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

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

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Research linking music preferences to personality is nearly as old as modern measures of personality themselves; early pioneers of personality research suggested that participants' ratings of heard music might even function as a kind of Rorschach test to reveal subconscious emotional tendencies (Cattell & Anderson, 1953). Over the following decades, the development of a widely validated five factor model (FFM) of personality led to greater comparability across personality studies (Digman, 1990). The five traits are comprised of Openness, which is the tendency to broadly enjoy arts, new ideas and experiences; Conscientiousness, which is the tendency to be responsible, organized and self-disciplined; Extraversion, which is the tendency to seek and enjoy social engagement and high energy activities; Agreeableness, which is the tendency to act cooperatively and helpfully rather than competitively; and Neuroticism¹, which is a tendency to experience negative emotions. These traits have been widely studied, for example in relation to job performance, mental health, and brain function (e.g., Caprara, Barbaranelli, Borgogni, & Perugini, 1993; Caspi & Shiner, 2006; Digman, 1990; Haas, Constable, & Canli, 2008; Hurtz & Donovan, 2000; Soldz & Vaillant, 1999), and in relation to music preference (Dollinger, 1993; Rawlings & Ciancarelli, 1997). However, it was not until Rentfrow and Gosling's (2003) seminal study that a factor-based model for measuring music preferences was attempted, resulting in the widely used Short Test of Music Preferences, or STOMP. Participants used a seven-point Likert scale to rate

¹ '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

correlates for liking Intense and Rebellious music. Dunn, de Ruyter, and Bouwhuis (2012) provide an overview of these inconsistencies (p. 4) and further point out that each study's factor analysis has resulted in slightly different factor models of musical preference. They note that genres including Rap, Dance, Blues Jazz and Classical have been grouped inconsistently and suggest that each group of participants may have had somewhat different perceptions of these genres. George et al. (2007), for example, ultimately chose to measure participants' preferences by genre rather than higher-order factors after being unable to recreate the four factor model supplied by the STOMP. Others chose to begin with a different set of genres than the STOMP, typically for cultural reasons. Brown (2012), for example, who conducted a study using Japanese university students, excluded Country music and including Enka, a popular genre specific to Japan. In this case, Brown related factors to the STOMP conceptually rather than mathematically. Purhonen, Gronow, and Rahkonen, (2009) employed PCA and found four similar factors to the STOMP when examining musical taste in a Finnish population, but did not relate these preference factors to personality. Desling et al. (2008) used a different questionnaire entirely, specific to their population of Dutch teenagers. Dunn et al. (2012) used the original STOMP but failed to fully replicate the STOMP factor model due to Pop not loading onto the Upbeat and Conventional dimension, and ultimately used Principal Component Analysis (PCA) to determine five factors of their own. They found some positive correlations between music listening behavior and stated preferences, but suggested that perceptual ambiguity of some genres, such as Pop, may have contributed to lower correlations (Dunn et al., 2012). These inconsistencies highlight musical genres as a problematic aspect in the quest for consistent and accurate measurement of music preferences. The ambiguity of genre labels, and differences between participants in their perception, is among the main difficulties in constructing a widely applicable model (Dunn et al., 2012); what comes to mind for one participant as an example of "Soft Rock" may be musically very different from another participant's conception. Indeed, Patchet and Cazaly (2000) investigated several large commercial genre taxonomies and found very

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Furthermore, a desire for broader appeal or to explore new creative ground can result in some artists

little overlap between them; Amazon and iTunes, at least, do not define Soft Rock the same way.

inconveniently employing musical tropes from multiple genres, or inventing new sounds altogether.

This, and the difficulty of conceptually separating very similar subgenres ultimately led Patchet and

Cazaly to abandon efforts to develop a cohesive genre taxonomy (Aucouturier & Pachet, 2003).

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

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

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

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

- H1) There will be a strong relationship between STOMP scores and the preference rating of stimuli of the same genre as identified by social-tagging.
- H2) Principal Component Analysis of music preference using social-tagging selected stimuli will corroborate previous findings regarding factors of music preference.
- H3) Previous findings regarding music preference and personality will be corroborated using social-tagging selected stimuli.

149 Methods

Participants

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

Stimuli

As survey results were intended for use in a larger study involving music preference and music-induced movement, one requirement for stimuli was that they were suitable for dancing. A revised and updated version of the STOMP (the STOMP-R) is available online and was used as a starting point for genre selection ("Short Test Of Music Preferences (STOMP) | Gosling," n.d.). This version includes genres not found in the original STOMP such as Reggae and Gospel, thus providing a broader initial pool of genres from which to choose. Genres that were not suitable for dancing (e.g., Classical, Opera) were eliminated, as were genres that were not thought to be relevant to a primarily Finnish population. Religious music was eliminated as European students have been found to be significantly less religious than students in North America (Höllinger & Smith, 2002), while World Music was, of the genres examined by Purhonen et al. (2009), the least likely to have been heard by Finns at all. These eliminations resulted in the choice of 16 initial genres:

Alternative, Bluegrass, Blues, Country, Dance/Electronica, Folk, Funk, Heavy Metal, Jazz, Oldies, Pop, Punk, Rap/Hip-Hop, Reggae, Rock, Soul/R&B.

Three online sources were accessed to collect the stimulus set: Last.fm, the Echo Nest API² and 7digital API. The initial stimulus set, which was collected in Saari & Eerola (2014), consisted of approximately 1,300,000 tracks, which were associated with 924,000 unique Last.fm tags. As identifying stimuli appropriate for a motion capture experiment was a principal aim of the process, a set of tags assumed to relate to danceability of a track were identified from the unique tags. For the identification, those tags that included "danceable", "dancing", "head banging", or "headbanging" as a separate phrase were considered. Consequently, tracks associated with any of these tags were retained in the set. Tracks strongly associated with genre tags were also retained. In order to obtain distinct genre subsets, tracks strongly associated to more than one of the genre tags were discarded. Next, the stimulus set was balanced in terms of genres by retaining no more than 200 tracks for each genre tag, which led to a set of 2407 tracks.

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

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² 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/)

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

Personality Measures

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

Procedure

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

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

Results

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

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

Genre	Musicians	Non-Musicians	T-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

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

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

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

Genre	Pearson's r	<i>p</i> -value
	(DF = 208)	
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

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

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

<<<Insert Figure 1 about here>>>

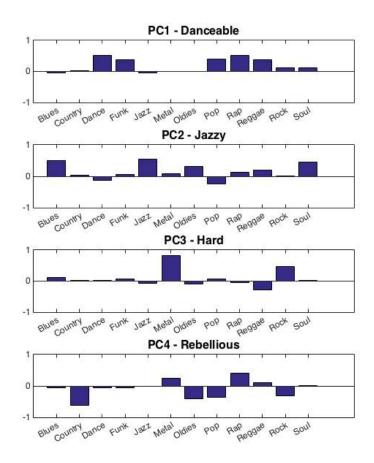


Figure 1: Principal Component Analysis, Varimax Rotation Results

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

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

TIPI, EQ and SQ scores were correlated with component scores to assess relationships

between personality and music preference. Liking for Danceable music was weakly positively correlated with Neuroticism (r = .14, p < .05). Liking for Jazzy music was positively correlated with Openness (r = .20, p < .01) and negatively correlated with Conscientiousness (r = -.17, p < .05). Liking for Hard music was negatively correlated with EQ score (r = -.17, p < .05), negatively correlated with Openness (r = -.21, p < .01) and negatively correlated with Extraversion (r = -.16, p < .05). Liking for Rebellious music was positively correlated with SQ score (r = .16, p < .05) and negatively correlated with Agreeableness (r = -.21, p < .01).

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

Discussion

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

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

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

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

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

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

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The relationships between personality and music preferences somewhat supports previous work. The positive correlation between Openness and liking for Jazzy music replicates previous findings linking Openness to preference for more complex music (Brown, 2012; Dunn et al., 2012; George et al., 2007; Greenberg et al., 2016; Langmeyer et al., 2012; Rentfrow & Gosling, 2003) corroborating evidence of this relationship being relatively stable across different samples. Dunn et al. (2012), also found a negative relationship between Conscientiousness and liking for Jazz, suggesting that this relationship, while not as strongly supported a the former, may not be spurious. Liking for Hard music was negatively correlated with Openness, which contradicts previous findings associating Openness with liking for genres such as Rock, Hard Rock, Alternative and etal (Delsing et al., 2008; Dunn et al., 2012; Rentfrow & Gosling, 2003). One explanation, given the relatively correlation between excerpt ratings (.38) with STOMP-R scores for Rock, may be that the excerpts did not accurately reflect listeners' perceptions of the genre. However, the correlation between STOMP-R and mean excerpt scores was the highest (.86) for Metal, which also had the highest loading for this dimension and was probably the main driver of results. Previous research has taken place in the United States, Holland and Japan, but current study is, to the authors' knowledge, the first large study of music preference and personality to be conducted from Finland, which supposedly boasts the largest number of metal bands per capita in the world ("A World Map of Metal Bands Per Capita - The Atlantic," n.d.). Notably fewer people dislike Metal in Finland than in the U.K. (Purhonen et al., 2009). Since previous research has found a relationship between familiarity and liking (e.g., North & Hargreaves, 1995), the Finnish population may be predisposed to enjoy Metal more than other populations due to exposure. It is probable that liking for Metal is perceived as less unusual Finland than in other parts of the world, as one would not need to be

particularly open to new experience in order to become familiar with the genre.

for conventional music such as Country and Oldies) was negatively correlated with Agreeableness. This is in line with Rentfrow and Gosling's (2003) finding that Agreeableness was positively correlated with liking for Upbeat and Conventional music, including Country and Oldies, although contrary to their finding that Agreeableness was associated with liking for Energetic and Rhythmic music, including Hip-Hop and Rap. This may have to do with the relationship of Rap/Hip-Hop and Country within the current study's PCA components, but could also be due to differences between Finland and the United States in terms of the perceived social significance and popularity of Rap/Hip-Hop. Liking for Danceable music was slightly positively correlated with Neuroticism. Both Brown (2012) and Langmeyer et al. (2012) found positive correlations between Neuroticism and liking for Pop, which loaded strongly onto the Danceable component in the current research. As Neuroticism is associated with a tendency to experience negative feelings (Haas et al., 2008; Letzring & Adamcik, 2015; Mezquita et al., 2015), this association may reflect participants' use of music in mood regulation (Koelsch, 2010; Saarikallio, 2011; Saarikallio & Erkkilä, 2007), although the effect is small. Although far less has previously been written regarding empathy, systemizing and music preference, the current results do somewhat support previous findings. Empathy was associated with decreased liking for Hard music, while liking for Rebellious music was positively correlated with systemizing. Although not identical to Greenberg's (2015) finding that high empathizers preferred Mellow music (e.g., Soft Rock, Jazz, Soul) while high systemizers preferred Intense music (e.g., Rock, Metal), the current results do not conflict with these findings. One could suspect, for example, that a person who dislikes harder music such as Metal may prefer mellower sounds, while

a person who enjoys understanding patterns and complex systems might be easily bored by

structurally simple music. Furthermore, analysis of STOMP-R results for individual genres revealed

that empathy was indeed positively correlated with liking for Blues, Funk and Soul, more directly

Liking for Rebellious music (which, as discussed above, can also be conceived of as a dislike

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

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

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

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

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

431	References
432	A World Map of Metal Bands Per Capita - The Atlantic. (n.d.). Retrieved from
433	http://www.theatlantic.com/entertainment/archive/2012/03/world-map-metal-band-population-
434	density/329913/
435	Aucouturier, JJ., & Pachet, F. (2003). Representing Musical Genre: A state of the art. Jouranl of
436	New Music Research, 32(1), 83–93. http://doi.org/10.1076/jnmr.32.1.83.16801
437	Baron-Cohen, S., Richler, J., Bisarya, D., Gurunathan, N., & Wheelwright, S. (2003). The
438	systemizing quotient: an investigation of adults with Asperger syndrome or high-functioning
439	autism, and normal sex differences. Philosophical Transactions of the Royal Society of
440	London. Series B, Biological Sciences, 358(1430). http://doi.org/10.1098/rstb.2002.1206
441	Baron-Cohen, S., & Wheelwright, S. (2004). The Empathy Quotient: An Investigation of Adults
442	with Asperger Syndrome or High Functioning Autism, and Normal Sex Differences. Journal
443	of Autism and Developmental Disorders, 34(2), 163–175.
444	Boer, D., Fischer, R., Strack, M., Bond, M. H., Lo, E., & Lam, J. (2011). How shared preferences in
445	music create bonds between people: values as the missing link. Personality & Social
446	Psychology Bulletin, 37(9), 1159–1171.
447	Brown, R. A. (2012). Music preferences and personality among Japanese university students.
448	International Journal of Psychology, 47(4), 259–268.
449	Bryson, B. (1996). "Anything But Heavy Metal": Symbolic Exclusion and Musical Dislikes.
450	American Sociological Review, 61(5), 884-899. http://doi.org/10.2307/2096459
451	Bu, J., Tan, S., Chen, C., Wang, C., Wu, H., Zhang, L., & He, X. (2010). Music Recommendation
452	by Unified Hypergraph: Combining Social Media Information and Music Content. In
453	Proceedings of the 18th ACM international conference on Multimedia (pp. 391–400). Firenze,
454	Italy.
455	Caprara, G. V., Barbaranelli, C., Borgogni, L., & Perugini, M. (1993). The "Big Five

456 Questionnaire": A new questionnaire to assess the five factor model. Personality and 457 Individual Differences, 15(3), 281–288. 458 Caspi, A., & Shiner, R. L. (2006). Personality development. *Handbook of Child Psychology*. 459 Cattell, R. B., & Anderson, J. C. (1953). The measurement of personality and behavior disorders by 460 the IPAT Music Preference Test. Journal of Applied Psychology, 37(6), 446–454. 461 Clark, S. S., & Giacomantonio, S. G. (2013). Music preferences and empathy: Toward predicting 462 prosocial behavior. Psychomusicology: Music, Mind, and Brain, 23(3), 177–186. 463 http://doi.org/10.1037/a0034882 464 Decety, J., & Jackson, P. L. (2004). The functional architecture of human empathy. Behavioral and 465 *Cognitive Neuroscience Reviews*, *3*(2), 71–100. 466 Delsing, M. J. M. H., Ter Bogt, T. F. M., Engels, R. C. M. E., Meeus, W. H. J., Bogt, T. F. M. Ter, 467 Engels, R. C. M. E., & Meeus, W. H. J. (2008). Adolescents' music preferences and 468 personality characteristics. European Journal of Personality, 22(2), 109–130. 469 http://doi.org/10.1002/per.665 470 Digman, J. M. (1990). Personality structure: Emergence of the five-factor model. Annual Review of 471 Psychology, 41(1), 417–440. 472 Dollinger, S. J. (1993). Research Note: Personality and Music Preference: Extraversion and 473 Excitement Seeking or Openness to Experience? *Psychology of Music*, 21(1), 73–77. 474 http://doi.org/10.1177/030573569302100105 475 Dunn, P. G., de Ruyter, B., & Bouwhuis, D. G. (2012). Toward a better understanding of the 476 relation between music preference, listening behavior, and personality. Psychology of Music, 40(4), 411–428. http://doi.org/10.1177/0305735610388897 477 478 Ehrhart, M. G., Ehrhart, K. H., Roesch, S. C., Chung-Herrera, B. G., Nadler, K., & Bradshaw, K.

(2009). Testing the latent factor structure and construct validity of the Ten-Item Personality

Inventory. Personality and Individual Differences, 47(8), 900–905.

479

- 481 George, D., Stickle, K., Rachid, F., & Wopnford, A. (2007). The Association Between Types of
- Music Enjoyed and Cognitive, Behavioral, and Personality Factors of Those who Listen.
- 483 *Psychomusicology*, 19(2), 32–56.
- 484 Gosling, S. D., Rentfrow, P. J., & Swann, W. B. (2003). A very brief measure of the Big-Five
- personality domains. *Journal of Research in Personality*, 37(6), 504–528.
- 486 Greenberg, D. M., Baron-Cohen, S., Stillwell, D. J., Kosinski, M., Rentfrow, P. J., Blacking, J., ...
- Fonagy, P. (2015). Musical Preferences are Linked to Cognitive Styles. *PLOS ONE*, 10(7),
- 488 e0131151. http://doi.org/10.1371/journal.pone.0131151
- 489 Greenberg, D. M., Kosinski, M., Stillwell, D. J., Monteiro, B. L., Levitin, D. J., & Rentfrow, P. J.
- 490 (2016). The Song Is You Preferences for Musical Attribute Dimensions Reflect Personality.
- 491 *Social Psychological and Personality Science*, 7(6), 597–605.
- 492 Haas, B. W., Constable, R. T., & Canli, T. (2008). Stop the sadness: Neuroticism is associated with
- sustained medial prefrontal cortex response to emotional facial expressions. *NeuroImage*,
- 494 *42*(1), 385–392.
- Harari, H., Shamay-Tsoory, S. G., Ravid, M., & Levkovitz, Y. (2010). Double dissociation between
- 496 cognitive and affective empathy in borderline personality disorder. *Psychiatry Research*,
- 497 *175*(3), 277–279.
- 498 Höllinger, F., & Smith, T. B. (2002). Religion and Esotericism among Students: A Cross-Cultural
- Comparative Study. *Journal of Contemporary Religion*, 17(2), 229–249.
- 500 http://doi.org/10.1080/13537900220125208
- Hu, X., & Downie, J. S. (2010). Improving Mood Classification in Music Digital Libraries by
- 502 Combining Lyrics and Audio. In Proceedings of the 10th annual joint conference on Digital
- 503 libraries. Queensland, Australia.
- Hurtz, G. M., & Donovan, J. J. (2000). Personality and job performance: the Big Five revisited.
- Journal of Applied Psychology, 85(6), 869.

506	Koelsch, S. (2010). Towards a neural basis of music-evoked emotions. Trends in Cognitive
507	Sciences, 14(3), 131–137.
508	Lamere, P. (2008). Social tagging and music information retrieval. Journal of New Music Research,
509	37(2), 101–114.
510	Langmeyer, A., Guglhör-Rudan, A., & Tarnai, C. (2012). What Do Music Preferences Reveal
511	About Personality? A Cross-Cultural Replication Using Self-Ratings and Ratings of Music
512	Samples. Music Preference and Personality Journal of Individual Differences, 33(2), 119–130.
513	http://doi.org/10.1027/1614-0001/a000082
514	Lawson, J., Baron-Cohen, S., & Wheelwright, S. (2004). Empathising and Systemising in Adults
515	with and without Asperger Syndrome. Journal of Autism and Developmental Disorders, 34(3),
516	301–310.
517	Letzring, T. D., & Adamcik, L. A. (2015). Personality traits and affective states: Relationships with
518	and without affect induction. Personality and Individual Differences, 75, 114-120. Retrieved
519	from http://search.proquest.com/docview/1650983472?accountid=11774
520	Mann, G. (2008). Why does country music sound white? Race and the voice of nostalgia. Ethnic
521	and Racial Studies, 31(1), 73-100. http://doi.org/10.1080/01419870701538893
522	Mezquita, L., Ibáñez, M. I., Villa, H., Fañanás, L., Moya-Higueras, J., & Ortet, G. (2015). Five-
523	factor model and internalizing and externalizing syndromes: A 5-year prospective study.
524	Personality and Individual Differences, 79, 98–103.
525	North, A. C., & Hargreaves, D. J. (1995). Subjective Complexity, Familiarity, and Liking for
526	Popular Music. Psychomusicology, 14(1966), 77–93.
527	Pachet, F., & Cazaly, D. (2000). A Taxonomy of Musical Genres. In Content-Based Multimedia
528	Information Access Conference (pp. 1238–1245). Paris, France.
529	Purhonen, S., Gronow, J., & Rahkonen, K. (2009). Social Differentiation of Musical and Literary
530	Taste Patterns in Finland. Research on Finish Society, 2, 39–49.

531	Rawlings, D., & Ciancarelli, V. (1997). Music Preference and the Five-Factor Model of the NEO
532	Personality Inventory. Psychology of Music 25, 25(2), 120-132. Retrieved from
533	http://search.proquest.com/docview/1338704/fulltext/1CA4C4E594DC48A5PQ/1?accountid=
534	11774
535	Rentfrow, P, & Gosling, S. D. (2006). Message in a ballad: the role of music preferences in
536	interpersonal perception. Psychological Science, 17(3), 236–242.
537	Rentfrow, P. J., Goldberg, L. R., & Levitin, D. J. (2011a). The structure of musical preferences: a
538	five-factor model. Journal of Personality and Social Psychology, 100(6), 1139-1157.
539	Rentfrow, P. J., Goldberg, L. R., & Levitin, D. J. (2011b). The structure of musical preferences: a
540	five-factor model. Journal of Personality and Social Psychology, 100(6), 1139-1157.
541	Rentfrow, P. J., & Gosling, S. D. (2003). The do re mi's of everyday life: The structure and
542	personality correlates of music preferences. Journal of Personality and Social Psychology,
543	84(6), 1236–1256. http://doi.org/10.1037/0022-3514.84.6.1236
544	Rentfrow, P. J., & Gosling, S. D. (2007). The content and validity of music-genre stereotypes
545	among college students. Psychology of Music, 35(2), 306–326.
546	http://doi.org/10.1177/0305735607070382
547	Repp, B. H., & Su, YH. (2013). Sensorimotor synchronization: a review of recent research (2006)
548	2012). Psychonomic Bulletin & Review, 20(3), 403–452.
549	Saari, P., & Eerola, T. (2014). Semantic Computing of Moods Based on Tags in Social Media of
550	Music. IEEE Transactions on Knowledge and Data Engineering, 26(10), 2548–2560.
551	Saari, P., Eerola, T., Fazekas, G., Barthet, M., Lartillot, O., & Sandler, M. B. (2013). The Role of
552	Audio and Tags in Music Mood Prediction: A Study Using Semantic Layer Projection. In
553	ISMIR (pp. 201–206).
554	Saarikallio, S. (2011). Music as emotional self-regulation throughout adulthood. <i>Psychology of</i>
555	Music, 39(3), 307–327.

556 Saarikallio, S., & Erkkilä, J. (2007). The role of music in adolescents' mood regulation. Psychology 557 of Music, 35(1), 88–109. 558 Schäfer, T., & Sedlmeier, P. (2009). From the functions of music to music preference. *Psychology* 559 of Music, 37(3), 279–300. 560 Shamav-Tsoory, S. G., Tomer, R., Goldsher, D., Berger, B. D., & Aharon-Peretz, J. (2004). 561 Impairment in cognitive and affective empathy in patients with brain lesions: anatomical and 562 cognitive correlates. Journal of Clinical and Experimental Neuropsychology, 26(8), 1113— 563 1127. 564 Shevy, M. (2008). Music genre as cognitive schema: extramusical associations with country and 565 hip-hop music. *Psychology of Music*, 36(1997), 477–498. 566 http://doi.org/10.1177/0305735608089384 567 Short Test Of Music Preferences (STOMP) | Gosling. (n.d.). Retrieved from 568 http://gosling.psy.utexas.edu/scales-weve-developed/short-test-of-music-preferences-stomp/ 569 Soldz, S., & Vaillant, G. E. (1999). The Big Five personality traits and the life course: A 45-year 570 longitudinal study. Journal of Research in Personality, 33(2), 208–232. 571 Song, Y., Dixon, S., Pearce, M., & Fazekas, G. (2013). Usings tags to select stimuli in the study of 572 music and emotion. In Proceedings of the 3rd International Conference on Music & Emotion 573 (ICME3) (pp. 11–15). Jyväskylä, Finland. 574 Sordo, M., Celma, O., Blech, M., & Guaus, E. (2008). The Quest for Musical Genres: Do the 575 Experts and the Wisdom of Crowds Agree? 9th International Conference on Music 576 Information Retrieval, 255–260. Retrieved from 577 http://books.google.com/books?hl=en&lr=&id=OHp3sRnZD-578 oC&oi=fnd&pg=PA255&dq=THE+QUEST+FOR+MUSICAL+GENRES+:+D 579 O+THE+EXPERTS+AND+THE+WISDOM+OF+CROWDS+AGREE+?&ots=oDMMp 580 DjBb1&sig=WF62T-bGIcEwTSP9Ab8nXErK-OU

581	Sullivan, M. (2001). African-American music as rebellion: From slavesong to hip-hop. Discoveries,
582	3(31–39), 21–39.
583	Tervo, M. (2014). From Appropriation to Translation: Localizing Rap Music to Finland. <i>Popular</i>
584	Music and Society. Taylor & Francis. http://doi.org/10.1080/03007766.2012.740819
585	Wakabayashi, A., Baron-Cohen, S., Wheelwright, S., Goldenfeld, N., Delaney, J., Fine, D.,
586	Weil, L. (2006). Development of short forms of the Empathy Quotient (EQ-Short) and the
587	Systemizing Quotient (SQ-Short). Personality and Individual Differences, 41(5), 929-940.
588	Watkins, S. C. (2001). A nation of millions: Hip hop culture and the legacy of black nationalism.
589	The Communication Review, 4(3), 373–398. http://doi.org/10.1080/10714420109359475
590	Zahavi, D. (2010). Empathy, embodiment and interpersonal understanding: from Lipps to Schutz.
591	Inquiry, 53(3), 285–306.
592	Zweigenhaft, R. L. (2008). A do re mi encore: A closer look at the personality correlates of music
593	preferences. Journal of Individual Differences, 29(1), 45–55.
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Appendix: Track list

Genre	Artist	Track	Excerpt
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 th 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	1:38 - 2:08
		Them Free	
Rock	Billy Idol	Don't You (Forget About	0:15 - 0:45
		Me)	
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

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.