms of the Spotify audio features, *energy, danceability, instrumentalness, tempo*, and *valence*. Finally, statistical analyses were conducted to examine whether there were any differences in audio features, depending on how the music was chosen.

Stage 1: Track identification

This study was based on a previous scoping review conducted by the same authors (Howlin & Rooney, in press), using an amended version of the original protocol (Howlin, Guerin, & Rooney, 2017). The search strategy used three core terms, music, listening, and pain, along with their variations and MESH terms. Each search was limited to include peer-reviewed articles, published in English as this was the only language of the research team. The search was limited to include articles published before 15 June 2017; however, no start date was used to increase the number of articles included in the review. The search string and limiters were then used in four

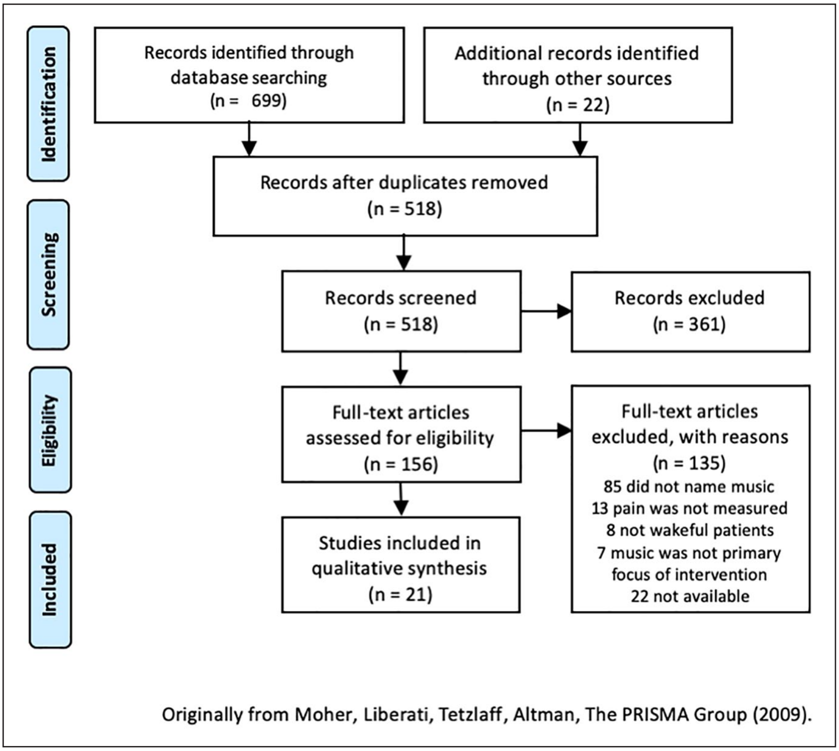

Figure 1. PRISMA flow chart of inclusion process.

databases: EBSCO Music Index and RILM, and EBSCOhost Psychology and Behavioral Sciences Collection, CINAHL Plus (EBSCO), and PubMed (Medline). Additional hand searching of the Cochrane database was also conducted in order to identify additional articles that meet the inclusion and exclusion criteria.

Study selection. A total of 721 studies were retrieved across the four databases, with 519 articles remaining after duplicate analysis (see Figure 1 for PRISMA flow chart). Two independent reviewers completed title and abstract screening, and included 154 articles for full-text review. Each article was then reviewed in full by at least one author to deduce the quality of the article and its suitability for inclusion based on the inclusion and exclusion criteria (see Table 2). A minimal quality appraisal was conducted to ensure that all studies included met the appraisal criteria of the five "fatal flaws" (see Table 2; Dixon-Woods et al., 2007). The overall outcome of each study was not taken into account when selecting the study for inclusion. Twenty-one studies were included in the final quantitative analysis.

Data extraction. Each article was checked to see if the specific music used in the music listening intervention was identified in the methods section or if a tracklist was included as a Supplemental material. A customized data extraction form was used to extract the titles of specific songs mentioned in each article.

Table 2. Full-text review, inclusion, exclusion, and quality appraisal criteria.

Inclusion criteria

Research studies were deemed suitable for inclusion if they met all of the following criteria:

1. The study evaluated pain experience of wakeful patients in the presence of music listening
2. The study was applied in a health care or laboratory setting
3. The study used receptive music listening where the person actively or passively listened to live or recorded music, as the primary intervention. This could be in conjunction with other activities, i.e., visualization or dance performance, but this is the minimum requirement for a Music Listening Intervention (MLI)
4. The study measured pain by self-report or pharmacological analgesic requirements
5. The study was empirical studies with primary data collection, including randomized, quasi-randomized, one armed trials, or qualitative accounts of MLIs
6. The study named the specific piece of music used in the intervention

Exclusion criteria

Research studies were excluded if they met one or more of the following criteria:

7. The study only focused on the process of making music
8. The study only focused on pain or injuries caused by performing music
9. The study primarily examined issues of hearing loss, hearing disorders, or other issues of aural health
10. The study focused on the use of music as part of a patient information material

"Fatal flaws" quality appraisal criteria

1. Are the aims and objectives of the research clearly stated?
2. Is the research design clearly specified and appropriate for the aims and objectives of the research?
3. Do the researchers display enough data to support their interpretations and conclusions?
4. Do the researchers provide a clear account of the process by which their findings were produced?
5. Is the method of analysis appropriate and adequately explicated?

Stage 2: track audio feature characterization

Classification. Each song was manually coded by a reviewer blind to the overall hypothesis, and subsequently classified in terms of how the music was chosen. This resulted in three choice categories: *Experimenter's Choice* (EC), where the experimenter chose the music without consideration of the patient's preferences; *Limited Choice* (LC), where patients picked music from a limited selection or the music was picked by the experimenter after checking the patients' general preferences; and *Patient Unlimited Choice* (PUC), where patients picked music from an unlimited selection. These categories were considered to reflect three levels of increasing choice, with the EC reflecting the lowest level of choice from the perspective of the patient, and PUC reflecting the greatest level of choice. In some studies, participants could listen to several pieces of music, and in other studies, participants were limited to one piece of music; however, this did not impact the track classification.

Audio feature analysis. Spotify audio features of energy, instrumentalness, danceability, tempo, and valence were extracted from the Spotify website (see Table 1 for definitions), using the Application Program Interface values from the main Spotify website. The statistical software package SPSS 24 was used to compare the audio features of the music depending on how it was chosen, and to investigate the relative contributions of each feature using a logistic ordinal regression.

Results

Twenty-one studies specifically named the music used to reduce pain effects. In total, 288 pieces of music were identified that were previously used in receptive music listening sessions with an

Table 3. Frequencies and descriptive statistics.

	PUC	LC	EC	Total
Frequency				
Included studies	4	3	14	21
Participants	232	91	739	1,062
Songs	153	51	64	268
Audio feature	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	
Energy*	.67 (.22)	.36 (.22)	.20 (.20)	
Instrumentalness*	.08 (.21)	.28 (.40)	.64 (.33)	
Danceability*	.55 (.17)	.42 (.16)	.32 (.16)	
Valence*	.51 (.25)	.34 (.22)	.25 (.23)	
Tempo	113.78 (31.27)	116.74 (30.79)	107.72 (29.46)	

PUC = Patient Unlimited Choice, where patients picked music from an unlimited selection; LC = Limited Choice, where patients picked music from a limited selection, or experimenters selected the music on the patient's behalf; EC = Experimenter's Choice, where the experimenter chose the music without consideration of the patient's music preferences.
*Difference significant at the alpha .001 level tested using one-way analysis of variance.

aim to reduce the experience of pain, 19 of these pieces of music were not available on Spotify, leaving 268 pieces of music available for further analysis. Each of the 268 pieces of music were classified by one researcher in terms of whether they were PUC, LC, or EC (see Table 3). This enabled us to identify the pattern of audio features present in music for pain management when it is self-chosen from an unlimited selection, self-chosen from a limited selection, or chosen by the experimenter. The mean values for each audio feature are displayed in Table 3, and demonstrate that patients choose music with high levels of energy (.67), moderate levels of danceability (.55) and valence (.51), and low levels of instrumentalness (.08).

In order to examine whether there was any difference in the patterns of audio features depending on how the music was chosen, one-way analyses of variance (ANOVAs) were used to compare the music selected by the PUC, LC, or EC (see Figure 2). Significant differences were found between the categories in the levels of energy, $F(2, 265) = 122.20$, $p < .001$, $\eta^2 = .480$; degree of instrumentalness, $F(2, 265) = 89.58$, $p < .001$, $\eta^2 = .403$; danceability, $F(2, 265) = 43.99$, $p < .001$, $\eta^2 = .249$; and valence, $F(2, 265) = 29.44$, $p < .001$, $\eta^2 = .182$; however, there was no difference between the three categories in the tempo of the music, $F(2, 265) = 1.62$, $p > .05$.

In order to understand the direction of these significant effects, post hoc tests were carried out which demonstrated that music energy was significantly higher in the LC category compared to the EC category ($p < .001$, 95% confidence interval [CI] [.071, .260]), and significantly higher in the PUC category compared to the LC category ($p < .001$, 95% CI [.225, .388]), with the greatest increase in music energy seen between PUC and EC ($p < .001$, 95% CI [.397, .547]). An opposite pattern was seen in relation to the degree of instrumentalness in the music. The degree of instrumentalness in the music was significantly lower in the LC category compared to the EC category ($p < .001$, 95% CI [–.530, –.198]), and also significantly lower in the PUC category compared to the LC category ($p = .003$, 95% CI [–.345, –.062]). Again, the greatest reduction in the degree of instrumentalness was seen between the EC category and the PUC category ($p < .001$, 95% CI [–.673, –.462]). Similar to the pattern seen with energy, levels of danceability were significantly higher in the LC category compared to the EC category ($p = .004$, 95% CI [.027, .176]), and significantly higher in the PUC category compared to the LC category

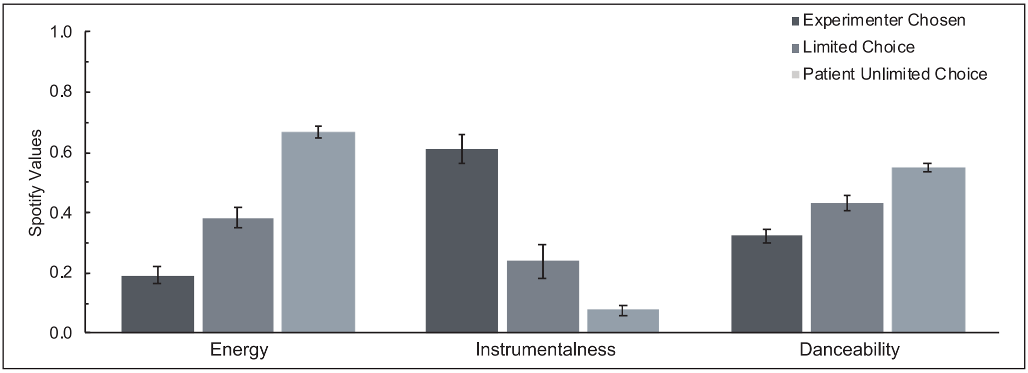

Figure 2. Displaying the mean Spotify audio feature values for energy, danceability, and instrumentalness, according to how the music was chosen. Error bars denote one standard error around the mean.

($p < .001$, 95% CI [.063, .192]), with the biggest increase in danceability seen in the PUC category compared to the EC category ($p < .001$, 95% CI [.169, .288]). Finally, in terms of valence, multiple comparisons demonstrated that music in the PUC category was significantly higher compared to music in the LC category ($p < .001$, 95% CI [.083, .266]) or the EC category; ($p < .001$, 95% CI [.174, .343]); however, no difference was found between the LC and EC categories ($p > .05$, 95% CI [–.023, .190]).

A logit ordinal regression was calculated to examine the likelihood that audio features are related to how the music was chosen. This allowed an estimation of the relative contribution of each audio feature in the characterization of patient-selected music. Evaluation of the regression model using the likelihood ratio test indicates that it is more effective than the null model, $\chi^2(5) = 189.91$, $p < .001$, with a Nagelkerke R^2 of .589. Examining the log of the odds estimates shown in Table 4 demonstrates that an increase in the level of music choice was positively related to music energy ($p < .001$) and music danceability ($p = .033$), but negatively related to music instrumentalness ($p < .001$). Valence and tempo did not significantly contribute to this model. Examining the odds ratios demonstrates that for a one unit increase in *energy*, the odds of the song being from a higher level of choice is 229.98, 95% CI [43.77, 1,208.34], Wald $\chi^2(1) = 41.26$, $p < .001$, times greater, given that the other variables in the model are held constant. Similarly, for every one unit increase in danceability, the odds of the song being from a higher level of choice is 9.91, 95% CI [1.20, 82.02], Wald $\chi^2(1) = 4.52$, $p = .036$, times greater, given that all the other variables in the model are held constant. For every one unit increase in instrumentalness, the odds of the song being from a lower level of choice is 0.15, 95% CI [0.07, 0.37], Wald $\chi^2(1) = 3.70$, $p < .001$, times greater, given that all the other variables in the model are held constant. In other words, the more choice people were given, the more likely they were to choose music with high energy and danceability, and less likely to be instrumental. In addition, the test of parallel lines, indicated that the assumption of proportional odds was met, $\chi^2(5) = 5.40$, $p < .05$, which indicates that the relationship between the predictors of energy, instrumentalness, and danceability holds consistently across the three levels of choice.

To summarize, the results demonstrate that as people are given more freedom to choose music to reduce their pain, they increasingly choose music that is significantly higher in energy and danceability, and lower in the degree of instrumentalness. Also, when we consider that instrumentalness is an index of the likelihood to contain lyrics, with values closer to one

Table 4. Ordinal regression results.

Predictor	Estimate	*SE*	Wald's χ^2	*df*	*p*	Exp(*B*)	95% CI for exp(*B*)	
							Lower	Upper
Energy	5.44	0.85	41.26	1	.000	229.98	43.77	1,208.34
Instrumentalness	−1.87	0.44	17.70	1	.000	0.15	0.07	0.370
Danceability	2.29	1.08	4.52	1	.036	9.91	1.20	82.02
Valence	−0.88	0.81	1.19	1	.338	0.42	0.09	2.01
Tempo	−0.01	0.01	3.71	1	.056	0.99	0.98	1.00
Test			χ^2	*df*	*p*			
Overall model test								
Likelihood ratio test			335.26	5	.000			
Goodness-of-fit test								
Pearson			571.56	529	.098			

Cox and Snell $R^2 = .506$. Nagelkerke $R^2 = .589$. In the column Exp(*B*), the results are presented as proportional odds ratios (the coefficient exponentiated). The lower and upper 95% CI have also been calculated, which can be interpreted as we would odds ratios from a binary logistic regression. The test of parallel lines, indicated that the assumption of proportional odds was met, $\chi^2(5) = 5.40$, $p = .369$, which indicates that the relationship between the predictors of energy, instrumentalness, and danceability holds consistently across the three levels of choice. CI: confidence interval.

indicative of no vocal content (see Table 1), we can see that music in the EC category, with a mean value of .64 ($SD = .33$) is more likely to have no vocal content compared to music in the PUC with a mean value of .08 ($SD = .21$). The logistic regression allowed us to evaluate the degree to which each factor contributed to an overall model characterizing the music chosen by participants. This demonstrated that music energy was the greatest contributor to the model, followed by danceability, and then instrumentalness, albeit to a much lower degree. It is important to note that the level of energy, danceability, and instrumentalness in the LC category and the PUC category were different from experimenters' choice in a linear way indicating that even when participants had an LC, the pattern of audio features departed from the music chosen by experimenters.

Discussion

The aim of this study was to focus on the decision making of patients and experimenters in music interventions, and characterize the different types of music that arise as a result of these choices. The results demonstrate that as people are given more choice, they are more likely to choose music with higher levels of energy and danceability, and less likely to choose instrumental music. It is important to note that the level of energy, danceability, and instrumentalness were different across conditions in a linear fashion, indicating that just having any choice matters, but that having more choice matters more. No difference was found in the overall tempo of the music chosen, with relatively high tempo music (~115 bpm) chosen overall, regardless of the method of selection. The role of valence is unclear from these results, with apparent differences between music chosen from an unlimited range compared to a limited range or no choice; however, these differences were not predictive in the regression model.

This is the first study to demonstrate that participants are more likely to choose high energy music with lyrics that is good to dance to, in pain management contexts. These findings are directly in contrast with studies that advocate music based on so-called *relaxation properties*, that is, low tempo, without lyrics, and without strong rhythms (Allred et al., 2010; Nilsson, 2008). This distinction is particularly important given that meta-analyses demonstrate that patient-chosen music is the best predictor of a successful music intervention compared to experimenter-chosen music (Garza-Villarreal et al., 2017; Tsai et al., 2014). By highlighting a clear trend in the type of music that is chosen by patients, we have identified a commonality across studies that was not previously identified. In addition, this study emphasizes the importance of allowing patients to choose from an unlimited range of music, rather than requiring them to choose from a limited range.

Identifying that patients choose music with higher levels of energy is directly consistent with *The Cognitive Vitality Model* of music listening interventions which emphasizes the motivational and energizing benefits of music listening in pain contexts (Howlin & Rooney, in press). High energy music can help motivate people with chronic pain (Gold & Clare, 2013), and participants reported that they choose upbeat and energizing music because they find it more distracting (Hsieh et al., 2014). The finding that patients are more likely to choose music with lyrics is also consistent with *The Cognitive Vitality Model*, which emphasizes the importance of lyrics as a means for listeners to immerse themselves in the musical content and meaning-making processes (Howlin & Rooney, in press). No specific pattern was observed in relation to music valence, across the three levels of choice. This is not entirely unexpected given that people can use music with different valences to produce the same overall effect in line with the concept of *functional equivalence* (Swaminathan & Schellenberg, 2015). Also this corresponds with previous findings that demonstrate that musical valence does not necessarily correspond to structural elements in a one-to-one fashion (Gabrielsson & Lindström, 2010), in this case, energy and danceability.

It is worth noting that although previous studies recommend using low tempo music (Nilsson, 2008), the music chosen by experimenters had a much wider range of tempos, exemplified by the large standard deviation. Similarly patient-chosen music also had a wide range of tempos, indicating that tempo is not a good descriptor for the music in each choice category. This recommendation is emphasized by several meta-analyses that find no link between music tempo and the effectiveness of music interventions (Garza-Villarreal et al., 2015; Lee, 2016). Music energy is a more complex way to characterize music compared to tempo, because it is a composite metric of basic music features such as dynamic range, perceived loudness, timbre, onset rate, and general entropy. Furthermore, music energy is not directly related to the valence or characteristic emotion of a song. This is evident when songs with a different valence receive similar energy ratings. For example, "Firestarter" by the Prodigy and "Smooth" by Santana were both songs chosen by the participants from an unlimited choice, and both songs had a high energy of over 0.9 on a range of 0 to 1.0. However, these songs are very different in terms of their valence, "Firestarter" has a negative valence, and "Smooth" has a positive valence, and this was also reflected in their Spotify audio features.

Findings from the current study raise the question of how Spotify quantitative audio features map onto perceived qualitative experiences of the music. The distinction between the audio features and the perception of the listener is comparable to how the frequency of a sound is both different and directly related to how a listener perceives pitch. Similarly, Spotify has labeled a specific combination of quantitative audio features as "danceability," but research is needed to explore how this maps onto a listener's perception of the music.

Similarities can be drawn between danceability and the perception of "groove." Danceability describes how suitable a track is for dancing, based on tempo, rhythm stability, beat strength, and overall regularity (see Table 1). Similarly, groove corresponds with an increased desire to move some part of the body (Madison, 2006), is more likely to occur at optimal tempos (Holbrook and Anand, 1990), depends on specific rhythmic patterns (Witek, Clarke, Wallentin, Kringelbach, & Vuust, 2014), and is induced by a repetitive rhythmical patterns that emerge at a comfortable rate (Madison, Gouyon, Ullén, & Hörnström, 2011). With evidence that perceived groove leads to increased excitability of the motor cortex (Stupacher, Hove, Novembre, Schütz-Bosbach, & Keller, 2013), is preferred by listeners (Fitch, 2016; Janata, Tomic, & Haberman, 2012), and highly correlated with enjoyment and pleasure responses (Labbé & Grandjean, 2014; Witek et al., 2014), research testing how quantitative audio features map onto to perceptions can make an important contribution to our understanding of the analgesic effects of music.

Another issue for consideration is that energy, instrumentalness, danceability, and valence have not been fully validated in terms of their construct validity, so it is unclear if these measures truly measure the audio features that they pertain to, or indeed overlap with musical constructs already in the music science literature. This would help to extend the use of these audio features to other research contexts, and in the development of music interventions for pain management on a daily basis. Nonetheless, it seems that there are clear differences in the patterns in the audio features found in music chosen by patients compared to music chosen by experimenters, and these patterns were consistent with what we might expect to see based on the literature. While this study provides a new insight into the type of music patients choose in music interventions for pain, it must be acknowledged that it is not clear whether these specific musical features are responsible for the overall outcomes found in previous studies (Lee, 2016).

Future clinical and lab studies are needed to determine the role of such choice and audio features in mediating analgesic benefits of music listening. Future meta-analyses could consider these audio features as potential moderators in music listening interventions and extract them accordingly, or prospectively control for patient choice. In addition, other combinations of music features such as time signature or modality could also be investigated in future research. Before this can become possible, it is important that music listening intervention studies publish the specific music chosen in each study (Robb et al., 2018), so that they can be evaluated fully. Nonetheless, these findings show that the more choice a patient is given, the more the features of the music move away from the experimenter-chosen music. Since several meta-analyses already demonstrate that patient-chosen music is the best predictor of a successful music listening intervention (Garza-Villarreal et al., 2017; Lee, 2016; Tsai et al., 2014), it seems that the type of music patients are choosing should also be considered in more detail. Moreover, this study emphasizes the importance of allowing patients to choose from an unlimited range of music, rather than restricting their choice from a limited range.

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