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1 Running head: PERSONALITY AND MUSIC PREFERENCE USING SOCIAL-TAGGING

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5 Personality and musical preference using social-tagging in excerpt-selection

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## Abstract

8  
9 Music preference has been related to individual differences like social identity, cognitive style, and  
10 personality, but quantifying music preference can be a challenge. Self-report measures may be too  
11 presumptive of shared genre definitions between listeners, while listener ratings of expert-selected  
12 music may fail to reflect typical listeners' genre-boundaries. The current study aims to address this  
13 by using a social-tagging approach to select music for studying preference. 2407 tracks were  
14 collected and subsampled from the Last.fm social-tagging service and the EchoNest platform based  
15 on attributes such as genre, tempo, and danceability. The set was further subsampled according to  
16 tempo estimates and metadata from EchoNest, resulting in 48 excerpts from 12 genres. Participants  
17 ( $n = 210$ ) heard and rated the excerpts, rated each genre using the Short Test of Music Preferences  
18 (STOMP), and completed the Ten-Item Personality Index (TIPI), the Empathy Quotient (EQ) and  
19 the Systemizing Quotient (SQ). Mean preference ratings correlated significantly with STOMP  
20 scores, suggesting that social-tagging can provide a fairly reliable link between perception and  
21 genre-labels. Principal Component Analysis (PCA) of the ratings revealed four musical  
22 components: 'Danceable,' 'Jazzy,' 'Hard,' and 'Rebellious.' Component scores correlated modestly  
23 but significantly with TIPI, EQ and SQ scores. These results support and expand previous findings  
24 linking personality and music preference, and provide support for a novel method of using crowd-  
25 tagging in the study of music preference.

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27

28 We take it for granted that the music we like and listen to says something important about us and  
29 make judgements about others based on their musical tastes (Boer et al., 2011; Rentfrow & Gosling,  
30 2006; Rentfrow & Gosling, 2003). Rentfrow and Gosling (2006), for example, analyzed the  
31 conversations of participants as they got acquainted, and found that participants discussed their  
32 musical tastes more than any other topic. They furthermore found that participants could use  
33 information about others' music preferences to make partly accurate guesses about their  
34 personalities.

35 Research linking music preferences to personality is nearly as old as modern measures of  
36 personality themselves; early pioneers of personality research suggested that participants' ratings  
37 of heard music might even function as a kind of Rorschach test to reveal subconscious emotional  
38 tendencies (Cattell & Anderson, 1953). Over the following decades, the development of a widely  
39 validated five factor model (FFM) of personality led to greater comparability across personality  
40 studies (Digman, 1990). The five traits are comprised of Openness, which is the tendency to  
41 broadly enjoy arts, new ideas and experiences; Conscientiousness, which is the tendency to be  
42 responsible, organized and self-disciplined; Extraversion, which is the tendency to seek and enjoy  
43 social engagement and high energy activities; Agreeableness, which is the tendency to act  
44 cooperatively and helpfully rather than competitively; and Neuroticism<sup>1</sup>, which is a tendency to  
45 experience negative emotions. These traits have been widely studied, for example in relation to job  
46 performance, mental health, and brain function (e.g., Caprara, Barbaranelli, Borgogni, & Perugini,  
47 1993; Caspi & Shiner, 2006; Digman, 1990; Haas, Constable, & Canli, 2008; Hurtz & Donovan,  
48 2000; Soldz & Vaillant, 1999), and in relation to music preference (Dollinger, 1993; Rawlings &  
49 Ciancarelli, 1997). However, it was not until Rentfrow and Gosling's (2003) seminal study that a  
50 factor-based model for measuring music preferences was attempted, resulting in the widely used  
51 Short Test of Music Preferences, or STOMP. Participants used a seven-point Likert scale to rate

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<sup>1</sup> 'Neuroticism' can be perceived as a negative trait and therefore sometimes it is re-conceptualized as Emotional Stability (or Emotionality), such that a positive correlation with Emotional Stability is the same as a *negative* correlation with Neuroticism. For the sake of consistency, results are reported in terms of Neuroticism in the current paper.

52 how much they liked each of a series of 14 musical genres: Blues, Jazz, Classical, Folk, Rock,  
53 Alternative, Heavy Metal, Country, Sound tracks, Religious, Pop, Rap/Hip-Hop, Soul/Funk,  
54 Electronica/Dance. These were found to be organized into four higher order factors: Reflective and  
55 Complex (Classica, Jazz, Blues and Folk), Intense and Rebellious (Alternative, Rock and Heavy  
56 Metal), Upbeat and Conventional (Country, Pop Religious and Soundtracks) and Energetic and  
57 Rhythmic (Rap/Hip-Hop, Soul/Funk, Electronica/Dance) (see Rentfrow and Gosling, Figure 6, p.  
58 1245). Rentfrow and Gosling found that Openness was positively correlated with liking for  
59 Reflective and Complex genres, and with liking for Intense and Rebellious genres. Meanwhile,  
60 Extraversion, Conscientiousness and Agreeableness were all positively correlated with liking for  
61 Upbeat and Conventional genres, while Neuroticism was negatively correlated with the same, and  
62 negatively correlated with liking for Reflective and Complex genres. Extraversion was also  
63 positively correlated with liking for Energetic and Rhythmic genres.

64 A number of studies seeking to replicate and extend Rentfrow and Gosling's findings have  
65 followed, with moderate success. Multiple studies have replicated the finding that Openness is  
66 associated with liking for music in the Reflective and Complex domain (Brown, 2012; Delsing et  
67 al., 2008; George, Stickle, Rachid, & Wopnford, 2007; Langmeyer, Guglhör-Rudan, & Tarnai,  
68 2012; Zweigenhaft, 2008). Other studies have expanded to include types of individual difference  
69 other than personality: Greenberg et al. (2015) found that trait Empathy was linked to preference for  
70 mellow music such as R&B and Soft Rock, while participants who were less empathetic and more  
71 systematic in their thinking preferred more intense music such as Punk, Metal and Hard Rock.  
72 Similarly, Clark and Giacomantonio (2013) found that the STOMP factor Reflective and Complex  
73 was positively related to empathy in males.

74 Inconsistencies have also emerged, however; George et al., (2007), for example, found  
75 Openness and Conscientiousness, rather than Extraversion and Agreeableness, to be correlated  
76 positively with liking for Dance/Electronica. Zweigenhaft (2008) did not find any personality

77 correlates for liking Intense and Rebellious music. Dunn, de Ruyter, and Bouwhuis (2012) provide  
78 an overview of these inconsistencies (p. 4) and further point out that each study's factor analysis has  
79 resulted in slightly different factor models of musical preference. They note that genres including  
80 Rap, Dance, Blues Jazz and Classical have been grouped inconsistently and suggest that each group  
81 of participants may have had somewhat different perceptions of these genres. George et al. (2007),  
82 for example, ultimately chose to measure participants' preferences by genre rather than higher-order  
83 factors after being unable to recreate the four factor model supplied by the STOMP. Others chose to  
84 begin with a different set of genres than the STOMP, typically for cultural reasons. Brown (2012),  
85 for example, who conducted a study using Japanese university students, excluded Country music  
86 and including *Enka*, a popular genre specific to Japan. In this case, Brown related factors to the  
87 STOMP conceptually rather than mathematically. Purhonen, Gronow, and Rahkonen, (2009)  
88 employed PCA and found four similar factors to the STOMP when examining musical taste in a  
89 Finnish population, but did not relate these preference factors to personality. Desling et al. (2008)  
90 used a different questionnaire entirely, specific to their population of Dutch teenagers. Dunn et al.  
91 (2012) used the original STOMP but failed to fully replicate the STOMP factor model due to Pop  
92 not loading onto the Upbeat and Conventional dimension, and ultimately used Principal Component  
93 Analysis (PCA) to determine five factors of their own. They found some positive correlations  
94 between music listening behavior and stated preferences, but suggested that perceptual ambiguity of  
95 some genres, such as Pop, may have contributed to lower correlations (Dunn et al., 2012).

96         These inconsistencies highlight musical genres as a problematic aspect in the quest for  
97 consistent and accurate measurement of music preferences. The ambiguity of genre labels, and  
98 differences between participants in their perception, is among the main difficulties in constructing a  
99 widely applicable model (Dunn et al., 2012); what comes to mind for one participant as an example  
100 of "Soft Rock" may be musically very different from another participant's conception. Indeed,  
101 Patchet and Cazaly (2000) investigated several large commercial genre taxonomies and found very

102 little overlap between them; Amazon and iTunes, at least, do not define Soft Rock the same way.  
103 Furthermore, a desire for broader appeal or to explore new creative ground can result in some artists  
104 inconveniently employing musical tropes from multiple genres, or inventing new sounds altogether.  
105 This, and the difficulty of conceptually separating very similar subgenres ultimately led Patchet and  
106 Cazaly to abandon efforts to develop a cohesive genre taxonomy (Aucoeur & Pachet, 2003).

107         One solution to this problem has been the creation of genre-free models of music preference.  
108 Rentfrow, Goldberg, and Levitin (2011) sought to re-conceptualize music preference by focusing  
109 on underlying musical features. The authors first developed preference factors based on  
110 participants' ratings of heard stimuli and then had judges assign attributes to the excerpts including  
111 musical and genre-based attributes. The five factors they defined were labeled Mellow,  
112 Unpretentious, Sophisticated, Intense and Contemporary. Recently, Greenberg et al. (2016)  
113 developed a three-factor solution using two familiar musical aspects—Arousal and Valence—and a  
114 third called Depth, which seems to be related to complexity and intellectual engagement. Openness  
115 positively correlated with a liking for Depth, and that some facets of Extraversion were correlated  
116 with liking for higher Arousal in music.

117         Though such models are undoubtedly very useful to music researchers, discarding genre-  
118 labels entirely within the measurement of preference may make the results less understandable and  
119 relevant for the everyday music listener. While few people would likely describe their own musical  
120 tastes in terms of arousal, valence and depth, genre is still common in average listeners' concepts of  
121 musical style (Lamere, 2008). Rentfrow and Gosling (2003) assessed participants' familiarity with  
122 70 genres and subgenres and found that the majority were familiar with broad genres but very few  
123 were familiar with all subgenres, suggesting genres are indeed a useful unit of measurement in  
124 preference. At the time, a new online phenomenon was only just becoming popular, and thus not yet  
125 available to researchers as a possible solution to the genre problem: social tagging (Lamere, 2008;  
126 Sordo, Celma, Blech, & Gaus, 2008).

127 Social tags may be defined as “free text labels that are applied to items such as artists, albums  
128 and songs” (Lamere, 2008, pp 101). Music-listening platforms such as Last.fm allow users to apply  
129 tags for purposes such as assisting in the retrieval of specific songs or groups of songs, organizing  
130 libraries, and documenting categories and opinions for social use. Sixty-eight percent of such tags  
131 of music are related to genre. Songs, artists, or albums may be tagged with multiple genres; thus, a  
132 song combining elements of Folk, Rock and Jazz can be tagged as all three without conflict  
133 (Lamere, 2008). Data from social tagging has been used, for example, in the development of  
134 automatic music recommendation systems (Bu et al., 2010), in the automatic classification of music  
135 according to mood and emotional content (Hu & Downie, 2010; Saari et al., 2013; Saari & Eerola,  
136 2014), and in developing hierarchical genre taxonomies, sometimes called “folksonomies” (Sordo  
137 et al., 2008). Song, Dixon, Pearce, and Fazekas (2013) successfully used social tags to select music  
138 stimuli for a study on music and emotion, but, at the time of writing, the authors know of no studies  
139 in which social tags have been used to select stimuli for the study of music preference.

140 The current study therefore aimed to replicate previous findings and address uncertainties in  
141 the relationships between music preference and personality, by employing a data-driven approach to  
142 stimuli selection using social tags to identify genres. The following hypotheses were tested:

143 H1) There will be a strong relationship between STOMP scores and the preference rating of  
144 stimuli of the same genre as identified by social-tagging.

145 H2) Principal Component Analysis of music preference using social-tagging selected stimuli  
146 will corroborate previous findings regarding factors of music preference.

147 H3) Previous findings regarding music preference and personality will be corroborated using  
148 social-tagging selected stimuli.

## 149 **Methods**

### 150 **Participants**



151 Participants ( $n = 210$ ) were recruited using University student and departmental e-mail lists  
152 and social media to complete an online survey and listening experiment. They ranged in age from  
153 19 to 68 years ( $M = 29.4$ ,  $SD = 10.3$ ) and were from 18 different countries. The most represented  
154 countries were Finland (69%), the United States (7.6%), Germany (6.7%) and Canada (6.7%). The  
155 majority were well educated, with 71% holding a Bachelor's or Master's degree. Forty-nine percent  
156 of participants had received some musical training during their lifetimes. Participants were entered  
157 into a lottery to win one of ten movie tickets (relevant to participants living in Finland only), and  
158 were also given feedback about their music preferences and personality upon completing the  
159 survey. Participants who completed the survey were also given the chance to sign up for a motion  
160 capture experiment for which they would earn two free movie tickets.

#### 161 **Stimuli**

162 As survey results were intended for use in a larger study involving music preference and  
163 music-induced movement, one requirement for stimuli was that they were suitable for dancing. A  
164 revised and updated version of the STOMP (the STOMP-R) is available online and was used as a  
165 starting point for genre selection ("Short Test Of Music Preferences (STOMP) | Gosling," n.d.).  
166 This version includes genres not found in the original STOMP such as Reggae and Gospel, thus  
167 providing a broader initial pool of genres from which to choose. Genres that were not suitable for  
168 dancing (e.g., Classical, Opera) were eliminated, as were genres that were not thought to be relevant  
169 to a primarily Finnish population. Religious music was eliminated as European students have been  
170 found to be significantly less religious than students in North America (Höllinger & Smith, 2002),  
171 while World Music was, of the genres examined by Purhonen et al. (2009), the least likely to have  
172 been heard by Finns at all. These eliminations resulted in the choice of 16 initial genres:  
173 Alternative, Bluegrass, Blues, Country, Dance/Electronica, Folk, Funk, Heavy Metal, Jazz, Oldies,  
174 Pop, Punk, Rap/Hip-Hop, Reggae, Rock, Soul/R&B.

175 Three online sources were accessed to collect the stimulus set: Last.fm, the Echo Nest API<sup>2</sup>  
176 and 7digital API. The initial stimulus set, which was collected in Saari & Eerola (2014), consisted  
177 of approximately 1,300,000 tracks, which were associated with 924,000 unique Last.fm tags. As  
178 identifying stimuli appropriate for a motion capture experiment was a principal aim of the process,  
179 a set of tags assumed to relate to danceability of a track were identified from the unique tags. For  
180 the identification, those tags that included "danceable", "dancing", "head banging", or  
181 "headbanging" as a separate phrase were considered. Consequently, tracks associated with any of  
182 these tags were retained in the set. Tracks strongly associated with genre tags were also retained. In  
183 order to obtain distinct genre subsets, tracks strongly associated to more than one of the genre tags  
184 were discarded. Next, the stimulus set was balanced in terms of genres by retaining no more than  
185 200 tracks for each genre tag, which led to a set of 2407 tracks.

186 In the next stage of the stimulus selection, the Echo Nest and 7digital APIs were accessed.  
187 First, tracks were matched against the Echo Nest and 7digital catalogues based on the artist names  
188 and track titles, and tracks found in both of the catalogues were retained. Tracks without an audio  
189 preview available from 7digital were discarded. The danceability of the tracks was validated by  
190 retaining only those tracks having non-zero danceability according Echo Nest, a measure based on  
191 computational extraction of the acoustic features of each track. Moreover, uniformity of the  
192 stimulus set in terms of tempo was ensured by including only tracks having tempo between 118 and  
193 132 BPM (beats per minute) as estimated by the Echo Nest; that is,  $\pm 12$  BPM of preferred  
194 spontaneous tempo (Repp & Su, 2013). To further narrow down the set, one track per artist was  
195 randomly selected, resulting in a set of 489 tracks from unique artists. Finally, four tracks were  
196 randomly subsampled from each genre, and genres having less than four tracks were excluded. This  
197 resulted in a set of 56 tracks from 14 genres.

---

<sup>2</sup> Since the data collection, the Echo Nest API has been taken down, but similar functionality exists in the Spotify Web API (<https://developer.spotify.com/web-api/>)

198 Excerpts were listened through by the authors to check for tempo and consistency of style.  
199 Excerpts representing Alternative and Folk were judged to be less suitable for dancing, due to  
200 inconsistent beat clarity and tactus levels, and were eliminated from the final stimuli set. The  
201 remaining 48 stimuli were used in the online listening experiment.

## 202 **Personality Measures**

203 FFM traits were measured using the Ten-Item Personality Inventory (TIPI), developed and  
204 validated by Gosling, Rentfrow and Swann (2003) and further validated by Ehrhart et al. (2009).  
205 This short test was chosen over longer versions in order to keep the total length of the survey within  
206 reason. In addition to personality, trait empathy and trait systemizing were also measured, as these  
207 traits have recently been shown to have some relationships with music preference (e.g., Greenberg et  
208 al., 2015). Empathy is a complex psychological process involving observation, memory, knowledge  
209 and reasoning, which allow for the understanding of others' emotions and perceptions (Decety &  
210 Jackson, 2004; Zahavi, 2010). It comprises both cognitive and affective processes (Harari, Shamay-  
211 Tsoory, Ravid, & Levkovitz, 2010; Shamay-Tsoory, Tomer, Goldsher, Berger, & Aharon-Peretz,  
212 2004). The Empathy Quotient (EQ), developed by Baron-Cohen and Wheelwright (2004), measures  
213 trait empathy as a whole, including both cognitive and affective aspects. Trait systemizing,  
214 measured by the Systemizing Quotient (SQ) can be defined as a drive or tendency to think  
215 analytically and in terms of systems; that is, in terms of predictable input, operation and output  
216 (Baron-Cohen, Richler, Bisarya, Gurunathan, & Wheelwright, 2003). Although trait systemizing  
217 and trait empathy vary independently of each other (rather than representing two opposite poles of a  
218 single trait), more than half of normal adults have been found to be stronger in one trait than the  
219 other (Lawson, Baron-Cohen, & Wheelwright, 2004). For the current study, trait empathizing and  
220 systemizing were measured using short-form versions of the EQ and SQ, developed and validated  
221 by Wakabayashi et al. (2006).

## 222 **Procedure**

223 The survey was administered using Survey Gizmo (www.surveygizmo.eu). Participants were  
 224 informed via an introduction page that their data would be kept private and used anonymously.  
 225 They were also informed that they would be listening to musical excerpts, and it was suggested that  
 226 they complete the survey in a quiet place using headphones. The TIPI, ES and SQ were filled out  
 227 prior to the listening experiment.

228 For the listening experiment, 30-second clips, including a one second fade-in and one second  
 229 fade-out, were presented to participants in a randomized order. Participants rated their liking for the  
 230 heard stimuli on a seven-point Likert scale. Participants could listen to an excerpt more than once.  
 231 After rating all 48 excerpts, participants then completed a version of the STOMP-R including only  
 232 the 12 genres used in the experiment. Data analysis was carried out using MATLAB and SPSS.

### 233 Results

234 As a first step, independent sample *t*-tests were used to determine whether there were  
 235 differences in personality between participants with and without musical training, since previous  
 236 research has shown that high levels of Openness predict involvement in music and the arts  
 237 (Rawlings & Ciancarelli, 1997). Results showed no significant differences in personality, trait  
 238 empathy or trait systemizing between participants with and without musical training (*p* ranged from  
 239 .07 to .91). However, *t*-tests revealed some differences between participants with and without  
 240 musical training in STOMP-R scores, shown in Table 1. Results suggested musicians liked Jazz,  
 241 Blues and Funk more than non-musicians while non-musically trained participants liked Metal  
 242 more than those with musical training.

243 *Table 1: Significant T-test results for STOMP-R (DF = 208)*

Genre	Musicians	Non-Musicians	<i>T</i> -statistic	<i>p</i> -value
Jazz	(M = 5.14, SD = 1.47)	(M = 4.46, SD = 1.80)	-2.98	< .01
Blues	(M = 5.12, SD = 1.28)	(M = 4.62, SD = 1.57)	-2.51	<.05
Funk	(M = 4.60, SD = 1.47)	(M = 4.19, SD = 1.52)	-2.01,	<.05

Metal (M = 3.48, SD = 2.16) (M = 4.14, SD = 2.29) 2.13, < .05

244

245 The results of the excerpt rating task indicated that, although there was a tendency towards  
 246 this same pattern of differences between musicians and non-musicians as in the STOMP-R, the only  
 247 difference that remained significant was that musically trained participants (M = 4.46, SD = 1.40)  
 248 rated the Jazz excerpts higher than non-musically trained participants (M = 3.39, SD = 1.44),  $t(208)$   
 249 = -2.92,  $p < .01$ .

250 Table 2 shows the distribution of STOMP-R scores. Correlation was run to examine the  
 251 relationship between STOMP-R scores and excerpt ratings. As shown in Table 1, all STOMP  
 252 genres correlated significantly and positively with mean excerpt ratings for each genre, with the  
 253 highest correlation being between Metal scores ( $r = .84$ ) and the lowest being between Funk scores  
 254 ( $r = .37$ ), suggesting that the chosen excerpts did indeed reflect the intended genres.

255 *Table 2. Correlation between STOMP scores and mean excerpt ratings for each genre.*

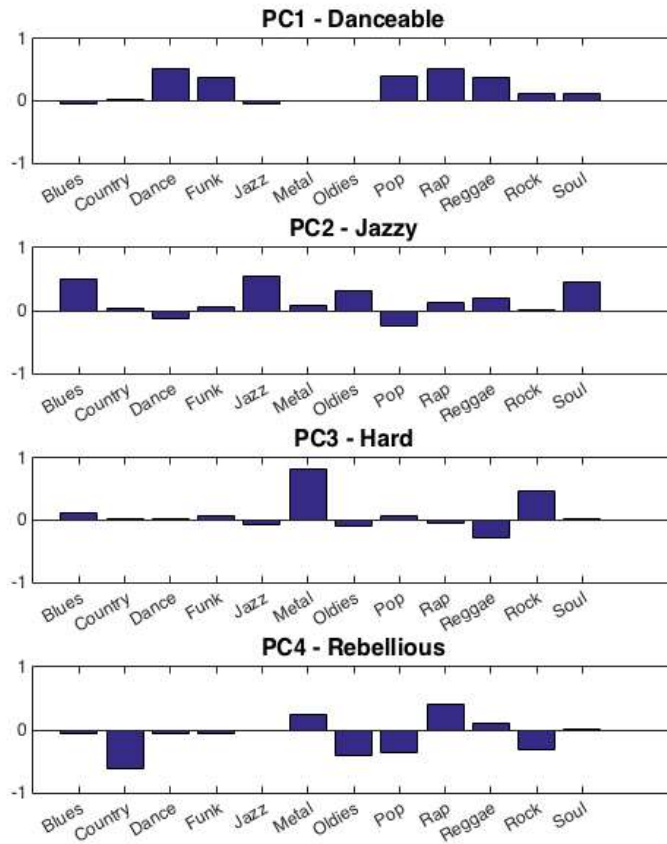
Genre	Pearson's $r$ (DF = 208)	$p$ -value
Blues	.61	<.001
Country	.69	<.001
Electronica/Dance	.53	<.001
Funk	.37	<.001
Jazz	.71	<.001
Metal	.84	<.001
Oldies	.53	<.001
Pop	.55	<.001
Rap	.70	<.001
Reggae	.60	<.001
Rock	.38	<.001
Soul	.48	<.001

256

257 To assess the relationships between genre preferences and to reduce the number of variables  
 258 prior to further analysis, Principal Component Analysis (PCA) was run on the mean excerpt ratings.

259 To simplify the interpretation, components were then rotated to align with coordinates using  
 260 varimax rotation, the results of which can be seen in Figure 1.

261 <<<Insert Figure 1 about here>>>



262

263 *Figure 1: Principal Component Analysis, Varimax Rotation Results*

264 Four components that collectively accounted for 75.5% of the total variance were retained for  
 265 further analysis. The first component accounted for 39.9% of the variance and included high  
 266 positive loadings on Pop, Dance and Funk; this component was therefore labeled Danceable. The  
 267 second component accounted for an additional 16% of the variance and included high positive  
 268 loadings on Blues, Jazz and Soul; this component was labeled Jazzy. The third component  
 269 accounted for 10.6% of the variance and included a very high positive loading on Metal and a  
 270 moderately high loading on Rock; this component was therefore labeled Hard. The fourth

271 component accounted for 8.96% of the variance and included a high positive loading for Rap/Hip-  
272 Hop and high negative loadings for Country and Oldies and a moderate negative loading for Pop;  
273 this component was therefore described as Rebellious.

274 TIPI, EQ and SQ scores were correlated with component scores to assess relationships  
275 between personality and music preference. Liking for Danceable music was weakly positively  
276 correlated with Neuroticism ( $r = .14, p < .05$ ). Liking for Jazzy music was positively correlated with  
277 Openness ( $r = .20, p < .01$ ) and negatively correlated with Conscientiousness ( $r = -.17, p < .05$ ).  
278 Liking for Hard music was negatively correlated with EQ score ( $r = -.17, p < .05$ ), negatively  
279 correlated with Openness ( $r = -.21, p < .01$ ) and negatively correlated with Extraversion ( $r = -.16, p$   
280  $< .05$ ). Liking for Rebellious music was positively correlated with SQ score ( $r = .16, p < .05$ ) and  
281 negatively correlated with Agreeableness ( $r = -.21, p < .01$ ).

282 As very little previous research has been done exploring relationships between trait empathy,  
283 trait systemizing and music preference, correlations between EQ and SQ scores and STOMP-R  
284 scores were also carried out to assess possible relationships in further detail. EQ score was  
285 positively correlated with liking for Blues ( $r = .19, p < .01$ ), liking for Funk ( $r = .25, p < .001$ ) and  
286 Soul ( $r = .25, p < .001$ ). There were no significant correlations between SQ scores and STOMP-R  
287 ratings.

## 288 **Discussion**

289 The current study examined relationships between music preferences and individual  
290 differences in personality, empathy and systemizing, using a novel, data-driven approach to excerpt  
291 selection. Previous music preference research involving listening tasks have employed industry  
292 standards (Dunn et al., 2012) and expert suggestion (Delsing et al., 2008; Rentfrow, Goldberg, &  
293 Levitin, 2011) to identify stimuli that are representative of desired musical genres, but this is, to the  
294 knowledge of the authors, the first attempt to use social tagging to identify such stimuli. Analysis  
295 showed correlations between participants' ratings of genres via the STOMP-R and their ratings of

296 the selected stimuli, suggesting that the stimuli were indeed representative of the desired genres.  
297 Although not directly comparable, it is worth noting that the majority of these correlations were  
298 noticeably higher than those found comparing STOMP-R ratings to participants' time spent  
299 listening to expert-selected stimuli (Dunn et al., 2012, pp 12). That participants' overall ratings of  
300 genres were higher than their rating of the excerpts indicates some room for improvement in the  
301 current method. However, it is unlikely that any small set of excerpts can adequately account for all  
302 ambiguity and differences in genre perception. The heard excerpts may simply not have reflected all  
303 participants' preferences within their preferred genres in general or in relation to a specific element  
304 of the excerpt, such as the lyrics or specific artist.

305 As the current data were collected in the context of a larger dance experiment, the included  
306 genres were limited to those that one could easily dance to and thus not directly comparable to  
307 previous works examining underlying factors of music preference. However, PCA did reveal  
308 similarities between the current data and previous findings, as well as some unique insights. The  
309 component labeled Jazzy is virtually identical to the component found by Dunn et al. (2012),  
310 labeled Rhythm 'n' Blues. The component labeled Hard is similar to a component Dunn et al.  
311 named Hard Rock, and also somewhat similar to Rentfrow and Gosling's (2003) Intense and  
312 Rebellious factor. The Danceable component includes some of the same elements and Rentfrow and  
313 Gosling's Energetic and Rhythmic factor, namely Funk and Electronica/Dance, but for both  
314 Rentfrow and Gosling as well as Dunn et al., Pop loaded onto a different component from these,  
315 suggesting that the Danceable component describes a broader range. Dunn et al. found Pop to be  
316 grouped with Soundtracks in a Soft Rock component; Rentfrow and Gosling found it to be grouped  
317 with Country and Folk in the Upbeat and Conventional. These differences may also reflect that  
318 participants do not perceive clear boundaries for Pop, or that their conceptions of what constitutes  
319 Pop may be quite broad. It is also possible, since the current dataset did not include genres like  
320 Folk, Religious or Soundtracks, that the musical features Pop shares with Funk and Dance, such as



321 tempo and instrumentation, were more prominent for participants in determining similarity than  
322 were extra-musical social factors such as social significance.

323 Social significance could, however, be important in the final component identified in the  
324 current paper: Rebellious. This component included a positive loading on Rap/Hip-Hop along with  
325 notably negative loadings on Country and Oldies, and a moderately negative loading for Pop, all of  
326 which are classified under ‘Upbeat and Conventional’ according to the latest version of the  
327 STOMP-R (“Short Test Of Music Preferences (STOMP) | Gosling,” n.d.). Although it would be  
328 foolish to suggest that no individual could enjoy both Rap and Country music, it is interesting to  
329 consider that dimensions of music preference might simultaneously include likes and dislikes.  
330 Dislikes have been implied by previous research in that preference components are treated as  
331 bipolar (i.e. a negative correlation between Conscientiousness and liking for Jazz interpreted as  
332 conscientious people *disliking* Jazz), but disliking has not been as thoroughly researched as liking.  
333 It is possible that in the current study’s Rebellious component, strong dislike of particular genres  
334 (e.g., Country) may have sociological bases that overshadow simple hedonic reactions to acoustic  
335 signals (Bryson, 1996). Both Rap/Hip-Hop and Country are often associated with mainstream  
336 American culture and complex historical and socioeconomic extra-musical factors therein (Mann,  
337 2008; Shevy, 2008; Sullivan, 2001; Watkins, 2001), and while cannot assume the same associations  
338 for a Finnish population, Tervo (2014) suggests Rap/Hip-Hop has been adapted by Finnish culture  
339 and maintains themes of marginalization and oppression (albeit sometimes humorously). Purhonen  
340 et al. (2009), however, found socioeconomic variables like education and income explained very  
341 little variance in liking for Hip-Hop and Electronic music, but that there were significant negative  
342 correlations between education and liking for their music dimension Popular Folk (similar in many  
343 ways to Rentfrow and Gosling’s Upbeat and Conventional; see Purhonen et al., Table 2, pp 43 for  
344 details), as well as positive correlations between liking for this dimension and living in ‘Village’ or

345 ‘Country’ areas, suggestive of socio-cultural influences at least for the negative loadings on the  
346 current Rebellious factor.

347 The relationships between personality and music preferences somewhat supports previous  
348 work. The positive correlation between Openness and liking for Jazzy music replicates previous  
349 findings linking Openness to preference for more complex music (Brown, 2012; Dunn et al., 2012;  
350 George et al., 2007; Greenberg et al., 2016; Langmeyer et al., 2012; Rentfrow & Gosling, 2003)  
351 corroborating evidence of this relationship being relatively stable across different samples. Dunn et  
352 al. (2012), also found a negative relationship between Conscientiousness and liking for Jazz,  
353 suggesting that this relationship, while not as strongly supported as the former, may not be spurious.

354 Liking for Hard music was negatively correlated with Openness, which contradicts previous  
355 findings associating Openness with liking for genres such as Rock, Hard Rock, Alternative and etal  
356 (Delsing et al., 2008; Dunn et al., 2012; Rentfrow & Gosling, 2003). One explanation, given the  
357 relatively correlation between excerpt ratings (.38) with STOMP-R scores for Rock, may be that the  
358 excerpts did not accurately reflect listeners’ perceptions of the genre. However, the correlation  
359 between STOMP-R and mean excerpt scores was the highest (.86) for Metal, which also had the  
360 highest loading for this dimension and was probably the main driver of results. Previous research  
361 has taken place in the United States, Holland and Japan, but current study is, to the authors’  
362 knowledge, the first large study of music preference and personality to be conducted from Finland,  
363 which supposedly boasts the largest number of metal bands per capita in the world (“A World Map  
364 of Metal Bands Per Capita - The Atlantic,” n.d.). Notably fewer people dislike Metal in Finland  
365 than in the U.K. (Purhonen et al., 2009). Since previous research has found a relationship between  
366 familiarity and liking (e.g., North & Hargreaves, 1995), the Finnish population may be predisposed  
367 to enjoy Metal more than other populations due to exposure. It is probable that liking for Metal is  
368 perceived as less unusual in Finland than in other parts of the world, as one would not need to be  
369 particularly open to new experience in order to become familiar with the genre.

370 Liking for Rebellious music (which, as discussed above, can also be conceived of as a dislike  
371 for conventional music such as Country and Oldies) was negatively correlated with Agreeableness.  
372 This is in line with Rentfrow and Gosling's (2003) finding that Agreeableness was positively  
373 correlated with liking for Upbeat and Conventional music, including Country and Oldies, although  
374 contrary to their finding that Agreeableness was associated with liking for Energetic and Rhythmic  
375 music, including Hip-Hop and Rap. This may have to do with the relationship of Rap/Hip-Hop and  
376 Country within the current study's PCA components, but could also be due to differences between  
377 Finland and the United States in terms of the perceived social significance and popularity of  
378 Rap/Hip-Hop. Liking for Danceable music was slightly positively correlated with Neuroticism.  
379 Both Brown (2012) and Langmeyer et al. (2012) found positive correlations between Neuroticism  
380 and liking for Pop, which loaded strongly onto the Danceable component in the current research. As  
381 Neuroticism is associated with a tendency to experience negative feelings (Haas et al., 2008;  
382 Letzring & Adamecik, 2015; Mezquita et al., 2015), this association may reflect participants' use of  
383 music in mood regulation (Koelsch, 2010; Saarikallio, 2011; Saarikallio & Erkkilä, 2007), although  
384 the effect is small.

385 Although far less has previously been written regarding empathy, systemizing and music  
386 preference, the current results do somewhat support previous findings. Empathy was associated  
387 with decreased liking for Hard music, while liking for Rebellious music was positively correlated  
388 with systemizing. Although not identical to Greenberg's (2015) finding that high empathizers  
389 preferred Mellow music (e.g., Soft Rock, Jazz, Soul) while high systemizers preferred Intense music  
390 (e.g., Rock, Metal), the current results do not conflict with these findings. One could suspect, for  
391 example, that a person who dislikes harder music such as Metal may prefer mellower sounds, while  
392 a person who enjoys understanding patterns and complex systems might be easily bored by  
393 structurally simple music. Furthermore, analysis of STOMP-R results for individual genres revealed  
394 that empathy was indeed positively correlated with liking for Blues, Funk and Soul, more directly

395 corroborating Greenberg's previous finding. Given the current study's tempo restrictions (all  
396 excerpts were between 118 and 132 BPM), it is perhaps unsurprising that we were unable exactly  
397 replicate Greenberg's work regarding Mellow music, as one character of this factor is slower  
398 tempos, which were not available in the current stimuli set.

399         In general, the strengths of the correlations found in the current study were weak to moderate,  
400 which is in line with virtually all previous work exploring the relationships between personality  
401 traits and music preferences (Brown, 2012; Delsing et al., 2008; Dunn et al., 2012; Greenberg et al.,  
402 2015, 2016; Langmeyer et al., 2012; Rentfrow & Gosling, 2003; Zweigenhaft, 2008). Nevertheless,  
403 the replication of many of these findings seems to indicate that a genuine effect is there to be  
404 detected. That the effect remains small, and that there are also many inconsistencies to be found  
405 between studies seems to indicate that there are other significant factors beyond personality which  
406 have an effect on music preferences. Some, such as the truly unique experiences of individuals  
407 which help to shape their tastes, are likely impossible to quantify and may be best studied  
408 qualitatively. Still, as the current results suggest, cultural and social contexts may influence the  
409 relationships of traits to preferences. Schäfer and Sedlmeier (2009) have suggested that the  
410 functionality of music to an individual may play an important role in determining music preference,  
411 including social functionality. Rentfrow and Gosling's (2006; 2007) findings suggest that music  
412 preference can be used in social signaling. Understanding and accounting for such influences in  
413 future research may result in a clearer and more consistent picture of the effects of personality and  
414 other individual differences on music preferences.

415         The information gained from social tagging of music, shown here to be an effective means of  
416 identifying music stimuli that are representative of specific genres, could also be used to gain  
417 further insight into music preference. Social tagging has been used, for example, to examine  
418 perceived emotional content in music (Saari et al., 2013; Saari & Eerola, 2014), which could  
419 provide important contextual information about preferences. Due to the unrestricted nature of most

420 tagging platforms, social tags can also include locations (e.g., “San Francisco” could indicate a band  
421 local to or popular in that area), information about specific instrumentation (e.g., “Female vocals” or  
422 “Erhu”), and popular opinions (e.g., “Amazing” or “Your Ears Will Bleed”), all of which could also  
423 be used in further research into individual music preferences (Lamere, 2008).

424         The results of the current study should be replicated and expanded with fewer restrictions  
425 regarding dancability and tempo, and with more control over potentially influential factors such as  
426 the affective content of lyrics, and with different populations. Further study is also needed to gain  
427 understanding into how individual traits beyond personality, such as empathy and systemizing are  
428 related to the kinds of music we like best. As the current study demonstrates, there is plenty of room  
429 for continued innovation in how we approach the study of this rich and complex topic.

430

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## Appendix: Track list

<b>Genre</b>	<b>Artist</b>	<b>Track</b>	<b>Excerpt</b>
Blues	Tom Waits	Big, Black Mariah (Live)	0:30 - 1:00
Blues	The Paul Butterfield Blues Band	Mystery Train	0:24 - 0:54
Blues	Ray Charles	I Got A Woman (Live at Newport Jazz)	2:40 - 3:10
Blues	Keb' Mo'	She Just Wants to Dance	0:32 - 1:02
Country	Dixie Chicks	Goodbye Earl	0:30 - 1:00
Country	Faron Young	Goin' Steady	1:04 - 1:34
Country	Brooks & Dunn	My Maria	0:38 - 1:08
Country	Martina McBride	Independence Day	0:49 - 1:19
Dance/Electronica	Betty Boo	Doin' The Do (Radio Mix)	2:16 - 2:46
Dance/Electronica	ThouShaltNot	Come A Time	0:30 - 1:00
Dance/Electronica	M People	Sight For Sore Eyes (Dance Remix)	0:40 - 1:10
Dance/Electronica	Lady GaGa	LoveGame (The Gaga Bender Mix)	2:18 - 2:48
Funk	Dazz Band	Let It All Blow	0:30 - 1:00
Funk	Groove Collective	Everything Is Changing	0:30 - 1:00
Funk	Marcia Griffiths	Electric Boogie	0:44 - 1:14
Funk	The Bar-Keys	Freakshow on the Dance Floor	0:46 - 1:16
Jazz	Jimmie Lunceford	Lunceford Special	0:53 - 1:23
Jazz	Sidney Bechet	Muskrat Ramble	0:06 - 0:36
Jazz	The Jazz Crusaders	Tough Talk (2003 Remaster)	1:03 - 1:33
Jazz	Fatima Spar und die Freedom Fries	Egyptian Ella	1:30 - 2:00
Metal	Metallica	Until It Sleeps	0:30 - 1:00
Metal	Lamb of God	Redneck	1:16 - 1:46
Metal	My Fate	Sinking	0:28 - 0:58
Metal	White Zombie	Thunder Kiss	0:31 - 1:01
Oldies	The Archies	Sugar, Sugar	0:30 - 1:00
Oldies	Maurice Williams and The Zodiacs	Stay	0:31 - 1:01
Oldies	The Del-Vikings	Whispering Bells	0:38 - 1:08
Oldies	Anne-Margret	Slowly	0:50 - 1:20
Pop	Geri Halliwell	Bag It Up	1:25 - 1:55
Pop	Christina Aguilera	Come On Over	0:30 - 1:00
Pop	The Feeling	Love it When You Call	0:38 - 1:08
Pop	Duran Duran	Want You More!	0:48 - 1:18
Rap/Hip-Hop	Dizzee Rascal	Dance Wiv Me	1:38 - 2:08
Rap/Hip-Hop	Run-DMC, Jason Nevins	It's Like That	0:37 - 1:07
Rap/Hip-Hop	The Sugarhill Gang	8 <sup>th</sup> Wonder	2:07 - 2:37
Rap/Hip-Hop	DJ Laz	Move Shake Drop (Remix)	0:30 - 1:00

Reggae	Bob Marley	Jah Live	0:30 - 1:00
Reggae	Culcha Candela	Partybus	0:35 - 1:05
Reggae	Sean Paul	Temperature	0:32 - 1:02
Reggae	Shaggy	Oh Carolina	0:43 - 1:13
Rock	Supergrass	Mary	1:30 - 2:00
Rock	Sting	If You Love Somebody Set Them Free	1:38 - 2:08
Rock	Billy Idol	Don't You (Forget About Me)	0:15 - 0:45
Rock	The Cardigans	Godspell	0:30 - 1:00
Soul/R&B	Aretha Franklin	Eleanor Rigby	0:45 - 1:15
Soul/R&B	James Brown	Let Yourself Go	0:30 - 1:00
Soul/R&B	Wilson Pickett	In The Midnight Hour	0:40 - 1:10
Soul/R&B	Boyz II Men	Under Pressure	0:30 - 1:00

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Note: All tracks were accessed as audio previews from 7digital. For ease of editing, some tracks also purchased privately. Please contact the author to request exact copies of the stimuli.