1   **Title:** Complexity matching: brain signals mirror environment information patterns during music

2   listening and reward

3   **Abbreviated title (50 character max)**: Brain-environment complexity matching

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20

21   Abstract

22   Understanding how the human brain integrates information from the environment with

23   ongoing, internal brain signals in order to produce individual perspective is an essential element

24   of understanding the human mind. Brain signal complexity, measured with multiscale entropy,

25   has been employed as a measure of information processing in the brain (Carpentier et al., 2016),

26   and we propose that it can also be used to measure the information available from a stimulus. We

27   can directly assess the correspondence, or functional isomorphism, between brain signal

28   complexity and stimulus complexity as an indication of how well the brain reflects the content of

29   the environment in an analysis that we termed *complexity matching*. Music makes an ideal

30   stimulus input because it is a multidimensional, complex signal, and because of its emotion and

31   reward-inducing potential. We found that electroencephalography (EEG) complexity was lower

32   and more closely resembled the musical complexity when participants performed a perceptual

33   task that required them to closely track the acoustics, compared to an emotional task that asked

34   them to think about how the music made them feel. Music-derived reward scores on the

35   Barcelona Music Reward Questionnaire (Mas-Herrero et al., 2013) correlated with worse

36   complexity matching and higher EEG complexity. Compared to perceptual-level processing,

37   emotional and reward responses are associated with additional internal information processes

38   above and beyond those in the external stimulus.

39   Significance Statement: Experience of our world is combination of the input from the

40   environment, our expectations, and individual responses. For example, the same piece of music

41   can elict happiness in one person and sadness in another. We researched this by measuring the

42   information in pieces of music and whether listener's brain more closely followed that, or

43   whether additional information was added by the brain. We noted when listener's were reacting

44   to how music made them feel, their brains added more information and the degree to which this

45   occurred related to how much they find music rewarding. Thus, we were able to provide clues as

46   to how the brain integrates incoming information, adding to it to provide a richer perceptual and

47   emotional experience.

48

49   Complexity matching: brain signals mirror environment information patterns during music

50   listening and reward

51

52   Some contemporary theories suggest that functional brain networks engage and

53   disengage to integrate information during cognitive processes (Tononi et al., 1994; McIntosh,

54   2000; Bressler and Kelso, 2001). This network activity generates highly variable and complex

55   brain signals; therefore, brain signal complexity can serve as an indicator of the information

56   processing of the system (Deco, Jirsa, & McIntosh, 2011; Ghosh et al., 2008; McIntosh,

57   Kovačević, & Itier, 2008). Accordingly, brain signal complexity is higher during states of greater

58   knowledge representation (e.g. Heisz, Shedden, & McIntosh, 2012), and increased following

59   longitudinal music training (Carpentier et al., 2016). The present study measured signal

60   complexity to investigate whether there is a correspondence between information patterns in

61   brain signals and those in the individual's environment. Furthermore, we were interested in

62   whether this correspondence would be related to the cognitive-affective state of the individual.

63   Music offers an ideal stimulus from which to measure information content. Complicated

64   music structures are created following application of combination rules to subordinate motifs.

65   This makes it possible to describe a functional isomorphism between the brain and environment

66   information by calculating music complexity and comparing it to the complexity of brain signals

67   of the listener. We propose that this measure of comparison between EEG complexity and music

68   complexity, or *complexity matching,* will provide a relative indication of the degree to which

69   environmental information structure is reflected in brain signal structure.

70   Complexity matching is calculated as Procrustes distance (Gower, 1975) between the

71   music and EEG multiscale entropy (MSE). MSE calculates sample entropy at multiple

72   timescales (Costa et al., 2002, 2005). Like brain signals, music also has structure at multiple

73   timescales, and MSE seems an appropriate measure of complexity for a given music passage.

74   Procrustes distance produces a quantity of similarity between the structure of the music and the

75   structure of the ensuing brain signals. A relatively high value of matching together with lower

76   EEG MSE would suggest that the brain has activated the necessary information processing

77   resources for immediate perception, and little else. Conversely, relatively lower complexity

78   matching but high neural complexity would suggest that internal processes, different from

79   immediate stimulus perception, dominate the neural response. This metric was inspired by the

80   ideas in Tononi et al. (Tononi et al., 1996)

81   The level of brain-environment information integration may be related to cognition and

82   subjective perspective. To examine the relationship between brain-environment matching and

83   cognitive-affective state, we calculated complexity matching while participants performed a

84   music perception task and a music emotion evocation task. We expect that active attention to the

85   acoustics of the music during the perceptual task will be accompanied by brain signal complexity

86   that more closely resembles the music, compared to the emotional task that involves additional

87   internally processes and, therefore, will provide less of a match to the environment.

88   We also analyzed the relationship between complexity matching and music-derived

89   reward scores from the Barcelona Music Reward Questionnaire (BMRQ). The ability to perceive

90   musical structure is essential to the enjoyment of music (Meyer, 1956; Huron, 2006): therefore, it

91   is possible that a certain minimum quantity of complexity matching may be required for the

92   listener to have the necessary appreciation of the underlying 'gist' or skeleton structure of the

93   piece. Perhaps without sufficient neural integration of music signals, the listener would be unable

94   to perceive separate noise sounds as unified. In accordance with our prediction that the emotional

95   task will be associated with a lower complexity match than the perceptual task, we expect that

96   higher music reward involves internally-driven, individual responses and therefore will correlate

97   with higher complexity and lower complexity matching.

98

99   **Materials and Methods**

100   *Participants*

101   Eighteen healthy young adults aged 19-35 (M = 26; 10 female) were recruited from the

102   Greater Toronto Area to take part in the study and provided written informed consent in

103   accordance with the joint Baycrest Centre-University of Toronto Research Ethics Committee.

104   Prior to arriving to the lab for the experimental session, participants completed an online

105   questionnaire about their music listening habits, and musical training was assessed as a 1-5 scale:

106   1) No formal training, cannot play an instrument; 2) Can play an instrument without formal

107   training; 3) Less than 1 year of formal music training; 4) Between 1-5 years of formal training;

108   and 5) More than 5 years of formal training.

109   ***Barcelona Music Reward Questionnaire***

110   Music reward is highly individual, and the BMRQ was developed to describe some of the

111   main facets of the variance in how people experience reward from music listening (Mas-Herrero

112   et al., 2013). Participants are asked to indicate the level of agreement with each of 20 statements

113   by using a 5-point scale ranging from (1) "fully disagree" to (5) "fully agree," with a higher

114   score indicating the subject experiences more music reward and a lower score indicating they do

115   not experience music associated rewarding feelings. These statements represent five major

116   factors of music reward: (1) Emotional Evocation; (2) Mood Regulation; (3) Musical Seeking;

117   (4) Social Reward; and (5) Sensory-Motor.

118   *Emotional Evocation* refers to the idea that music can both convey and induce emotion

119   (also referred to as emotional contagion), such as joy or sadness, and that listeners might seek out

120   music that contains emotion (Juslin and Laukka, 2004; Juslin and Västfjäll, 2008; Vuoskoski and

121   Eerola, 2012). The BMRQ distinguishes evoked feelings, which may be short-lived and vary

122   across a single music piece; from the way some listeners use music to alter their own longer

123   lasting mood or hedonic state after the song has finished (e.g. Carter, Wilson, Lawson, & Bulik,

124   1995; Västfjäll, 2001). *Mood Regulation* refers to the idea that music can be used to comfort,

125   relieve stress, or enhance relaxation (for a review see Juslin & Sloboda, 2010), and a particular

126   point has been raised about the use of music in marketing or film to manipulate and induce

127   hedonic states (Cohen, 2001). *Musical Seeking* can also be referred to as "knowing about music."

128   This facet describes that some listeners get reward from extracting, pursuing, sharing, and

129   seeking information regarding specific music pieces, composers, performers, or other

130   information related to music. Listeners may also experience pleasure when recognizing music

131   quotations or allusions to other works. *Social Reward* may be gained by music through its

132   enhancement of social bonds or social cohesion (Cross and Morley, 2009). Lastly, the *Sensory-*

133   *Motor* facet captures reward experienced by the pull music has over some people to move to

134   music.

Behaviour Tasks

136   Forty operatic and classical musical segments were selected after piloting for a range of

137   emotional reactions of the listener and of pitch and tempo. The pieces spanned a range with only

138   instruments to both instruments and voice. For this study, we wanted to ensure the range of

139   individual experience was as broad as possible to get reasonable ranges of arousal and valence

140   ratings and comparable volatility in the perceptual task. Segment lengths ranged between 0:40-

141   1:17 min. This choice was made to allow each segment to conclude naturally at the end of a

142   musical phrase, rather than ending abruptly in the middle. Thirty pieces were selected for the

143   emotional task and ten pieces for the perceptual task (Table 1). Importantly, there was no

144   difference in the music complexity (MSE) between the tasks ($p > 0.1$).

Table 1. *List of songs for each tasks*

Emotional Valence Songs

- Adams "Nixon in China, 'Beginning'"
- Adams "Disappointment Lake"
- Bach "No. 3 Aria 'Es Ist Vollbracht'"
- Barber "Adagio for Strings"
- Brahms "Intermezzo No. 2 in A Major, Op. 118"
- Delibes "Lakmé/Flower Duet"
- Elgar "Variation IX (Adagio) 'Nimrod'"
- Galvany "Oh My Son"
- Gluck "Armide Act Iv Air Sicilien"
- Goodall "Belief"
- Ives "Three Places in New England Orchestral Set No.1"
- Liszt "Totentanz"
- Monteverdi "Zefiro Torna"
- Mozart "Cosi fan tutte"
- Mozetich "The Passion of Angels"
- Penderecki "Threnody to the Victims of Hiroshima"
- Puccini "O soave fanciulla"
- Rameau "Entrée de Polymnie"
- Richter "Vivaldi's Summer"
- Rossini "Barbiere di Siviglia: Largo Al Factotum"
- Schroer "Field of Stars"
- Schumann-Liszt "Liebeslied (Widmung)"
- Staniland "Solstice Songs No. 2 Interlude"
- Stravinsky "Glorification of the Chosen One"
- Tarrega "Recuerdos De La Alhambra"
- Verdi "Messa Da Requiem: Dies Irae-Tuba Mirum Part 1"
- Verdi "Messa Da Requiem: Dies Irae-Tuba Mirum Part 2"

- Part "Spiegel im Spiegel"

- Wagner "Die Walkurie, Act 3: Ride of the Valkyries"
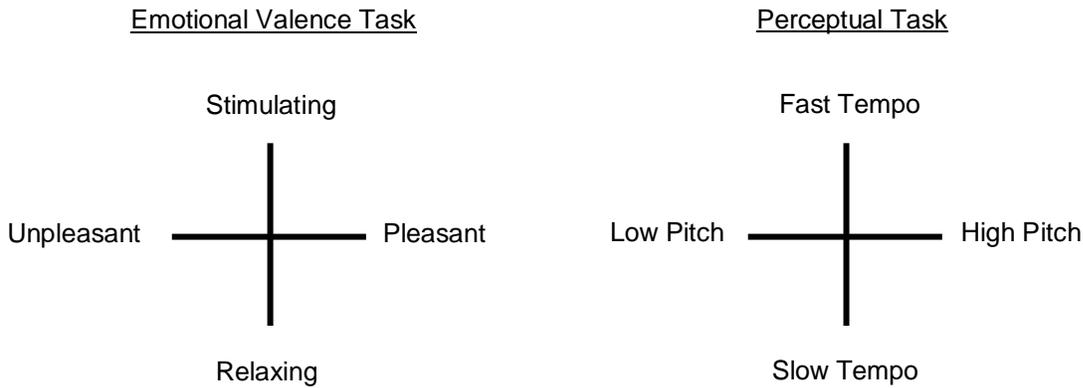- Wagner "Tristan Und Isolde/ Act 2 – Prelude"

Perceptual Songs

- Beethoven "Sonata in A Major Op. 69"
- Brahms "Violin Concerto in D, Op 77-3"
- Glass "Glassworks Opening"
- Haydn "Cello Concerto in D Major"
- Mozart "Symphony No. 40 in G-minor, K. 550, Finale"
- Praetorious "Praeambulum"

- Strauss – Der Rosenkavalier Act III/Duet-Denouement and Grand Waltz – Coda"
- Strauss "September"
- Vivaldi "Concerto for Violin, Stings and Harpsichord in G"
- Vivaldi "Stabat Mater"

145

146   During the emotional task, a computer screen in front of participants showed four

147   quadrants marked on two dimensions: Stimulating-Relaxing, and Pleasant-Unpleasant (Figure 1).

148   Participants were asked to move a mouse around the quadrant space in a continuous manner

149   during each song based on *how the music made them feel* on the two dimensions. Participants

150   were explicitly instructed to report of their own feelings during music listening, and not the

151   alternative of reporting on what emotions they believe are expressed in the music (emotional

152   conveyance). The task design was modeled after the *valence-arousal model* of Hunter &

153   Schellenberg, 2010. They labeled their dimensions high arousal-low arousal and positive

154   valence-negative valence, and we altered our labels after pilot tests to be more intuitive for

155   subjects. This valence-arousal model is designed to capture a wide range of emotions. In their

156   study, difference valence and arousal combinations were associated with multiple different

157   emotions. For example, high arousal/negative valence was correlated with distress, fear and

158   anger, low arousal/positive valence was associated with feelings of peace, contentment and

159   relaxation. Participants from our pilot sample gave similar reports. In this way, it is possible to

160   capture a larger range of emotions without limiting responses to more specific emotions.

161   The perceptual task mimicked the emotional task, with the difference being participants

162   were required to assess pitch and tempo for each song (Figure 1). Once again, a screen in front of

163   them displayed four quadrants with two dimensions (High-Low Pitch and Fast-Slow Tempo),

164   and participants moved a mouse in a continuous manner on the screen based on the pitch and

165   tempo of each song.

Emotional Valence Task   Perceptual Task

Stimulating   Fast Tempo

Unpleasant —— Pleasant   Low Pitch —— High Pitch

Relaxing   Slow Tempo

166

167   **Figure 1.** Participants viewed screens with each of the above quadrants during each task. They were asked to move
168   a mouse continuously around the quadrant space depending on how the music was making them feel in that moment
169   (emotional task) or based on their judgments of pitch and tempo (perceptual task).
170

Experimental Procedure

172   The experimental session began with five perceptual task songs, followed by all thirty

173   emotional songs, and concluded with the remaining five perceptual songs. Perceptual songs were

174   always presented in the same order. Emotional songs were presented in one of two

175   counterbalance orders. Pieces in the first order were curated to have a sense of flow between

176   them and avoid jarring transitions from one song to the next that may disrupt emotional

177   experiences. The second order was the reverse of the first. There was no significant effect of

178   counterbalance order on any of our measures. All stimuli were presented through ER 3A insert

179   earphones (Etymotic Research, Elk Grove, U.S.A.), while participants were seated in a

180   soundproof room.

181   *EEG Recording and Pre-Processing*

182   EEG was recorded using a 64+10 Biosemi Active Two System at a sampling rate of 512

183   Hz. Continuous EEG recordings were bandpass filtered at 0.5-90 Hz, with a notch filter at 55-65

184   Hz for line noise. The shortest music segment was 40 seconds, so EEG data for each song was

185   segmented into 4 x 10 s epochs and baseline corrected based on a 200 ms pre-stimulus interval.

186   Trials with excessive signal amplitude were rejected. Ocular and muscle artifact removal was

187   performed on the remaining concatenated trials using Independent Component Analysis (ICA)

188   implemented in EEGLAB (Delorme and Makeig, 2004). The highest number of trials lost for any

189   subject was 8 out of 40, 7 subjects retained all trials, and the average number rejected trials from

190   remaining subjects was 2.67, with no difference in trial rejection between conditions.

191   We performed source estimation at the 68 ROIs of the Desikan-Killiany Atlas (Desikan

192   et al., 2006), using sLORETTA (Pascual-Marqui, 2002) as implemented in Brainstorm (Tadel et

193   al., 2011). Brainstorm is documented and freely available for download under the GNU general

194   public license (http://neuroimage.usc.edu/brainstorm). Source reconstruction was constrained to

195   the cortical mantle of the brain template MNI/Colin27 defined by the Montreal Neurological

196   Institute (Holmes et al., 1998). Current density for one source orientation (X component) was

197   estimated for 15,768 equally spaced vertices and the source waveform was mapped at the 68

198   brain regions of interest as an average taken over all vertices in each region. Multiscale Entropy

199   was calculated on the source waveform at each ROI for each subject as a measure of brain signal

200   complexity.

201   **Data Analyses**

202   *Multiscale Entropy*

203   MSE has been previously validated as a measure of brain signal complexity (Catarino et

204   al , 2011; McIntosh et al., 2008; Mišić, Mills, Taylor, & McIntosh, 2010). We calculated MSE in

205   two steps using the algorithm available at www.physionet.org/physiotools/mse. First, the source

206   EEG and music signals were progressively down-sampled into multiple coarse-grained

207   timescales where, for scale t, the time series is constructed by averaging the data points with non-

208   overlapping windows of length t. Each element of the coarse-grained time series, $y_j^{(\tau)}$, is

209   calculated according to Eq. (2):

210
$$y_j^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i, 1 \le \frac{N}{\tau} \qquad (1)$$

211   The number of scales is determined by a function of the number of data points in the

212   signal and MSE was calculated for 100 timescales [sampling rate (512Hz) * epoch (10,000

213   ms)/50 time points per epoch = maximum of 102.4 scales].

214   Second, the algorithm calculates the sample entropy (S_E) for each coarse-grained

215   timeseries $y_j^{(\tau)}$:

216
$$S_E(m, r, N) = ln \frac{\sum_{i=1}^{N-m} n_i' m}{\sum_{i=1}^{N-m} n_i' m + 1} \qquad (2)$$

217   Sample entropy quantifies the predictability of a time series by calculating the conditional

218   probability that any two sequences of m consecutive data points that are similar to each other

219   within a certain similarity criterion (r) will remain similar at the next point ($m+1$) in the data set

220   (N), where N is the length of the time series (Richman & Moorman, 2000). In this study, MSE

221   was calculated with pattern length set to m = 2, and similarity criterion was to r = 0.5. The value

222   r is defined as a proportion of the standard deviation of the original data (Costa, Goldberger, &

223   Peng, 2004; Richman & Moorman, 2000). MSE estimates were obtained for each participant's

224   EEG source time series as a mean across single-trial entropy measures for each timescale.

225   Music pieces were imported into Matlab using the *wavread* function at a sampling rate of

226   11.25 kHz (MathWorks, Inc. Release 2011b). Music auditory signal MSE was subsequently

227   calculated with the same parameter values and the same number of timescales as the EEG source

228   MSE.

229   ***Complexity Matching***

230   Complexity matching applies Procrustes analysis to measure the equivalence of the MSE

231   curve for the auditory signal of a song (X_1) and the MSE curve of the EEG source time series of a

232   participant listening to that song (X_{2j}), for all j ROIs individually (Gower, 1975). It minimizes the

233   sum of the squared deviations between matching corresponding points (landmarks) from each of

234   the two data sets (MSE curves), allowing for scaling, translation and orthogonal rotation of X_1 to

235   fit X_{2j}, where choice of label X_1 or X_2 is arbitrary. X_1 and X_{2j} must have the same number of i

236   sample points, or 'landmarks', and Procrustes matches X_{1i} to X_{2ij}. In our simple case of two

237   vectors, the rotation matrix T such that X_1 best fits X_{2j} is given as $T = V'U$ from the singular

238   value decomposition $X_1'\,X_{2j} = U'SV$. Without translation and scaling this problem is known as

239   Procrustes rotation. Dissimilarity of X_1 and X_{2j} is given as the *Procrustes distance*:

$$distance = \sum_{i=1} (X_1 - T(X_{2j}))^2 \qquad (3)$$

241   A smaller distance value denotes greater similarity between the two curves, or a closer match

242   between them. The analysis returns a distance value for each ROI for each participant. Procrustes

243   distance was calculated using the Matlab function *procrustes* (MathWorks, Inc. Release 2011b).

244   Figure 2 presents a conceptual depiction of our implementation of *complexity matching*.

245
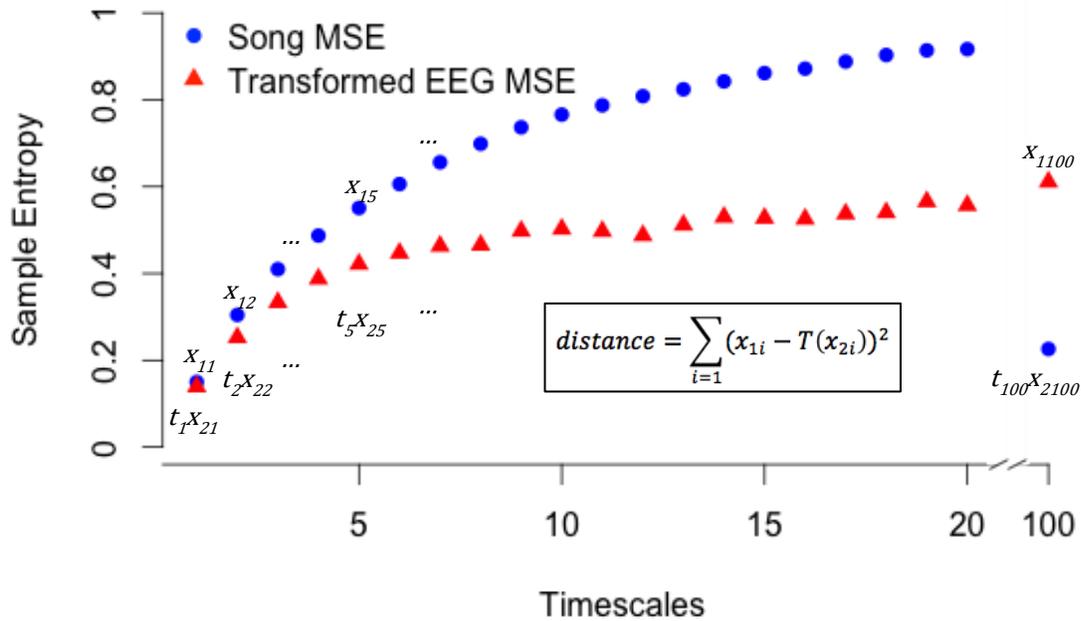
Figure 2. Complexity matching applies Procrustes' analysis to determine a linear transformation (scaling,
translation and orthogonal rotation) of the points in X_2 (EEG source MSE for a given ROI) to best match the points
in X_1 (song MSE). The goodness-of-fit criterion is the sum of squared errors, and Procrustes distance is the
minimized value of this dissimilarity measure. Distance is standardized by a measure of the scale of X_1.

250

Spectral Power

252   Studies have found that MSE and power spectrum density (PSD) provide complementary

253   information on neural signals (Gudmundsson et al., 2007; McIntosh et al., 2008; Mišić et al.,

254   2010). For example, both measures follow similarities for time maturational changes, but with

255   different spatial and temporal patterns (McIntosh et al., 2008; Lippé et al., 2009; Mišić et al.,

256   2010). Mišić and colleagues (2014) found substantial differences between PSD and MSE effects.

257   In their sample, individuals with Autism Spectrum Disorder (ASD) displayed only group main

258   effects on PSD, but a group x task interaction on MSE, and the effects were different both

259   spatially and temporally. This indicates that MSE captures an aspect of neural information

260   processing in ASD above and beyond what can be gleaned from a traditional analysis of spectral

261   power.

262   To determine the extent to which training- and task-based differences in MSE are related

263   to spectral density, we computed PSD for all single-trial time series. Single-trial power spectra

264   were computed using the Fast Fourier Transform. To capture the relative contribution from each

265   frequency band, all time series were first normalized to mean = 0 and SD = 1. Given the

266   sampling rate of 512 Hz and 5,120 data points per trial, the frequency resolution was effectively

267   0.100 Hz and the analysis was constrained to the [0.100, 90] Hz range, with a notch filter for line

268   noise at 55-65 Hz.

269   ***Partial Least Squares***

270   Task partial least squares analysis (PLS) was used to statistically assess task and epoch

271   related effects in MSE and PSD. Task PLS is a multivariate statistical technique similar to

272   canonical correlation which employs singular value decomposition (SVD) to extract latent

273   variables (LVs) that capture the maximum covariance between the task design and neural

274   activity. Each LV consisted of: (1) a singular vector of design scores, (2) a singular vector of

275   saliences showing the distribution across brain regions and sampling scales, (3) a singular value

276   (s) representing the covariance between the design scores and the singular image (McIntosh et

277   al., 1996; McIntosh and Lobaugh, 2004).

278   The statistical significance of each LV was determined using permutation testing (Good,

279   2000; McIntosh and Lobaugh, 2004). The rows of X are randomly reordered (permuted) and the

280   new data were subjected to SVD as before, to obtain a new set of singular values. This procedure

281   was repeated 500 times to generate a sampling distribution of singular values under the null

282   hypothesis that there is no association between neural activity and the task. An LV was

283   considered significant if a singular value equal to or greater than that of the LV was present less

284   than 5% of the time in random permutations (i.e. $p < 0.05$).

285   The reliability of each statistical effect was assessed through bootstrap estimation of

286   standard error confidence intervals of the singular vector weights in each LV (Efron and

287   Tibshirani, 1986). Random sampling with replacement of participants within conditions

288   generated 500 bootstrap samples. In the present study, this process allowed for the assessment of

289   the relative contribution of brain regions and timescales to each LV. Brain regions with a

290   salience weight over standard error ratio > 3.0 correspond to a 99% confidence interval and were

291   considered to be reliable (Sampson et al., 1989).

292   Finally, the dot product of an individual subject's raw MSE data and the singular image

293   from the LV produces a brain score. The brain score is similar to a factor score that indicates

294   how strongly an individual subject expresses the patterns on the latent variable and allowed us to

295   estimate 95% confidence intervals for the effects in each group and task condition.

296   Behavioural PLS (bPLS) is a variation on task PLS for analyzing the relationship

297   between brain measures and the behaviour (McIntosh and Lobaugh, 2004; Krishnan et al., 2011).

298   Similar to task PLS the SVD results in mutually orthogonal LVs, where each LV contains 1) a

299   singular vector of saliences for the behavioural measures, (2) a singular vector of saliences for

300   brain activity, (3) a singular value (s) representing the covariance between the behaviour scores

301   and the singular image. Behaviour saliences indicate task-dependent differences and brain

302   saliences indicate ROI-dependent differences in the brain-behaviour correlation.

303

304   **Results**

305   One participant was excluded from the study for mild hearing loss determined by

306   audiogram, and one other was removed for excessive motion during EEG recording, leaving

307   N=16 subjects. Two participants did not complete the music-training questionnaire, leaving 14

308   subjects. For music training, of the N=14 participants: 7 reported no formal training, 1 reported

309   can play an instrument without formal training, 1 reported less than 1 year of formal music

310   training, 2 reported between 1-5 years of formal training, and 4 reported more than 5 years of

311   formal training. Thus, this sample does not include a sufficient number of participants who fulfill

312   the common requirements for musicianship (e.g. at least 10 years of formal music training,

313   Fujioka et al., 2004), and we did not proceed with analysis of the effects of music training.

314   Multiscale entropy curves of sound signals from a sample of the songs are visualized in

315   Figure 3 for illustration purposes.
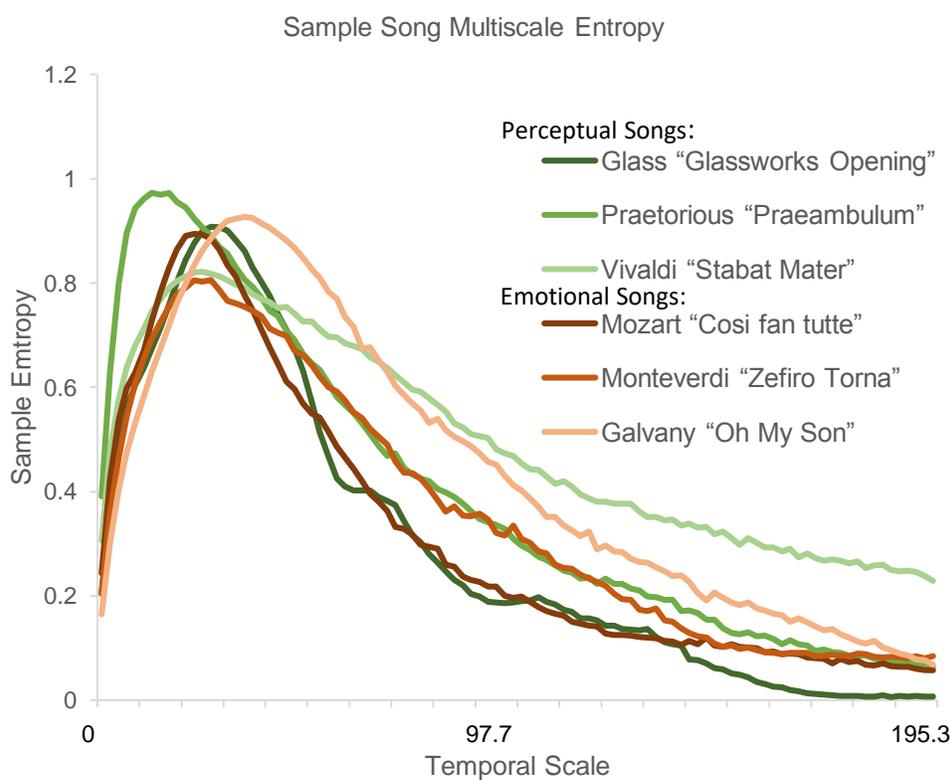
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317

318   **Figure 3.** Exemplary multiscale entropy values obtained from the sound signals of a small sample of the songs from
319   each group. Temporal scale, in milliseconds, refers to the number of data points averaged within non-overlapping
320   windows, hence the left most values represent fine temporal scales and right more coarse scales.
321

322   ***Emotional and Perceptual Tasks***

323   We did not observe any within-task effects of emotional (e.g. stimulating compared to

324   relaxing) or pitch/tempo (fast compared to slow) dimension ratings on any of our brain measures

325   (MSE, Procrustes distance or PSD; all PLS $p > .10$). This may be due to the high level of

326   variance between subjects' emotional responses (Figure 4), or because the continuous nature of

327   the behaviour ratings is not well suited to the dichotomization necessary for the present types of

328   analyses.
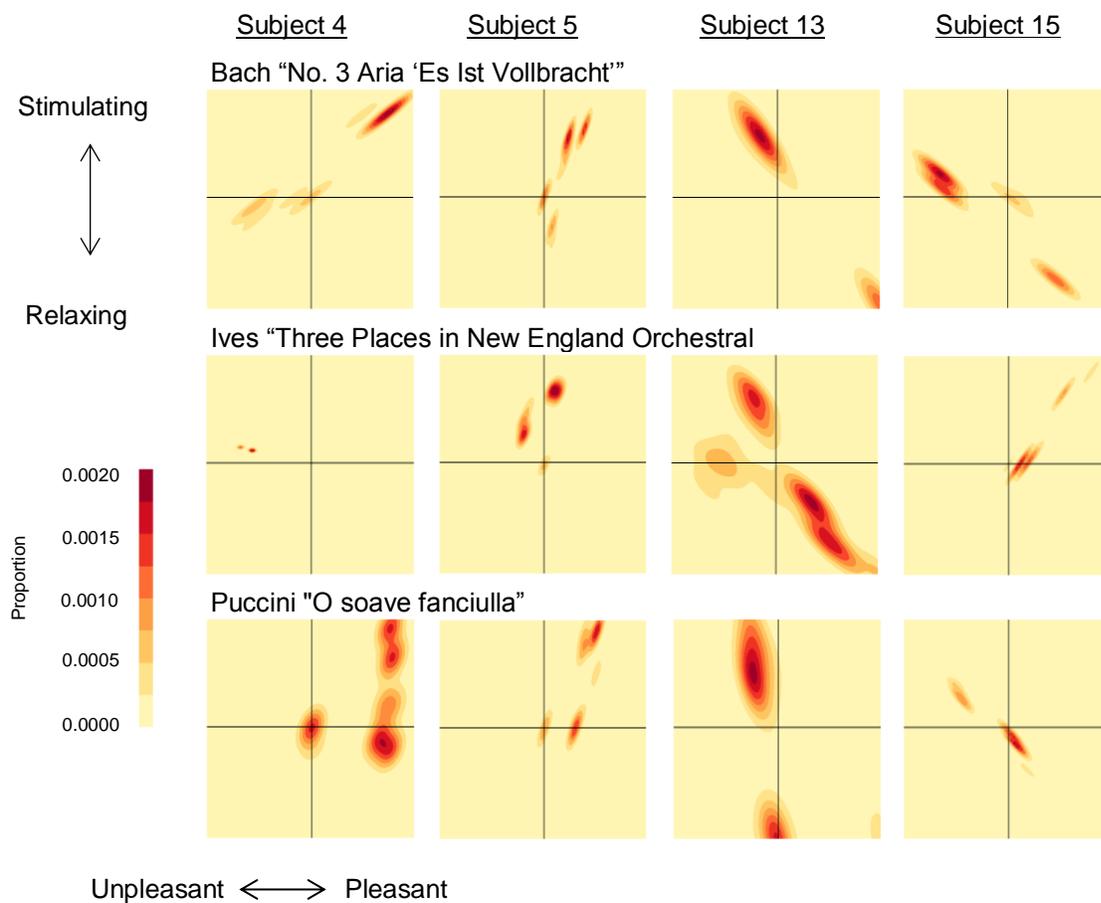
329

330   **Figure 4.** Example single-subject, single-song behaviour heat maps for the emotional valence task. Note the
331   variation between individuals in both the valence felt and the variability of the valence within each participant and

332 song (i.e. some participants were stable in one quadrant while some participants felt a greater range during the same
333 song).

334

335   Examining both tasks across all four epochs, the emotional task was generally associated

336 with higher EEG source MSE at time scales below 20, compared to the perceptual task that

337 showed higher MSE at coarser timescales (>40) (LV = 1, p << 0, Singular Value = 1.81, 31.6%

338 cross-block covariance; Figure 5; Figure 6). Both tasks showed an increase in MSE at finer

339 timescales (<20) and a decrease in coarse scale MSE across epochs from the beginning to the end

340 of the piece of music. The spatial distribution of these effects was such that the emotional task

341 was associated with higher MSE in finer timescales (Figure 5A) in bilateral bank of the superior

342 temporal sulcus (bankSTS) and inferior parietal cortex; left hemisphere caudal and rostral middle

343 frontal, and precentral regions; right mPFC, paracentral, pars triangularis, rostral ACC,

344 precuneus, SP MT, and ST. The negative bootstrap ratios (Figure 5B) are reliable in bilateral

345 insula, cingulate, ST, PCC, cuneus, and pericalcarine; left FG, mOFC, SF, parahippocampal,

346 PCC, precuneus, and lingual; and right hemisphere MF, FP, OFC, IFG, postcentral, entorhinal,

347 and temporal cortex.

348
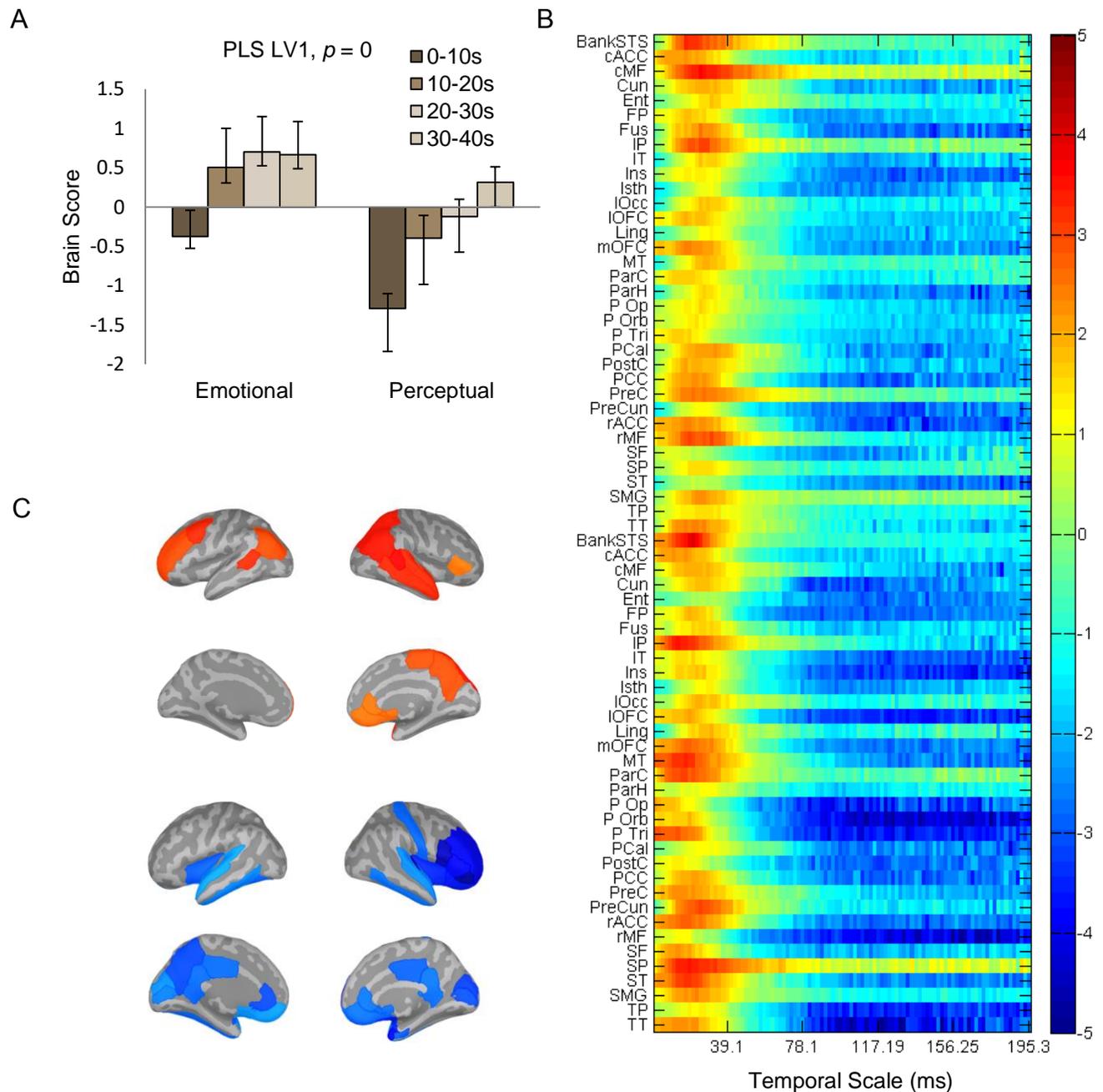
Figure 5. PLS first latent variable for the examination of effects of between tasks and within-task epochs on MSE. (A) The bar graph depicts the data-driven contrast highlighting higher MSE on all epochs of the emotional task compared to the perceptual task, as well as epoch effects within each task, significantly expressed across the entire data set, as determined by permutation tests. (B) Cortical regions at which the contrast was most stable as determined by bootstrapping. Values represent the ratio of the parameter estimate for the source divided by the bootstrap-derived standard error (roughly z scores). (C) Cortical visualization of stable bootstrap values for fine (top) and coarse (bottom) scales.
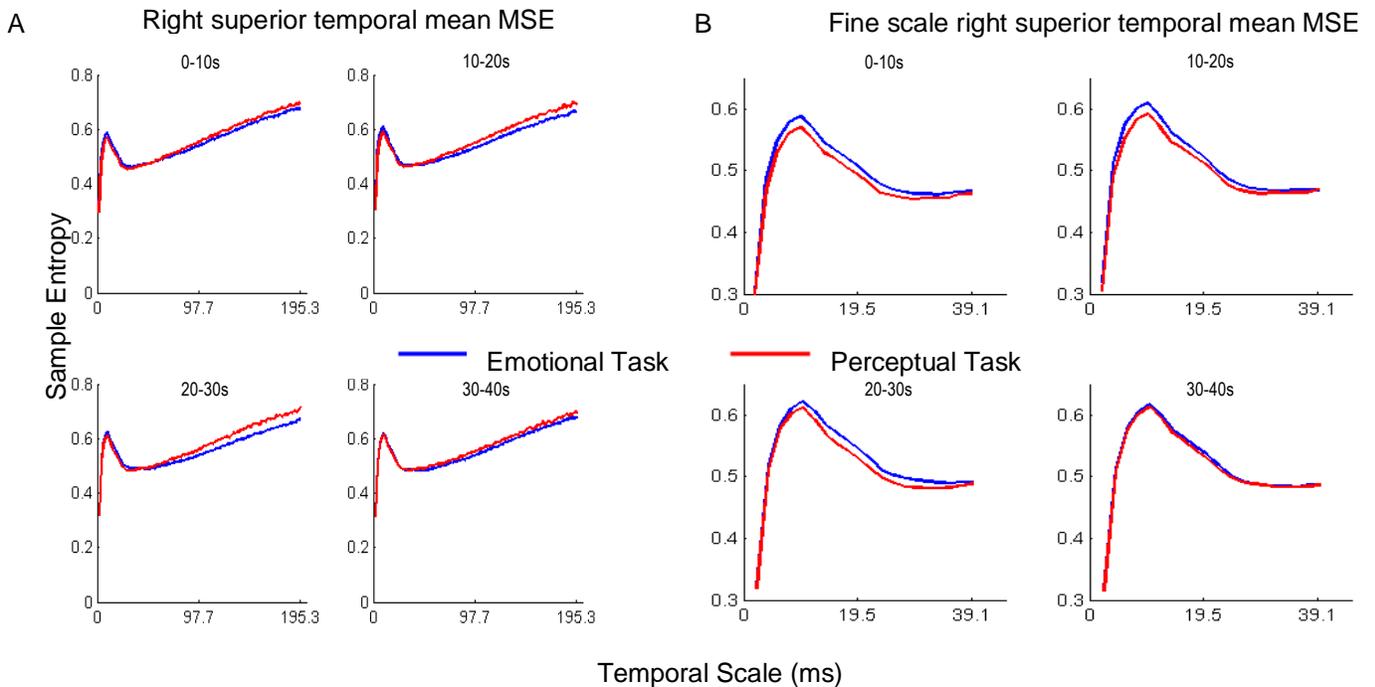
Figure 6. Mean MSE across participants for right superior temporal cortex ROI. (A) All temporal scales, B) Zoomed into visualize higher MSE for the emotional task at fine scales (<39.1 ms).

Procrustes' distance was greater during the emotional task than the perceptual task in most brain sources (LV = 1, $p = 0$, Singular Value = 0.81, 54.1% of the cross-block covariance; Figure 7). All brain regions showed this effect of lower complexity matching on the emotional task except for bilateral entorhinal, FP, IT, parahippocampal, TP; left bankSTS MT, pars opercularis, ST; and right FG.
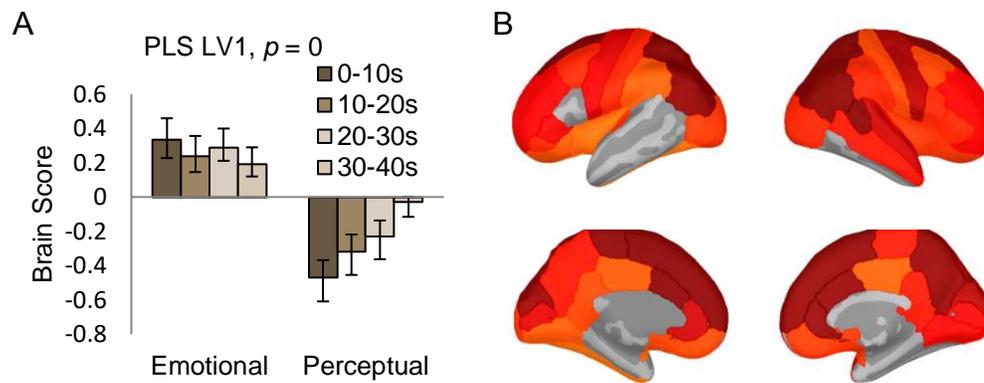
Figure 7. First significant PLS result for the examination of effects of between tasks and within-task epochs on Procrustes' distance. (A) The bar graph depicts the data-driven contrast highlighting greater distance on all epochs of the emotional task compared to the perceptual task, as well epoch effects within each task, significantly expressed across the entire data set, as determined by permutation tests (p = 0). (B) Cortical regions at which the contrast was most stable as determined by bootstrapping. Values represent the ratio of the parameter estimate for the source divided by the bootstrap-derived standard error (roughly z-scores).

Music Reward

The participant sample size (N=16) did not provide sufficient power to allow for the accurate assessment of brain-behaviour relationships on each of the five sub-factors of the BMRQ. Therefore, an average score across all sub-factors was calculated and used as the overall measure of music reward. Participant scores on this measure of reward had mean = 3.84 (SD = 0.47) on the 1-5 scale, suggesting this sample overall experiences a medium level of music related reward. Behavioural PLS assessed the correlation of the participant reward scores with MSE, distance and PSD on the two tasks and four epochs.

A strong positive correlation between MSE and reward was apparent during both tasks and all epochs. However, had we reported all epochs, the analysis would have included 8 conditions for only a total N=16; therefore we opted to not report the results of all epochs of both tasks in order to increase the validity of the statistical analysis and reduce the likelihood of a Type II error. Here we only report the positive correlation between MSE and reward during the

391   first and last epoch of both tasks to demonstrate that the effect is relatively stable from the

392   beginning to the end of the music (PLS LV1 $p = 0$, $r^2 = .38$, Singular Value = 61.53, 74.4% of

393   cross block covariance; Figure 8), and note that the pattern of effect similar for the middle two

394   epochs. This effect was reliable in bilateral medial OFC, inferior frontal, cingulate, temporal and

395   occipital regions, left precuneus and right superior frontal cortex.

396

397
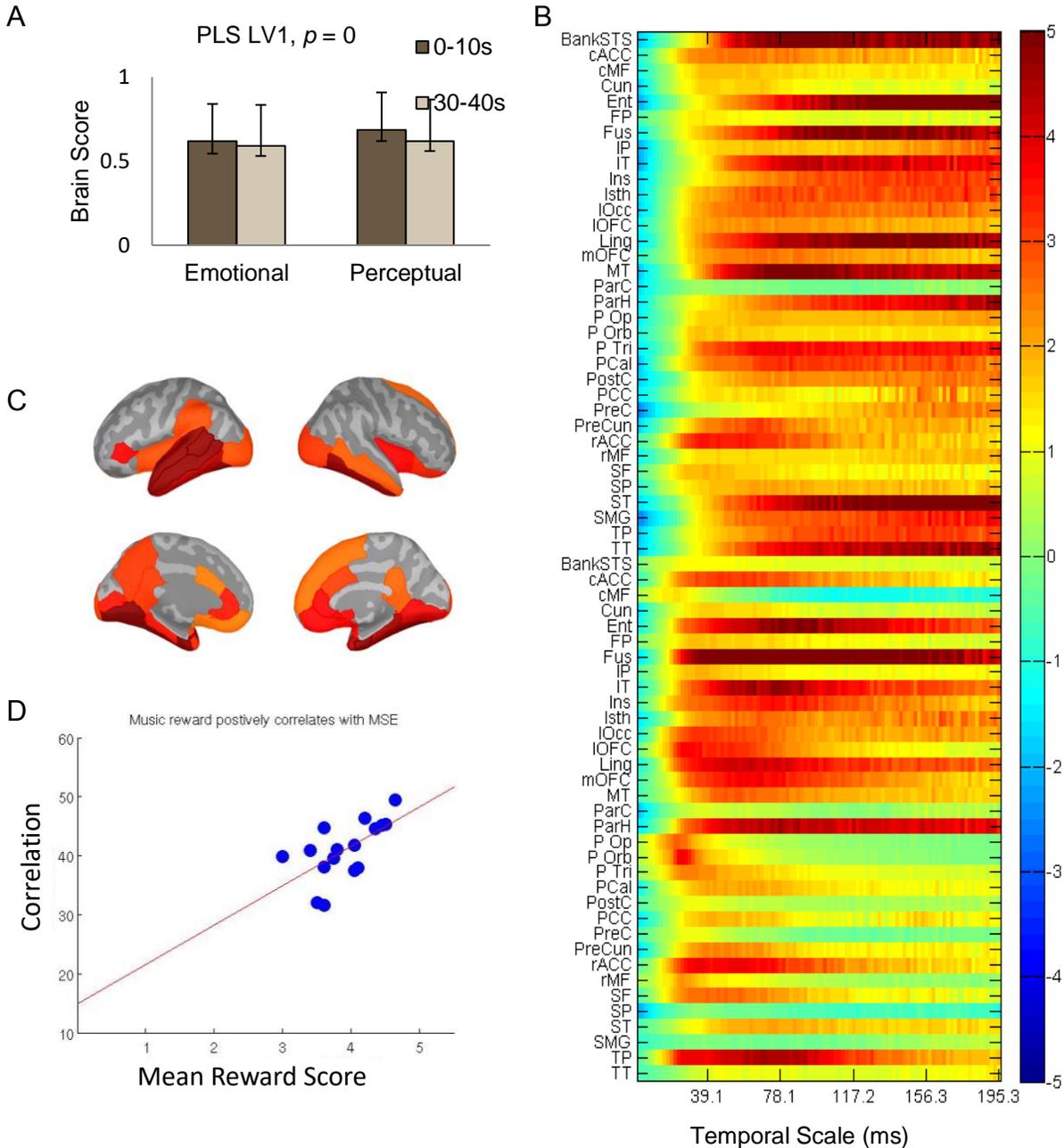
Figure 8. Behaviour PLS result examining the correlation between MSE and BMRQ reward score on both tasks and epochs E1 and E4. (A) Brain scores depict participants scores on the brain-behaviour relationship significantly expressed by the latent variable, as determined by permutation tests (p = 0). (B) Brain regions and frequencies at which the relationship was most stable as determined by bootstrapping. Together A and B indicate a positive correlation between MSE and BMRQ score in the highlighted regions. (C) Highlights bootstrap values from B for spatial regions where effect was stable. Values are taken as peak across scales 20-60. (D) Scatterplot of the brain scores from the first epoch with BMRQ reward scores depicts the positive relationship ($r^2 = .38$).

406   A significant positive correlation was observed between distance and reward during only

407   the emotional task for all epochs (PLS LV1 $p = .012$, $r^2 = .13$, Singular Value = 4.29, 72.9% of

408   cross-block covariance; Figure 9; perceptual task $p > .10$). This effect was localized to the right

409   hemisphere frontal regions, rACC, IP, inferior and middle temporal, and lOcc.
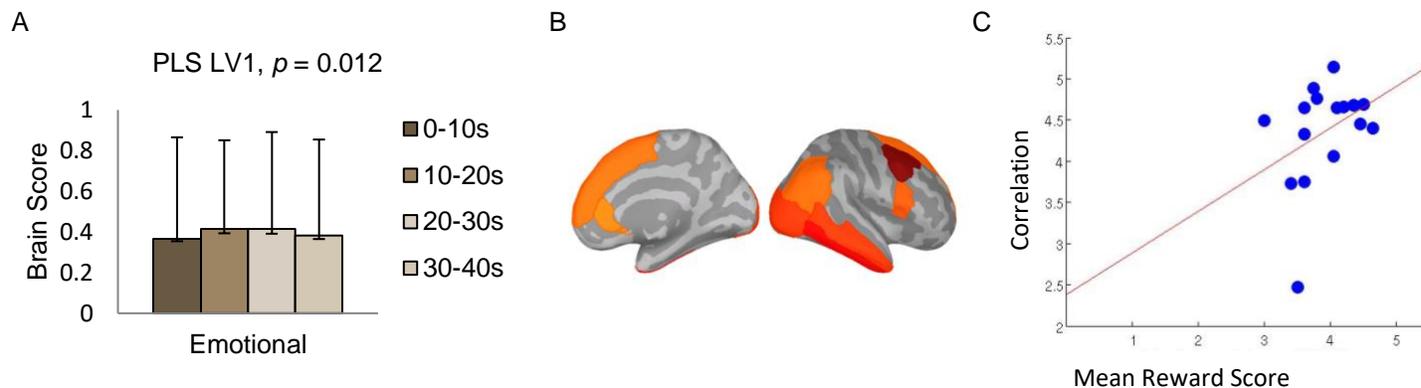
411   **Figure 9.** Behaviour PLS result examining the correlation between complexity distance on all epochs of the
412   emotional task and BMRQ music reward score. (A) Brain scores depict participants score on the brain-behaviour
413   relationship significantly expressed by the latent variable, as determined by permutation tests (p = .012). (B) Brain
414   regions and frequencies at which the relationship was most stable as determined by bootstrapping. Together A and B
415   indicate a positive correlation between distance and BMRQ score in the highlighted regions. (C) Scatterplot of the
416   brain scores from the first epoch with BMRQ reward scores further displays this positive relationship ($r^2 = .13$).

418   ***Spectral Power***

419   Higher gamma power was observed during the emotional task, and this effect increased

420   across epochs (PLS LV1, $p = 0$, Singular Value = .40, 25.5% of cross-block covariance; Figure

421   10) in all spatial regions except for bilateral precentral gyrus and left pars triangularis. In

422   comparison, the perceptual task was dominated by power at lower frequencies at the beginning

423   of the piece of music, and this effect lessened over time.
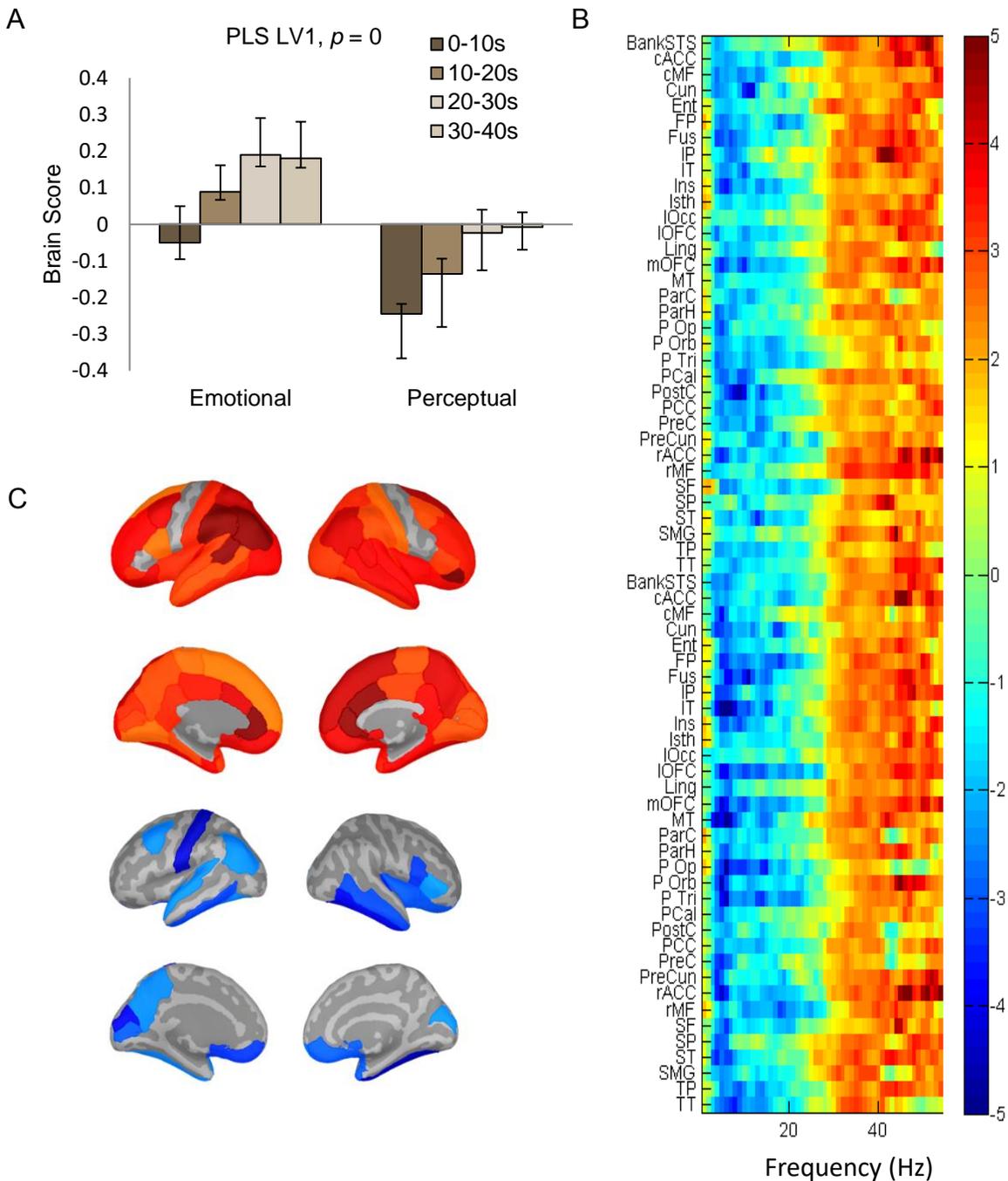
424
425 **Figure 10.** First significant PLS result for the examination of effects of between tasks and within-task epochs on
426 PSD. (A) The bar graph depicts the data-driven contrast highlighting the differences in spectral power profile
427 between tasks, and their similar epoch effect, significantly expressed across the entire data set, as determined by
428 permutation tests (p = 0). (B) Cortical regions and frequencies at which the contrast was most stable as determined
429 by bootstrapping. (C) Cortical visualization of stable bootstrap values (peak within each frequency band) for alpha
430 (top) and gamma (bottom) band frequencies.
431

432   There was a positive correlation between music-derived reward as measured by BMRQ

433   score and all spectral frequencies (PLS LV1, $p = 0$, $r^2 = .57$, Singular Value = 44.49, 66.46 of

434   cross-block covariance; Figure 11). The effect was spatially widespread across 58 of the 68

435   parcellated regions.
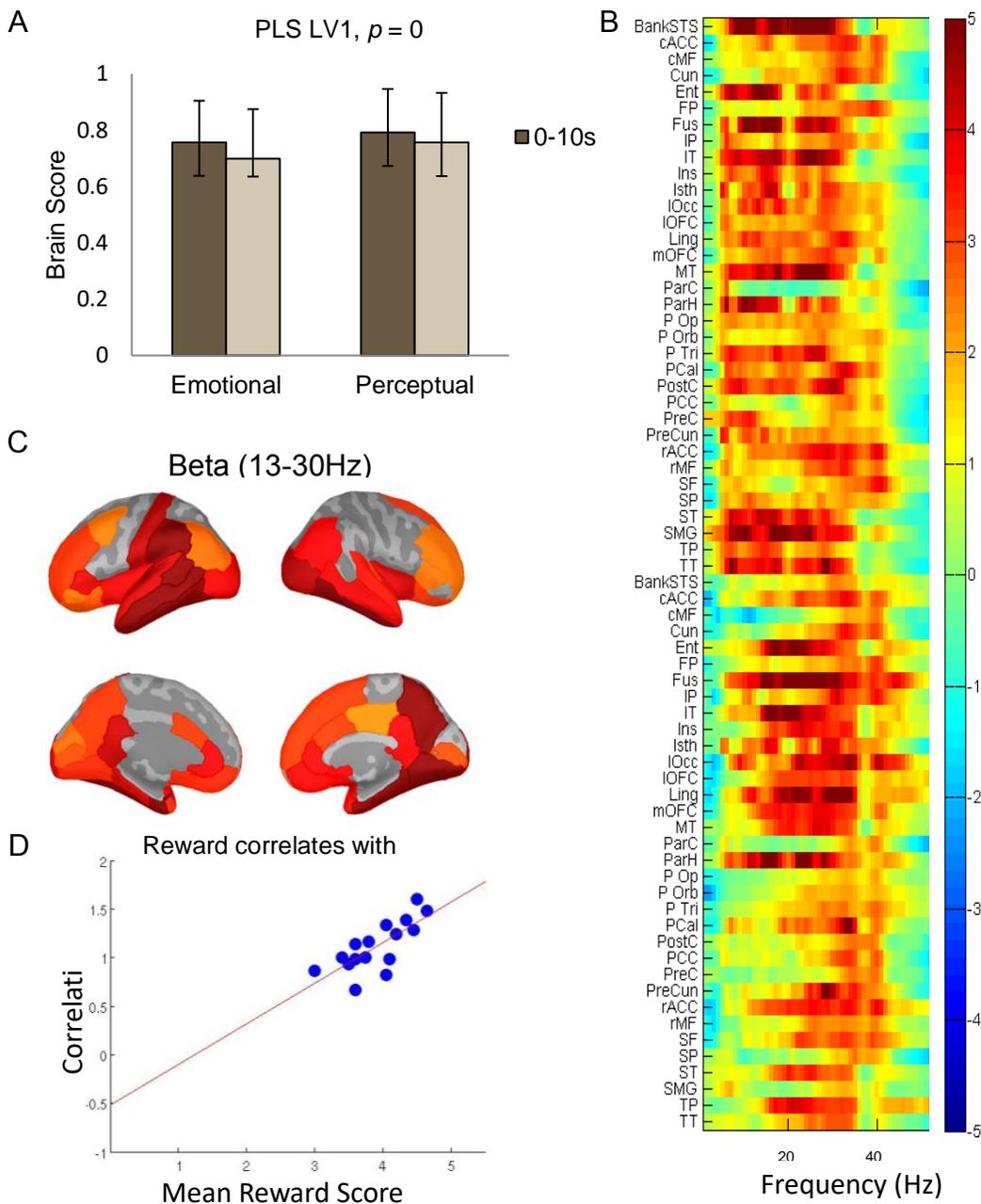
436
437   **Figure 11.** bPLS result examining the correlation between PSD and BMRQ reward score on both tasks and epochs
438   E1 and E4. (A) Brain scores for the brain-behaviour correlation (p = 0). (B) Bootstrap ratios for brain regions and
439   frequencies. Together A and B indicate a positive correlation between PSD and BMRQ scores across all frequencies
440   in the highlighted regions. (C) Spatial regions from B where effect was stable in the beta band frequency (13-30 Hz).

441   (D) Scatterplot of the brain scores from the first epoch with BMRQ reward scores depicts the positive relationship
442   ($r^2 = .57$).

443

Discussion

445   We found higher complexity matching in widespread brain regions during the perceptual

446   task than on the emotional task, using Procrustes' distance to compare the MSE of EEG signals

447   to the MSE of the music itself. This indicates that brain signal complexity more closely

448   resembles the complexity of the music environment when participants were attending to the

449   acoustics of the music compared to when they were thinking about how the music makes them

450   feel. These results support a mapping of environmental information to the brain using complexity

451   esatimation, and that the level of neural 'mirroring' is related to the type of cognitive processing

452   conducted.

453   Analysis of the EEG MSE values alone found that MSE was higher in relatively finer

454   timescales (<48.8ms) during the emotional task than the perceptual task, and that both groups

455   showed an increase of this pattern as the music progressed. These MSE results demonstrate that

456   emotion is associated with *higher information structure*, while the complexity matching results

457   indicate the role of *different information structures* from environment input. The MSE results

458   and the complexity matching results together suggest that the emotional task engaged additional

459   processes, above and beyond the bottom-up sound perception information.

460   The brain regions that displayed this MSE effect are frequently linked to music cognition

461   (e.g. right temporal, inferior frontal gyrus; Zatorre et al., 2002) and self-referential emotional

462   processing (e.g. medial PFC; Amodio & Frith, 2006; Denny et al., 2012; Ochsner et al., 2004).

463   The effect was also observed in regions that operate as integrative hubs (e.g. medial parietal) that

464   are densely connected to neighboring regions and have long-range interconnections, enabling

465   efficient global integration of information necessary for healthy cognitive function (Hagmann et

466   al., 2008; Zamora-López et al., 2010; van den Heuvel and Sporns, 2011). This effect is spatially

467   and temporally (<48.8ms) similar to increased complexity associated with musical training

468   (Carpentier et al., 2016), and in other studies where higher MSE has been linked to performance

469   on cognitive tasks that require higher information processing (Mišić et al., 2010; Heisz et al.,

470   2012). Additionally, due to longer stimulus presentation, the current study opens up the analysis

471   to coarser scales, up to 195.3ms, well beyond what has been possible in our previous studies and

472   other empirical studies of cognition and brain MSE. We observed that MSE was initially higher

473   in the perceptual task and decreased over time in the temporal scale range of 78.1-195.3ms, and

474   we are not aware of any previous studies that have examined empirical brain complexity at this

475   scale. We suggest the possibility that complexity at these slow timescales is indicative of an

476   initial distributed and re-entrant search for neural templates associated with the music upon first

477   listening, followed by a decrease of this activity as the brain settles into the neural solution for

478   ongoing stimulus processing. However, further investigation of the link between cognition and

479   complexity at these scales is required.

480   Higher music reward scores on the BMRQ were associated with a lower complexity

481   match and higher EEG MSE. This negative correlation between complexity matching and reward

482   was only observed on the emotional task, not on the perceptual task. Similar to the emotional

483   task above, we suggest that reward is associated with additional internal information above and

484   beyond that of the external stimulus. The complementary MSE and matching results suggest that

485   music reward requires a brain state that is quantitatively and qualitatively different than the

486   brain's requirements for music sound perception alone. Music reward is associated with the

487   activation of multiple different intrinsic processes and high information integration. In other

488   words, music reward is a product of 'the more you add' to perception on top of immediate

489   sensory events.

490   The observed relationship between higher neural information processing and music

491   reward may be generated by the direct reward experience itself, since pleasurable responses to

492   music are associated with particular patterns of cortical and subcortical activity not observed

493   during neutral music perception. Multiple studies have reported connections between music

494   reward and BOLD activity in vmPFC and OFC, and also IFG, ACC and sensory motor areas

495   (Blood and Zatorre, 2001; Salimpoor et al., 2013). The relationship between complexity and

496   reward in the present study was observed in temporal regions, as well as paralimbic and cortical

497   regions involved in emotional processing (e.g. OFC, insula). Another proposal, not mutually

498   exclusive to the first, is that the effects capture intermediate internal states that are important to

499   generating the reward response. For example, the activity may reflect processes related to the

500   BMRQ factors, such as musical knowledge, or other factors not directly measured by the

501   BMRQ, like visual imagery or episodic memories evoked by the music (Juslin and Västfjäll,

502   2008; Vuoskoski and Eerola, 2012). Consistent with this notion, the spatial reliability of the

503   correlation between distance and music reward suggest that frontal regions (superior, middle,

504   inferior frontal) were processing internally generated information patterns, while inferior

505   temporal and anterior cingulate cortex were involved in both the distance and MSE effects.

506   Integration may be a requirement for the commonly highlighted role of expectancy in

507   music reward. The theory that rewarding emotional responses to music are derived from

508   expectations and anticipation during music listening was first extensively described by Meyer

509   (1956; see also Huron, 2006). It explains that the expectations are generated from explicit and

510   implicit knowledge of music structure and patterns, and composers create emotional arousal by

511   playing with 'tension and release.' Anticipation of a familiar rewarding segment of music has

512   been linked to caudate dopamine release and BOLD activity prior to nucleus accumbens

513   dopamine activity at peak reward response (Salimpoor et al., 2011). Music expectations were not

514   behaviourally evaluated in the present study, but there is a logical link between them and brain

515   signal complexity. Generation of expectations requires sufficient understanding and neural

516   representation of the structure and patterns in the music. Therefore, it may be that enjoyment of a

517   piece of music needs to be associated with a minimum amount of information processing that

518   would allow the listener to appreciate the music as a coherent whole, rather as a sequence of

519   individual notes. Further investigation of listeners' enjoyment of individual music pieces, rather

520   than as general trait music reward, is required to substantiate this theory and make a stronger

521   connection between brain complexity and music pleasure.

522   While there were no notable differences in complexity between the song sets for each

523   task, and the sets were selected to be acoustically and thematically similar, the songs were not

524   identical for both tasks. This leaves open the possibility that other differences in the chosen

525   songs are responsible for the observed brain differences between songs. This does raise

526   interesting options for the future study of how different stimuli properties may influence brain

527   complexity.

528   *Spectral Power*

529   Congruent with the MSE pattern of the trade-off between faster and slower timescales,

530   we observed higher gamma power in the emotional task, compared to lower frequency power

531   associated with the perceptual task, as well as a decrease across time in low frequency power in

532   regions typically linked to music processing and an increase in gamma in these and most other

533   regions. Gamma activity has been repeatedly implicated as important for perceptual binding and

534   may be associated with binding of musical features at the sensory level and matching of external

535   acoustic information to internal thought processes for the formation of meaningful concepts

536   (Bertrand & Tallon-Baudry, 2000; Crone et al., 2001; Keil et al., 1999; Rodriguez et al., 1999;

537   Tallon-Baudry et al., 1998). Gamma activity is commonly found to be higher in adult musicians

538   when listening to music and may reflect enhanced binding of musical features (Bhattacharya and

539   Petsche, 2001, 2005; Shahin et al., 2008; Pallesen et al., 2015). There is also suggestion that

540   gamma activity may be related to musical expectations (Snyder and Large, 2005). In a study

541   conducted by Fujioka and colleagues (2009) gamma amplitude increased from baseline for each

542   tone of a repeating pattern, and this effect continued on trials where the tone was unexpectedly

543   omitted. None of these studies of the spectral effects of musical training or music listening

544   conducted spatial analysis; therefore, it is difficult to place this facet of our results in the context

545   of the other literature. However, our observation of increased gamma power in auditory and

546   some associative regions is consistent with the hypothesis of the role of gamma in perceptual

547   binding.

548   *Conclusions*

549   EEG complexity was higher and different from music complexity during the emotional

550   task in which participants were reflecting on how the music made them feel, compared to the

551   perceptual task that had participants track pitch and tempo. Complexity matching was also

552   correlated with BMRQ score, such that music reward was associated with higher neural signal

553   information and a worse match to the bottom-up music information. These results suggest that

554   complexity matching can assess the degree to which some cognitive-affective states are

555   associated with internal information integration which differs from the neural representation of

556   bottom-up sensory information processing.

557

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