Mariusz Kleć

THE INFLUENCE OF LISTENER PERSONALITY ON MUSIC CHOICES

Abstract *To deliver better recommendations, music information systems need to go beyond standard methods for the prediction of musical taste. Tracking the listener's emotions is one way to improve the quality of recommendations. This can be achieved explicitly by asking the listener to report his/her emotional state or implicitly by tracking the context in which the music is heard. However, the factors that induce particular emotions vary among individuals. This paper presents the initial research on the influence of an individual's personality on his or her choice of music. The psychological profile of a group of 16 students was determined by a questionnaire. The participants were asked to label their own music collections, listen to the music, and mark their emotions using a custom application. Statistical analysis revealed correlations between low-level audio features, personality types, and the emotional states of the students.*

Keywords music recommendation, listener personality

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1. Introduction

The type of music one wants to hear depends on a number of factors, such as one's current disposition, health condition, current activity, musical training, recent listening history, and so forth [10]. The preference also depends on environmental factors such as time, weather, noise, light, temperature, and more [21, 30]. Mobile and portable devices create opportunities for easily gathering contextual information. Positive correlations have been reported between specific situations and musical preferences in this situation [20].

Therefore, instead of explicitly asking listeners about their emotional states, it is possible to track the listener's context and derive their emotional state implicitly. Such an approach has been used in music-choice systems; a mobile music-retrieval system (MRS) that has been developed to track the following environmental factors to adjust its recommendation: location, time, day of week, ambient noise level, temperature, and weather conditions [24]. However, the user of the system must describe the songs manually by the use of appropriate tags.

Additionally, there was no evaluation of this particular system; thus, is unclear whether the environmental factors were appropriately chosen and whether the system is more effective than others. In another system [22], the authors used Bayesian networks to infer the emotions of the listener based on environmental factors such as temperature, humidity, ambient noise, light level, weather, season, and time. In this system, users must explicitly express their musical preferences in each possible contextual dimension.

Consequently, the system infers the current emotions from the environmental factors and computes scores for songs that are used to propose an appropriate playlist. The system was evaluated by ten users by comparing the recommendations with a randomly chosen playlist. The evaluation showed that users were more satisfied with the playlist recommended by the context-aware engine.

Another important issue is the induction of emotions by musical listening, which could be applied in marketing, music therapy, or work-performance improvement [13, 16]. The first extensive investigation of these topics can be found in Meyer's book from 1956 [18]. This book, as well as [2], highlights three important areas that should not be confused. First, there is a clear distinction between perceived emotions and induced emotions. Second, emotions perceived in music are not necessarily induced in the listener. And finally, the personality of the user influences the induction of emotions.

1.1. Emotions

Listeners use music to change their emotions or release them. They may try to relieve stress or match their current emotions with music. Further, some people enjoy listening to sad music. In general, people listen to music to feel comforted. Composing and performing music involves different interdisciplinary perspectives, including psychology, musicology, sociology and biology; in each of these, emotions play an essential role. Descriptions exist of the ways in which emotions can be communicated via musical structure and how our emotions are influenced while listening to music [11]. Subsequently, automatic emotion and mood classification, emotion induction, and mood labeling have gained importance in music information retrieval (MIR) [4, 6, 7, 32].

1.1.1. Emotions and mood

The terms "emotions" and "mood" are sometimes used interchangeably. Consequently, it is important to be clear about the difference. Based on prior studies [14, 23], we can conclude that mood is something that people have difficulties in expressing, while emotions can be better recognized. People pay more attention to emotions rather than moods. Further, mood is persistent and obscure. Emotions are instinctive and peculiar and are typically of shorter duration than moods [11]. These distinctions allow moods and emotions to be distinguished. The focus here is towards emotions rather than moods, because emotions are instinctive, and individuals are fully aware of a particular felt emotion. On the other hand, the awareness of being in a particular mood may be partial or even absent.

1.1.2. Emotions in music

To address emotions with respect to music, it is important to introduce models that classify emotions into a usable taxonomy. Psychologists have considered discrete models that assume no overlap between different basic emotions, and dimensional models that assume that all emotions can be described as combinations of a few dimensions rather than as individual entities [8, 31]. Russell (1980) [26] organized 28 emotional words in a circle, in which the two axes corresponded to a pair of components with opposite meanings: positiveness and arousal.

Subsequently, the Russell model was simplified by Barrett-Russell. This simplified version is presented in Figure 1 (left side); this representation was implemented in the application described in this paper. Individual emotions in this application can be described as points in this two-dimensional space.

The experiments described in this paper (see Section 2) use the same model to describe expressed and induced emotions. Therefore, it is important to underline the differences between these two emotion types. Expressed emotions are built into music by a composer and can be recognized in the composition by the listener. In contrast, induced emotions are felt by the listener while listening to the composition. There is no direct relationship between felt and perceived emotions [27]. Some emotions are more likely to be perceived than expressed by the music. However, both types of emotion provide primary motivation for listening to music [20].

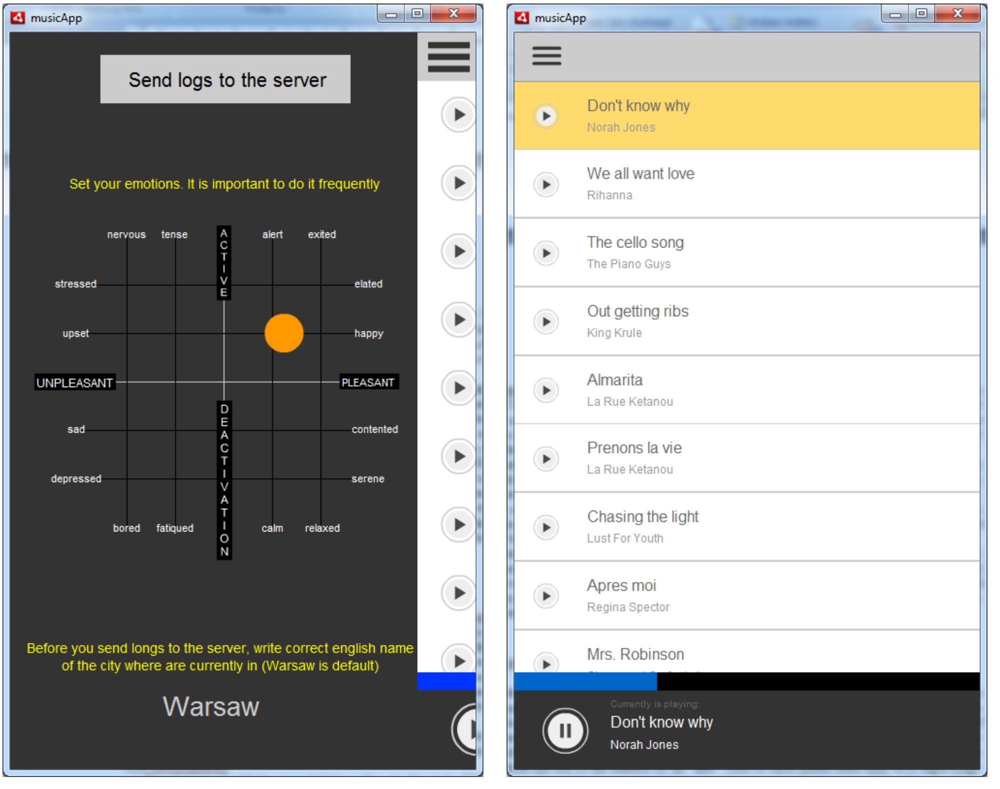

Figure 1. The user interface of the application used in the experiment. The application was created in Adobe AIR using the Action Script 3.0 programming language. The expanded menu is presented on the left-hand side. This gives access to a two-dimensional emotion navigator, a button for sending logs to the server, and a text field for providing a city name (for the Yahoo weather API). The right side shows a panel with the playlist and music player.

1.2. Personality types and musical choice

Personality research investigates whether and how personality types relate to behavior [17]. Recent research has revealed important information about the relationship between individual differences and musical preferences [1, 3]. Rentfrow and Gosling [25] found that musical preferences can be organized in terms of reflective/complex, intense/rebellious, upbeat/conventional, and energetic/rhythmic music. They also discovered that these dimensions are associated with differences in personality and self-perception. Further, intelligence may partly determine an individual's music choices. People with higher IQ tend to prefer reflective/complex to upbeat/conventional music. The motivation for listening to the more complex kind of music (like classical or jazz) is not emotional arousal but rather intellectual experience, implying higher levels of cognitive processing [1]. Several studies have suggested that extroverts are more likely to use music to increase their arousal during monotonous tasks such as cleaning or jogging. In contrast, background music can cause interference with other cognitive tasks in introverts [5]. Research also exists that addresses the use of music for emotional regulation. People who are characterized by affectivity, neuroticism, and emotional stability are more likely to use music to foster emotions [10, 12]. Conversely, people who are characterized as conscientious and low in creativity are more likely to not use music for emotional regulation.

The most-common technique for personality measurement is to ask people to rate whether particular adjectives apply to themselves. The originator of psychological personality types was Carl Jung [9], who developed the concepts of introversion (focusing on the internal world) and extraversion (focusing on the outside word) in 1921. He divided the cognitive functions of a person into two groups: judging (either thinking or feeling) and perceiving (either sensing or intuition). Subsequently, Katharine Cook Briggs and her daughter developed their own methodology, based on Jung's theory. They designed a psychometric questionnaire to measure psychological preferences related to how people perceive the world and make decisions [19]. In their model, there are four possible pairs of personality traits. Every person possesses one of the traits from each pair. Each person's personality is then described by a four-letter acronym:

- Introversion (I) or Extraversion (E): A tendency to focus on the outer world (E) or on one's own inner world (I).
- Intuition (N) or Sensing (S): A tendency to focus on the basic information one receives (S) versus whether one interprets this information and adds meaning (N).
- Thinking (T) or Feeling (F): When making decisions, a tendency to first look at logic and consistency (T) or to instead consider the people involved and the specific circumstances (F).
- Judging (J) or Perceiving (P): In dealing with the outside world, a tendency to make decisions (J) versus remaining open to new information and options (P).

The combination of four letters that expresses a personality type is called the Myers-Briggs Type Indicator (MBTI)[1]; it is one of the most-popular personality descriptors used today. The students that took part in the experiments described here took the test (available at http://www.16personalities.com). This is a slightly modified version of the MBTI methodology in that it uses scales to collect responses rather than responses consisting of binary answers (i.e., yes or no). Each student was classified as 1 of 16 personality types.

2. Experiment

The experiment was conducted with English-speaking first-year university students during their computer workshop course. They participated in the development of an application for listening to music (see Figure 1). Later, they were asked to create their personality profile using the modified MBTI methodology. For this purpose, they

[1] `http://www.myersbriggs.org/my-mbti-personality-type/mbti-basics/`

completed a questionnaire consisting of 60 questions[2]. The questionnaire classifies participants as 1 of the 16 personality types. Additionally, each student was asked to choose at least 20 favorite songs from their private collections. They described each of these in an XML file in terms of title, artist, genre, tempo, and the emotions perceived in the chosen pieces. Tempo was measured manually by means of an online BPM counter[3]. Emotions were described using a two-dimensional navigator (EN) implemented in the application (see Figure 1). Students primarily listened to the music during the classes but were also permitted to engage in listening at home. This process lasted for three days (until the school semester ended). During the listening phase, the participants were asked to indicate their own emotions using the EN.

The students were also asked to save 30-second excerpts of their music for feature extraction. This process was performed in Matlab using the MIRToolbox [15]. Each musical file was down-sampled to 22,050 Hz. The audio features were extracted using a 0.74s frame length with half overlap. There were 29 different audio features. Each of them was aggregated by four statistics over frames: mean, standard deviation, slope (the linear slope of the trend along frames), and entropy (the Shannon entropy of the auto-correlation function). These statistics were calculated for each of the features that relate to spectral characteristics (MFCC and its two deltas, spread, brightness, skewness, flatness, etc.), timbre (low energy, spectral flux), rhythm (onsets, attack time, attack slope), and tonality (the distribution of energy among the pitch classes, as described by a chromagram). Ultimately, each song was characterized by a 248-dimensional vector. The final database consisted of 755 events recorded by 15 students (5 male and 10 female) from 255 songs. All events consisted of logs from students belonging to 1 of 6 personality types: ENFJ, ENFP, ENTP, ESTJ, INTJ, and ISFP[4]. However, only the first three types (ENFJ, ENFP, and ENTP) contributed significantly to the logs (see Table 1).

Table 1

Table presents number of events and participants in original and filtered data-sets.

Personality type	Original data-set		Filtered data-set	
	no. of events	no. of people	no. of events	no. of people
ESTJ	15	1	0	0
ENFJ	230	4	**89**	**4**
ENFP	230	5	**68**	**5**
ENTP	200	3	**68**	**3**
INTJ	37	1	0	0
ISFP	43	1	0	0

Accordingly, further analysis was performed on a filtered data-set that consisted of data from only three personality types, with no repetition of songs. The final

[2] `http://www.16personalities.com`
[3] `http://www.beatsperminuteonline.com/`
[4] `http://www.16personalities.com/personality-types`

filtered data-set contained 225 events, where each event referred to a unique song. The filtered data-set, together with the configuration of the experiments in WEKA, are available to download from `www.mariuszklec.com/publications/features_personalities_exps.zip`.

The following are descriptions of the three personalities that were chosen for further analysis[5]:

- **ENFJ**: Warm, empathetic, responsive, and responsible. Highly attuned to the emotions, needs, and motivations of others. Finds potential in everyone, wants to help others fulfill their potential. May act as a catalyst for individual and group growth. Loyal and responsive to praise and criticism. Sociable, facilitates others in a group, and provides inspiring leadership.
- **ENFP**: Warm, enthusiastic, and imaginative. Sees life as full of possibilities. Makes connections between events and information very quickly, and confidently proceeds based on the patterns he/she sees. Wants a lot of affirmation from others, and readily gives appreciation and support. Spontaneous and flexible, often relies on his/her ability to improvise and verbal fluency.
- **ENTP**: Quick, ingenious, stimulating, alert, and outspoken. Resourceful in solving new and challenging problems. Adept at generating conceptual possibilities and then analyzing them strategically. Good at reading other people. Bored by routine, will seldom do the same thing the same way, and turns to one new interest after another.

Although some research has addressed the relationship between individual differences and musical preferences (see Chapter 1.2), none have taken a low- and mid-level signal analysis perspective but rather have considered semantic phrases like "energetic", "complex", "reflective", and so forth. The current approach considers correlations of low- and mid-level audio features with personality traits. To the best of the author's knowledge, no published research exists that deals with such correlations.

To derive a set of audio features that best discriminated personality traits, three methods for attribute selection were used: information gain (IG), gain ratio (GR), and symmetric uncertainty (SU). All of these methods are implemented in WEKA[6]. They evaluate the worth of an attribute by measuring its information gain, gain ratio, and symmetrical uncertainty with respect to a class (i.e., personality trait). In this process, the attributes are ranked by their individual evaluation for a given attribute-selection method. According to the rank, the N "best" attributes (features) were considered, where N was 2, 4, 6, 8, 10, 15, and 20. Hereafter, attributes and features will be used interchangeably, as both refer to the dimensionality of the data-set.

Six different classifiers were trained on these data-sets: logistic regression (LR), neural network (NN), support vector machine (SVN), K-nearest neighbors (K-NN), C4.5 decision tree (C4.5), and random forest (RF). The data-sets were evaluated

[5] `http://www.myersbriggs.org/my-mbti-personality-type/mbti-basics/the-16-mbti-types.htm`

[6] `http://www.cs.waikato.ac.nz/ml/weka/`

via ten-fold cross-validation tests (CV). The final results present the averages after running the CV tests ten times with different shuffled data.

The ideal solution would achieve the highest accuracy with the lowest dimensionality of the data-set. For this reason, a higher rank was assigned to results obtained from the low dimensionality data-sets. Next, the discounted cumulative gain (DCG) measure (see equation 1) was applied to each of the given attribute-selection methods.

$$\begin{aligned} DCG(L,c) &= \sum_i u(I,c) \cdot d(i) \\ d(i) &= \frac{1}{max(1, \log_2 i)} \end{aligned} \tag{1}$$

Where $u(i,c)$ is the accuracy for given data-set i and learning algorithm c, $d(i)$ is a discount factor for the accuracy. It measures the "usefulness" (gain) of the accuracy depending on its position in the ranked list. The highest "gain" occurs for data-sets with low dimensionalities (2 and 4). The "gain" of accuracy is discounted when the dimensionality of the data-sets increases. Averaging the results affected by DCG highlights the feature-selection algorithm with the greatest ability to discriminate personality traits, focusing on efficiency for the low-dimensionality data-sets.

Additional analyses considered correlations between the induced emotions and musical tempo for the three tested personality traits.

3. Results

The results in Figure 2 show that the infoGain attribute-selection method gave the highest accuracy; the average DCG over all data-sets was the highest (249.31). However, symmetrical uncertainty also performed very well (248.03). It is worth noting that each of the attribute-selection algorithms generated better results than the original data-set with 248 dimensions. Attribute-selection methods reduce the dimensionality of the data-set by selecting a sub-set of already-existing features. Principal component analysis (PCA), in turn, reduces the dimensionality by converting a set of possibly correlated features into a set of linearly uncorrelated components, using an orthogonal transformation. This process represents a completely different approach to dimensionality reduction, although the PCA generated far-worse results than all of the other attribute-selection methods (see Figure 2).

It is notable that the two feature-selection methods (IG and SU) with the greatest ability to discriminate music according to personality traits used exactly the same set of three "best" features (see rows in bold in Table 2). These features are the tonal chromagram (the entropy of peak magnitude) and the first coefficient of the delta MFCC (slope and mean). The two-dimensional data-sets with these features were sufficient to obtain better accuracy than all of the other data-sets with C4.5 and K-NN (see Table 3).

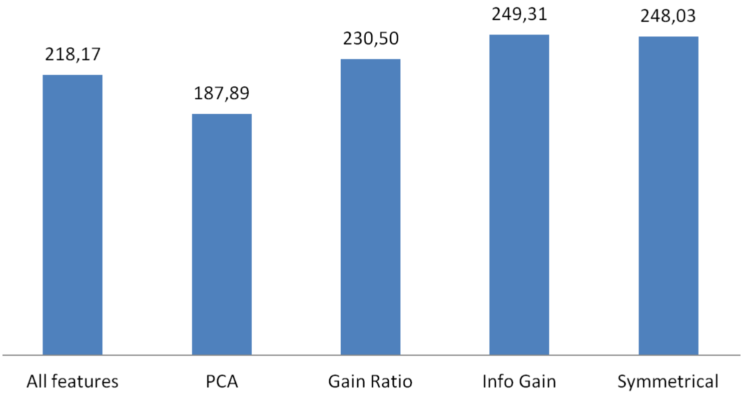

Figure 2. Height of bars indicates average DCG value (over all machine-learning algorithms) for given feature-selection algorithm.

Table 2

Table presents 20 out of 248 audio features as selected by two algorithms' info gain and symmetrical uncertainty.

Rank	Info Gain	Symmetrical Uncertainty
1	**chromagram (peak magnitude period entropy)**	**chromagram (peak magnitude period entropy)**
2	**dmfcc 1 (slope)**	**dmfcc 1 (slope)**
3	**dmfcc 1 (mean)**	**dmfcc 1 (mean)**
4	spec. dmfcc 7 (std)	spec. rolloff95 (slope)
5	spec. ddmfcc 7 (std)	spec. spread (slope)
6	spec. rolloff95 (slope)	chromagram (peak mag. slope)
7	spec. ddmfcc 6 (std)	spec. ddmfcc 7 (std)
8	spec. spread (slope)	spec. dmfcc 7 (std)
9	spec. mfcc 7 (std)	rhythm onsets (peak position mean)
10	spec. dmfcc 9 (std)	spec. ddmfcc 6 (std)
11	rhythm onsets (peak position mean)	chromagram (centroid period entropy)
12	spec. dmfcc 6 (std)	spec. mfcc 7 (std)
13	spec. entropy (slope)	spec. ddmfcc 4 (std)
14	spec. ddmfcc 4 (std)	spec. dmfcc 9 (std)
15	chromagram (peak mag. slope)	spec. dmfcc 6 (std)
16	chromagram (centroid period entropy)	spec. entropy (slope)
17	spec. mfcc 5 (mean)	spec. mfcc 5 (mean)
18	spec. mfcc 6 (mean)	spec. mfcc 6 (mean)
19	spec. mfcc 9 (std)	spec. mfcc 7 (mean)
20	spec. mfcc 8 (std)	spec. mfcc 13 (std)

Table 3

Table presents values of accuracies in training five machine-learning algorithms. It also contains values of DCG for each attribute-selection method. The maximum values are in bold.

10-fold cross validation results (accuracies)							
Rank(i)	Attr. selection(L)	C4.5	RF	K-NN	NN	SVN	LR
1	gainRatio 2	42.32	39.45	43.72	43.4	44.99	44.87
2	gainRatio 4	58.98	61.35	48.58	51.31	47.31	58.67
3	gainRatio 6	**61.45**	**64.88**	**53.74**	57.42	50.03	63.08
4	gainRatio 8	59.47	64.27	48.06	57.46	50.38	**63.53**
5	gainRatio 10	58.46	63.86	49.88	**58.45**	**56.64**	63.26
6	gainRatio 15	57.47	62.55	47.46	56.14	54.9	61.66
7	gainRatio 20	56.1	63.92	47.4	55.87	56.39	62.16
	DCG(gainRaio)	237.05	248.68	207.35	226.88	214.65	248.38
1	infoGain 2	**64.69**	55.5	**57**	56.16	43.02	62.66
2	infoGain 4	63.86	**64.84**	48.08	59.04	55.64	62.6
3	infoGain 6	61.13	64.05	50.66	**60**	55.57	63.28
4	infoGain 8	60.01	62.81	50.92	59.48	55.57	63.38
5	infoGain 10	59.2	63.69	51.05	57.81	**55.68**	**63.64**
6	infoGain 15	57.47	62.55	47.46	56.14	54.9	61.66
7	infoGain 20	55.56	62.5	46.48	55.31	55.6	61.69
	DCG(infoGain)	264.64	266.05	219.4	249.11	226.53	270.11
1	Symmetr. l2	**64.69**	55.5	**57**	56.16	43.02	62.66
2	Symmetr. l4	62.75	63.97	49.7	**59.22**	51.14	**63.57**
3	Symmetr. l6	61.02	**64.45**	53.74	56.79	49.9	63.08
4	Symmetr. l8	59.97	64.1	49.33	59.22	55.35	63.41
5	Symmetr. 10	59.12	63.68	48.6	56.45	55.88	62.76
6	Symmetr. 15	57.55	63.39	47.55	57.89	54.14	61.25
7	Symmetr. 20	55.79	63.39	47.4	56.06	**56.26**	62.16
	DCG(Symmetr.)	263.52	266.71	221.48	247.5	218.37	270.56
1	PCA 2	33.97	40.61	35.94	37.39	39.57	38.39
2	PCA 4	40.42	41.62	42.6	43.18	42.73	45.92
3	PCA 6	39.66	42.88	43.59	45.6	44.84	49.26
4	PCA 8	39.46	46.71	46.85	45.62	45.74	50.07
5	PCA 10	37.48	46.73	45.78	48.7	47.71	51.92
6	PCA 15	38.67	**52.05**	**48.58**	51.47	52.16	55.09
7	PCA 20	**41.54**	52.04	43.48	**51.53**	**53.66**	**55.52**
	DCG(PCA)	165.04	191.44	182.3	191.39	193.3	203.87
1	All features	51.56	55.74	43	48.63	49.58	55.58

From Figure 3, we can conclude that listeners felt positive emotions while listening to their music. But the question remains as to whether the music itself had a positive effect on their emotions. The positive affect might have been caused by other factors, such as the perspective that the holidays would start shortly after the experiment was complete (and thus, the participants may have been in good moods in general). Moreover, although emotions were skewed towards the direction of pleasant, we can not make any definitive statements about the activation of the participants' emotions.

Figure 3. Barrett-Russell emotional topology [18], wherein each point represents emotions present while participants listened to music. X-axis represents unpleasant (when x <0) and pleasant (when x >0) emotions and Y-axis deactivated (when y <0) and activated emotions (when y >0).

Figure 4 shows that the tempo of the music decreased after 8 p.m and was the highest in the middle of the day. This is unsurprising, as people usually want to relax in the evening. However, a more-interesting question is what other musical characteristics differentiate music played at different times of day. Figure 5 shows that the preferred tempo for listening might also depend on personality type.

The statistics presented in Figure 6 underline the individual character of ENF, showing the difference between emotions induced in the listener and emotions perceived in the music. The difference was greatest for the ENFP-personality type, which signifies that such individuals tended to listen to emotions in music that were different from those induced in them. For example, they listened to unpleasant emotions while feeling pleasant emotions and vice versa. This characteristic is confirmed in the description of this personality type[7], which underlines their "free spirit", independence, and constant search for deeper meaning.

[7] http://www.16personalities.com/enfp-personality

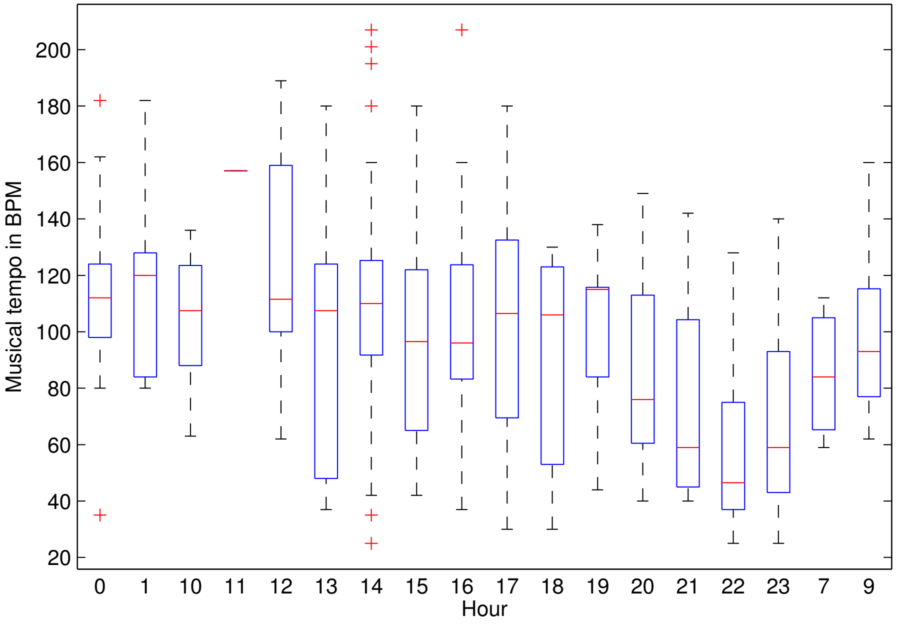

Figure 4. Musical tempo by hour of day.

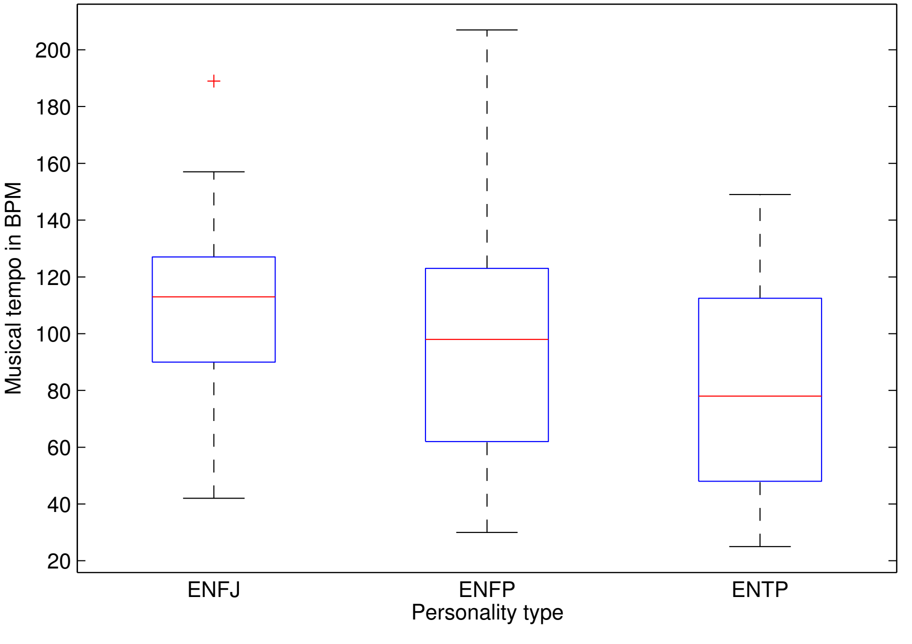

Figure 5. Musical tempo by personality type.

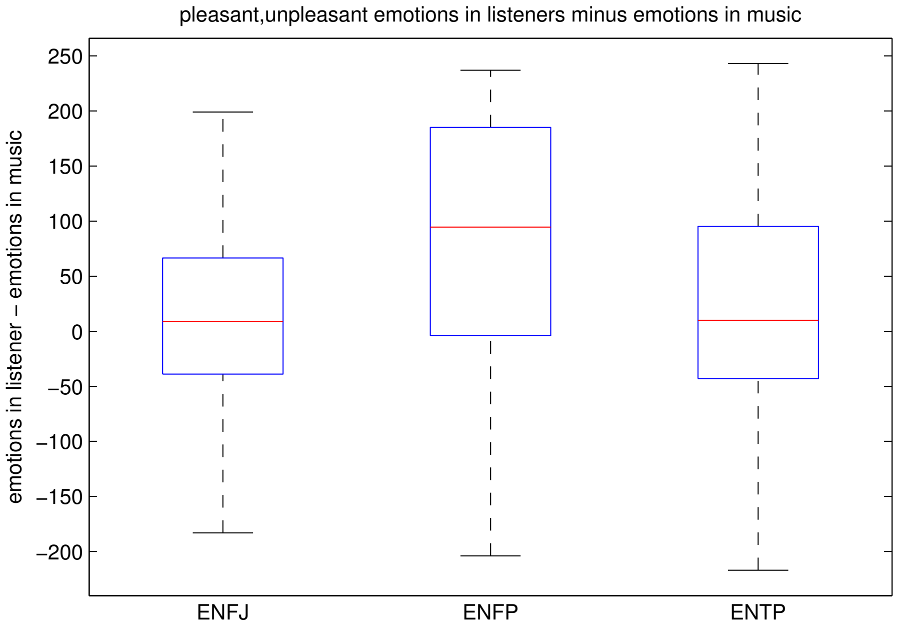

Figure 6. Difference between induced emotions and emotions perceived in music grouped by three personality types.

4. Conclusions

The initial hypothesis was that there would be correlations between personality traits and the use of music. In the current data, three personality types (ENFJ, ENFP, and ENTP) were correlated with low- and mid-level audio features. The set of 248 features were derived from the musical pieces that were heard by the participants, including spectral features, timbre, rhythm, and tonality. However, most of the features were not originally engineered for music representation. Music data mining, due to its subjective characteristic, should use perceptually important characteristics of a piece of music. This was true of the experiment reported here: the tonal chromagram (the peak period entropy) was selected as the best predictor of the three personalities (see Table 2). Indeed, the chromagram was developed specifically for music representation. It shows the distribution of energy among 12 musical pitches (C,C#,D,D#,E,F,F#,G,G#,A,A#,B). Music is characterized by its emotional charge, which is primarily dictated by the chord (pitch class) progression. This progression determines the style, mood, and final perception of a song. Listeners judge these things subconsciously when deciding whether they like a piece of music or not. In this context, the chromagram is a very good candidate for music representation, especially for predicting the musical tastes of individuals with different personality types. However, in this study, 10-fold CV tests were performed on a very small data-set

(225 instances) that was collected from 12 students. In replication, only 22 instances were evaluated. Even if the tests were repeated ten times with different randomized data, such few instances leads to skewing the results toward the selected sample of people; namely, one group of first-year university students. The number of participants was too small to draw a final conclusion about the kinds of music different personality types prefer to listen to. The research described in this paper is only an initial step towards linking personality traits and audio characteristics. Accordingly, the author intends to extend the current research by conducting much-larger-scale research in the near future. Additionally, the author plans to incorporate another personality questionnaire. To the best of the author's knowledge, the 16 personality questionnaire used in the current study is the only such tool that is publicly available at no cost. All other questionnaires require a permit for their use. Further, most of these questionnaires may be used only by psychologists [28]. However, the Big Five personality model may be used without cost for scientific purposes.

The Big Five model is based on five broad dimensions used by some psychologists to describe human personality and psyche: openness to experience, conscientiousness, extroversion, agreeableness, and neuroticism [28]. The author's plan is to use IPIP-BFI-44[8] [29] as the personality questionnaire, recruit a larger participant sample size, and use a fixed set of songs that are carefully selected from the magnatune.com website. The author also plans to obtain ratings of the music to provide a baseline for evaluation of the final personalized music recommendation system.

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Affiliations

Mariusz Kleć

Polish-Japanese Academy of Information Technology, Faculty of Information Technology, Department of Multimedia Warsaw, Poland, mklec@pjwstk.edu.pl

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