# The music in you : investigating personality-based recommendation



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# The Music in You:

# Investigating Personality-Based Recommendation

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en
prof.Dr. A.G. Kohlrausch

Copromotor:
B. de Ruyter lic.psych.

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# 1

## Music Recommendation based on Personality: Theoretical Foundations

As much as music is a form of entertainment to keep our feet tapping, it also helps each of us express who we are to others in our social environment (North & Hargreaves, 1999; Rentfrow & Gosling, 2006). When individuals communicate that they like a certain style of music, such as Jazz or Rap, they also communicate a part of their personality to others (Rentfrow & Gosling, 2003). For entertainment purposes, current technologies have given individuals a nearly limitless amount of digitally stored music at their fingertips, calling forth a digital era of music. Whether intentional or unintentional, individuals can select from a vast amount of digital music available to them for their listening entertainment, but can also select this music as a passive way to describe themselves with more detail than ever before.

While the digital era of music gives individuals a potentially unique entertainment experience with greater descriptive detail, it also introduces problems. One such problem is information overload, which is attributable to the vast amount of digitally stored music with which individuals are confronted. For instance, with tens of thousands of rock songs available to be downloaded, how do individuals decide which songs to purchase for their highest entertainment value? Several methods could be used to address this question and many of these methods could also employ various idiosyncratic characteristics known to be related to music selection. One method that could be used to address this question could be by leveraging the relation between individuals' personality and the music that they like. Motivated by previous research that has investigated the relation between personality and music preference the current thesis attempts to build on this previous work and aims to create a more detailed understanding of this relation. Ultimately, the present thesis attempts to provide a possible resolution to the information overload problem by showing how personality could be used to recommend songs that individuals will likely find entertaining.

Toward these ends, the remainder of this introductory chapter gives a review of the relevant literature in three key areas. The review starts with the information overload problem and the recommender technologies used to curtail this problem. Subsequently, the second section gives a review of the literature concerning personality psychology, which is used to outline the approach for this thesis. Why personality is considered in the present thesis instead of other possible characteristics is addressed in the second section. The third section discusses the previous research that has investigated the relation between personality and music preferences. This chapter is then concluded with an outline of the remaining chapters in this thesis.

## 1.1 The Information Overload Problem

The information overload problem has been attributed to the advent of the computer, digital technology, and especially, the Internet (Bowman, Danzig, Manber, & Schwartz, 1994; Landauer, 1995; Larson, 1991; Perugini, Gonçalves, & Fox, 2004; Shneiderman, 1998). Blair (1980) has accurately described this problem in terms of two *futility points*. The first futility point refers to the maximum amount of displayed information that the user is willing to begin browsing through. The second futility point refers to the amount of information that users are willing to browse through before giving up their search. Information overload has been an important reason for the development of the information retrieval research field. As a result, several tools have been introduced to curtail information overload. These tools include search engines and retrieval systems, but also recommender technologies, which are specifically used to resolve overload linked to digital music information search and retrieval (e.g., Li, Myaeng, & Kim, 2007; Pauws, 2000; Yoshii, Goto, Komatani, Ogata, & Okuno, 2008).

Also known as recommender systems or recommender agents, research that has investigated recommender technologies has largely been in response to information overload. Indeed, a clear majority of papers on recommender technologies have alluded to information overload as its raison d'être within the first few lines (e.g., Anand, Kearney, & Shapcott, 2007; Herlocker, Konstan, Terveen, & Riedl, 2004; Lekakos & Giaglis, 2006; Middleton, Shadbolt, & de Roure, 2004; Montaner, López, & de la Rosa, 2003). Three essential approaches for recommender technologies have been used to describe how the amount of information provided to the user is refined to help manage overload (Adomavicius & Tuzhilin, 2005):

1. *Content-Based (CB)*: recommended items are provided based on similarities to previous items preferred by the user.
2. *Collaborative Filtering (CF)*: recommended items are provided based on reported preferences from other users found to have similar tastes to the user in question.
3. *Hybrid*: combines CB and CF approaches.

Burke (2002) and Montaner et al. (2003) have listed additional approaches, but the three approaches listed above are consistently used throughout the literature on recommender systems. Arguably, Collaborative Filtering (CF) has been the most utilized of these approaches (Deshpande & Karypis, 2004; Herlocker et al., 2004). Though, one could argue that the Hybrid approach provides the opportunity for improved recommender performance because it complements the benefits and drawbacks noted with the Content-Based (CB) and CF approaches (Burke). Regardless of whether or not a Hybrid approach is used, most research on music recommenders contains at least an element of CF as part of its approach (Bertin-Mahieux, Eck, Maillet, & Lamere, 2008).

It has been suggested that CF approaches imitate social techniques individuals use to get informed about novel experiences, commonly known as word-of-mouth (Resnick & Varian, 1997). For instance, individuals ask friends for suggestions about a good movie, music, or restaurant. Despite their success, one recognized issue with CF approaches is cold start (Lam, Vu, Le, & Duong, 2008; Rashid et al., 2002; Schein, Popescul, Ungar, & Pennock, 2002). Simply put, cold start refers to the difficulties encountered by recommender algorithms when a new item or new user is added to a CF system. So, now there are two connected problems with respect to users' music information overload. First, there is the information overload problem discussed so far, wherein recommender technologies attempt to alleviate users' information overload with the rapidly expanding choices that digital music provides to them. Second, in its attempt to achieve this end, recommender technologies encounter difficulties with new items and new users.

Research has often tried to tackle cold start by including content metadata, which addresses the new item problem (e.g., Nathanson, Bitton, & Goldberg, 2007; Rashid et al., 2002; Sarwar, Karypis, Konstan, & Riedl, 2001; Schein et al., 2002). Alternatively, other researchers (e.g., Lam et al., 2008) have suggested further improvements addressing cold start in CF systems can be gained via user characteristics (i.e., characteristics that are inherently part of the user). Doing so would specifically address the new user problem. Though few researchers have tackled the cold start problem by leveraging users' characteristics, this research has shown promise (e.g., Lam et al., 2008; Lekakos & Giaglis, 2006; Nguyen, Denos, & Berrut, 2007). So far, this research has only looked at surface-level characteristics (e.g., gender, age). Nonetheless, Lam et al. have argued that further improvements in this specific research area may be gained by measuring more detailed user characteristics. Personality is known to be a relatively stable user characteristic (John & Srivastava, 1999), which has been shown to reliably describe various personal habits and behaviours (Gosling, 2008; Rentfrow & Gosling, 2003). So incorporating detailed user characteristics, such as personality, could address the information overload and cold start problems, and possibly improve prediction in current CF systems.

Granted, there are numerous factors involved when someone selects a particular song, album, or genre of music to be played. Arguably, these factors include, but are not limited to: emotions, mood, personal experience, social context, environment, culture, and what music is available. So, why might personality provide improved recommender technologies instead of, or in addition to, using some of these other factors? As a quick and initial answer to this question, personality is only one solution among a variety of alternative solutions, some of which have been mentioned. In turn, this means that personality is not necessarily better or worse than using, for example, emotions. Each solution deserves to be specifically researched to see how it could benefit current recommender technologies. Nonetheless, by providing the specific definition, theory, and model of personality used in this thesis, the following section delineates the unique opportunity that personality measures afford for predicting music preferences.

## 1.2 Personality

The music that individuals voluntarily listen to at any given point in time is a product of who they are and their current situation. This statement reflects an interactionist approach to music selection. Interactionism emphasizes that individuals' behaviour is a product of the dynamic relation between their personality and their situation, which includes their environment, needs, experience, goals, etc. (Buss, 1987; Krahé, 1992; Magnusson & Endler, 1977). With respect to music selection, this approach emphasizes that individuals select music that will reflect their personality, whether intentionally or unintentionally (Buss, 1987; Rentfrow & McDonald, in press). Through its adoption, this approach consequently provides a definition of personality, which has been argued to be implicitly shared among interactionist researchers (Krahé). This definition is provided by Endler (as cited in Krahé) and states that, "*Personality* [*sic*] is a person's coherent manner of interacting with himself or herself and with his or her environment" (p. 71). Furthermore, Buss has argued that the interactionist approach maintains a flexibility that allows researchers to use one of many possible personality theories.

There are several theories of personality that help guide personality research in different ways (e.g., learning theories, psychodynamic theories, existential theories). The dispositional, or trait theory of personality is one such theory. As its name suggests, trait theory suggests that adjectives, like outgoing, shy, happy, or sad, are indications of an individual's personality. Within trait theory, the Big Five model of personality is arguably the most accepted trait model that currently exists (John & Srivastava, 1999). This model has often been used to investigate the relation between personality and music preferences. In fact, since Rentfrow and Gosling (2003) first related the Big Five to music preferences, all subsequent research in this area has followed suit (e.g., Chamorro-Premuzic & Furnham, 2007; Delsing, Ter Bogt, Engels, & Meeus, 2008; George, Stickle, Rachid, & Wopnford, 2007; Rentfrow & Gosling, 2006; Zweigenhaft, 2008). As its name implies, the Big Five measures five personality dimensions (Costa & McCrae, 1992), which are identified and described as:

1. *Neuroticism (N)*[1] – an individual's propensity to feel fear, sadness, embarrassment, anger, guilt, and other emotions of negative affect.
2. *Extraversion (E)* – an individual's propensity to be sociable, talkative, assertive, active, and indicates their preference toward stimulating and exciting environments.
3. *Openness to Experience (O)* – an individual's propensity toward intellectual curiosity, imagination, aesthetic and emotional sensitivity, and originality.
4. *Agreeableness (A)* – an individual's propensity toward being altruistic, helpful, sympathetic, and empathetic toward others.
5. *Conscientiousness (C)* – an individual's propensity toward cleanliness, orderliness, having self-determination, and self-control.

[1] *Neuroticism* has also been referred to as *Emotional Stability*.

Each of these dimensions represents a continuous scale with opposite extremes. Higher scores for a given dimension are interpreted such that the individual should be more consistent in personality with the dimension label and description (e.g., Extraversion), whereas lower scores are interpreted such that the individual should be more consistent with personality adjectives that are opposite to the dimension label and description (e.g., Introversion).

Having outlined an approach, definition, and model of personality, an extended answer may be given to the question posed regarding the relevance and unique opportunity personality affords for predicting music preferences. Naturally, this answer is developed from an interactionist perspective and is provided in two parts. First, the reliability of personality characteristics expressed by research on the Big Five model (Costa & McCrae, 1992) indicates that these characteristics are relatively stable across time. In contrast to transitory factors that impact music selection at a given moment in time, like mood or emotions (cf. Juslin & Sloboda, 2008), this relative stability permits more reliable estimates of general music preferences over longer periods of time and across various contexts. Still, the second part of this answer provides perhaps the most intriguing and motivating reason for using personality to predict music preferences.

This second part addresses the development of personality and music preferences during adolescence or formative years. These formative years are viewed as a critical period for psychological development from both a social science perspective (e.g., Allport, 1961; Erikson, 1968; Glenn, 1974; Rubin, Rahhal, & Poon, 1998; Sroufe & Cooper, 1988) and neuroscience perspective (e.g., Choudhury, Blakemore, & Charman, 2006; Giedd et al., 1999; Gogtay et al., 2004; Paus, 2005; Van Essen, Marder, & Heinemann, 2007). Specifically, these formative years are also seen as a critical period for personality development (Allport; Erikson).

With respect to music, Levitin (2006) has stated that music preferences are formed during the formative years as well, and remain relatively stable throughout an individual's lifetime. Music preferences are further argued to be influenced by environmental factors, such as the individual's social experiences and cultural background. Similarly, traits are shown to vary by geographic location (Rentfrow, Gosling, & Potter, 2008), which suggests that personality is also influenced by environmental factors during the formative years. Furthermore, Levitin has stated that personality has a predictive influence over music preferences. Thus, the established stability of both personality and music preferences after the formative years provides a unique opportunity to leverage the predictive relation that personality has with music preferences. This relation inherently accounts for social and cultural differences and by reasserting an interactionist perspective, this relation also inherently accounts for an individual's propensity for experiencing certain moods or emotions, or to select certain social environments (Buss, 1987; Krahé 1992; Swann, Rentfrow, & Guinn, 2002).

In conclusion, at least for individuals past their formative years, it is asserted that personality has a predictive relation with music preferences, which accounts for certain situational factors, such as individuals' cultural background or their propensity to select certain social environments and experience certain emotions. Figure 1.1 illustrates the hypothesized post-formative relations among personality, music preferences, and situation in the context of the present thesis. Given these relations, personality provides a unique possibility to broadly define an individual's music preferences regardless of a specific affective (i.e., emotional or mood) state or social environment. This could be usefully incorporated into music recommender technologies in an effort to alleviate the new user problem described in the previous section. Having outlined the problem space and why personality is a potential solution to this problem, the next section gives an overview of the literature that has related personality to music preferences.

## 1.3 Personality and Music Preferences

Prior to 2003, early research relating music preference with personality was diverse in terms of researchers' motivation and their ways to measure personality (e.g., Arnett, 1992; Cattell & Anderson, 1953; Cattell & Saunders, 1954; Litle & Zuckerman, 1986; McCown, Keiser, Mulhearn, & Williamson, 1997; McNamara & Ballard, 1999; Rawlings, Barrantes i Vidal, & Furnham, 2000). As previously stated, research since 2003 has addressed the issue of how personality is measured, and has worked toward a general understanding and model of music preferences related to personality (e.g., Chamorro-Premuzic & Furnham, 2007; Delsing et al., 2008; George et al., 2007; Rentfrow & Gosling, 2003; Zweigenhaft, 2008).

The research since 2003 began with Rentfrow and Gosling (2003), who proposed a four-factor model of music preferences, which was subsequently related to personality. Research attempting to confirm Rentfrow and Gosling's model has had mixed results, however. For example, George et al. found an eight-factor model when they included 30 music genres, compared to the 14 genres used in Rentfrow and Gosling's original research.

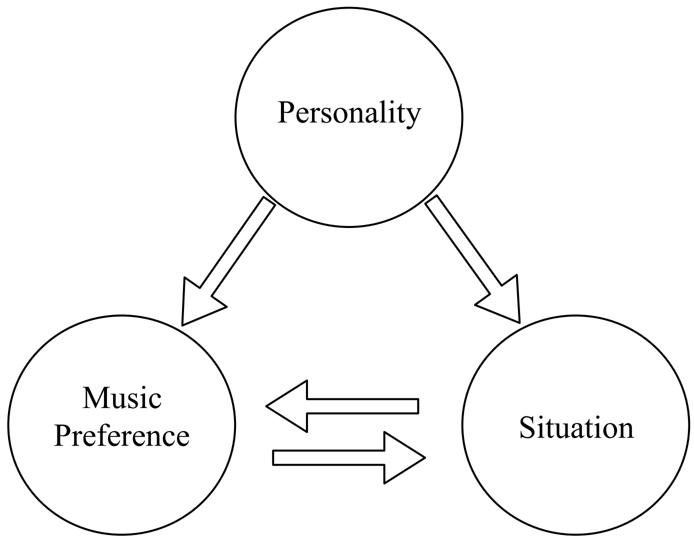



*Figure 1.1*. Hypothesized post-formative relations between personality, music preference, and situation. Arrows indicate direction of influence.

Furthermore, both George et al. and Delsing et al. found subtle differences in the factor structure when comparing their model to Rentfrow and Gosling's. On the one hand, Rock, Heavy Metal, and Alternative genres consistently grouped themselves together. On the other hand, genres like Rap and Dance/Electronica, or Blues, Jazz, and Classical, were inconsistently grouped; sometimes under the same factor and sometimes not. These findings suggest different notions of genre categorization among these different participant samples. Therefore, despite statements from Delsing et al. and George et al. supporting Rentfrow and Gosling's model of music preferences, their findings indicate that further research is needed.

Research correlating music preferences with the Big Five personality dimensions has provided mixed results as well. Examples of mixed correlation results are presented in Table 1.1, which summarizes the significant correlations found between the Big Five and music preferences in research studies since 2003. The first column provides the original four music preference dimensions included in Rentfrow and Gosling's (2003) model, followed by the genres contained within each of these dimensions in the second column. The third through sixth column indicate the significant correlations between music preferences by genre and abbreviated traits for each of the referenced research papers shown as column headings: 1) Rentfrow and Gosling (R & G; 2003), 2) Delsing et al. (D et al.; 2008), 3) George et

*Table 1.1*
Significant correlations found between the Big Five and music preferences in research studies since 2003.

| Music Dimension | Genre | Correlated Trait Dimensions R & G | D et al. | G et al | Z |
|---|---|---|---|---|---|
| Reflective & Complex | Blues | O | -- | O | O |
| | Classical | O | O, N | O | - |
| | Folk | O | -- | E, C | O |
| | Jazz | O | O, N | O | O |
| Intense & Rebellious | Alternative | O | -- | O, A, C | - |
| | Heavy Metal | O | O | O, A, C | - |
| | Rock | O | O | O, A, C | - |
| Upbeat & Conventional | Country | E, A, C, O | -- | E, C | - |
| | Pop | E, A, C, O | E, A | O, A, C | O |
| | Religious | E, A, C, O | -- | - | O |
| | Soundtracks | E, A, C, O | -- | -- | A, O |
| Energetic & Rhythmic | Dance/ Electronica | E, A | E, A | O, C | - |
| | Rap/Hip-hop | E, A | E, A | O, A, C | E, O |
| | Soul/Funk | E, A | E, A | -- | O |

*Note*. Referenced material: R & G = Rentfrow & Gosling, 2003; D et al. = Delsing et al., 2008; G et al. = George et al., 2007; Z = Zweigenhaft, 2008. Dimension abbreviations: N = Neuroticism; E = Extraversion; O = Openness; A = Agreeableness; C = Conscientiousness. Abbreviations denote significant correlations ($p$ < .05) between dimension and genre. Correlation is positive unless an underlined abbreviation is shown, indicating a negative correlation. Single dashes (-) indicate no significant correlations found in that particular study. Double dashes (--) indicate that the genre was not considered in that particular study.

al. (G et al.), and 4) Zweigenhaft (Z; 2008). Please refer to page 5 for dimension abbreviations and their descriptions. Underlined abbreviations denote negative correlations. Otherwise, the correlation is positive. A single dash indicates no significant correlations found in that particular study, whereas double dashes indicate that the genre was not considered in that particular study. While there are a number of consistent findings among the studies summarized in this table, it is evident that there are also several inconsistencies across the studies as well. Indeed, there are conflicting results (e.g., Pop, Rap/Hip-hop) in which some research has reported a positive correlation for a given trait, while other research has reported a negative correlation for the same trait.

Perhaps a reason for these inconsistencies is how personality and music preferences have been measured and related. First, it has been argued that genre categorization is inconsistent (Aucouturier & Pachet, 2003), which indicates that there is no clear definition of what does, or does not, encapsulate a genre. As a result, participants taking part in the various studies relating personality to music preferences (e.g., Delsing et al., 2008; George et al., 2007; Rentfrow & Gosling, 2003; Zweigenhaft, 2008) may have different preconceived notions of what a given genre represents when reporting their music preferences. Thus, the exact nature of these reported music preferences is still vague. Moreover, most of these studies measured participants' personality using the Big Five dimensions. Certain measures of the Big Five, such as the NEO PI-R (Costa & McCrae, 1992) also measure more detailed, facet-level traits. It has been argued that finer, facet traits could provide a better understanding of the relation between personality and music preferences (Rentfrow & Gosling; Zweigenhaft). These issues present challenges that remain in order to better understand how personality is related to music preferences and how a better understanding can be used to improve current recommender technologies. The objectives of the present thesis address these challenges.

## 1.4 Outline and Objectives.

Several steps are taken in the thesis to show whether personality is related to music preferences, how these variables are related, and how personality can be used to improve on current recommender technologies.

Chapter 2 begins by investigating whether music listening behaviour is related to reported music preferences, as well as to personality. That chapter's objective is to address the need for a better understanding of how music listening behaviour is related to both reported music preferences and to personality. Results from Chapter 2 show that reported music preferences are strong indicators of music listening behaviour. Some results from that chapter contradict previous findings that have related personality and music preferences. Nonetheless, the results also further support Buss' (1987) interactionist argument that individuals manipulate their environment to reflect aspects of their personality.

Turning to Chapter 3, its objective was to explore the predictive improvements that could be gained by using facet traits versus the Big Five dimensions. To this end, analyses presented in Chapter 3 show how participants' facet traits are regressed on participants' preference ratings to specific musical pieces, and how these results compare to similar regression parameter values obtained using the Big Five personality dimensions. The results consistently show predictive improvements using facets versus the Big Five dimensions. Consequently, the results provide support for previous researchers who have argued for a more fine-grained analysis of relevant personality traits (e.g., Rentfrow & Gosling, 2003; Zweigenhaft, 2008).

Motivated by the findings provided in Chapters 2 and 3, Chapter 4 presents research that has built and confirmed a model of music preferences given personality measures using specific, iconic musical pieces. Chapter 4 completes its objective by providing a new predictive framework for music preferences given measured personality traits, which is based on music stimuli. The predictive framework could potentially be implemented in a music recommender system.

The objective for Chapter 5 was to build on the research completed in Chapter 4 by demonstrating how objective audio-extracted music features can be used to discriminate between modelled music preference categories. The music preference categories were derived from the predictive framework presented in Chapter 4. By using audio-extracted features to discriminate among these categories, it becomes possible to predict music preferences while reducing issues brought on by genre ambiguity (Aucouturier & Pachet, 2003). The results presented in Chapter 5 also give better insight into the fundamental properties of music that are differentially preferred and enjoyed by individuals with different personalities. In this way, the results given in that chapter provide a basis for transcending vague genre classification and for automating music classification necessary for recommender systems.

Chapter 6 applies the framework for music preferences given personality and compares its performance to a Collaborative Filtering (CF) algorithm, which is commonly used to reduce information overload issues related to music selection (e.g., Li et al., 2007; Yoshii et al., 2008). This objective was met with results indicating that while the framework is able to predict music preferences with reasonable accuracy, it is still not as accurate compared to CF algorithms. Still, the results from Chapter 6 do support the argument that, if further improved, personality could be used to supplement CF algorithms in recommender technologies and help curtail cold start problems associated with new users.

Lastly, Chapter 7 develops conclusions to the research presented in the present thesis. In that chapter, the previous chapters are briefly reviewed and the interpretations from the results from all the chapters are integrated. This has been done to give a comprehensive response to how music is not only entertaining, but is uniquely suited to describe aspects of who we are.

# 2

## Investigating Relations between Personality, Music Preferences, and Music Listening Behaviour

Music is arguably one of the most ubiquitous and ingrained aspects of our daily lives (Levitin, 2006). It is perhaps for this reason that music has generated an expansive amount of interest within various disciplines ranging from philosophy (Kivy, 2002) to computer science (evidenced by a range of journal titles and conferences), and culminating into its own research discipline known as musicology. Music has also caught the attention of various research areas within psychology (cf. Rentfrow & Gosling, 2003). While a considerable amount of information can be obtained from all this literature, the present chapter focuses on the area of personality psychology and advancing research that has investigated the relation between personality and music preferences.

In 2003, Rentfrow and Gosling noted that there had been little research investigating the relation between personality and music preferences. Rentfrow and Gosling were interested in providing a comprehensive understanding of music preferences and its relation to personality. Over a series of six studies, they thoroughly investigated the importance of music in people's lives, how reported music preferences mapped onto basic preference dimensions, and how these basic dimensions could be related to personality. Their first study supported their idea that individuals view music as an important discussion point when talking to others and that music preference provides useful information about others' characteristics.

Subsequent to their first study, Rentfrow and Gosling (2003) used studies two and three in this series of six to develop their own model of music preferences. Rentfrow and Gosling recruited several thousands of university students across studies two and three, and measured students' music preferences via self-reports for 14 genres: Alternative (Rock), Blues, Classical, Country, Dance, Folk, Funk, Heavy Metal, Jazz, Pop, Rap, Religious, Rock, and Soundtracks. From these two studies, Rentfrow and

Gosling (2003) used factor analytic methods and found four orthogonal music preference dimensions that broadly described music preferences, which the researchers interpreted and labelled. The first dimension, *Reflective and Complex*, broadly described music preferences for Classical, Jazz, Blues, and Folk music. The second dimension, *Intense and Rebellious*, described music preferences for Alternative, Rock, and Heavy Metal. The third dimension, *Upbeat and Conventional*, broadly described music preferences for Country, Pop, Religious and Soundtracks. The fourth dimension, *Energetic and Rhythmic*, described music preferences for Rap/Hip-hop, Soul/Funk, and Electronica/Dance. Rentfrow and Gosling presented these four dimensions as their model of music preferences.

Up to their third study, Rentfrow and Gosling's model was based on reported music preferences using their own music preference measure, which had participants rate their music preferences on a 7-point Likert scale ranging from 1 (*Strongly dislike*) to 7 (*Strongly like*). In order to validate their model further, Rentfrow and Gosling's (2003) fourth study catalogued the music content of personal libraries from participants around the US.

Study five of the six study series used subjective music attribute ratings from seven independent judges to investigate perceptual attributes that might be generalized among the music within each of Rentfrow and Gosling's music preference dimensions. Finally, study six related music preference dimension scores from several thousand participants to their measured Big Five personality scores and other characteristic measures (e.g., cognitive ability, self-views). Their results are summarized in Chapter 1 of the present thesis and in Table 1.1 on page 9.

Since Rentfrow and Gosling's (2003) landmark study, research relating personality to music preferences has gained interest (e.g., Chamorro-Premuzic & Furnham, 2007; Delsing, Ter Bogt, Engels, & Meeus, 2008; George, Stickle, Rachid, & Wopnford, 2007; Rentfrow & Gosling, 2006; Zweigenhaft, 2008). As a result, this research has provided valuable insights into possible comprehensive descriptions concerning music preferences, how music is used, and how these descriptions and uses relate to the Big Five personality dimensions. Nonetheless, this research and much of the research prior to it (e.g., Arnett, 1992; Litle & Zuckerman, 1986; Rawlings & Ciancarelli, 1997) has almost exclusively relied on individuals' self-reports to measure and broadly define music preferences according to genre. Perhaps Rentfrow and Gosling (2003) came closest to directly measuring individuals' music listening habits by investigating individuals' personal libraries in the researchers' fourth study. Still, library content does not indicate how often one song is listened to compared to another and it is certainly conceivable that some songs in a personal library are rarely, if ever, listened to. Therefore, it is argued that cataloguing the musical content of a digital library does not constitute a direct measure of music listening behaviour.

From an interactionist perspective, music listening behaviour is a reflection of both individuals' personality and their situation variables (e.g., their environment, social context). This suggests that individuals will listen to different music in different situations. Buss (1987) argues however, that individuals will choose or manipulate their environment to match their personality. This argument has been supported by research and literature unrelated to music preferences (e.g., Gosling, 2008; Gosling, Ko, Mannarelli, & Morris, 2002; Sulloway, 1996). To build on that research, the present study attempts to answer if individuals are likely to actively select and listen to music that reflects their personality, and if this listening behaviour matches their expressed music preferences, regardless of the environment that they are in.

## 2.1 Objectives and Hypotheses

The first objective for the present study was to confirm Rentfrow and Gosling's (2003) model of music preferences. The second objective was to build on previous research investigating personality and music preferences by directly measuring observed music listening behaviour in one specific environment, namely an office/desk environment. This measurement does not give an exhaustive account of individuals' music listening behaviour. Still, it provides a reasonably accurate account of individuals' music listening behaviour in one specific environment. Much of the previous research that has related personality to music preferences has assumed that reported music preferences accurately reflect listening behaviour (e.g., Arnett, 1992; Delsing et al., 2008; George et al., 2007; Litle & Zuckerman, 1986; Rawlings & Ciancarelli, 1997; Rentfrow & Gosling, 2003, 2006; Zweigenhaft, 2008). The assumption that reported music preferences accurately reflects listening behaviour is explicitly tested in the current chapter. The last objective for the present study was to further investigate the relations between reported music preferences, music listening behaviour, and personality. Buss (1987) has argued that individuals will manipulate their environment to match their personality. Given Buss' argument, it is expected that correlations between music listening behaviour and personality should be consistent with reported music preferences and personality when the environment variable is held constant. Therefore, the hypotheses for the present study were as follows:

H1. Music preferences data will confirm Rentfrow and Gosling's (2003) model of music preferences.
H2. Reported music preferences will be positively correlated with listening behaviour for the same genre.
H3. Correlations between reported music preferences and personality will be consistent with the correlations between music listening behaviour and personality for the same genres.

## 2.2 Method

*Participants*

Participants ($N$ = 395; 335 males) volunteered following a recruitment announcement advertised to individuals using an experimental music database (see *Materials*). All participants were employees of Royal Philips Electronics. Ages ranged from 22 to 60 years ($M$ = 36.7, $SD$ = 8.93). Five participants did not provide their age. There were 29 nationalities represented in this sample. Most participants were Dutch ($n$ = 202), but reported nationalities included the US ($n$ = 50), France ($n$ = 35), Germany ($n$ = 18), Belgium ($n$ = 16), UK ($n$ = 11), Other European countries ($n$ = 33), Other Americas ($n$ = 6), and Asia/Pacific ($n$ = 10). Fourteen participants did not specify their nationality. Due to attrition, not all participants completed all parts of the study. The entire sample ($N$ = 395) finished at least the music preferences measure (STOMP, see *Materials*), but did not necessarily provide sufficient listening behaviour data (see *Procedure*) or complete the personality measure (NEO PI-R, see *Materials*). Participant sub-sample 1 ($n$ = 267; 227 males) finished the STOMP and provided sufficient listening behaviour data, but did not necessarily finish the NEO PI-R. Participant sub-sample 2 ($n$ = 138; 114 males) completed the STOMP and NEO PI-R, and provided sufficient listening behaviour data. The mean age for sub-sample 1 was $M$ = 36.5 years ($SD$ = 8.77). The mean age for sub-sample 2 was $M$ = 36.4 years ($SD$ = 8.71). Nationalities for these sub-samples were proportionally similar to the complete sample.

*Materials*

The music database used was an experimental platform available to participants via the company's Intranet. This database contained nearly 70,000 audio recordings, which were originally uploaded by its users. These recordings were tagged according to an industry standard (All Music Guide (AMG), 2007) into 1 of 16 music genre categories: Alternative (Rock), Blues, Classical, Country, Dance, Folk, Funk, Heavy Metal, Jazz, Pop, Rap, Religious, Rock, R'n'B, Soundtracks, and an Other category. The Other category included miscellaneous items (e.g., underground music, comedy). With exception to the R'n'B and the Other category, these genres matched the 14 genres used by Rentfrow and Gosling (2003). Participants' music listening behaviour was measured in two ways:

1. *Song Count* tracked the number of songs selected for listening, per genre, by each participant. For each participant, this number was divided by their total number of songs listened to. So, the dependent variable was the percentage of songs that started playing (i.e., listened to) within each genre for each participant relative to the total number of songs listened to.
2. *Listening Duration* tracked the time duration (in seconds) of music listened to, per genre, by each participant. For each participant, this number was divided by their total listening time. So, the dependent variable was the listening time percentage within each genre for each participant relative to the total listening time.

Participants' music listening behaviour for Song Count and Listening Duration included all data from songs selected multiple times. Furthermore, a minimum criterion was identified to help ensure that the measured listening behaviour was accurate. Participants were not forced to use the experimental database when listening to music while working at their office desk. Consequently, it was possible for them to use other means to listen to music (e.g., other applications available on their computer, personal music devices, radio). Therefore, a minimum criterion of at least 100 songs was imposed to estimate participants' typical listening behaviour when working at their office desk. This meant that participants' minimum amount of time listening to music was roughly 200 minutes.

In addition to tracking participants' music listening behaviour, two psychometric measures were used in the current experiment:

1. *Short Test of Music Preference (STOMP)* measured participants' reported music preferences (Rentfrow & Gosling, 2003). Participants rated their music preference toward 14 genres serving as items. These items loaded onto the four dimensions described in Rentfrow and Gosling's model of music preferences. Items were rated on a scale from 1 (*Strongly dislike*) to 7 (*Strongly like*).
2. *Revised NEO Personality Inventory (NEO PI-R)* measured participants' personality (Costa & McCrae, 1992). Participants rated 240 items on a scale from 1 (*Strongly Disagree*) to 5 (*Strongly Agree*), which loaded onto the Big Five personality trait dimensions. This provided aggregated scores for the five dimensions, as well as the six facet traits contained within each dimension. Participants could complete the NEO PI-R in either English (Costa & McCrae, 1992), or in Dutch (Hoekstra, Ormel, & de Fruyt, 2003).

*Procedure*

After providing informed consent, participants were given the option to complete a survey in either English or Dutch. Once the language had been selected, participants completed the survey, which consisted of demographic information (age, gender, nationality, and years of musical training), the STOMP, and the NEO PI-R. The survey was given to the participants using a web interface via the Philips Company Intranet. Screenshots of the various parts of the survey are provided in Appendix A. Once the entire survey had been completed, participants were debriefed and thanked for their participation. If the participant had completed the NEO PI-R, they were also provided with a personality report as reward. Participants' music listening behaviour was then tracked for a minimum period of 3 months using the music database. The database was available to participants via the Philips Intranet and was easily accessible while at their office desk.

## 2.3 Results

*Confirming the Existing Model of Music Preferences*

With 395 participants who had completed the STOMP scale, a large enough sample had been obtained to test the first hypothesis and conduct Confirmatory Factor Analysis (CFA) of the STOMP dimensions specified by Rentfrow and Gosling (2003). The CFA was conducted to confirm and test the robustness of their model of music preferences. Using LISREL

(Jöreskog & Sörbom, 2007), CFA was conducted on participants' music preference ratings obtained via the STOMP. A chi-square ($\chi^2$) goodness-of-fit tests the null hypothesis that the data fit well with the proposed model (Tabachnick & Fidell, 2007). Still, the chi-square statistic is influenced by the sample size, wherein larger sample sizes might lead to prematurely rejecting the null hypothesis. So, in addition to a chi-square, several goodness-of-fit criteria were used to assess the relevancy of the model. The statistical criteria included the Root Mean Square Error of Approximation (RMSEA) and the Standardized Root Mean Square Residual (SRMR). Decision rules regarding the cut-off criteria for RMSEA and SRMR indicate that values should be below .10 and .08, respectively (Tabachnick & Fidell). Other goodness-of-fit criteria may also be applied, such as the Goodness of Fit Index (GFI) and the Adjusted Goodness of Fit Index (AGFI). The GFI and AGFI provide estimates of the proportion of variance accounted for by the model. Figure 2.1 illustrates the standardized parameter estimates for the CFA model from the data obtained from the present study.

The obtained music preference data gave a significant chi-square for the goodness-of-fit of the CFA model, $\chi^2$ (71, $N$ = 395) = 499.27, $p$ < .001, suggesting that the fit was not optimal. Additional fit criteria statistics also indicated that the obtained data did not fit well with the existing model. Specifically, both the RMSEA = .12 and the SRMR = .10 were greater than the cut-off criteria noted above. Therefore, unlike Rentfrow and Gosling's results, the current results suggest that their model does not accurately explain patterns in participants' music preferences reported in the present sample.

To further investigate how these data differed from the data obtained by Rentfrow and Gosling (2003) to build their model of music preferences, Principal Components Analysis (PCA) used the STOMP ratings from the current sample to explore alternative music preference dimensions. Table 2.1 provides the 6-factor, Varimax-rotated PCA solution obtained using SPSS 15.0 (SPSS, 2006). Each of these 6 factors had an eigenvalue greater than 1 and cumulatively accounted for 70% of the total variance from participants' reported music preferences. Cells in Table 2.1 indicate the factor loading for the indicated genre (rows) and factor (columns). Factor loadings printed in bold indicate the highest loading for that genre, which meant that the indicated factor had the greatest contribution in the predicted variance for that genre. With exception to the Bass-Heavy label, the factors were labelled based on genre categorization by AMG (2007). The Bass-Heavy label was used to describe the audio characteristics often found in the

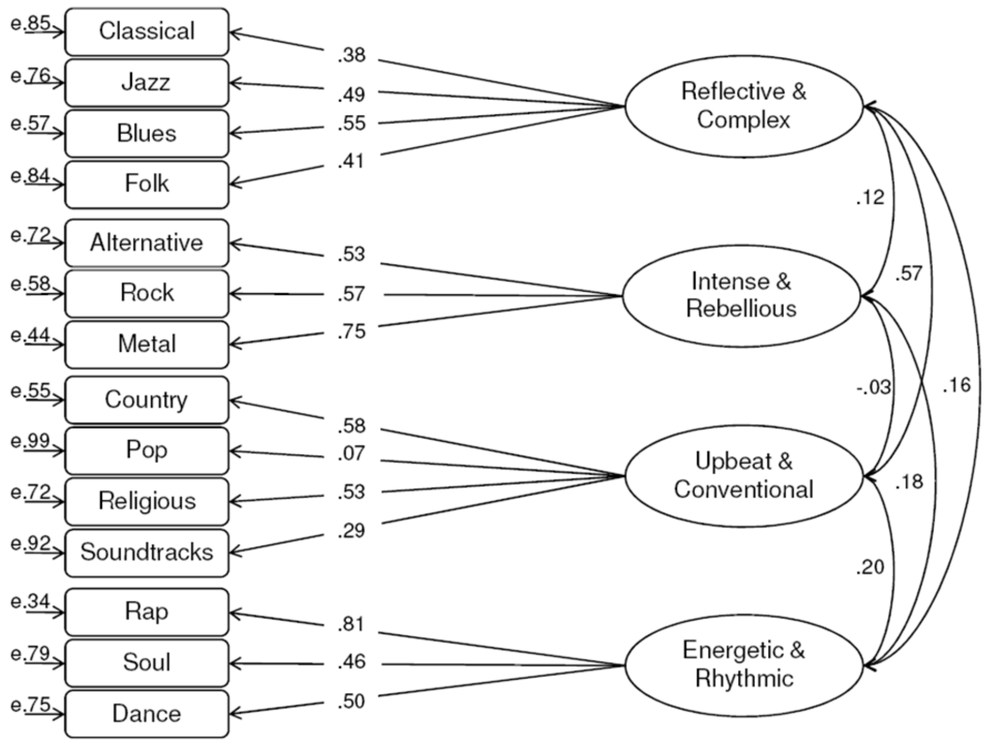



*Figure 2.1.* Standardized parameter estimates for the CFA model from the obtained music preference data. $\chi^2$ (71, $N$ = 395) = 499.27, $p$ < .001 (GFI = .77, AGFI = .85, RMSEA = .12, SRMR = .10). Values shown on the far right denote correlations between latent factors. Path coefficients shown down the middle of the diagram are the estimated effect sizes between latent factors on the right and measured variables on the left. Error variance (e) values shown on the far left denote the proportion of variance in the measured variables that is not accounted for by the latent variables.

music contained within this factor. From Table 2.1, genres loading most on: Factor 1) Hard Rock were Alternative, Rock, and Heavy Metal; Factor 2) Country were Country and Folk; Factor 3) R'n'B were Jazz, Blues, and Funk/Soul; Factor 4) Bass-Heavy were Rap/Hip-Hop and Dance/ Electronica; Factor 5) Soft Rock were Pop and Soundtracks; and finally, Factor 6) Classical were Classical and Religious.

By comparison, Rentfrow and Gosling's (2003) 4-factor solution accounted for 59% of the total variance from participants' reported music preferences. Furthermore, only the genres that made up the Hard Rock

*Table 2.1*
PCA factor loadings from the 14 genres using a 6-factor, varimax-rotated solution.

| | Music Preference Factors | | | | | |
|---|---|---|---|---|---|---|
| Genre | Rhythm 'n Blues | Hard Rock | Bass Heavy | Country | Soft Rock | Classical |
| Jazz | ***.774*** | .069 | .097 | -.154 | -.017 | .278 |
| Blues | ***.754*** | -.006 | -.182 | .311 | .001 | .061 |
| Soul | ***.703*** | .063 | .383 | .113 | .072 | -.143 |
| Heavy Metal | -.061 | ***.812*** | .083 | .134 | .024 | -.141 |
| Alternative | .134 | ***.763*** | .161 | -.077 | -.143 | .222 |
| Rock | .106 | ***.655*** | -.176 | -.057 | *.548* | -.110 |
| Rap | .113 | .017 | ***.842*** | .119 | .056 | -.089 |
| Dance | .010 | .111 | ***.763*** | -.109 | .056 | .098 |
| Country | .020 | -.112 | .007 | ***.834*** | .145 | .069 |
| Folk | .146 | .164 | -.016 | ***.731*** | -.079 | .118 |
| Pop | .077 | -.002 | .097 | .015 | ***.869*** | -.155 |
| Soundtracks | -.157 | -.061 | .149 | .079 | ***.613*** | *.507* |
| Classical | .222 | .013 | -.132 | .043 | -.020 | ***.762*** |
| Religious | -.024 | -.016 | .163 | *.429* | -.140 | ***.603*** |

*Note*. $N = 395$. All factor loadings $|.400|$ or larger are provided in italics; factor loadings in **bold** represent highest factor loadings for each genre given each dimension.

factor were found to be identical to the genres that made up Rentfrow and Gosling's Intense and Rebellious music preference dimension. Based on the inconsistencies between the current results and those results reported by Rentfrow and Gosling, it seemed prudent to conduct further analyses at the genre level, rather than using Rentfrow and Gosling's dimensions.

*Reported Music Preferences versus Listening Behaviour*

Further analysis at the genre level began by comparing reported music preferences to listening behaviour. Due to insufficient listening behaviour from some of the participants, this analysis used sub-sample 1 ($n$ = 267) reported in the Method section.

In addition to the minimum listening behaviour criterion, the data were filtered in two ways. First, correlations were calculated between Song Count and Listening Duration for each of the 16 genres. Among these 16 correlations, no correlation was found less than $r = .97$. These correlation coefficients suggest that these two measures are largely redundant, and so only one needed to be used for results analyses. Therefore, it was decided that only Listening Duration percentages needed to be used for the remainder of the analyses because this measure was arguably slightly more accurate as a measure of participants' entire music listening behaviour (e.g., participants may not listen to an entire song after selecting it, and classical songs tend to be longer than songs from other genres). From this point on then, Listening Duration percentages will be referred to as Duration scores.

Second, it was necessary to determine whether there were differences in Duration scores depending on language used to complete the experiment (English vs. Dutch) or gender (male vs. female). A 2 (language) × 2 (gender) × 16 (genre) mixed ANOVA was conducted to find out if participants' Duration scores differed depending on language or gender for the 16 genres tracked. For this reason, only the interaction effects for language × genre and gender × genre were considered. There were no effects found that were due to the interaction between language × genre, $F(15, 3{,}945) = 0.90$, *n.s.*, or gender × genre, $F(15, 3{,}945) = 1.16$, *n.s.* The results indicate that participants' music listening per genre was not influenced by their gender, or whether the participant completed the survey in English or Dutch. Further analysis also checked if participants' musical training or age was related to the amount of time they had listened to particular genres. To test for this, linear regressions were conducted separately for musical training and age, given Duration scores across genres. Analysis revealed no relation between musical training and Duration scores, $R^2 = .05$, $F(15, 196) = .75$, *n.s.*[1] Age and Duration scores were related however, $R^2 = .17$, $F(15, 247) = 3.48$, $p < .001$. These effects indicated that age was positively related to both Folk Duration scores, partial $\beta = .17$, $t(250) = 2.83$, $p < .01$, as well as to Pop Duration scores, partial $\beta = .26$, $t(250) = 3.68$, $p < .001$. The latter results concerning age and Duration scores suggest that older participants tended to listen to Folk and Pop music more than younger participants. Nonetheless, given that age accounted for a significant proportion of variance in only 2 of 16 genres, it was not necessary to use age as a covariate for music preferences in further analyses. Therefore, there was no need to compare results separately for gender or language, or account for musical training or age in further analyses.

Comparisons between reported music preferences to listening behaviour were done in two complementary ways: (1) correlation between amount of

[1] There were missing data for musical training, resulting in a smaller *df* in the denominator than expected.

music available on the database per genre and mean Duration scores per genre, and (2) correlations between participants' STOMP ratings and their Duration scores.

First, the distribution of the music content available on the experimental database was compared to participants' mean Duration scores per genre. The comparison was done to see if participants' listening behaviour may have been influenced by what music was available and whether this presents a potential bias in the sampled listening behaviour compared to listening behaviour reflected by music industry sales (e.g., British Phonographic Industry (BPI), 2008; IT Facts, 2008). Table 2.2 indicates the percentage of music listening time available per genre relative to the total amount of music listening time available in the database. The percentages were calculated by considering the length of each recording in the music database once. The first column Table 2.2 lists the genre categories in which the various music recordings were assigned, while the second column indicates the percentage of music available for the particular genre relative to the total amount of music available in the database. Table 2.2 indicates that the distribution of songs available on the database was unevenly divided across genres. There are two interesting observations that can be drawn from the information described in Table 2.2. First, the information in this table provides a reasonable representation of the music preferences among all database users considering that it was these users who uploaded the music contained in the database. Second, the users' music preferences reflect the current state of industry music sales in the UK and US, particularly with respect to Rock and Pop genres (cf. BPI, 2008; IT Facts, 2008).

The music database information given in Table 2.2 can be compared to Figure 2.2, which provides a boxplot of the participants' Duration scores for each of the same genres. Figure 2.2 shows that many participants did not listen to music from certain genres (e.g., Blues, Folk, Soundtracks). As a result, median values for these genres were at or near zero. Those participants who did listen to music from these genres are indicated in Figure 2.2 as outliers for the indicated genre. In sum, one can interpret the outliers as fans for music from that genre.

A correlation was computed to indicate whether participants' listening behaviour reflected what was available on the music database. Specifically, the correlation tested if music listening time available per genre on the database (Table 2.2) was correlated with the mean Duration scores per genre and collapsed across participants (Figure 2.2). The result was $r = .99$, indicating that, indeed, participants' listening behaviour reflected what music was

*Table 2.2*
Percentage of music listening time available per genre relative to the total amount of music listening time available in the database.

| Genre | Music Available (%) |
|---|---|
| Alternative | 1.08 |
| Blues | 0.66 |
| Classical | 4.35 |
| Country | 0.57 |
| Dance | 10.11 |
| Folk | 0.71 |
| Funk | 0.58 |
| Heavy Metal | 1.16 |
| Jazz | 3.88 |
| Pop | 13.24 |
| Rap | 1.90 |
| Religious | 0.22 |
| Rock | 47.27 |
| R'n'B | 0.52 |
| Soundtracks | 0.10 |
| Other | 13.66 |

available on the database. The magnitude of this correlation might suggest that participants' listening behaviour is equal to chance probabilities solely dependent on the amount of music available for a given genre. Therefore, more correlations had to be done to test if participants sought out what music they reportedly enjoyed.

To complement the previous analysis, the second comparison made between reported music preferences and listening behaviour investigated correlations between participants' STOMP ratings and their Duration scores. The current analysis tested whether participants' reported music preferences were related to their listening behaviour, regardless of the content available on the music database. The analysis directly tested the second hypothesis that reported music preferences are positively correlated with listening behaviour for the same genre. Table 2.3 gives a matrix of the correlations between participants' STOMP ratings and their Duration scores per genre. Columns in this table discriminate between participants' reported music preferences by genre, while rows discriminate between their measured listening behaviour by genre. Correlation values presented in bold across the

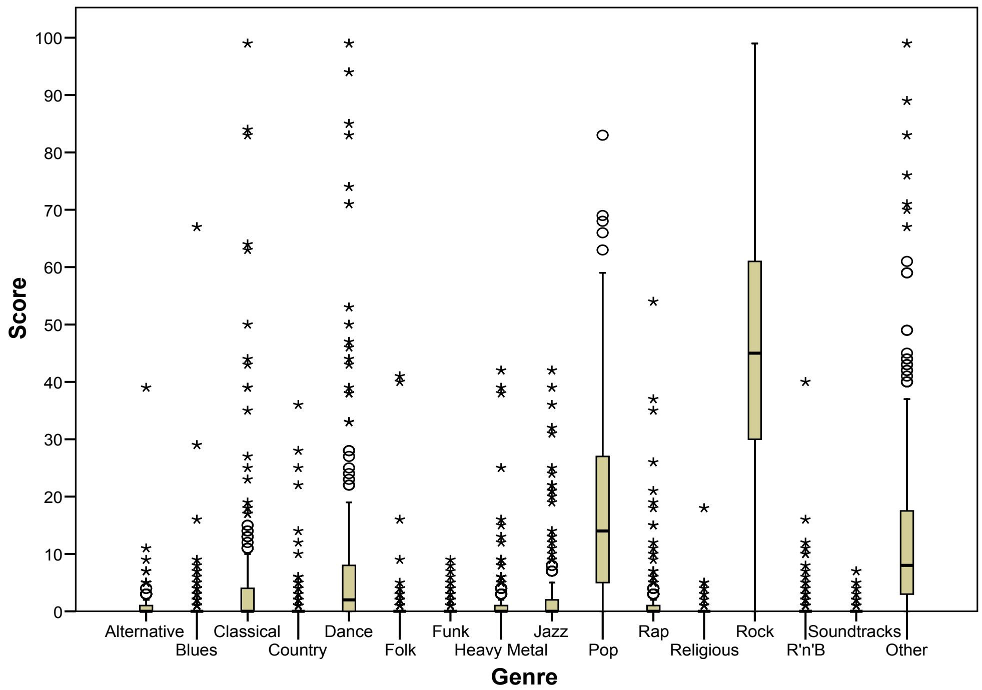



*Figure 2.2.* Boxplot of the participants' Duration scores (i.e., percent of total listening time) per tracked genre from the music database ($N = 267$). Boxed areas in this figure represent the quartile range between the first (lower) quartile and third (upper) quartile. The median is represented by a line dissecting the boxed areas. The lines extending outside of the boxed areas encapsulate 99% of the variance in participants' Duration scores, or ±2.698 *SD* above and below the median. Music in many of the genres shown in this figure was not listened to by a majority of the participants, which resulted in median values at or near zero. Outliers are indicated by markings outside the 99% variance boundaries, where ° is an outlier greater than $p < .01$ and * is an outlier greater than $p < .001$.

diagonal in this matrix indicate expected positive correlations between participants' reported music preferences and their listening behaviour for the same genre.

As seen in Table 2.3, participants' STOMP ratings were nearly always significantly positively correlated to their Duration scores for the same genre. The lone exception to this trend was for Alternative. Alternative is often considered a sub-genre of Rock (AMG, 2007). So, the possibility that Alternative ratings would be correlated to Rock Duration scores was also

*Table 2.3*

Correlation coefficients between participants' STOMP scores and their Listening Duration scores per genre.

| Listening Duration Genre | STOMP Genre | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Classical | Blues | Jazz | Folk | Alter-native | Rock | Heavy Metal | Country | Pop | Reli-gious | Sound-tracks | Rap | Soul | Dance |
| Classical | **.33**** | -.10 | .02 | .00 | -.11 | -.11 | -.21** | -.02 | -.04 | .06 | .03 | -.08 | -.10 | -.10 |
| Blues | .00 | **.22**** | -.05 | .08 | .00 | -.02 | .03 | -.04 | -.06 | -.05 | -.14* | .01 | .16** | -.12 |
| Jazz | .09 | .06 | **.37**** | .00 | .06 | .00 | -.04 | -.15* | -.05 | -.05 | -.25** | -.02 | .14* | .05 |
| Folk | .08 | -.01 | -.05 | **.16*** | .03 | -.06 | .01 | .11 | -.03 | .04 | -.03 | -.05 | -.02 | -.01 |
| Alternative | -.11 | -.13* | -.04 | -.06 | **.11** | .13* | .16* | -.03 | .05 | -.06 | -.01 | .06 | -.05 | .13* |
| Rock | -.21** | .00 | -.01 | -.05 | .38** | **.33**** | .44** | -.13* | .00 | -.12 | -.09 | .00 | .04 | -.07 |
| Heavy Metal | -.17** | -.15* | -.11 | -.10 | .11 | .11 | **.28**** | -.11 | -.06 | -.10 | -.09 | .00 | -.04 | -.05 |
| Country | .01 | .04 | -.05 | .18** | .10 | -.09 | -.04 | **.27**** | .04 | .07 | .03 | -.01 | .06 | -.03 |
| Pop | -.10 | .10 | -.12* | .00 | -.33** | -.04 | -.13* | .22** | **.20**** | .03 | .07 | -.14* | -.08 | -.24** |
| Religious | .06 | .00 | -.02 | -.06 | -.08 | -.29** | -.12 | .05 | -.18** | **.26**** | .02 | -.07 | -.08 | -.10 |
| Soundtracks | -.05 | -.03 | -.09 | .05 | -.06 | -.03 | -.13* | .12 | .06 | -.04 | **.14*** | .00 | -.12 | .00 |
| Rap/Hip-hop | -.10 | .04 | .01 | .11 | -.04 | .03 | .02 | .01 | .08 | .08 | .07 | **.42**** | .17** | .15* |
| Soul /Funk | -.14* | .23** | .02 | .12* | -.10 | -.05 | .01 | .07 | -.05 | .10 | -.15* | .04 | **.24**** | -.07 |
| Dance/ Electronica | -.03 | -.08 | .04 | -.12 | .02 | -.17** | -.07 | -.16** | -.09 | .01 | -.04 | .13* | .05 | **.43**** |
| R'n'B | -.02 | .07 | .14* | -.13* | -.16** | -.13* | -.13* | -.03 | .05 | -.08 | .06 | .12 | **.16*** | .07 |
| Other | .18** | -.01 | .00 | .10 | -.16** | -.14* | -.29** | .13* | -.05 | .08 | .21** | -.07 | -.13* | -.03 |

*Note*. $N = 267$. Correlation values in **bold** indicate expected significant positive correlations between participants' reported music preferences and their listening behaviour for the same genre.

* $p < .05$, ** $p < .01$.

considered, and that Rock ratings would be correlated to Alternative Duration scores. As indicated in Table 2.3, both of these correlations were positive and significant. Reported preference to Heavy Metal was also significantly and positively correlated to listening behaviour for both Alternative and Rock. Finally, while no R'n'B STOMP rating was recorded, R'n'B was considered comparable with Soul for the purposes of the current study after careful consideration using industry sources (AMG). Given this, Funk/Soul ratings were also correlated with R'n'B Duration scores. This final correlation was also positive and significant.

*Personality, Music Preferences, and Listening Behaviour*

The third and final hypothesis contended that correlations between reported music preferences and personality are consistent with the correlations between music listening behaviour and personality for the same genres. To test this hypothesis, participants' measured personality traits and their reported music preferences were correlated and compared to the correlations between participants' traits and their listening behaviour. Due to incomplete or unreturned NEO PI-R surveys, the current analyses used sub-sample 2 ($n$ = 138) reported in the Method section. Table 2.4 provides correlations between participants' personality trait dimensions and reported music preferences/listening behaviour per genre. Columns separate correlations by trait dimension, further divided by correlations between participants' measured trait dimensions and their reported music preferences (S), or their Duration scores (D). Rows separate correlations by genre. Looking at Table 2.4, only two pairs of correlations provided consistent significant findings between participants' personality and their music preferences. These consistent correlations were between Neuroticism and Classical ($r$ = .20, $p$ < .05 for S, and $r$ = .18, $p$ < .05 for D), and between Openness to Experience and Jazz ($r$ = .27, $p$ < .01 for S, and $r$ = .18, $p$ < .05 for D).

## 2.4 Discussion

The present study has built on previous research concerning music preferences and personality by investigating the nature of the relation between reported music preferences and listening behaviour, and how personality is related to these variables. As expected, participants' reported music preferences for various genres were nearly always correlated with their listening behaviour for the same genre; 16 of the 17 correlations were significant. The current study also attempted to confirm results from

*Table 2.4*
Correlations between participants' personality trait dimensions and their reported music preferences/listening behaviour per genre.

| | N | | E | | O | | A | | C | |
|---|---|---|---|---|---|---|---|---|---|---|
| Genre | S | D | S | D | S | D | S | D | S | D |
| Blues | -.13 | -.15 | .05 | .06 | -.04 | -.06 | .09 | .06 | -.03 | .00 |
| Classical | .20* | .18* | -.08 | -.04 | .15 | .14 | .02 | .02 | -.09 | -.24** |
| Folk | .06 | .26** | -.03 | -.18* | .10 | .11 | .20* | .05 | .00 | -.05 |
| Jazz | .08 | .11 | .04 | -.15 | .27** | .18* | -.05 | .01 | -.19* | -.15 |
| Alter-native | .11 | -.06 | .05 | .03 | .18* | .06 | -.04 | .11 | -.09 | .03 |
| Heavy Metal | -.04 | -.02 | .10 | .03 | -.04 | .02 | -.18* | -.11 | .05 | .09 |
| Rock | -.04 | -.15 | .02 | .11 | .20* | .02 | .07 | -.09 | .06 | .08 |
| Country | .05 | .14 | .01 | .10 | -.16 | .00 | .13 | .15 | -.10 | .09 |
| Pop | -.16 | -.13 | .20* | .03 | .02 | -.10 | .23** | .09 | .13 | .16 |
| Religious | .11 | -.06 | -.01 | .17* | .01 | .05 | .04 | .09 | -.13 | .04 |
| Sound-tracks | .15 | .04 | .10 | -.14 | -.04 | .09 | .01 | .18* | .07 | .05 |
| Dance | -.15 | .03 | .22* | -.07 | .02 | -.11 | .06 | .05 | .09 | .01 |
| Rap | -.18* | -.07 | .21* | .05 | .04 | -.04 | .00 | -.07 | .14 | .00 |
| Soul | .05 | .02 | .03 | -.03 | .13 | -.17* | .00 | -.03 | -.05 | -.11 |

*Note*. $N$ = 138. N = Neuroticism; E = Extraversion; O = Openness; A = Agreeableness; C = Conscientiousness. S = STOMP preference ratings, D = Duration scores.
* $p < .05$, ** $p < .01$.

previous research relating music preferences and personality. The results from the present study are discussed in the following sub-sections in order of the hypotheses, beginning with the Confirmatory Factor Analysis (CFA), which attempted to confirm Rentfrow and Gosling's (2003) model of music preferences.

*Confirming the Existing Model of Music Preferences*

The present study began with a CFA of Rentfrow and Gosling's (2003) model of music preferences to determine whether to use their music preference dimensions, or genre categorization when analyzing the remaining results. CFA results did not confirm their model of music preferences. For this reason, further analysis used genre to categorize participants' music preferences. Additional Principal Components Analysis (PCA) was subsequently used to explore structural differences in music preferences observed in the present sample compared to Rentfrow and Gosling's model.

The PCA revealed a 6-factor structure in the present sample versus a 4-factor structure provided by Rentfrow and Gosling's model. Only Rock, Alternative, and Heavy Metal genres were consistently grouped in both factor structures, which also consistently grouped in previous research (e.g., Delsing et al., 2008; George et al., 2007). Whereas Rentfrow and Gosling labelled this factor as Intense and Rebellious, it was labelled Hard Rock in the 6-factor structure. The Hard Rock label was used in agreement with other researchers (i.e., Delsing et al, 2008; Zweigenhaft, 2008), who have questioned the original label used by Rentfrow and Gosling. Therefore, the Hard Rock label suggests that this factor is more a reflection of the industry nomenclature of Rock music (AMG, 2007), rather than thematic attitudes conveyed by Rentfrow and Gosling's labels.

The remaining five PCA factors demonstrate subtle inconsistencies between the present results and the results from other research. For instance, while Rap and Dance genres grouped together in the PCA, these genres are grouped separately in other research (e.g., Delsing et al.; George et al.). Conversely, Blues and Jazz were grouped separately from Classical in the PCA, but grouped together in other research (e.g., Delsing et al.; Rentfrow & Gosling). The inconsistencies among research results suggest differences between samples and cultures regarding how genre labels are viewed; what content is represented by a genre label, and how it is related to other genre labels. For example, while the present study recruited participants within Europe, Rentfrow and Gosling recruited participants within the U.S., while still other researchers recruited participants within the Netherlands or Canada (i.e., Delsing et al. and George et al., respectively). If the illustrated inconsistencies are due to cultural differences, then the abstract music dimensions proposed in Rentfrow and Gosling's model of music preferences likely add to the ambiguous nature of genre labels. Therefore, the present results indicate that Rentfrow and Gosling's model is not as robust as originally believed, at least not across cultures.

*Reported Music Preferences versus Listening Behaviour*

As previously stated, participants' reported music preferences (via the STOMP) were generally correlated with their listening behaviour. This main finding was preceded by a comparison between the music database content and participants' mean Duration scores per genre. The resulting correlation from the comparison ($r$ = .99) led to the possibility that participants' listening behaviour might simply be the result of what music was available. This conclusion is not supported by the results from the main finding, however, which showed that participants sought out and listened to genres they reportedly preferred. Of course, correlations between participants' reported music preferences and their listening behaviour were not nearly as close to 1 as the correlation mentioned above, but there are several reasons that account for this. First, by correlating the database content with the mean Duration scores, the analysis only considered how often *all* participants listened to content within each music genre. Differences in personal music taste among the participants were removed from that comparison. As a result, participants' listening behaviour reflected the database content, which was provided by its users (including participants) and mirrors current trends in the music industry (e.g., BPI, 2008; IT Facts, 2008). Second, participants could rate several genres high (or low) when reporting their music preferences, but they cannot listen to every highly preferred genre 100% of the time. Third, while it was possible to get a reasonably accurate measure of participants' music listening behaviour in one context (i.e., at work), it was not possible to measure their listening behaviour in all contexts of daily life over a period of several months. Last, the perception of what a genre label represents is often confused and overlapping. This genre ambiguity was evidenced by the results from the Confirmatory Factor Analysis, as well as significant between-genre correlations like the correlations between Rock and Alternative. The latter three reasons all introduce errors when attempting to correlate reported music preferences with music listening behaviour, resulting in lower correlation coefficients. This may be particularly true for genre labels that are broadly defined (e.g., Pop), potentially vaguely conceived by our participants (e.g., Folk), or both (e.g., Soundtracks). So, given these limitations, it was sufficient to get significant correlations a majority of the time to conclude that reported music preferences reasonably reflect music listening behaviour.

*Personality, Music Preferences, and Listening Behaviour*

The broad nature of genre might also partly explain why correlation results between music preferences and the Big Five personality traits have varied so greatly across the research investigating this relation. Such inconsistencies were also found in the present results. On the one hand, there were several significant correlations when considering reported music preferences, such as positive correlations between Extraversion and Pop, Dance, and Rap genres, which matched some of the previous research (e.g., Delsing et al., 2008; Rentfrow and Gosling, 2003). On the other hand, listening behaviour data provided positive correlations between Extraversion and Religious music, as well as between Agreeableness and Soundtracks, which is again similar to previous findings (e.g., Rentfrow & Gosling). Nonetheless, the only consistent correlations found after considering both reported music preferences and listening behaviour was between Neuroticism and Classical music, as well as between Openness to Experience and Jazz. Furthermore, only the latter of these two correlations was also consistent when compared with previous research (e.g., Delsing et al., 2008; George et al., 2007; Rentfrow & Gosling, 2003; Zweigenhaft, 2008). Consequently, the inconsistencies between the present results and previous research suggest it is difficult to discern which robust relations between personality and music preferences really exist, and which relations have been found by chance.

## 2.5 Summary and Conclusion

Overall, the results from the present study indicate that reported music preferences are correlated to listening behaviour. Nevertheless, the predominantly low correlation coefficients found between reported music preferences and listening behaviour emphasized the ambiguous nature of genre labels (Aucouturier & Pachet, 2003). The ambiguous nature of genre labels also helps explain the inability to confirm Rentfrow and Gosling's (2003) model of music preferences. In the end, a 6-factor solution was reached using the current results, compared to Rentfrow and Gosling's 4-factor solution. Furthermore, the explanation concerning genre ambiguity also helps to account for the differences between the current results and previous results (e.g., Delsing et al., 2008; George et al., 2007; Rentfrow & Gosling, 2003; Zweigenhaft, 2008), concerning the numerous inconsistent correlations found between personality and music preferences. If genre ambiguity contributes to the apparent inconsistencies among results, then it might be useful to explore alternative ways to ascertain music preferences. Therefore, Chapter 3 presents research that has explored song preferences, as well as genre preferences, to see what benefits can be gained when using songs to determine music preferences and how music preferences for specific songs might be related to personality.

# 3

## Exploring the Relation between Personality and Song Preference

The recent increase of investigations concerned with the relation between personality and music preferences has led to many different and sometimes contradictory findings describing this relation (e.g., Delsing, Ter Bogt, Engels, & Meeus, 2008; George, Stickle, Rachid, & Wopnford, 2007; Rentfrow & Gosling, 2003; Zweigenhaft, 2008). The inconsistent findings concerning the relation between personality and music preferences were further verified by the findings in Chapter 2. As suggested in Chapter 2, these findings may be partly attributed to the ambiguous nature of genre classification (Aucouturier & Pachet, 2003). Conceivably then, the genre ambiguity issue could be partly addressed by measuring music preferences at a greater level of detail. Specifically, it should be possible to strengthen the predictive relation between personality and music preferences by measuring individuals' preferences for specific musical pieces.

Further strengthening of the predictive relation between personality and music preferences might also be gained by using finer detailed measurement of the Big Five, known as facet-level traits (Costa & McCrae, 1992). There are 30 facet traits measured within the Big Five model, 6 facets within each of the Big Five dimensions.[1] It has been suggested that facet-level traits could provide a better or clearer understanding of music preferences given personality (Rentfrow & Gosling; Zweigenhaft). Zweigenhaft used the NEO PI-R (Costa & McCrae) to measure the facet-level traits of 83 participants, and related these traits to their genre music preferences recorded by the STOMP (Rentfrow & Gosling). In doing so, Zweigenhaft reported over 200 correlations, all but guaranteeing that spurious correlation

[1] Please refer to Costa and McCrae (1992) for a full description of each of these facets.

results were also reported. As a result, it is difficult or impossible to disentangle genuine correlations from spurious ones. The outcome taken from Zweigenhaft's (2008) results further emphasizes the inconsistency seen among the results summarized in Table 1.1 in Chapter 1.

As an alternative to correlation analyses, regression analyses can limit the number of personality facet traits found to be significantly related to music preferences. By using regression, only the facets that uniquely contribute to a significant proportion of the variance that explains measured music preferences are reported. Facet traits that do not explain a larger or unique proportion of variance compared to other facet traits are not reported, even if these facet traits were correlated with measured music preferences. In this way, it is possible to evaluate the relation between facets and music preferences, while limiting the chances of spurious results. Furthermore, by using regression, it is possible to evaluate how much of the variance in measured music preferences is explained by the Big Five personality dimensions, and compare this explained variance with the amount explained by using personality facets.

## 3.1 Objectives and Hypotheses

The present study builds on the results from Chapter 2. Specifically, it addresses the inconsistent results from previous studies (e.g., Delsing et al., 2008; George et al., 2007; Rentfrow & Gosling, 2003; Zweigenhaft, 2008) by exploring how measuring both personality and music preferences in greater detail can lead to predictive improvements in the relation between these two variables. Measuring music preferences in greater detail is done by using specific music clips. By using music clips to investigate preferences, other aspects related to music preferences can also be investigated, such as how music clip familiarity is related to music clip preferences. The literature indicates that individuals tend to prefer music that is familiar to them (e.g., Levitin, 2006). The present study also continues to investigate the relation between reported music preferences and listening behaviour, which began in Chapter 2. The research started in Chapter 2 is extended by analyzing the relation between reported music preferences and preference toward specific music clips. Lastly, greater detail in personality measurement provided the opportunity to investigate the improvements gained by using personality facets, compared to broader personality traits when predicting music preferences. Therefore, based on the reviewed literature, the hypotheses for the present study were:

H1. Music clip familiarity will be positively correlated with music clip preference.
H2. Reported preference for each genre will be positively correlated with preference ratings for music clips from the same genre.
H3. Facet-level personality descriptors will provide stronger predictive relations to music clip preferences by genre compared to the Big Five dimension-level personality descriptors.

## 3.2 Method

*Participants*

Participants (*N* = 36; 25 males) volunteered following an announcement advertised to employees of Royal Philips Electronics. Participants ranged across several professions (e.g., administrative, human resources, research, etc.), as well as across 10 different nationalities: Dutch (*n* = 21), other nationalities (*n* = 15). Participants' ages ranged from 21 to 47 years (*M* = 28.1, *SD* = 5.5).

*Materials*

Participants listened to 18 different music clips using Beyerdynamic DT990 PRO headphones, which were played from a computer using a RME DIGI96/8PAD 24-bit PCI digital audio card. Each music clip lasted 10 seconds taken from what was the most representative portion of the entire music recording (i.e., song), which typically was the refrain or chorus due to its recurring nature (Levitin, 2006). Based on the genres used by Rentfrow and Gosling (2003), these music clips ranged across nine different genres: Blues, Classical, Country, Heavy Metal, Jazz, Pop, Rap/Hip-Hop, Rock, Soul/Funk (2 music clips per genre). A third party who had expertise in music selected the specific music clips within each of the listed genres. Selected music clips were taken from a library of several thousand music pieces, which had been categorized by genre according to industry sources (i.e., All Music Guide (AMG), 2007). No artist or song was represented twice in different music clips. Furthermore, each genre had one music clip that had a fast-paced tempo (>140 beats per minute or bpm), while the other had a slow-paced tempo (<100 bpm). This division between slow and fast tempo was made because tempo is an easily recognizable property of music (Levitin, 2006), which has been related to arousal (Dillman Carpentier &

Potter, 2007), and so might be related to Extraversion (e.g., Arnett, 1992; Litle & Zuckerman, 1986; McNamara & Ballard, 1999).

Participants used the computer interface to rate the following three items after each music clip on a 5-point Likert scale:

1. In your opinion, how much do you like this song?
   (1 = *Strongly Dislike*, 5 = *Strongly Like*)
2. In your opinion, how familiar are you with this song?
   (1 = *complete unfamiliarity*, 5 = *complete familiarity with song title and artist known*)
3. Using the following list, please select the genre that, in your opinion, is best representative of this song.
   (18 different genres listed, including the genres listed above)

In addition to providing demographic information (age, gender, and years of music training), participants were asked to fill out the following questionnaires:

1. *Music Preference List* was a list of 18 popular music genres that participants ranked according to how often they enjoyed listening to each genre, and also allowed them to list (and rank) genres they felt were missing. The 18 genres included the 9 genres listed above plus Alternative Rock, Electronica/Dance, Folk, New Age, R'n'B, Reggae, Religious/Gospel. Also, Rock was divided into Classic Rock (Rock before 1990) and Modern Rock (Rock after 1990), and Rap/Hip-Hop was divided into Rap and Hip-Hop. Permitting participants to add and rank additional genres allowed for the chance to find other, potentially pertinent genres for future research. The dependent variable taken from this measure was music preference ranking that ranged from 1 to 20. Any unranked genres were given a default score of 20.
2. *Revised NEO Personality Inventory (NEO PI-R)* measured participants' personality (Costa & McCrae, 1992). Participants rated 240 items on a scale from 1 (*Strongly Disagree*) to 5 (*Strongly Agree*), which loaded onto the Big Five personality trait dimensions. The NEO PI-R gave aggregated scores for the five dimensions, as well as the six facets within each dimension. Participants were able to complete the NEO PI-R in either English

(Costa & McCrae, 1992), or in Dutch (Hoekstra, Ormel, & de Fruyt, 2003).

*Procedure*

After giving consent, participants provided their demographic information and completed the Music Preference List. Participants were then placed in front of a computer to listen to and rate each of the 18 music clips, provided in counterbalanced order. Lastly, participants were asked to complete the NEO PI-R before being debriefed and thanked for their participation. Screenshots of the various interfaces are provided in Appendices A and B.

## 3.3 Results

The analyses of results began by testing whether familiarity predicted preference ratings for each music clip. To calculate an overall effect of familiarity on preference ratings, one squared correlation coefficient was calculated across all 18 music clips, for all participants. An F-test of this squared correlation coefficient indicated that familiarity predicted a significant proportion of variance in clip preference ratings, $r^2 = .17$, $F(1, 646) = 128.06$, $p < .001$. The result of the F-test suggests that there is a positive linear relation between music preference and music familiarity. Plainly stated, preference for a given piece of music increases as one grows more familiar with that music and vice versa.

Analyses continued by checking the adequacy of the music clips used in the present study. Checking the adequacy of the music clips was done in two complementary ways: (1) assessing how participants categorized the music clips by genre, and (2) investigating correlations between reported music preferences and music clip preference ratings.

How participants categorized the music clips by genre was assessed by tabulating their frequency counts of the music clip genre categorization into a confusion matrix, which is provided in Table 3.1. The table gives the assigned genre and tempo category for each of the 18 music clips in the first two columns. The table field gives the frequencies for how participants categorized each music clip, designated by row, according to genre, designated by column. Numbers given in bold represent the frequency of matches between the experimentally-assigned music clip genre category and how participants categorized that music clip. For the purposes of the current analysis, participants' categorization frequencies for Rap and Hip-Hop were merged as "Rap," and Classic Rock and Modern Rock were merged as

*Table 3.1*
Confusion Matrix of Participants' Music Clip Genre Categorization.

| Music Clip | Tempo | Genre: Blues | Classical | Country | Folk | Funk | Heavy Metal | Jazz | Pop | R'n'B | Rap | Rock | Alt. Rock | Other | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Blues | Slow | **28** | 0 | 2 | 0 | 1 | 0 | 1 | 3 | 1 | 0 | 0 | 0 | 0 | 36 |
| | Fast | **22** | 0 | 2 | 0 | 0 | 0 | 3 | 1 | 1 | 0 | 6 | 0 | 1 | 36 |
| Classical | Slow | 0 | **35** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 36 |
| | Fast | 0 | **33** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 36 |
| Country | Slow | 6 | 0 | **8** | 3 | 1 | 0 | 6 | 12 | 0 | 0 | 0 | 0 | 0 | 36 |
| | Fast | 0 | 0 | **32** | 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 36 |
| Funk | Slow | 1 | 0 | 0 | 0 | **17** | 0 | 3 | 6 | 6 | 3 | 0 | 0 | 0 | 36 |
| | Fast | 2 | 0 | 0 | 0 | **19** | 0 | 1 | 6 | 2 | 0 | 4 | 0 | 2 | 36 |
| Heavy Metal | Slow | 0 | 0 | 0 | 0 | 0 | **20** | 0 | 1 | 0 | 0 | 6 | 9 | 0 | 36 |
| | Fast | 0 | 0 | 0 | 0 | 1 | **29** | 0 | 0 | 0 | 0 | 5 | 1 | 0 | 36 |
| Jazz | Slow | 10 | 0 | 0 | 0 | 0 | 0 | **23** | 2 | 1 | 0 | 0 | 0 | 0 | 36 |
| | Fast | 3 | 0 | 0 | 1 | 0 | 0 | **29** | 1 | 1 | 0 | 0 | 0 | 1 | 36 |
| Pop | Slow | 1 | 0 | 0 | 1 | 0 | 0 | 0 | **22** | 0 | 0 | 11 | 1 | 0 | 36 |
| | Fast | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **29** | 0 | 0 | 6 | 1 | 0 | 36 |
| Rap | Slow | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 | 7 | **18** | 0 | 0 | 1 | 36 |
| | Fast | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **36** | 0 | 0 | 0 | 36 |
| Rock | Slow | 1 | 0 | 0 | 0 | 2 | 0 | 0 | 1 | 2 | 0 | **28** | 2 | 0 | 36 |
| | Fast | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 2 | 0 | 0 | **31** | 0 | 0 | 36 |
| Total | | 74 | 68 | 44 | 9 | 41 | 52 | 66 | 96 | 21 | 57 | 97 | 14 | 9 | 648 |

*Note*. $N = 36$. Numbers in **bold** indicate matching categorization frequency count between music clip genre category and genre categorization by participants. The "Other" genre category is a compilation of the Dance, Reggae, and Religious/Gospel genre categories.

"Rock." Merging these genre categories was done based on how closely these specific genres were related, which is also why previous research has not separated these genres (e.g., Rentfrow & Gosling, 2003). As indicated in Table 3.1, the assigned genre categories given to many of the music clips matched participants' genre categorization for a majority of the cases.

The second way that the adequacy of the music clips were checked was by investigating correlations between reported music preferences and music clip preference ratings. Reported music preferences were measured using the exploratory music preference list as described in the Method section. The music preference list also gave participants the opportunity to provide and rank additional genres that they listen to, though this was done by only 10 participants. Additional genres added by participants mainly consisted of traditional music from various cultures or regions of the world (e.g., East Indian, Greek Folk, "Nederlandstalig") or very specific styles within already specified genres (e.g., Contemporary Classical). Due to how preferences were measured, it is necessary to state explicitly how the music preferences for Rap and Rock would be analyzed considering participants' preference rating for the clips from the same genres. Hip-Hop and Rap genres were ranked within three positions of each other by 27 participants. The same statement can be said of Classic Rock and Modern Rock for 25 participants. For the present investigation, participants' reported preference ranking for Rap was used rather than for Hip-Hop because the associated music clips provided to participants were specifically identified under the Rap genre (AMG, 2007). Given the release dates of the Rock clips used in the present investigation participants' preference ranking for Classic Rock was considered for the current analyses rather than Modern Rock.

Having specifically stated how participants' preference ratings for Rap and Rock would be analyzed, the relation between reported music preferences and preference ratings for each clip from each genre was analyzed by calculating Spearman's rho ($r_s$). The Spearman's rho correlations were calculated between participants' music preference rankings for a given genre and their preference ratings for each of the music clips from the same genre. The Spearman's rho correlations are given in Table 3.2, which indicates that 12 of the 18 possible correlations were positive and significant. It makes sense that participants' preference toward a given genre does not mean that they will like every given music clip or song taken to represent that genre.

The assessment regarding how participants categorized the music clips by genre, and how their reported music preferences were correlated to their

*Table 3.2*
Spearman's rho correlations between reported music preferences and clip preference ratings.

| Music Clip | $r_s$ |
|---|---|
| Slow Blues | .40* |
| Fast Blues | .45** |
| Slow Classical | .59** |
| Fast Classical | .57** |
| Slow Country | .39* |
| Fast Country | .42* |
| Slow Heavy Metal | .63** |
| Fast Heavy Metal | .63** |
| Slow Jazz | .26 |
| Fast Jazz | .24 |
| Slow Pop | .01 |
| Fast Pop | .34* |
| Slow Rap/Hip-Hop | .40* |
| Fast Rap/Hip-Hop | .71** |
| Slow Rock | .18 |
| Fast Rock | .53** |
| Slow Soul/Funk | .07 |
| Fast Soul/Funk | .22 |

*Note*. $N = 36$.
* $p < .05$, ** $p < .01$

preference ratings for each music clip was done to assess the adequacy of the music clips for the present study. Taken together, the results from the two complementary analyses suggest that most of the selected songs were reasonable representations of the genres from which they were taken. Subsequently, the current results facilitated the last set of analyses that were conducted.

The final hypothesis was about whether personality measured at the facet-level would predict music clip preference by genre better than personality measured at the dimension-level. The analysis began by checking if participants' preference ratings for the two music clips within each of the nine genres were minimally consistent to be considered as a single measure of music clip preference for that genre. For the purposes of the current study, minimally consistent meant that the correlations between preference

*Table 3.3*
Correlations between participants' preference ratings for the two music clips categorized within each genre.

| Genre | r |
|---|---|
| Blues | .55** |
| Classical | .49** |
| Country | .07 |
| Heavy Metal | .61** |
| Jazz | .52** |
| Pop | -.10 |
| Rap/Hip-Hop | .49** |
| Rock | .23 |
| Soul/Funk | .35* |

*Note*. $N = 36$.
* $p < .05$, ** $p < .01$

ratings for both music clips within each genre are significant. Table 3.3 provides the correlations for preference ratings between both music clips within each genre. The results indicated that six of the nine correlations identified in Table 3.3 were significant. Therefore, clip preference ratings for these six identified genres were summed and analyzed with respect to their relation to personality.

There were still several steps involved in order to analyze how both dimension- and facet-level personality traits could predict music preference ratings by genre. First, stepwise regression at the dimension-level revealed the traits that uniquely predicted a significant proportion in the preference ratings for each genre. Second, stepwise regression at the facet-level revealed the traits that uniquely predicted a significant proportion in the preference ratings for each genre. Finally, an ensuing F-test on the $F_{\text{change}}$ determined if the unique proportion of variance predicted at the facet-level was significantly greater than the proportion of variance predicted at the dimension-level. These steps are illustrated in Table 3.4, which indicates the proportion of variance ($R^2$) for music clip preference ratings by genre and tempo, given personality measured at the dimension- and facet-level, and predictive improvement ($F_{\text{change}}$).

The first column in Table 3.4 separates the regression findings by genre and tempo level. The second and third columns give the dimension traits that uniquely predicted a significant proportion of variance in clip prefe-

*Table 3.4*
Squared correlation coefficients ($R^2$) and predictive improvement between dimension- and facet-level personality traits predicting clip preference ratings.

| Genre/Tempo | Dimension | $R^2$ | Facet | $R^2$ | $F_{change}$ | $p <$ |
|---|---|---|---|---|---|---|
| Genre | | | | | | |
| Blues | *Conscientiousness* (*C*) | .20** | *Competence* (*C1*) | .24** | 2.12 | *n.s.* |
| Classical | Neuroticism (N) | .15* | Aesthetics (O2), *Altruism* (*A3*) | .32** | 4.51 | .05 |
| Heavy Metal | Neuroticism (N), Openness to Experience (*O*) | .08 | *Feelings* (*O3*), Anxiety (N1), *Self-Consciousness* (*N4*) | .51** | 8.97 | .001 |
| Jazz | *Conscientiousness* (*C*) | .14* | *Competence* (*C1*), *Actions* (*O4*) | .37** | 6.33 | .01 |
| Rap/Hip-hop | Extraversion (E) | .11* | *Modesty* (*A5*) | .13* | 3.37 | *n.s.* |
| Soul/Funk | - | - | - | - | - | - |
| Tempo | | | | | | |
| Slow Tempo | *Conscientiousness* (*C*) | .05 | *Competence* (*C1*) | .21** | 10.05 | .01 |
| Fast Tempo | *Conscientiousness* (*C*) | .03 | *Deliberation* (*C6*) | .12* | 3.38 | *n.s.* |

*Note*. $N = 36$. Items in *Italics* represent negative relations. Dash marks (-) indicate no significant relations found.
* $p < .05$, ** $p < .01$

rence ratings by genre/tempo and their squared correlation coefficient, respectively. The fourth and fifth columns provide the facet traits that uniquely predicted a significant proportion of variance in music clip preference ratings by genre/tempo and their squared correlation coefficient, respectively. The last two columns give the $F_{change}$ statistic and the level of significance ($p$ <) for $F_{change}$. As illustrated in Table 3.2, there were no significant predictors at the dimension-level for two of the six genres, and no significant dimension-level predictors for fast and slow tempo. In these cases where there were no significant predictors at the dimension-level, the dimensions with their $R^2$ coefficients that correspond to significant predictors at the facet-level are provided as a basis for comparison. Dash marks are used to show no significant findings for the one case in which no traits at either the dimension- or facet-level significantly predicted preference ratings (i.e., Soul/Funk). All but one of the regressions made at the facet-level were significant. Given the $F_{change}$ statistic, there were significant improvements between dimension-level and facet-level $R^2$ coefficients in three of the five genres tested. The most striking finding with this analysis was for Heavy Metal, for which there was no significant $R^2$ coefficient at the dimension-level. Nonetheless, three facets uniquely accounted for a significant proportion of variance in music clip preference ratings and combined for an $R^2 = .51$, $F(3, 32) = 11.01$, $p < .001$.

## 3.4 Discussion

The present study investigated predictive improvements in music preference gained by using song preference and personality facet measurements. Results indicated predictive improvements to music clip preference ratings using personality facets, compared to the Big Five dimensions, for five of the six genres tested in this way. Furthermore, the predictive improvements were significant for three of the six genres. The sample size ($N = 36$) and the limited number of songs per genre (i.e., 2) meant that the increases in the effect size ($R^2$ coefficient) when going from the dimension-level to the facet-level had to be twice as large to achieve significance. Such an increase in the effect size would suggest a substantial improvement in the predictive accuracy when using facet-level traits compared to dimension-level traits. The twofold increase in the effect size was found to be the case for Classical and Jazz, but the increase is particularly underscored when considering Heavy Metal. Heavy Metal did not have any significant predictors at the dimension-level, but there were three significant predictors at the facet-level that accounted for over 50% of the variance in song preference.

There were also significant increases in the $R^2$ coefficients when predicting preference ratings by tempo (fast and slow) using personality facets versus dimensions. Nonetheless, tempo was not found to be related to Extraversion or any of its facets, contrary to what was originally anticipated. Considering the scale of the present experiment in terms of both sample size and the number of songs used, the current results are certainly exploratory in nature. The current results do, however, support arguments that personality facets can improve our understanding of the relation between personality and music preferences (e.g., Rentfrow & Gosling, 2003; Zweigenhaft, 2008). It is possible that the significant traits and corresponding $R^2$ coefficients reported here will be challenged in future studies containing more songs and more participants. Regardless, the consistency of these predictive increases suggests that at least some of these results are reliable. For the results that do prove to be reliably in future studies, the present findings mark a substantial improvement toward understanding music preferences given personality measures.

The present study also tested whether music clip familiarity was related to music clip preference, and further investigated the link between reported music preference and listening behaviour, via preference ratings to specific music clips. Not surprisingly, music clip familiarity was positively related to music clip preference. Clip familiarity accounted for 17% of the variance found in the music clip preference scores. Furthermore, reported music preferences taken by the music preference list rankings were often positively correlated with music clip preference ratings for the same genre. In a majority of the cases, the correlations between reported preferences and clip preference ratings were at or above .40. The significant correlations lend support to the notion that it is possible to measure music preferences using audio stimuli (i.e., music recordings or songs), rather than using reported music preferences according to genre. Nevertheless, the significant correlations reported between reported music preferences and music clip preference ratings were nowhere close to perfect, and there were still several correlations that were not significant. Consequently, the present findings also suggest that, at times, there are substantial differences between reported music preferences for a given genre, and preference for a given song within that genre.

Naturally, there are differences in the popularity of a music recording or song within a given genre. That is, just because individuals report preference to a given music genre does not mean that they will like every song categorized within that genre. The non-significant correlation findings help support Aucouturier and Pachet's (2003) argument that genre classification is vague and inconsistent for music listeners. This has been emphasized by the low correlations between both song preference ratings for songs within Country, Pop, and Rock. Furthermore, with respect to Rock and Pop, these findings echo the conclusions made about the results from Chapter 2; that variation in preference within Rock and Pop might be due to the broad nature of the styles that comprise both of these genres.

# 4

## Modelling the Relation between Personality and Music

The majority of research relating personality and music preferences has used genre categories to express music preferences (e.g., Delsing, Ter Bogt, Engels, & Meeus, 2008; George, Stickle, Rachid, & Wopnford, 2007; Rentfrow & Gosling, 2003, 2006). Literature on the matter of genre and its meaning have suggested that static compositions of music genres are elusive (e.g., Chandler, 2000; Longhurst, 1995; Negus, 1996). Consequently, any attempt to assert a lasting definition for a given music genre is impossible. The literature has been supported by research evidence documenting the vague and inconsistent nature of music genres (e.g., Aucouturier & Pachet, 2003; Pachet & Cazaly, 2000). If definitions of music genres are in constant flux, then the relation between personality and music preferences based on genres and their attached social identities (North & Hargreaves, 1999; Rentfrow & Gosling, 2006) are also prone to change. Thus, deeper insight into the nature of music preferences is necessary to improve our understanding of the relation between music preferences and personality. A deeper insight may be achieved by using music stimuli instead of genre categories as units of analysis.

In the present chapter, music stimuli are used to improve our understanding of the relation between personality and music preferences. The chapter builds on the work from the previous chapters and takes the important step toward modelling the relation between music preferences and personality using music stimuli. The music stimuli used play a central role in the investigation provided in the present chapter. The chapter has been separated into three sections. The first section explains how the music stimuli has been selected, while the second and third sections build a model of personality and music preference using music stimuli and implement tests to confirm this model, respectively. Before arriving at these three sections, the remainder of this introduction reviews the relevant literature and objectives for the present chapter.

### 4.1.1 Genre, Music Preferences, and Personality

As discussed so far in the present thesis, music has been a topic that has garnered a lot of interest from various disciplines and has inevitably led to the evolution of its own multi-disciplinary field known as musicology. Moreover, music has also piqued the diverse research interests of nearly every area of study within psychology (see Rentfrow & Gosling, 2003; Rentfrow & McDonald, in press). As a result, one can find research papers or literature overviews on a broad array of subjects concerned with music: from cultural comparisons in music perception (e.g., Krumhansl, Toiviainen, Eerola, Toiviainen, Järvinen, & Louhivuori, 2000), to music correlates in brain activity (e.g., Blood & Zatorre, 2001); and from social perceptions of music genres (e.g., North & Hargreaves, 1999), to individual perception of musical cues (e.g., Juslin, 2000). Early research examining the relation between personality and music preferences was sparse and varied somewhat with respect to how both personality and music preferences were measured (e.g., Arnett, 1992; Cattell & Anderson, 1953; Cattell & Saunders, 1954; Litle & Zuckerman, 1986; McCown, Keiser, Mulhearn, & Williamson, 1997; McNamara & Ballard, 1999; Schwartz & Fouts, 2003). It has only been in the last two decades that there has been considerable interest in understanding individual differences in music preferences, how these differences are related to personality, and how this understanding impacts our broader music knowledge (Rentfrow & McDonald, in press). It is this more recent research literature that has provided the foundation for the approach presented in this chapter, and so, more emphasis will be placed on the recent research literature.

Since 2003, research relating personality and music preferences has aligned itself with respect to how both personality and music preferences were measured. The aligning was arguably due to a paper by Rentfrow and Gosling (2003). In their paper, Rentfrow and Gosling described their research where they developed, confirmed, and validated their own measure of reported music genre preferences and related these preferences to the Big Five personality dimensions. Like Rentfrow and Gosling, later research relating music preferences to personality measured reported music preferences according to genre and related these preferences to the Big Five (e.g., Delsing et al., 2008; George et al., 2007; Zweigenhaft, 2008). The genre categories used among the later research literature have been highly similar and included genres such as Blues, Classical, Country, Dance, Heavy Metal, Jazz, Pop, R'n'B, Rap, and Rock. Participants in each of these studies rated their preference to these and other genres on either 5-point or 7-point Likert scales. Afterward, these preferences were often grouped according to preference ratings and then related to the Big Five. Table 1.1 in Chapter 1 indicated how preferences for genres had been grouped by recent research into music preference dimensions, but to reiterate briefly, these dimensions are labelled as follows and include music from the listed genres:

- *Reflective and Complex*: include Blues, Classical, Folk, and Jazz;
- *Intense and Rebellious*: include Alternative (Rock), Heavy Metal, and Rock;
- *Upbeat and Conventional*: include Country, Pop, Religious, and Soundtracks;
- *Energetic and Rhythmic*: include Dance/Electronica, Hip-Hop/Rap, and Soul/Funk.

Rentfrow and Gosling’s (2003) paper is a major contribution to research on personality and music preferences and aligned much of this research because it was arguably the first in this area to present a meaningful structure of music preferences firmly based in a theoretical approach (Rentfrow & McDonald, in press). Research that has followed Rentfrow and Gosling’s approach has supported their model of music preferences (e.g., Delsing et al., 2008; George et al., 2007). Nevertheless, this later research has presented subtle differences in the model, which has been attributed to cultural differences. For example, Delsing et al. did not use Blues, Country, or Folk in their investigation because these genres were seen as too unfamiliar to a Dutch population. Certain labels were also changed (e.g., Pop was re-labelled Top40/Charts). Furthermore, George et al. provided a greater level of distinction between genres, such as having four different Religious-type genres because of their Christian university student sample. Both Delsing et al. and George et al. found four music preference dimensions (among eight dimensions for George et al.) that they argued were highly similar to Rentfrow and Gosling’s dimensions with relatively few exceptions. Still, these subtle differences are obvious signs of how cultural differences impact the interpretation of genre labels and, as a result, impede a universal understanding of the relation between personality and music preferences.

Differences among cultures with respect to how genres are portrayed and perceived have been noted in several different academic disciplines. For instance, philosophical dissertations on the nature of genre have indicated that genres are in constant flux, which prevents the existence of static definitions of genre (e.g., Chandler, 2000; Samson, 2009). Furthermore, music sociologists have pointed out that genre labels are often used by the music industry as part of their strategy to distribute and market music (e.g., Longhurst, 1995; Negus, 1996). Last, musicologists have also noted a lack of consensus regarding how the music industry has classified music according to genre (e.g., Aucouturier & Pachet, 2003; Pachet & Cazaly, 2000). Looking toward future research investigating the relation between personality and music preferences, Rentfrow and McDonald (in press) have noted the potential limitations that genre categories can have on this research. To counter these limitations, they have proposed using measures that use music stimuli to gauge music preferences.

Over the last 50 years, there have been several occasions where researchers have used auditory stimuli to investigate music preferences (e.g., Cattell & Anderson, 1953; Cattell & Saunders, 1954; Kopacz, 2005; McCown et al., 1997; Rawlings, Barrantes i Vidal, & Furnham, 2000; Rawlings, Hodge, Sherr, & Dempsey, 1995). Most recently, Kopacz asked 145 Polish students (60 males) between the ages of 19-26 to complete a Polish version of the 16 PF[1] personality inventory (as cited by Kopacz, 2005) and provide the researcher with their favourite song. Kopacz then analyzed roughly 145 music pieces[2] (i.e., songs) on nine different, operationally-defined, musical properties, which included tempo, melodic themes, rhythm, meter, and leading instrument timbre. Kopacz pointed out numerous relations between participants' personality and musical properties found in their favourite songs. For instance, Kopacz found several personality factors related to the number of melodic themes and suggested that individuals who are more extraverted tended to enjoy music with faster tempi. Despite interesting results from Kopacz and other researchers who have used music stimuli to investigate music preferences, none of this research was dedicated to providing a model of music preference similar to the one provided by Rentfrow and Gosling (2003). While early research

[1] PF stands for Personality Factors, but by name, this test is commonly referred to as the 16 PF personality inventory.

[2] Some songs were given to Kopacz by more than one participant.

used many music pieces that focused primarily on Classical music (e.g., Cattell & Anderson, 1953; Cattell & Saunders, 1954), more recent research used a small selection of samples from a broader range of musical genres to investigate the relation between personality and music preference (e.g., Rawlings et al., 1995; 2000). In sum, this research has been mainly focused on exploring relations between personality and music preferences, rather than building a model of music preferences using music stimuli.

When constructing their model of music preferences, Rentfrow and Gosling's (2003) incorporated interactionist theory as an important part of the foundation for their structured and comprehensive approach. Briefly, this theory suggests that individuals either consciously or subconsciously reflect their personalities via the social and physical environments that they engage themselves in (Rentfrow and McDonald, in press). Previous research has looked at several different environments and has shown how personality is reflected by the manner in which individuals present themselves or their belongings (e.g., Buss, 1987; Gosling, 2008; Gosling, Ko, Mannarelli, & Morris, 2002; Swann, Rentfrow, & Guinn, 2002). The same research has also demonstrated that interpersonal judgements are fairly accurate when made on the basis of how individuals maintain their personal space. Similarly, other research has shown that people make interpersonal judgements about individuals' personality based on their music preferences and that these judgements can also be fairly accurate (e.g., North & Hargreaves, 1999; Rentfrow & Gosling, 2006). It is difficult to determine whether Rentfrow and Gosling's model is based on the musical qualities contained in the music, or if it is based on the social perceptions attached to the social groups that listen to music from a given genre. In either case, Rentfrow and Goslings model has made suitable use of interaction theory to make a strong contribution to research relating personality with music preferences. Therefore, incorporating Rentfrow and Gosling's approach to modelling music preferences using music stimuli and basing this approach on interactionist theory when relating this model to personality is a logical step when attempting to improve our understanding of the personality characteristics associated with specific music preferences.

Much of the research concerned with interactionist theory noted above has used the Big Five trait theory when conducting these investigations (e.g., Gosling et al., 2002; Rentfrow & Gosling, 2003). Moreover, Costa and McCrae's (1992) dimension and facet descriptions of the Big Five traits are very much in line with an interactionist approach. The Big Five trait dimensions were originally introduced in Chapter 1, but are briefly re-introduced here as a reference. The Big Five measures five trait dimensions that have been identified and described by Costa and McCrae (1992) as:

*Neuroticism* (N) – an individual's propensity to feel fear, sadness, anger, and other emotions of negative affect.

*Extraversion* (E) – an individual's propensity to be sociable, assertive, active, and prefer exciting environments.

*Openness to Experience* (O) – an individual's propensity toward intellectual curiosity, imagination, and originality.

*Agreeableness* (A) – an individual's propensity toward being altruistic, helpful, and empathetic toward others.

*Conscientiousness* (C) – an individual's propensity toward cleanliness, orderliness, determination, and self-control.

Rentfrow and Gosling (2003) related the Big Five dimensions to their music preferences model during their original investigations. They have expressed that further improvements in our understanding of the relation between personality and music preferences would be gained by including facet-level descriptions of personality, which further discriminate among personality descriptions within the Big Five dimensions. Since then, Zweigenhaft (2008) has investigated the relations between Rentfrow and Gosling's model of music preferences and personality at both the dimension and facet level of the Big Five. In his study, Zweigenhaft recruited 83 university students and analysed the relations between all possible combinations of personality dimensions, personality facets, Rentfrow and Gosling's music preference dimensions, and genres within these music preference dimensions. In his results, Zweigenhaft proceeded to report over 200 correlations. Consequently, it is difficult to distinguish authentic correlations from spurious ones due to the sheer number of correlations that were made. Nevertheless, by conducting regression analyses similar to the analyses demonstrated in Chapter 3, it is possible to investigate relations between personality facets and music preferences while limiting the possibility of spurious results. So, it is expected that incorporating personality facets into a model of music preferences based on personality will lead to increased prediction accuracy.

### 4.1.2 Chapter Objectives

The primary objective of the present thesis is to build on previous research that has investigated the relation between personality and music preferences. The secondary objective is to use the knowledge gained from the primary objective and apply this knowledge to personalized music recommendation technologies. The current chapter plays a central role for both of these objectives by modelling preferences according to music stimuli, which is subsequently related to personality. Based on the literature review, the accuracy of a personalized music recommendation is best served by modelling preferences based on appropriate music stimuli, which is then related to personality facets to improve prediction accuracy and improve our understanding of the relation between personality and music preferences. Thus, three objectives are specified for this chapter: (1) find suitable stimuli to be used for modelling music preferences; (2) construct a preliminary structure of music preferences based on these stimuli and relate this structure to personality; (3) confirm the preliminary structure of music preferences and its relation to personality. Each of these objectives is presented as a section in this chapter. The second and third objectives were achieved via online studies that sampled participants internationally and within a language-specific (Dutch/Flemish) geographic area, respectively. Confirming a model of preferences based on music stimuli between these two samples helped to limit culturally-specific effects of music preferences.

## 4.2 Music Selection

Prior to conducting the proposed online studies, great care was taken to select music stimuli that best reflect stereotypical music preferences in each of the genres represented. Genres were used as a foundation to select music stimuli for two reasons: (1) it allowed comparison with the majority of previous research that has used genre categories to relate music preference with personality (e.g., Delsing et al., 2008; George et al., 2007; Litle & Zuckerman, 1986; Rawlings & Ciancarelli, 1997; Rentfrow & Gosling, 2003); and (2) it has been abundantly used to characterize and market music from an industry perspective (e.g., Amazon.com, 2007; All Music Guide (AMG), 2007; Last.fm, 2007). Despite the aforementioned problems found to exist when using genre labels, simply put, genre is the most utilized and accessible method of music classification available. Furthermore, genre is the only method of classification that allows for some comparability with previous research. Therefore, it was necessary to use genre as a point of departure for the present research. It was also important to select music that provided some breadth among the stimuli as well, so that as many specific audiences as possible would be represented by the music stimuli. Ultimately, it was necessary to obtain at least 100 different music samples necessary for the extracted audio feature analysis described in the next chapter (J. Skowronek, personal communication, June 18, 2007). This resulted in a multi-step music selection process, which is described in the current chapter section.

The first step in the selection process was deciding what genres would be represented by the music stimuli. Previous research that has investigated the relation between personality and music preferences has unanimously cited genres that include: Classical, Jazz, Pop, and Rock (e.g., Delsing et al., 2008; George et al., 2007; Litle & Zuckerman, 1986; Rawlings & Ciancarelli, 1997; Rentfrow & Gosling, 2003). Other genres nearly always cited, sometimes under a different name (e.g., Rap vs. Hip-Hop), included: Blues, Country, Dance, Heavy Metal, Rap, and R'n'B. Thus, these 10 genre categories were used as the foundation to select music clips.

Given the large number of music samples necessary for the extracted audio feature analysis, it also seemed reasonable to vary the music samples according to specific audio criteria. Despite some articles showing relations between personality and music preferences related to tempo (Kopacz, 2005; McNamara & Ballard, 1999; Weaver, 1991), the study provided in Chapter 3 revealed no strong relation between personality and operationally defined variations in tempo. So, other criteria were used to vary the music samples for the proposed online studies, which would partly mimic the previous work by McCown, Keiser, Mulhearn, and Williamson (1997).

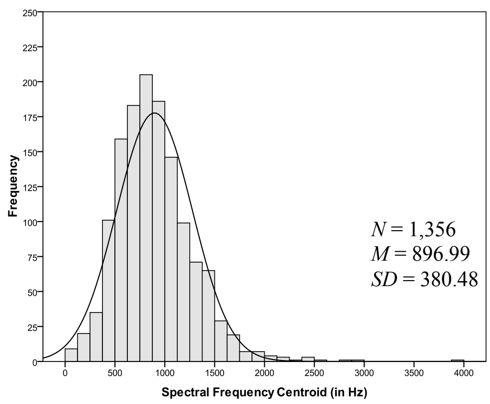
Briefly, McCown and his colleagues asked 145 university students to select between two different music stimuli or clips that they preferred in a forced-choice experiment. Each clip lasted 30 s, but one of the two clips received bass enhancement. Operational definitions of bass can vary. In this case, McCown et al. had operationally defined bass to include frequencies below 200 Hz. Consequently, the clips that received bass enhancement had a 12 dB increase in amplitude at 36, 63, 110, and 190 Hz using a Radio Shack band equalizer. A total of 21 pairings were presented to participants. So, the dependent variable was the number of times participants had selected bass enhanced clips versus non-bass enhanced clips, and ranged from 0 to 21. Lastly, pairings represented several different music genre categories (e.g., Classical, Country, Rock). McCown et al. found that males were more likely to prefer bass enhanced clips compared to females, and participants with higher scores for Psychoticism or Extraversion were also more likely to prefer bass enhanced clips.

The findings provided by McCown et al. (1997) present two clear possibilities regarding how audio features might be related to music preferences. First, individuals may vary in the amount of bass that they enjoy in their music. Second, individuals may also vary with respect to the central frequencies that they enjoy in their music. That is, some individuals might prefer music that contains a lot of low musical notes, while other individuals might prefer music with a lot of high notes, and still other individuals might prefer something in between. While these two audio features are related, they are not inextricably linked. For example, a given Dance song could have a high amount of bass, but still have a lot of higher notes coming from synthesized sounds. The study by McCown et al. had not distinguished between these two possibilities. So, to build on McCown et al.'s study and their findings, the amount of bass and the central frequencies were two audio features that were used to vary the music stimuli for the proposed online studies. How specific music clips were selected for the online studies according to genre and variations in bass and frequency is explained in the remainder of this section, beginning with a description of the music sampling.

### 4.2.1 Music Sampling Method

A total of 1,356 music tracks were retrieved from a music database library made available at Philips Research. The number of tracks per genre category was as follows: Blues ($n$ = 93); Classical ($n$ = 163); Country ($n$ = 108); Dance ($n$ = 228); Heavy Metal ($n$ = 70); Jazz ($n$ = 148); Pop ($n$ = 119); R'n'B ($n$ = 163); Rap ($n$ = 115); Rock ($n$ = 149). Music was pre-categorized in this library to the various genres using an industry standard (AMG, 2007). Using Audacity (2006), each music track was changed from stereo sound to mono sound and a music clip lasting approximately 20 s was taken from each track. The clips were taken from what was believed to be the most representative portion of the entire track, which typically was the refrain or chorus owing to its recurring nature (Levitin, 2006). Furthermore, the first and last 500 ms of each clip was faded in and out, respectively.

After the clips were faded, these clips were ready to be analyzed. Clips were analyzed by two measures computed with MatLab (2006): (1) the Spectral Frequency Centroid (SFC), and (2) a feature known as the "relative bass amount." The SFC provided the average frequency extracted from each clip measured in Hz. The relative bass amount calculated the difference



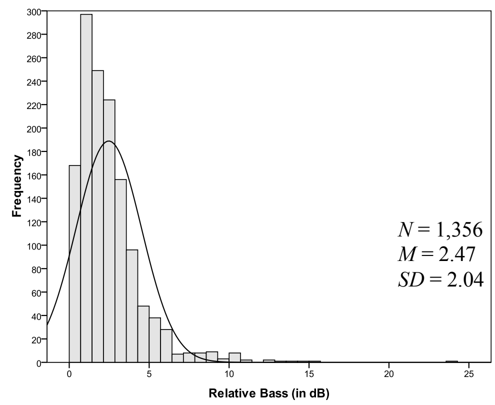




Figure 4.1. *Frequency distributions for the Spectral Frequency Centroids (SFC) and the relative bass measurements taken from the entire music clip dataset.*

between the mean power spectrum for the whole frequency range measured in a given clip, minus the mean power spectrum under 500 Hz measured in the same clip. The relative bass is calculated in dB with 0 dB meaning that all the signal energy was below 500 Hz. Given that music usually contains energy in signals above 500 Hz as well, the calculated difference is usually positive. So, higher positive numbers resulting from the calculation indicate that there is less relative energy in signals below 500 Hz compared to the total signal energy.

The 10 genres that were to be used as a basis for music clip selection had been determined at this point, but how these music clips would be varied according to SFC and bass had not yet been determined. To determine these criteria, SFCs and relative bass were compared according to genre, which is reported in the music sampling results in the next section.

### 4.2.2 Music Sampling Results

Frequency distributions for SFCs and relative bass measurements were initially analysed for all the music clips together, as well as separately for the music clips within each of the 10 genres. Figure 4.1 provides the SFC and relative bass frequency distributions for the entire music clip dataset. These frequency distributions indicate a normal Gaussian distribution for the SFC measure and perhaps a slightly positive skew for the relative bass measure. There were also some extreme SFC scores that came from the Dance genre, and extreme relative bass scores that came from the Classical genre.

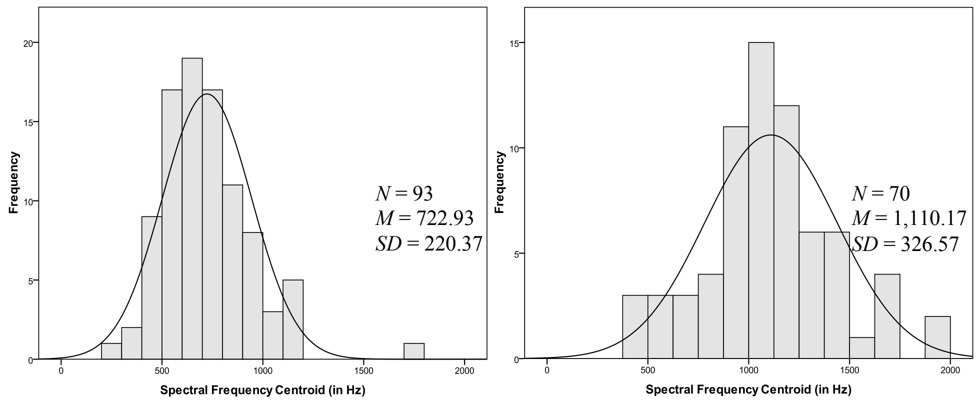



*Figure 4.2.* SFC frequency distributions for Blues music (left) and Heavy Metal music (right). These distributions emphasize SFC differences among the music from the different genres.

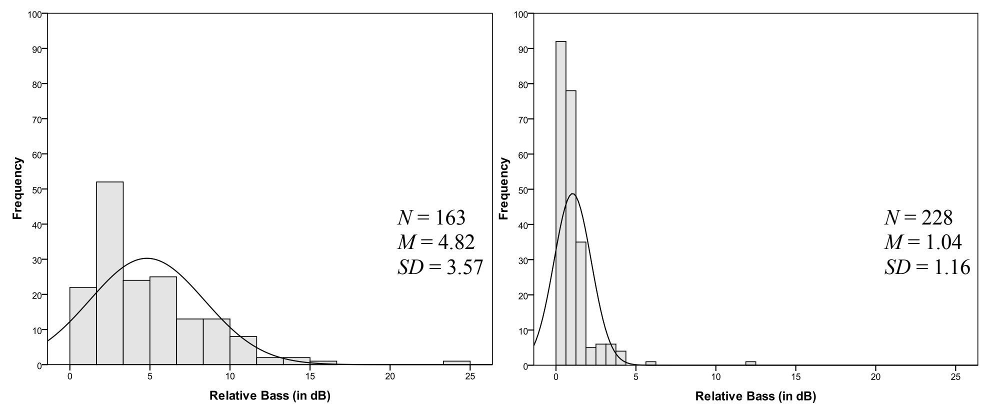



*Figure 4.3.* Relative bass frequency distributions for Classical music (left) and Dance music (right). These distributions emphasize differences in the amount of bass among the music from the different genres.

The frequency distributions for SFCs and relative bass per genre were subsequently analyzed to further investigate the objective differences in audio features taken from the music clip dataset. All of these frequency distributions are provided in Appendix C, and also show similar Gaussian distributions within each genre compared to the distributions given in Figure 4.1. There were visible differences in the means and standard deviations among these distributions, however. These differences among the genres for both the SFC and the relative bass measurements are shown in Figures 4.2 and 4.3, respectively. The genres for each of these distributions are indicated in the figure captions.

*Table 4.1*
Means and standard deviations for SFC and relative bass per genre.

| | | Spectral Frequency Centroid (in Hz) | | Relative Bass (in dB) | |
|---|---|---|---|---|---|
| Genre | *n* | *M* | *SD* | *M* | *SD* |
| Blues | 93 | 722.93 | 220.37 | 2.67 | 1.46 |
| Classical | 163 | 770.05 | 241.01 | 4.82 | 3.57 |
| Country | 108 | 744.21 | 213.60 | 2.79 | 1.41 |
| Dance | 228 | 884.64 | 549.59 | 1.04 | 1.16 |
| Heavy Metal | 70 | 1,110.17 | 326.57 | 2.29 | 0.99 |
| Jazz | 148 | 757.60 | 331.70 | 3.05 | 1.93 |
| Pop | 119 | 1,026.24 | 346.29 | 2.42 | 1.12 |
| R'n'B | 163 | 992.89 | 341.75 | 2.25 | 1.30 |
| Rap | 115 | 1,029.12 | 374.22 | 1.22 | 0.58 |
| Rock | 149 | 1,002.28 | 318.96 | 2.51 | 1.14 |

Comparisons among means were made to statistically test differences between the various genres for SFC and relative bass. The means and standard deviations for SFC and relative bass per genre are shown in Table 4.1. Genres are listed down the left-most column, followed by the number of items within each genre sub-sample. The SFC means and standard deviations per genre are provided in the next two columns, and the relative bass means and standard deviations per genre in the last two columns. A MANOVA was done to see if genres significantly varied with respect to mean SFC and relative bass. In this MANOVA, the 16 genres were levels of the independent variable, while SFC and relative bass were Dependent Variables (DVs). An $F$-test of the Wilks' Lambda ($\Lambda$) criterion showed that the overall effect of genre on the DVs was significant, $F(18, 2{,}690) = 47.76$, $p < .001$. This result supported further univariate analyses of the differences between genres for each of the DVs separately. The univariate $F$-tests were also significant for both SFC, $F(9, 1{,}346) = 18.13$, $p < .001$, and relative bass $F(9, 1{,}346) = 59.89$, $p < .001$. These results indicated that the music within these genres varied with respect to mean SFC and mean relative bass. Scheffé post-hoc tests were done to investigate the differences in means between the genres separately for SFC and for relative bass. For SFC, music from Blues, Classical, Country, and Jazz were all measured to have a lower mean SFC compared to music from Heavy Metal, Pop, R'n'B, Rap, and Rock (all $p < .001$). Dance music, however, fell in between music from all the genres with respect to SFC. Dance music was measured to have a higher mean SFC when compared to Blues, Country, and Jazz music (all $p < .05$).

Dance music was also measured to have a lower mean SFC compared to Heavy Metal, Pop, and Rap music (all $p < .05$). For relative bass, the mean for Classical music was higher compared to the mean for music from all other genres (all $p < .001$). This meant that, on average, Classical music had significantly less bass relative to the total energy signal when compared to music from all other genres. Next, Blues, Country, Jazz, Pop, R'n'B, and Rock music were all higher in mean relative bass compared to Dance and Rap music (all $p < .001$). Finally, the mean relative bass for Jazz music was also higher compared to the mean relative bass for R'n'B music ($p < .01$).

### 4.2.3 Discussion and Final Music Selection

The results obtained from the objective audio feature comparisons between genres show clear differences in the mean Spectral Frequency Centroid (SFC) and mean relative bass. These results are interesting because it gives a first impression of some of the objective differences in audio features among music according to genre, which has been proposed to be one reason why we find differences in music preferences among individuals (Levitin, 2006; Rentfrow & McDonald, in press). Furthermore, the objective comparisons reflect the stereotyped audio features and aesthetic interpretations that have been typically designated to some of these genres in previous research (e.g., Arnett, 1992; McNamara & Ballard, 1999; Rentfrow & Gosling, 2003; Schwartz & Fouts, 2003). For instance, Rentfrow and Gosling noted differences in the use of acoustic (e.g., Blues, Classical, and Jazz) versus electric instruments (e.g., Heavy Metal, Rap, and Rock) in various genres. Combined with Rentfrow and Gosling's results, the current results suggest that music employing more acoustic instruments tends to have a lower SFC and higher relative bass when compared to music employing more electric instruments. Moreover, the music identified as having higher SFCs or lower relative bass (e.g., Heavy Metal, Rap, Rock), is more often associated with perceived negative behavioural tendencies in its audiences, such as anger, aggression, and reckless behaviour (e.g., Arnett, 1992; McNamara & Ballard, 1999; Schwartz & Fouts, 2003).

While these are interesting results, the diversity in SFC and relative bass among the music taken from the various genres introduced a definite challenge to select clips from different genres using these audio features. For example, Blues music had several samples that had an SFC below 500 Hz, but was very limited in the number of samples that had an SFC above 1000 Hz, while the reverse was true for Heavy Metal music. A similar argument could also be made with respect to relative bass distributions among the genres. These observations are demonstrated in Figure 4.2 and Figure 4.3 in the results above. Ultimately, it was decided that the music clips used for the proposed online studies would vary according to the 10 genre categories, but also 3 levels of SFC and 2 levels of bass. These variations resulted in a 10×3×2 matrix and a total of 120 clips when two sample clips were used for each cell in this matrix. A table is provided in Appendix D, which represents the matrix and gives the final clip selection and their SFC and relative bass. How these clips were selected according to SFC and bass is described next.

It was impossible to obtain a completely varied range for both SFCs and relative bass across all genres. So, SFC was considered first because there was greater variation across the identified genres. Three categories of SFC were defined, a low range category (below 600 Hz), a mid range category (between 700-1000 Hz), and a high range category (above 1100 Hz). The low range category was reasonably close to bass frequencies (i.e., below 500 Hz), while the mid range category suitably encompassed the mean SFC obtained from most of the identified genres. Most importantly, however, these categories provided an objective selection of music clips within each category, regardless of genre. There was also sufficient separation in the measured SFCs between these categories.

Next, it was impossible to vary the relative bass within these SFC categories that could be universally applied to all genres. That is, while nearly all Classical music with a SFC below 600 Hz also had relative bass values that were above 1 dB, there were relatively few examples of Dance or Heavy Metal music with those characteristics. Nonetheless, it was possible to modify the power in the bass frequencies below 500 Hz for the music clips using Audacity (2006). As a result, two categories of bass were made, one with and one without bass enhancement. This method was very similar to the method introduced by McCown et al. (1997), except that in this case half of the music clips received a 3 dB increase in all frequencies below 500 Hz, instead of a 12 dB increase in amplitude at 36, 63, 110, and 190 Hz using a band equalizer. Also, bass enhancement was generally given to the music clips that had measured lower on relative bass (i.e., had more bass) compared to other music clips within a given genre × SFC category. This ensured a distinct difference in the bass between music clips in any given category, but also allowed for flexibility in the audio characteristics that represent the differences in musical styles across genre.

Lastly and most importantly, several industry references (i.e., Amazon.com, 2007; AMG, 2007; Last.fm, 2007) and other references (i.e., About.com, 2007; DigitalDreamDoor.com, 2007; Wikipedia, 2007) describing artists/composers and their audiences were used to identify iconic artists and composers within each of the 10 identified genres. Identifying iconic artists and composers using these references offered the best chance to reflect stereotypical music preferences in each of the genres represented. Most of the music clips were taken from iconic artists and composers. However, some clips were from lesser known artists and composers, which was primarily due to the availability of music. Attempts were also made to select diverse artists in each genre category who were prominent across several different decades and from several different nationalities. The diversity of artists within each genre helped to ensure that there was a breadth of the music represented within each genre in addition to focusing on iconic artists and composers. This concluded the music selection that was done to investigate music preferences using specific music stimuli.

## 4.3 Online Study 1: Building a Model of Music Preferences given Personality

With the stimuli selected, it was now possible to collect experimental data to model music preferences based on audio stimuli. The model could then be related to the personality facets identified by Costa and McCrae (1992) to give a more accurate picture of the relation between personality and music preferences. The approach taken to build this model followed Rentfrow and Gosling's (2003) approach, but with two notable exceptions: (1) preference was measured using ratings toward music stimuli instead of ratings toward music genres; (2) music preferences were regressed on personality facets to facilitate prediction algorithms instead of conducting correlation analyses between music preferences and personality traits. Due to the exploratory nature of constructing a preliminary model of music preferences related to personality, no specific hypotheses are stated with respect to how this model should be structured. Still, other hypotheses are given based on the literature presented in Chapter 1 and at the beginning of this chapter.

First, using music stimuli to measure music preferences introduced a new variable, which was how familiarity with certain music was potentially related to music preferences. Interactionist theory, as well as common sense, would suggest that familiarity is highly correlated to music preferences. Nonetheless, it is not suggested that familiarity necessarily leads to preference. Instead, it is simply asserted that these two variables are intricately linked. So, while the first hypothesis provided below will reflect this assertion, familiarity will not be statistically controlled for when constructing the model of music preferences based on personality.

The online study also provided the opportunity to replicate some of Rentfrow and Gosling's (2003) findings. By using their Short Test of Musical Preference (STOMP), it was possible to confirm their model of music preference using this sample. Also, results from Rentfrow and Gosling, as well as from Chapter 3 of this thesis suggest that preference ratings toward specific music clips should be related to preference scores toward the genres from which these music clips were derived. This is an important hypothesis in itself, but also serves to further validate the music clips selected for constructing a model of music preferences using these stimuli. Finally, other analyses will be done to provide a better overall picture of the data. For instance, a descriptive analysis concerning how participants categorized the music clips according to genre will be presented. In summary, the current hypotheses are as follows:

H1. Familiarity with a given music clip is positively related to preference for the same clip.
H2. Music preference scores obtained via the STOMP confirms the model provided by Rentfrow and Gosling (2003).
H3. Preference ratings toward music stimuli grouped by genre are correlated to preference scores toward the same genre.

### 4.3.1 Online Study 1: Method

*Participants*

Participants ($N$ = 354; 165 males) volunteered in response to recruitment announcements provided over the Internet via several means (e.g., mailing lists, forums, Facebook). Most participants reported having American nationality ($n$ = 153), followed by Canadian ($n$ = 64), British ($n$ = 31), and various other nationalities from around the world ($n$ = 106). Participants' ages ranged from 18 to 68 years ($M$ = 31.52, $SD$ =11.02).

*Materials*

Participants listened to 120 different music clips streamed over the Internet and played from their own computer. Each clip lasted 20 seconds taken from what is the most representative portion of the entire music recording (i.e., song), which typically was the refrain or chorus owing to its recurring nature (Levitin, 2006). Based on the genres used by Rentfrow and Gosling

(2003), these music clips ranged across ten different genres: Blues, Classical, Country, Dance, Heavy Metal, Jazz, Pop, R'n'B, Rap, and Rock (12 clips per genre). No music recording was represented twice in different music clips. Furthermore, music clips were separated according to three levels of Spectral Frequency Centroid (SFC) and two levels of bass enhancement. How these music clips were selected and varied according to genre, SFC, and bass was described in Section 4.2.3. of the present chapter. The final clip selection and their SFC and relative bass statistics are listed in a table provided in Appendix D.

Clips were only labelled by the order number in which they were given to participants. A screenshot of this interface is provided in Appendix B.

For each music clip, participants answered the following items given with each song (the Likert-scale anchors are provided in brackets):

1) In your opinion, how much do you like this song? (1 = *Strongly Dislike*, 2 = *Dislike*, 3 = *Neutral*, 4 = *Like*, 5 = *Strongly Like*)

2) Are you familiar with this song? (1 = *Not at all*, 2 = *Maybe a little*, 3 = *I know I've heard it before*, 4 = *I'm very familiar with the song*, 5 = *I'm a big fan*)

3) Using the following list, please select the genre that best represents this song. (Included the 10 different genres listed above, plus Reggae and Funk genres)

4) In your opinion, would you like to have this song and songs similar to this (from the same artist, etc.) recommended to you in the future? (1 = *Certainly not*, 2 = *Unlikely*, 3 = *Maybe, I don't care either way*, 4 = *Probably*, 5 = *Definitely*)

5) Would you consider adding this song to your music collection (e.g., any form of downloading, CD purchase)? (1 = *Never*, 2 = *Unlikely*, 3 = *Maybe, I don't care either way*, 4 = *Probably*, 5 = *Definitely or already have it in my collection*)

Questions 1, 4, and 5 were summed and used as a measure of participants' music preference per song, which values ranged from 3 to 15 ($M$ = 8.99, $SD$ = 3.67). The internal consistency of these questions

(Cronbach's alpha) was α = .95. In addition to providing demographic information (age, gender, nationality, years of music training, and hours per week listening to music), participants were asked to fill out the following questionnaires:

1. *Short Test of Music Preference* (STOMP) was used to measure participants' reported music preferences (Rentfrow & Gosling, 2003). Participants are asked to rate their general music preference toward 14 genres serving as items. These items load onto four music preference dimensions described earlier in this chapter.
2. *Revised NEO Personality Inventory* (NEO PI-R) measured participants' personality (Costa & McCrae, 1992). Participants rated 240 items on a scale from 1 (*Strongly Disagree*) to 5 (*Strongly Agree*), which load onto the Big Five personality traits. This provided aggregated scores for the five dimensions, as well as the six facets contained within each dimension.

*Procedure*

After viewing an Informed Consent page, participants began the experiment over the Internet by providing their demographic information. The rest of the experiment was divided into two halves. In one half, both questionnaires (STOMP and NEO PI-R) were presented to the participants. In the other half, participants were asked to listen to the 120 music clips, one at a time, and respond to items that were presented with each clip. These clips were presented in a counterbalanced Latin-square design. After completing the demographics page, approximately half of the participants proceeded by first completing the questionnaires and, second, listening and responding to questions about the music clips. The rest of the participants completed these two halves in reverse order. Lastly, participants were provided with a debriefing screen at the end of the experiment, with a link to their own NEO PI-R personality report, which had been automatically generated from their responses. Screenshots of the various interfaces are provided in Appendices A and B.

### 4.3.2 Online Study 1: Results

The data obtained from this sample was analysed in six ways. First, the data analysis began with looking at how participants categorized the music clips into the various genre categories provided to them. Second, the relation between participants' familiarity toward the various music clips and their preference scores toward the same clips was investigated. Third, a Confirmatory Factor Analysis (CFA) was done on the STOMP dimensions to replicate Rentfrow and Gosling's (2003) findings. Following this analysis, the fourth way the data was analysed was correlating participants' STOMP scores for each genre with their preference scores for the music assigned to each of these same genres. Fifth, a Principal Components Analysis (PCA) was done using participants' preference scores to find out how their music preferences could be grouped using these music clips. Finally, the sixth way the data was analysed investigated the relation between personality and music preference. This analysis regressed participants' predicted music preference scores for each of the PCA components on their personality facet scores obtained from the NEO PI-R. The remainder of the results section provides the results for each of these six analyses in the order given above.

*Music Categorization*

Data analysis began by investigating how participants categorized the music clips into the various genre categories provided to them. In this analysis, clips were first separated according to how they were selected according to the industry references (e.g., Amazon.com, 2007; AMG, 2007; Last.fm, 2007) for each of the 10 genre categories. Once this had been done, how participants categorized the music clips into genre categories was examined separately for each of the clips' industry-referred categories. As a result, Table 4.2 illustrates how participants categorized music clips within each of the 10 industry-referred genre categories.

Table 4.2 indicates some of the patterns that appeared as a result of the present examination. In many instances, participants' categorization of the music clips closely matched the industry-referred categorization. Table 4.2 indicates that participants' categorization closely matched the industry-referred categorization for Blues, Classical, Country, Jazz, Pop, and Rap. Participants' categorization of the music clips from Dance, Heavy Metal, R'n'B, and Rock was more heterogeneous however. Nevertheless, with exception to Heavy Metal, participants' categorization of music clips was always better than 50% according to the industry-referred categorization.

*Familiarity and Music Preference*

To answer if participants' familiarity toward a given music clip affected their preference ratings toward the same clip, one squared correlation

*Table 4.2*
Confusion Matrix of Participants' Categorization of Music Clips by Genre.

| | Frequency (Percent) of Categorization by Genre | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Music Clip Genre | Blues | Classical | Country | Dance | Funk | Heavy Metal | Jazz | Pop | R'n'B | Rap | Reggae | Rock |
| Blues | **2,736** | 7 | 212 | 15 | 102 | 8 | 242 | 74 | 492 | 4 | 12 | 344 |
| | **(64.4)** | (0.2) | (5.0) | (0.4) | (2.4) | (0.2) | (5.7) | (1.7) | (11.6) | (0.1) | (0.3) | (8.1) |
| Classical | 31 | **3,316** | 99 | 329 | 27 | 4 | 68 | 242 | 56 | 3 | 58 | 15 |
| | (0.7) | **(78.1)** | (2.3) | (7.7) | (0.6) | (0.1) | (1.6) | (5.7) | (1.3) | (0.1) | (1.4) | (0.4) |
| Country | 119 | 68 | **3,511** | 6 | 10 | 1 | 51 | 316 | 94 | 1 | 3 | 68 |
| | (2.8) | (1.6) | **(82.7)** | (0.1) | (0.1) | (0.0) | (1.2) | (7.4) | (2.2) | (0.0) | (0.1) | (1.6) |
| Dance | 13 | 419 | 5 | **2,591** | 150 | 25 | 6 | 701 | 42 | 27 | 15 | 254 |
| | (0.3) | (9.9) | (0.1) | **(61)** | (3.5) | (0.6) | (0.1) | (16.5) | (0.4) | (0.6) | (0.4) | (6.0) |
| Heavy Metal | 16 | 14 | 17 | 189 | 49 | **1,164** | 4 | 467 | 46 | 76 | 10 | 2,196 |
| | (0.4) | (0.3) | (0.4) | (4.4) | (1.2) | **(27.4)** | (0.1) | (11.0) | (1.1) | (1.8) | (0.2) | (51.7) |
| Jazz | 399 | 60 | 19 | 2 | 29 | 2 | **3,167** | 155 | 346 | 3 | 36 | 30 |
| | (9.4) | (1.4) | (0.4) | (0.0) | (0.7) | (0.0) | **(76.6)** | (3.6) | (8.1) | (0.1) | (0.8) | (0.7) |
| Pop | 25 | 17 | 79 | 124 | 53 | 2 | 9 | **3,402** | 241 | 42 | 25 | 229 |
| | (0.6) | (0.4) | (1.9) | (2.9) | (1.2) | (0.0) | (0.2) | **(80.1)** | (5.7) | (1.0) | (0.6) | (5.4) |
| Soul (R'n'B) | 272 | 19 | 62 | 107 | 220 | 0 | 175 | 865 | **1,851** | 499 | 35 | 143 |
| | (6.4) | (0.4) | (1.5) | (2.5) | (5.2) | (0.0) | (4.1) | (20.4) | **(43.6)** | (11.7) | (0.8) | (3.4) |
| Rap | 10 | 1 | 1 | 286 | 113 | 7 | 1 | 314 | 209 | **3,266** | 27 | 13 |
| | (0.2) | (0.0) | (0.0) | (6.7) | (2.7) | (0.2) | (0.0) | (7.4) | (4.9) | **(76.9)** | (0.6) | (0.3) |
| Rock | 45 | 18 | 25 | 32 | 47 | 130 | 17 | 1,263 | 124 | 3 | 17 | **2,527** |
| | (1.1) | (0.4) | (0.6) | (0.8) | (1.1) | (3.1) | (0.4) | (29.7) | (2.9) | (0.1) | (0.4) | **(59.5)** |

*Note*. $N = 354$. Numbers given in **bold** represent correct categorizations. Numbers in parentheses indicate percentages.

coefficient was calculated across all 120 songs, for all participants. The squared correlation coefficient was $r^2$ = .39, $F$(1, 42,478) = 27,378.15, $p$ < .001, indicating that participants' familiarity toward each music clip was positively related to their preference score toward the same clip.

Despite this significant relation, familiarity was not controlled for when further investigating how the music stimuli could be grouped according to music preferences and how these music preference groups were related to personality. The rationale behind this decision was mainly based on the notion that people will often listen to music that they enjoy, and so become very familiar with that music. In a quantitative sense, the relation between music preference and familiarity has not been shown to be causal in either direction, and so is assumed to be bi-directional. If familiarity were to be statistically controlled during further analyses, then the variation taken out of the analysis that is attributable to familiarity might also be taking important variation out of the analysis that explains music preference. Therefore, shared variation between music preference and familiarity was not taken out during further analyses.

*STOMP Confirmatory Factor Analysis*

A Confirmatory Factor Analysis (CFA) was done using participants' obtained STOMP data to replicate Rentfrow and Gosling's (2003) findings. Similar to Chapter 2, this CFA was carried out using LISREL (Jöreskog & Sörbom, 2007). Figure 4.4 gives the standardized parameter estimates for the STOMP CFA model using participants' obtained scores. A chi-square test indicated a poor fit for the data, $\chi^2$ (91, $N$ = 354) = 1,266.4, $p$ < .001. Nonetheless, the chi-square goodness-of-fit test is prone to rejecting the null hypothesis when working with large sample sizes (Tabachnick & Fidell, 2007). Consequently, how well a CFA model accounts for the variance in the data is typically determined by fit criteria statistics. Fit criteria statistics typically include the Root Mean Square Error of Approximation (RMSEA) and the Standardized Root Mean Square Residual (SRMR). Decision rules regarding the cut-off criteria for RMSEA and SRMR indicate that values should be below .10 and .08, respectively (cf. Hu & Bentler, 1999; Loehlin, 1998). In addition, cut-off values for additional criteria such as Goodness of Fit Index (GFI) and Adjusted Goodness of Fit Index (AGFI) should each be above .90. For the current analysis, these values were: RMSEA = .11, SRMR = .11, GFI = .86, and AGFI = .80. Therefore, unlike Rentfrow and Gosling's results, the current results suggested that the obtained data did not fit the existing model well. While the data seemed to fit reasonably well for

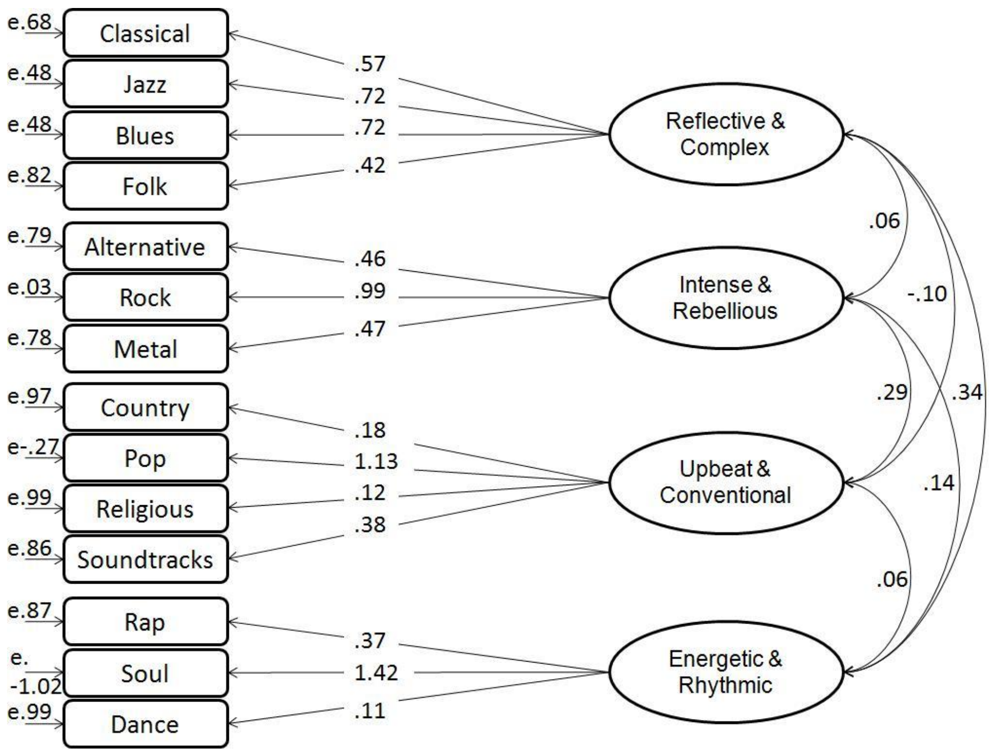



*Figure 4.4*. Standardized parameter estimates for the CFA STOMP model given the data obtained from the present study. $\chi^2$ (91, $N$ = 354) = 1,266.40, $p$ < .001 (GFI = .86, AGFI = .80, RMSEA = .11, SRMR = .11). Values shown on the far right denote correlations between latent factors. Path coefficients shown down the middle of the diagram are the estimated effect sizes between latent factors on the right and measured, explanatory variables on the left. Error variance (e) values shown on the far left denote the proportion of variance in the explanatory variables that is not accounted for by the latent variables.

the music dimensions, Reflective and Complex and Intense and Rebellious, the overall poor fit is particularly evident for the remaining music dimensions, Upbeat and Conventional and Energetic and Rhythmic. Specifically, the path coefficients that were over 1.0 for Pop (Upbeat and Conventional) and for Soul (Energetic and Rhythmic) were clear indications that this model was incorrect. Under normal circumstances, path coefficients and error variances should be between 0 and positive 1. So, the abnormal path coefficients and error variances for Pop and Soul indicate multicollinearity for these two variables. In this instance, multicollinearity meant that Pop and Soul were linearly related to other explanatory variables, like Rock and Blues, respectively. To fix this issue, it would be necessary to drop explanatory variables, draw new paths between latent and explanatory variables, draw new cross-correlations paths between explanatory variables, or a combination of these modifications to the model. While the modifications would improve the likelihood that the model would show acceptable fit criteria statistics, it would also substantially change from Rentfrow and Gosling's (2003) original model of music preferences. So, the modifications were not done in order to facilitate comparison between the results found in the present study and the results provided by Rentfrow and Gosling.

*Reported Genre Preference versus Song Scores*

The fourth data analysis investigated the relation between participants' reported genre preference and their preference toward the various music clips. The current analysis was done by correlating participants' STOMP scores for each genre with their preference ratings for the music assigned to each of these same genres according to industry-referred genre categories (e.g., AMG, 2007). In doing so, the current analysis provided an indication of how well the selected music clips represented their affiliated genres, given participants' preferences. For the analysis, R'n'B was considered equivalent to Rentfrow and Gosling's Soul/Funk genre category. Table 4.3 shows the correlation coefficients between participants' STOMP scores (rows) and their music preference ratings (columns).

Given the results provided in Table 4.3, there are many significant correlations. What is most important however, are the patterns of correlations that can be discerned from this table. First, the diagonal through this table shows strong positive correlations indicating that participants often gave high preference ratings to music clips that were from genre categories for which they had also given a high genre preference score (all $p < .01$). Furthermore, for any column in Table 4.2, the correlations between STOMP scores and preference ratings were strongest for the matching genre categories. Second, positive correlations were consistently found between participants' STOMP scores and their preference ratings for genre categories that could be grouped into the same preference dimensions described by Rentfrow and Gosling (2003; all $p < .01$). For example, all the possible combinations for Blues, Classical, and Jazz between participants' STOMP scores and their preference ratings were all consistently correlated in this manner. Third and last, clips from exceptional genres like Classical

*Table 4.3*
Correlation coefficients between participants' STOMP scores and their music preference ratings.

| STOMP Genre | Music Preference Genre: Blues | Classical | Country | Dance | Heavy Metal | Jazz | Pop | R'n'B | Rap | Rock |
|---|---|---|---|---|---|---|---|---|---|---|
| Blues | **.74**** | .32** | .25** | .09 | .16** | .55** | .03 | .30** | .10 | .28** |
| Classical | .22** | **.78**** | .11* | -.04 | -.17** | .50** | -.07 | -.02 | -.25** | -.03 |
| Country | .12* | -.06 | **.75**** | -.07 | .01 | .00 | .31** | .22** | .13* | .12* |
| Dance | -.10 | -.10 | -.09 | **.68**** | .17** | -.03 | .15** | .14** | .34** | .15** |
| Heavy Metal | .17** | .00 | -.03 | .25** | **.68**** | -.06 | -.01 | .03 | .12* | .33** |
| Jazz | .42** | .46** | .05 | .07 | -.06 | **.79**** | -.13* | .11* | -.05 | .06 |
| Pop | .03 | .01 | .25** | .32** | .17** | -.05 | **.63**** | .45** | .27** | .34** |
| Soul (R'n'B) | .42** | -.01 | .10 | .31** | .20** | .34** | .14** | **.53**** | .49** | .25** |
| Rap | .07 | -.27** | .08 | .28** | .23** | -.02 | .19** | .47** | **.83**** | .18** |
| Rock | .25** | -.09 | .09 | .22** | .59** | .03 | .17** | .22** | .15** | **.56**** |

*Note*. $N = 354$. Correlations indicated in **bold** represent same genre correlations.
* $p < .05$, ** $p < .01$.

and Jazz showed fewer significant positive correlations than music clips from mainstream genres, particularly from R'n'B and Rock.

*Principal Components Analysis*

A Principal Components Analysis (PCA) was conducted to identify the exploratory dimensions of participants' music preferences among the 120 clips tested. The Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO statistic) for this analysis was .91, indicating strong patterns of music preference scores toward the music clips within the dataset. Due to the large number of data points, however, there was an imminent danger of over-extracting the number of components. Overextraction could have negative implications when trying to confirm the model in future experimental samples (Zwick & Velicer, 1986). To avoid overextraction, several criteria were used to decide how many components would be retained (cf. Floyd & Widaman, 1995): the Kaiser-Guttman criterion (i.e., eigenvalues equal to or greater than 1), scree test (Cattell, 1966), and the interpretability of the component loadings for a given solution.

Using the Kaiser rule, an initial PCA solution comprised of 17 components was found, which accounted for approximately 70% of the variance in participants' music preference scores toward the music clips. Nonetheless, the interpretability of these 17 components was less than desirable. To objectively define the interpretation, these components were classified in one of two categories in accordance with Zwick & Velicer:

1. Major Components (MJCs) – were components with an eigenvalue greater than one and three or more items (i.e., music clips) with a substantial component loading.

2. Minor Components (MNCs) – were components with an eigenvalue greater than one and fewer than three items with a substantial component loading.

For our purposes, a value that exceeded |.600| was considered to be a substantial component loading. Using this classification, nine MJCs and eight MNCs were found with this initial PCA. Additionally, visual inspection of the scree plot supported a possible nine component solution with a slight hook in the elbow of the scree curve between the 9th and 10th component (Floyd & Widaman, 1995). Figure 4.5 provides the PCA scree

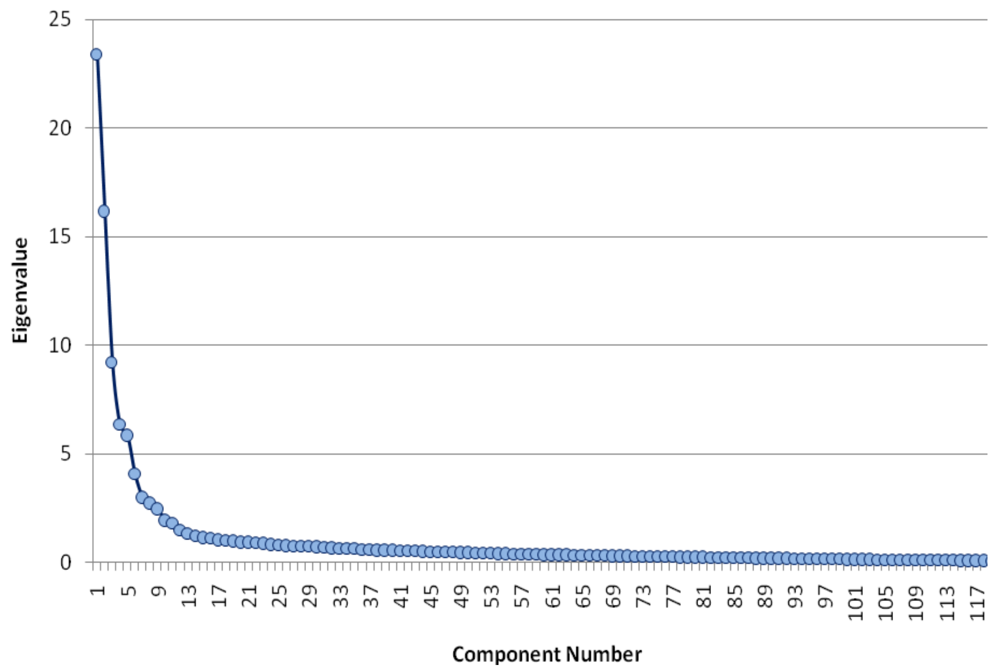



*Figure 4.5.* Scree plot indicating the eigenvalues (y-axis) for each of the potential 120 components (x-axis). The scree curve indicates a slight hook in the elbow of the curve in the division between the 9th and 10th component.

plot. Subsequently, the number of extracted factors was reduced from 17 to 9 to match these criteria. The reduction of factors translated into a reduction in the variance in participants' preference scores that could be accounted for by the model, but other values are unaffected (e.g. component loadings). The resulting 9-component solution accounted for approximately 61% of the variance in participants' music preference scores toward the music pieces. Furthermore, this solution resulted in component eigenvalues that were all above 2 and all components with an eigenvalue less than 2 were left out of this final solution. Lastly, all components in this solution could be defined as MJCs, which made these components more discernable and interpretable.

After resolving how many components would be retained, rotations on the 9-component solution were done to increase the interpretability of this solution and facilitate participants' component score estimates (Nunnally, 1967). The most commonly used rotation method is Varimax rotation (Floyd & Widaman, 1995), which is further evidenced by previous work in psychology that has developed measures of personality (e.g., Costa &

McCrae, 1992), and of music preferences (e.g., Rentfrow & Gosling, 2003). Varimax rotation is an orthogonal rotation method, which attempts to maximize the variance of the loading values within each component (Loehlin, 1998; Nunnally, 1967). In this case, a loading value, or loading, is the correlation between preference scores toward a given song and extracted scores for a given component. By maximizing the variance of the loadings within each component, Varimax rotation maintains orthogonal (i.e., uncorrelated) relations among factors. Despite the popular use of Varimax rotation, it was assumed that participants' music preferences toward one musical style, or component, could potentially be correlated with another musical style. This justified implementing an oblique rotation, which in this case was Promax rotation.

Briefly, a Promax rotation is a two step process, which begins by obtaining a Varimax rotation solution (Loehlin, 1998). This solution is then modified to an oblique rotation that reduces low loadings to near-zero values. In this way, the contrast between high and low loadings is improved. Regardless of the rotation, both the Varimax and Promax rotation solutions provided highly similar results.[3] Nonetheless, the Promax rotation left open the possibility for correlations among components, and did provide a rotation solution that improved the distinction between high and low component loadings within each component. This distinction is best illustrated by a scatterplot of the PCA pattern matrix loadings along the first two principal component axes, which is given in Figure 4.6. Therefore, it was for these reasons that Promax rotation was used to communicate the final 9-component solution.

Once song clips had been grouped into the nine music preference categories according to this 9-component solution, a team of seven experts from psychology, music information retrieval, and digital signal processing were consulted to help label these categories. These music preference categories were subsequently labelled by unanimous agreement among these seven experts. These labels are provided as column headings in Table 4.4., which gives an abbreviated pattern matrix for the 9-component Promax-rotated solution. The first and second columns in this table list music clip titles and artists/composers, respectively, which are grouped according to these categories. Subsequent to the first two columns, the nine components are labelled with the factor loadings in this matrix listed down these

[3] Indeed, other orthogonal and oblique rotations were performed that also gave similar results to the Varimax and Promax rotation solutions.

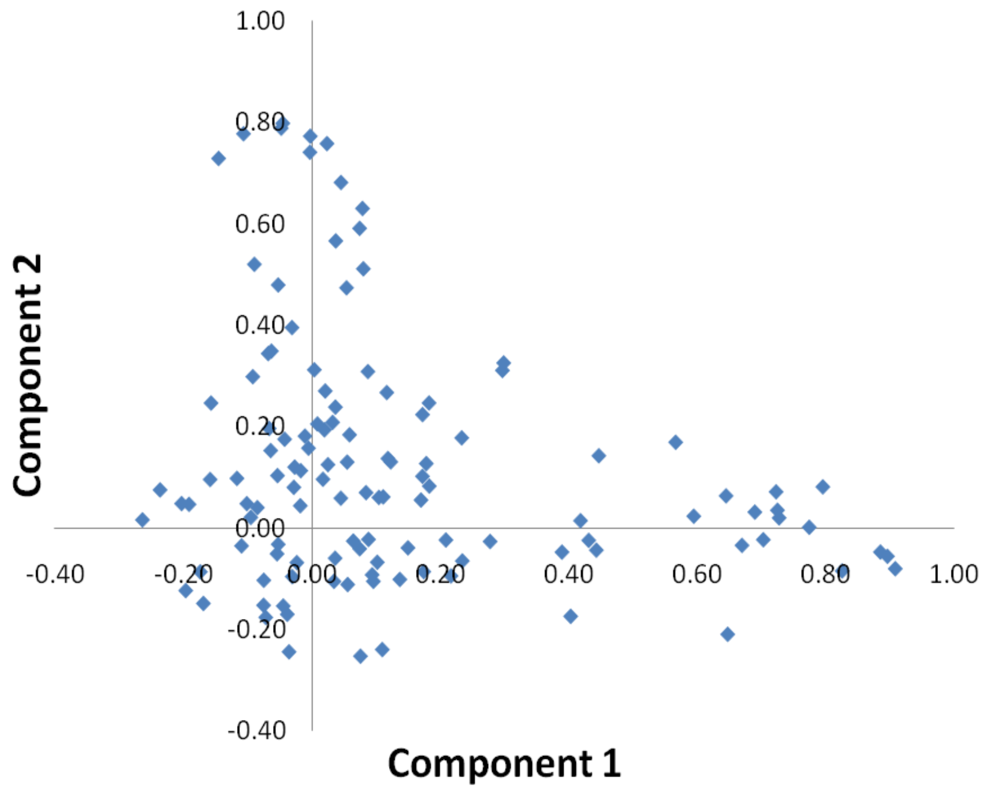



*Figure 4.6.* Scatterplot of the PCA pattern matrix loadings along the first two principal component axes. Each point indicates the loadings for each of the 120 music clips. This figure illustrates how well the first (X-axis) and second component (Y-axis) fit the music preference data by how closely the loadings (data points) fall along these two axes.

columns in relation to music clip. The abbreviated pattern matrix gives a representative sample of the complete pattern matrix. In doing so, the abbreviated pattern matrix emphasizes: (1) the music clips that had the strongest preference loadings associated with one component (i.e., one music audience), or (2) the music clips that had strong preference loadings associated with more than one music audience. Following the advice by Floyd and Widaman (1995), Table 4.4 presents an abbreviated pattern matrix, while complete tables providing both the structure matrix and pattern matrix can be found in Appendix E.

*Table 4.4*
Factor loadings from the abbreviated pattern matrix for the 9-component Promax-rotated PCA solution.

| Music Clip Title | Artist/ Composer | CAAP | Jazz | Modern Chart Pop | Hard Rock | Classical | American Country | Blues - Rock | Early Chart Pop | Dance/ Electronica |
|---|---|---|---|---|---|---|---|---|---|---|
| Dangerous | Busta Rhymes | ***.907*** | -.081 | -.282 | -.063 | .063 | .086 | .096 | .098 | .028 |
| Dirt Off Your Shoulder | Jay Z | ***.895*** | -.057 | -.249 | .039 | .030 | .118 | .011 | -.056 | -.050 |
| Country Grammar | Nelly | ***.884*** | -.048 | -.075 | -.021 | -.014 | .037 | .044 | -.056 | -.087 |
| Lester Swings | Lester Young | -.046 | ***.797*** | -.101 | -.043 | .136 | -.015 | .157 | -.091 | .073 |
| Locomotion | John Coltrane | -.048 | ***.788*** | -.195 | .023 | .138 | .013 | .092 | -.109 | .061 |
| All Blues | Miles Davis | -.107 | ***.777*** | -.133 | -.067 | .095 | -.029 | .114 | -.038 | .072 |
| Fall at Your Feet | Crowded House | -.174 | -.087 | ***.784*** | -.164 | -.123 | .078 | .153 | .111 | .163 |
| Back for Good | Take That | .034 | -.106 | ***.750*** | -.137 | .022 | .036 | .018 | .050 | -.096 |
| Life for Rent | Dido | -.158 | .246 | ***.733*** | .004 | -.100 | .031 | -.040 | -.047 | .192 |
| Canto Della Terra | Andrea Bocelli | -.024 | -.069 | ***.549*** | .014 | *.487* | -.040 | .053 | -.048 | .024 |
| Baby One More Time | Britney Spears | *.430* | -.025 | ***.509*** | -.113 | .098 | .080 | -.179 | -.043 | -.056 |
| Back in Black | AC/DC | .055 | -.112 | -.198 | ***.783*** | .022 | .079 | .127 | .055 | -.031 |
| Paranoid | Black Sabbath | -.076 | -.153 | -.164 | ***.756*** | .076 | .058 | .169 | .226 | .029 |
| Smoke on the Water | Deep Purple | -.075 | -.104 | -.033 | ***.755*** | .139 | -.066 | .260 | .172 | -.182 |
| Nookie | Limp Bizkit | *.442* | -.044 | -.213 | ***.518*** | .140 | .034 | .042 | -.269 | .117 |
| Till Eulenspiegels lustige Streiche | Richard Strauss | .008 | .204 | .064 | .112 | ***.856*** | .004 | -.132 | .018 | -.059 |
| Symphony No. 3, “Eroica” | Ludwig van Beethoven | .019 | .193 | .019 | .038 | ***.845*** | -.055 | -.015 | .027 | -.094 |

*Note*. $N = 354$. All factor loadings |.400| or larger are provided in *italics*; the highest factor loadings within each component are in **bold**. CAAP = Contemporary African American Popular; Modern Chart Pop = 80s to current Pop; Early Chart Pop = 60s and 70s Pop.

*Table 4.4 (continued)*

Factor loadings from the abbreviated pattern matrix for the 9-component Promax-rotated PCA solution.

| Music Clip Title | Artist/ Composer | CAAP | Jazz | Modern Chart Pop | Hard Rock | Classical | American Country | Blues - Rock | Early Chart Pop | Dance/ Electronica |
|---|---|---|---|---|---|---|---|---|---|---|
| Piano Concerto No. 1 | Peter Ilitch Tchaikovsky | .036 | .238 | .053 | .052 | ***.840*** | -.061 | -.045 | -.023 | -.108 |
| My Heart Skips a Beat | Buck Owens | -.096 | .020 | .100 | .041 | .032 | ***.809*** | .011 | .078 | .097 |
| I Don't Rock the Jukebox | Alan Jackson | .104 | .060 | .082 | .103 | -.106 | ***.786*** | .070 | -.238 | -.138 |
| All the King's Horses | Luther Allison | -.019 | .043 | .028 | .243 | .010 | -.051 | ***.778*** | .069 | .048 |
| I Smell Trouble | Johnny Winter | .032 | .208 | -.042 | .123 | -.093 | -.041 | ***.777*** | .013 | .055 |
| Nice Problem to Have | The Jeff Healey Band | .058 | .183 | -.032 | .154 | -.011 | -.086 | ***.727*** | -.005 | .047 |
| Pitiful | Big Maybelle | .053 | *.473* | -.031 | -.011 | -.109 | -.044 | ***.552*** | .085 | .039 |
| You Keep Me Hangin' On | Diana Ross & the Supremes | .216 | -.095 | .277 | -.075 | .025 | -.104 | -.067 | ***.659*** | .014 |
| Space Oddity | David Bowie | -.264 | .015 | .053 | .161 | .002 | .068 | .007 | ***.623*** | .209 |
| Something | The Beatles | -.117 | .097 | .144 | .116 | .053 | -.084 | .068 | ***.606*** | -.087 |
| Jumpin Jack Flash | Rolling Stones | -.055 | -.052 | -.098 | *.462* | .075 | -.025 | .099 | ***.543*** | -.058 |
| I Walk the Line | Johnny Cash | .044 | .058 | -.203 | .168 | -.157 | *.478* | -.120 | ***.499*** | .039 |
| Talisman | Air | -.086 | .039 | .189 | .013 | -.034 | .117 | -.010 | .038 | ***.730*** |
| Push Upstairs | Underworld | .277 | -.027 | .091 | .012 | .051 | -.054 | .005 | -.019 | ***.662*** |
| Destiny | Vanessa-Mae | .075 | -.254 | *.506* | .027 | .185 | -.031 | .148 | -.099 | ***.590*** |
| Du Hast | Rammstein | .095 | -.106 | -.057 | *.434* | .129 | .047 | -.028 | -.095 | ***.522*** |

*Note*. $N = 354$. All factor loadings |.400| or larger are provided in *italics*; the highest factor loadings within each component are in **bold**. CAAP = Contemporary African American Popular; Modern Chart Pop = 80s to current Pop; Early Chart Pop = 60s and 70s Pop.

*Relating Music Preference Components to Personality Facets*

Once the Principal Components Analysis (PCA) had been used to identify the music preferences components, the task was to relate participants' predicted scores toward each of these components to their personality facet scores. As mentioned in the Method section, personality facets are more specific aspects of each of the Big Five personality dimension trait descriptors: Neuroticism (N), Extraversion (E), Openness to Experience (O), Agreeableness (A), and Conscientiousness (C; Costa & McCrae, 1992).

Prior to looking at this relation between participants' predicted music preferences and their personality, it was necessary to ensure that this relation would not be biased by other factors, such as gender, age, and music training. So, to investigate how these other factors influenced participants' predicted scores toward the nine music preference components, a 2 (gender) × 9 (component) mixed ANCOVA was done with participants' predicted component scores as the DV, and age and years of music training as covariates. Tests of within-subjects effects showed participants' predicted scores toward each of the nine components had significant interaction effects with gender ($F$ = 10.53 (8, 2,800), $p < .001$, partial $\eta^2 = .03$), age ($F$ = 21.17 (8, 2,800), $p < .001$, partial $\eta^2 = .06$), and music training ($F$ = 12.66 (8, 2,800), $p < .001$, partial $\eta^2 = .04$). Given these results, variance in participants' predicted music preference scores accounted for by gender, age, and music training was partitioned out. So, further statistical testing used the residual scores of participants' component scores.

Using these residual scores, nine stepwise regressions were done to ascertain predictive equations for participants' preferences toward the nine music categories given their personality facet scores. Table 4.5 provides the standardized regression coefficients (β) per music preference component given personality facets. In Table 4.5, the top row identifies each of the music preference components (categories), along with its associated multiple regression coefficient of determination ($R^2$). The personality facets found to significantly predict a proportion of variance in any one these music preference components are listed down the first column. The cells in the table field provide the standardized regression coefficients (β) for the designated music preference component given the designated personality facet. All $R^2$ and β values were significant at $p < .05$. To confirm these results, a randomly selected sub-sample from the current participant sample was taken and nine regression analyses were done to provide the $R^2$ between participants' actual scores from this sub-sample, and their predicted scores

*Table 4.5*

Standardized regression coefficients (β) per music preference component given personality facets.

| | Component ($R^2$ = ) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Personality Facet | CAAP (.19) | Jazz (.11) | Modern Chart Pop (.08) | Hard Rock (.09) | Classical (.13) | American Country (.07) | Blues-Rock (.06) | Early Chart Pop (.10) | Dance/ Electronica (.17) |
| N1: Anxiety | | | | | | | | .10 | |
| N5: Impulsiveness | | | | | | | -.11 | | |
| E1: Warmth | . 34 | | .17 | | | | | | |
| E4: Activity | | | | | | -.14 | | | |
| E5: Excitement-Seeking | .27 | | | .26 | -.12 | | .17 | .13 | |
| O1: Fantasy | | | | | | | | .09 | |
| O2: Aesthetics | | .16 | -.11 | -.19 | .22 | | .14 | | .17 |
| O3: Feelings | | | | | -.11 | | | | |
| O4: Actions | | .14 | -.13 | | | | | | .16 |
| O5: Ideas | | .13 | | .15 | .21 | | | | |
| O6: Values | | | | | -.18 | -.20 | | .12 | .15 |
| A2: Straight-forwardness | | | | | | -.15 | | | |
| A3: Altruism | -.20 | | | | | | -.16 | | -.15 |
| A6: Tender-Mindedness | | | | | | .13 | | | |
| C1: Competence | | | | | | | | .22 | |
| C2: Order | .13 | | | | | | | | |
| C4: Achievement Striving | | | | | | | | | .19 |
| C5: Self-Discipline | | | .13 | | | | | -.20 | -.23 |

*Note*. $N = 354$. Cells represent standardized regression coefficient (β). All values shown are significant at $p < .05$.

for each of these predictive equations (Tabachnick & Fidell, 2007). These $R^2$ values were then compared to the $R^2$ values provided by the original predictive equations that are provided in Table 4.5. With exception to the American Country component, the $R^2$ values drawn from the sub-sample were significant and comparable to the $R^2$ values from the original analyses. This suggested that eight of the nine predictive equations were reasonably stable, with exception to the predictive equation for American Country. Thus, while eight of nine predictive equations may be generalized to be representative of a larger population, the predictive equation for American Country may not be generalized beyond the International sample used in the current study.

### 4.3.3 Online Study 1: Discussion

Online study 1 was mainly concerned with building a preliminary model of music preferences related to personality, which incorporates music stimuli to assess preferences. How this preliminary model was built was shown in the last two sub-sections of the Results by: (1) using Principal Components Analysis (PCA) to group participants' preference ratings for music stimuli, and (2) conducting regression analyses to relate participants' predicted preferences derived from the PCA to participants' personality facet scores. Results from the PCA provided a preliminary 9-component model of music preferences that often reflected current genre categories. Furthermore, the regression analyses showed some relations between participants' personality and their predicted music preferences that were similar to previous research findings (e.g., Delsing et al., 2008; George et al., 2007; Rentfrow & Gosling, 2003; Zweigenhaft, 2008). Before these results are addressed in further detail, the current discussion will begin by addressing the results for each of the three hypotheses specified at the beginning of Section 4.3.

*Familiarity and Music Preference*

As stated at the beginning of the current section, the first hypothesis asserted that participants' familiarity is positively related to their preference score for the same song. It was not surprising to find that this was the case. This relation proved to be quite strong ($r$ = .62), which further emphasizes that people tend to seek out and play music that they like. Similar to Chapter 3, it was good to formally test this relation since much of the previous research on music preferences and personality had not used music as auditory stimuli to measure music preferences (e.g., Delsing et al., 2008; George et al., 2007;

Rentfrow & Gosling, 2003; Zweigenhaft, 2008), and those who had used music had not reported this relation (e.g., Cattell & Saunders, 1954; McCown, Keiser, Mulhearn, & Williamson, 1997). Nevertheless, it was also argued that removing the variance attributable to familiarity might remove variance attributable to music preference as well, which is important for the present investigation. For this reason, familiarity was not statistically controlled for when investigating the remaining results.

*STOMP Confirmatory Factor Analysis*

The second hypothesis asserted that Rentfrow and Gosling's (2003) model of music preferences would be confirmed by participants' music preference scores obtained via the STOMP. Similar to the findings presented in Chapter 2, the Confirmatory Factor Analysis (CFA) that was done to resolve this hypothesis did not replicate Rentfrow and Gosling's model. Also similar to the findings presented in Chapter 2, Pop proved to be a variable that did not fit into this model as expected, which was evidenced by its abnormal path coefficient and error variance (both should be between 0 and 1.0). The same abnormal result was found for Soul, while parameter estimates for Religious, Soundtracks, and Dance were found to be quite low. As a result, this meant the data fit Rentfrow and Gosling's model with respect to their Reflective and Complex and Intense and Rebellious music dimensions, but provided a very poor fit for the remaining dimensions, Upbeat and Conventional, and Energetic and Rhythmic.

One of the reasons why the data obtained in the present study might not have fit Rentfrow and Gosling's model is due to the participant sample that was obtained. Rentfrow and Gosling's model was based entirely on an American sample, and though many of the participants in the present study were also from the US, the sample was not exclusively American. Still, a clear majority of participants in the present study came from English-speaking countries from around the world (i.e., American, $n$ = 153; Canadian, $n$ = 64; British, $n$ = 31; other English-speaking, $n$ = 41). Consequently, it would appear that there are strong cultural differences to music perception even across these English-speaking countries. Rentfrow and Gosling's model of music preferences was not modified to fit potential cultural differences as Delsing et al. (2008) and George et al. (2007) had done. Therefore, the results obtained from the present study support the notion that modifications are necessary to accommodate cultural differences. This notion has also been acknowledged by Rentfrow and McDonald (in press).

Other reasons why Rentfrow and Gosling's model was not confirmed in the present study was illustrated by the results indicating that: (1) participants' had inconsistently categorized the music clips, and (2) the pattern of correlations found between these music clips and participants' reported preference scores toward genres did not always reflect what would be expected in Rentfrow and Gosling's model. These reasons are connected to the third hypothesis and so are discussed in the next section.

*Reported Genre Preference versus Song Scores*

The third hypothesis of the present study addressed whether participants' STOMP scores for each genre would be positively correlated with their music clip preference ratings categorized according to the same industry-referred genre categories (e.g., AMG, 2007). This hypothesis was confirmed. Indeed, there were strong positive correlations found between participants' STOMP scores and their music clip preference ratings for the music clips derived from the same genre. In fact, preference ratings for any given genre are shown to have the strongest correlations with the STOMP preference scores for the same genre. Furthermore, the average among these matched genre correlations was $r$ = .70, with no correlation falling below .50. The present findings further validate the selection of music clips, showing that participants who reportedly prefer music from a given genre, such as Blues or Rock, also tended to like the music clips that were selected from the same genre. Conversely, if participants did not prefer music from a given genre, they also tended to dislike the music clips from the same genre.

In addition to this central finding that confirmed the third stated hypothesis, the pattern of correlations found amongst the genres that are shown in Table 4.3 helps to provide an overall interpretation of the results. For instance, STOMP preference scores for Blues, Classical, and Jazz generally had the strongest positive correlations with music clips taken from these genres. This finding helps explain why Rentfrow and Gosling's (2003) Reflective and Complex music preference dimension is consistently found to be valid based on the current results and in previous research (e.g., Delsing et al., 2008). Furthermore, participants often categorized the music clips from these three genres according to how these clips were initially categorized according to industry standards (e.g., Amazon.com, 2007; AMG, 2007; Last.fm, 2007).

Another music preference dimension that has been consistently found in the current study as well as in previous research (e.g., Delsing et al., 2008) has been Intense and Rebellious. The robustness of the Intense and Rebellious dimension can be explained by the current results. At first glance, it might appear that this dimension should not be so robust given participants' categorization of Rock and Heavy Metal music clips in the present study. Specifically, the participants were unable to categorize music clips from the Heavy Metal and Rock genres as accurately as the music from Blues, Classical, and Jazz genres according to the initial, industry-defined categorization. Participants often categorized the Heavy Metal clips as Rock music. Consequently, it would appear that participants view Heavy Metal music as a style within Rock, which is in agreement with current music genre hierarchies (e.g., AMG, 2007) and is also reflected by the current correlation results. This argument could also easily extend to Alternative, which is also known as Alternative Rock music. The Alternative genre label was originally used as a label to describe Rock music that was not considered mainstream, hence the title, "Alternative." Furthermore, the four correlation coefficients that were obtained between participants' STOMP scores for Heavy Metal and Rock music and their preference ratings for the music clips from these genres are quite strong. Participants who reportedly liked Rock music often also liked the Heavy Metal clips and vice versa. The correlation between Heavy Metal preference scores and Rock clip ratings was the weakest of the four, but still quite strong ($r$ = .33). The present findings suggests that some participants who like Heavy Metal music found the Rock music clips slightly soft in comparison to the Heavy Metal clips, which warranted lower preference ratings from these participants. In sum, it would appear that the Intense and Rebellious music dimension found originally by Rentfrow and Gosling is robust because the music genres that are contained in this dimension are seen as belonging to the same transcending Rock music category by both industry standards (e.g., AMG, 2007) and by individuals.

It seemed that preference ratings for the Rock music clips were positively correlated with preference scores to most of the other genres, which suggests that Rock music is broadly liked by most audiences. This was also the case for music clips from Pop and R'n'B. While the strong positive correlations between Heavy Metal and Rock music helped describe the robustness of Rentfrow and Gosling's (2003) Intense and Rebellious dimension, this was not the case for Pop and R'n'B. With respect to Pop, participants often categorized music clips from Pop and from other genres as Pop (e.g., Dance, R'n'B, and Rock). Given the categorization results, it would appear that the Pop genre could be a default category with a very high response bias. As explained in Section 4.2.3 of this chapter, the clips that were selected were often from artists or composers that are seen as iconic within that genre. As a result, many of the artists from these more mainstream genres could also be seen as popular, or Pop artists. Based on correlations between participants' preference ratings for Country music and the various genre preference scores, it would appear that the clips from this other genre in the Upbeat and Conventional music dimension have a smaller audience compared to Pop. As a result, Pop appears to be a mismatch for the Upbeat and Conventional dimension.

Interestingly, this finding seems to partly support Delsing et al.'s (2008) research, in which Pop was renamed Top40/Charts music and grouped with Trance/Techno music (i.e., Dance music). Dance clips were also often categorized as Pop music by participants in the present study. This might help explain why Dance also seemed out of place for Rentfrow and Gosling's Energetic and Rhythmic dimension. Still, there were strong positive correlations found between music preference scores for Dance, R'n'B, and Rap, and their correlation permutations with clip preference ratings for the same genres. Perhaps further investigation on this matter presented in the next sub-section will shed more light on these contradictory results.

*Principal Components Analysis*

As stated earlier in this Discussion section, the primary objective for the first online study was to build a preliminary model of preferences based on music stimuli, which is subsequently related to personality. The first step toward building this model used Principal Components Analysis to group the music stimuli according to patterns in participants' preference ratings for these stimuli. This resulted in a preliminary 9-component model of music preferences. After consulting with a team of experts from psychology, music information retrieval, and digital signal processing the labels for these categories were unanimously agreed on and reflected several genre labels currently used in industry (e.g., AMG, 2007). This might suggest that genre labels describe patterns in music preference reasonably well. This argument is further supported by the results concerning music categorization and correlations between STOMP preference scores and music clip ratings by genre discussed in the previous sub-section. Still, there were several instances where music clips did not neatly group according to genre. For example, music originally categorized according to genre as Heavy Metal, Pop, and Rock were mostly mixed between the PCA categories Modern Chart Pop, Early Chart Pop, and Hard Rock. So, there seems to be an aspect of time period related to these categories. Also, music originally categorized as R'n'B often fell into the PCA categories Modern Chart Pop and Contemporary African American Popular (CAAP). This might help explain the results concerning Rentfrow and Gosling's Energetic and Rhythmic dimension of music preference alluded to in the previous sub-section. In sum, it appears that preference toward music in several of these mainstream genres is very much intertwined and dependent more on other characteristics of the music, like when the music was originally made or the associations that have been made with a specific cultural community. Therefore, though genre categories do provide a reasonably accurate picture of music preferences, these results suggest that further improvements can be made.

There are three reasons to suggest that greater accuracy can still be sought after. First, it should be kept in mind that music selected for this study was based on converging information from three different music industry sources (i.e., Amazon.com, 2007; AMG, 2007; Last.fm, 2007). This meant that the music selected for this study was likely more prototypical for each of the identified genres, rather than fringe music for these genres. By basing music preferences on more prototypical examples, it is more likely that core personality characteristics that are associated with audiences that enjoy these prototypical examples will be found.

Second, despite the likelihood that most of the music contained in this study was more prototypical, there were instances where preference for specific music clips would bleed across music preference components. For example, the song Nookie, by Limp Bizkit was most often liked by participants who also reported enjoying music that would typically be classified as Hard Rock or Heavy Metal. Nonetheless, this particular song was also often liked by participants who reported enjoying other music that would typically be classified as Rap or Hip-Hop. There may have been instances when the same participants liked both Heavy Metal and Rap music, but there was a sufficient number of times where this was not the case. Otherwise, Heavy Metal and Rap music would have fallen under the same component in the PCA, which is clearly not the case. There is even one instance shown in Table 1 where the music clip does not group with any of the music that it is categorized with according to genre. Vanessa-Mae is typically considered as a Classical artist (e.g., AMG, 2007), but here her song, Destiny, was more likely to be preferred by participants who also reported enjoying music that would be either classified as Pop or, alternatively, Dance. Therefore, this helps provide insight on the personality characteristics that are shared between music audiences.

Third, Pachet and Cazaly (2000) argue that there are consistency issues with respect to genre taxonomies, and in particular, with respect to the distinction between Rock and Pop music. Nonetheless, given the results from the PCA, it appears that audiences might be able to adequately distinguish between several categories of Rock and Pop music, based on their music preferences. Therefore, greater accuracy could be gained by grouping music according to preference and not according to genre. This also offers an additional reward. By leveraging music preference groups and relating these groups to audio features, it might be possible to identify the relevant music groups according to preference by its various audiences, and not by potentially arbitrary music classification according to various industry sources. This will be addressed in the next chapter.

*Relating Music Preference Components to Personality Facets*

The second step toward building this model of music preferences related to personality saw the regression of participants' predicted music preferences toward each of the nine music preference categories on their personality facet measures. If part of this main objective was to improve our understanding of the relation between music preferences and personality, it was believed that relating music preferences to more detailed personality facets from the Big Five dimensions would help achieve this. Only one previous study is known to have looked at the relation between music preferences and personality at this more detailed level (i.e., Zweigenhaft, 2008). Nonetheless, over 200 correlations had been computed in that analysis, which makes it difficult to discern true significant findings from spurious ones. Though the analysis from the current study was exploratory in nature, the stepwise regression would help prevent spurious findings. With exception to results for American Country, re-tests of the results using a randomly drawn sub-sample indicated that these results were reliable. The $R^2$ values indicate medium effect sizes for each of the regression equations.

The nine stepwise regressions provided several relations to music preferences and personality that supported similar relations found in previous research. Most notably, Aesthetics, which is a facet under Openness to Experience, was found to be positively related to Blues-Rock, Classical, and Jazz. These three preference categories reflect music from

Rentfrow and Gosling's Reflective and Complex music dimension, which has often been found to be related to Openness to Experience (e.g., Delsing et al., 2008; George et al., 2007; Rentfrow & Gosling, 2003; Zweigenhaft, 2008). Furthermore, Contemporary African American Popular (CAAP) music was found to be positively related to Excitement-Seeking, which is a facet found under Extraversion. CAAP music contains mostly music that reflects Rap and R'n'B genres. Previous research has also found these genres to be correlated with either Excitement-Seeking or Extraversion (e.g., Delsing et al., 2008; Rentfrow & Gosling, 2003; Zweigenhaft, 2008). This latter finding could be due to the predominantly greater intensity of bass sounds in Rap (McCown et al., 1997), but this will be further addressed in Chapter 5. Therefore, the present findings are believed to be fairly robust and are expected to be confirmed in the study reported in the next section. Still, the relations between personality and music preferences do need to be confirmed because of the exploratory nature of the regression analyses conducted in the present study.

### 4.3.4 Online Study 1: Summary and Conclusions

The main objective for Online Study 1 was to build a preliminary model of music preferences related to personality, which incorporates music stimuli to assess preferences. Results show that while genre does provide a reasonable level of accuracy to measure music preferences, there are cases where songs are often enjoyed by audiences of two different genres. The initial models revealed distinct personality traits that are related to certain music preferences, but these findings need to be confirmed in another sample. Therefore, these results are promising, but need to be confirmed in order to provide a better understanding of music preferences based on music stimuli and how this is related to personality.

## 4.4 Online Study 2: Confirming the Model of Music Preferences given Personality

Having built a preliminary model of music preferences and personality, the objective for the third and final section of the present chapter was to confirm the structure of the preliminary model and its relation to personality. Hypotheses were generated for the current study because there was now a known structure to music preferences with the music stimuli that were used and there were known predictive relations between this music preference structure and personality facets. Hypothesis 3 (H3) through to Hypothesis

12 (H12), shown below, reflect the known structure and predictive relations to personality that were found in the first online study.

Prior to these 10 hypotheses, however, two hypotheses from Section 4.3, Online Study 1, were restated. The first hypothesis below restates the second hypothesis stated for Online Study 1 and is stated as an attempt to replicate Rentfrow and Gosling's model of music preferences once more. The sample for this study was more homogeneous with respect to geographic location compared to the sample for Online Study 1. It would be interesting to see whether this has any effect on the results. The third hypothesis from Online Study 1 was formulated to test whether preference ratings toward music clips were related to participants' STOMP scores toward the genres from which these music clips were derived. The third hypothesis listed for Online Study 1 is restated below as the second hypothesis. Given the results from Online Study 1, it is expected that a strong positive relation will be found between participants STOMP scores and their music clip preference ratings. This would further validate the selection of the music clips for both online studies, but more importantly, it would be interesting to see how demographic differences might affect some of the results. In turn, the results concerning the relation between reported music preferences (i.e., STOMP scores) and preference ratings for specific audio clips will provide some insight into geographic differences with respect to music preference and genre perception. Similarly, how participants from the current study categorized music will also be described just as in Online Study 1. Again, however, the categorization results were only investigated to enrich the overall interpretation of the results. So, no formal hypotheses are formulated for the categorization analysis.

Lastly, the first hypothesis was not reiterated here because of the strong relation found between familiarity and music preference in the previous section and also in Chapter 3. Though important, the relation between familiarity and music preferences has already shown itself to be quite robust from previous results presented in Chapter 3 and Chapter 4, Section 4.3. Furthermore, the relation does not further enable overall interpretation of the current results, and so has not been reported here. In summary, the current hypotheses are as follows:

H1. Music preference scores obtained via the STOMP will replicate the model provided by Rentfrow and Gosling (2003).

H2. Preference ratings toward music stimuli grouped according to industry genre categorization (AMG, 2007) are positively correlated to preference scores toward the same genre.

H3. The structure of preferences using music stimuli found by the current results will replicate the structure of music preferences reported in the Results from Online Study 1.

H4. Participants' derived music preference scores for Contemporary African American Popular (CAAP) music are positively related to personality facets Warmth (E1), Excitement-Seeking (E5), and Order (C2), while negatively related to Altruism (A3).

H5. Participants' derived music preference scores for Jazz music are positively related to personality facets Aesthetics (O2), Actions (O4), and Ideas (O5).

H6. Participants' derived music preference scores for Modern Pop Chart music are positively related to personality facets Warmth (E1) and Self-Discipline (C5), while negatively related to Aesthetics (O2) and Actions (O4).

H7. Participants' derived music preference scores for Hard Rock music are positively related to personality facets Excitement-Seeking (E5) and Ideas (O5), while negatively related to Aesthetics (O2).

H8. Participants' derived music preference scores for Classical music are positively related to personality facets Aesthetics (O2) and Ideas (O5), while negatively related to Excitement-Seeking (E5), Feelings (O3), and Values (O6).

H9. Participants' derived music preference scores for American Country music are positively related to personality facets Tender-Mindedness (A6), while negatively related to Activity (E4), Values (O6), and Straightforwardness (A2).

H10. Participants' derived music preference scores for Blues-Rock music are positively related to personality facets Aesthetics (O2) and Excitement-Seeking (E5), while negatively related to Impulsiveness (N5) and Altruism (A3).

H11. Participants' derived music preference scores for Early Chart Pop music are positively related to personality facets Anxiety (N1), Excitement-Seeking (E5), Fantasy (O1), Values (O6), and Competence (C1), while negatively related to Self-Discipline (C5).

H12. Participants' derived music preference scores for Dance/ Electronica music are positively related Aesthetics (O2), Actions (O4), Values (O6), and Achievement Striving (C4), while negatively related to Altruism (A3) and Self-Discipline (C5).

### 4.4.1 Online Study 2: Method

*Participants*

Participants ($N$ = 133; 85 males) volunteered in response to recruitment announcements provided over the Internet via several means (e.g., mailing lists, forums), as well as recruitment posters advertised across the Eindhoven University of Technology Campus. Most participants were reportedly Dutch ($n$ = 124), while the remaining participants reported having Belgian nationality ($n$ = 9). Participants' ages ranged from 18 to 60 years ($M$ = 26.59, $SD$ =11.35).

*Materials*

The materials used in this study were identical to those materials described in sub-section 4.3.1, Online Study 1: Method, with one notable exception. The Internet interface was provided in Dutch. This further meant that the personality inventory used in this study was the Dutch-translated version of the NEO PI-R, translated and authored by Hoekstra, Ormel, and de Fruyt (2003). This version of the NEO PI-R is still scored and interpreted in the same manner as the original English version of the NEO PI-R described in sub-section 4.3.1.

*Procedure*

The procedure used in this study was identical to the procedure described in sub-section 4.3.1, Online Study 1: Method.

### 4.4.2 Online Study 2: Results

Similar to how the data had been reported for 4.3.2, Online Study 1: Results, data analyses from the current study began with a simple analysis that described how participants' categorized the music clips according to genre labels. Following the categorization results, results concerning the Confirmatory Factor Analysis (CFA) on the STOMP dimensions are reported. The CFA sub-section addressed the first stated hypothesis for the present study and attempted to replicate Rentfrow and Gosling's (2003) findings. The third sub-section addressed the second hypothesis stated for the present study and investigated the correlation between participants' STOMP scores for each genre and their preference scores for the music assigned to each of the same genres categorized according to industry standards (AMG, 2007). A second CFA for the present study is presented in the fourth sub-section of the results. The second CFA addressed the third hypothesis and attempted to replicate the structure for preferences using music stimuli. The fifth and final section addressed H4 to H12 stated for this study. Each of these hypotheses asserted different relations between participants' music preference scores derived from the preferences model using music stimuli and their personality facet scores.

*Music Categorization*

Data analysis began with how participants categorized the music clips into the genre categories provided to them. Just as in Online Study 1, clips were separated according to each of the 10 industry-defined genre categories and frequencies were calculated with respect to how participants felt that these music clips should be categorized by genre. Table 4.6 provides a confusion matrix of the participants' categorization of music clips by genre.

The patterns illustrated in Table 4.6 were remarkably similar to the patterns that appeared in Online Study 1. Just as in Online Study 1, there were many instances where participants' categorization of the music clips closely matched the industry-referred categorization. Patterns that illustrate matching categorization between participants and industry can be found in the table for Blues, Classical, Country, Jazz, Pop, and Rap. Also similar to Online Study 1, participants' categorization of the music clips from Dance, Heavy Metal, R'n'B, and Rock was more heterogeneous, which can also be found in Table 4.6. Lastly, participants' categorization of Heavy Metal and R'n'B clips were both instances where this categorization was lower than 50% in accordance with industry-referred categorization.

*STOMP Confirmatory Factor Analysis*

The Confirmatory Factor Analysis (CFA) from Online Study 1 was done on a very heterogeneous sample of participants geographically located around the world. Another CFA was done for this study to see if different results might be obtained from a more geographically-homogeneous sample. Again, this analysis attempted to find the same music preference dimensions stipulated in Rentfrow and Gosling's (2003) model of music preferences.

*Table 4.6*
Confusion Matrix of Participants' Categorization of Music Clips by Genre.

| | Frequency (Percent) of Categorization by Genre | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Music Clip Genre | Blues | Classical | Country | Dance | Funk | Heavy Metal | Jazz | Pop | R'n'B | Rap | Reggae | Rock |
| Blues | **2,736** | 7 | 212 | 15 | 102 | 8 | 242 | 74 | 492 | 4 | 12 | 344 |
| | **(64.4)** | (0.2) | (5.0) | (0.4) | (2.4) | (0.2) | (5.7) | (1.7) | (11.6) | (0.1) | (0.3) | (8.1) |
| Classical | 31 | **3,316** | 99 | 329 | 27 | 4 | 68 | 242 | 56 | 3 | 58 | 15 |
| | (0.7) | **(78.1)** | (2.3) | (7.7) | (0.6) | (0.1) | (1.6) | (5.7) | (1.3) | (0.1) | (1.4) | (0.4) |
| Country | 119 | 68 | **3,511** | 6 | 10 | 1 | 51 | 316 | 94 | 1 | 3 | 68 |
| | (2.8) | (1.6) | **(82.7)** | (0.1) | (0.1) | (0.0) | (1.2) | (7.4) | (2.2) | (0.0) | (0.1) | (1.6) |
| Dance | 13 | 419 | 5 | **2,591** | 150 | 25 | 6 | 701 | 42 | 27 | 15 | 254 |
| | (0.3) | (9.9) | (0.1) | **(61)** | (3.5) | (0.6) | (0.1) | (16.5) | (0.4) | (0.6) | (0.4) | (6.0) |
| Heavy | 16 | 14 | 17 | 189 | 49 | **1,164** | 4 | 467 | 46 | 76 | 10 | 2,196 |
| Metal | (0.4) | (0.3) | (0.4) | (4.4) | (1.2) | **(27.4)** | (0.1) | (11.0) | (1.1) | (1.8) | (0.2) | (51.7) |
| Jazz | 399 | 60 | 19 | 2 | 29 | 2 | **3,167** | 155 | 346 | 3 | 36 | 30 |
| | (9.4) | (1.4) | (0.4) | (0.0) | (0.7) | (0.0) | **(76.6)** | (3.6) | (8.1) | (0.1) | (0.8) | (0.7) |
| Pop | 25 | 17 | 79 | 124 | 53 | 2 | 9 | **3,402** | 241 | 42 | 25 | 229 |
| | (0.6) | (0.4) | (1.9) | (2.9) | (1.2) | (0.0) | (0.2) | **(80.1)** | (5.7) | (1.0) | (0.6) | (5.4) |
| Soul | 272 | 19 | 62 | 107 | 220 | 0 | 175 | 865 | **1,851** | 499 | 35 | 143 |
| (R'n'B) | (6.4) | (0.4) | (1.5) | (2.5) | (5.2) | (0.0) | (4.1) | (20.4) | **(43.6)** | (11.7) | (0.8) | (3.4) |
| Rap | 10 | 1 | 1 | 286 | 113 | 7 | 1 | 314 | 209 | **3,266** | 27 | 13 |
| | (0.2) | (0.0) | (0.0) | (6.7) | (2.7) | (0.2) | (0.0) | (7.4) | (4.9) | **(76.9)** | (0.6) | (0.3) |
| Rock | 45 | 18 | 25 | 32 | 47 | 130 | 17 | 1,263 | 124 | 3 | 17 | **2,527** |
| | (1.1) | (0.4) | (0.6) | (0.8) | (1.1) | (3.1) | (0.4) | (29.7) | (2.9) | (0.1) | (0.4) | **(59.5)** |

*Note*. $N = 354$. Numbers given in **bold** represent correct categorizations. Numbers in parentheses indicate percentages.

Just as in the previous analysis, this CFA was carried out using LISREL (Jöreskog & Sörbom, 2007). Figure 4.7 gives the standardized parameter estimates for the STOMP CFA model using participants' obtained scores. A chi-square test for goodness-of-fit indicated that the data was a poor fit with the proposed model, $\chi^2$ (91, $N$ = 133) = 249.09, $p < .001$. Furthermore, fit criteria statistics again showed that the data did not fit Rentfrow and Gosling's model well: Root Mean Square Error of Approximation (RMSEA) = .14, Standardized Root Mean Square Residual (SRMR) = .12, Goodness of Fit Index (GFI) = .79, and Adjusted Goodness of Fit Index (AGFI) = .69. Just as with the results for Online Study 1, the data seemed to fit reasonably well for the music dimensions, Reflective and Complex and Intense and Rebellious, while the overall poor fit is evident for the dimensions, Upbeat and Conventional and Energetic and Rhythmic. Also similar to Online Study 1, multicollinearity for certain explanatory genre variables evidenced by path coefficients or error terms that were negative or greater than 1. Figure 4.7 shows multicollinearity problems for Pop (Upbeat and Conventional), Soundtracks (Upbeat and Conventional), and Rap (Energetic and Rhythmic). As in Online Study 1, the multicollinearity problems were not remedied by drawing additions paths or dropping explanatory variables in order to facilitate structural comparisons between the results from the present study and the results provided by Rentfrow and Gosling (2003).

*Reported Genre Preference versus Song Scores*

The third data analysis investigated the relation between participants' reported genre preference and their preference toward the various music clips. The current analysis provided an indication of how well the selected music clips represented their affiliated genres, given participants' preferences. The analysis was done by correlating participants' STOMP scores for each genre with their preference ratings for the music assigned to each of these same genres according to industry-referred genre categories (e.g., AMG, 2007). As in Online Study 1, R'n'B was considered equivalent to Renfrow and Gosling's Soul/Funk genre category. Table 4.7 shows the correlation coefficients between participants' STOMP scores (rows) and their music preference ratings (columns).

Similar to Online Study 1, there are many significant correlations that can be described and are shown in Table 4.7. Most importantly, the diagonal in the table shows strong positive correlations indicating that

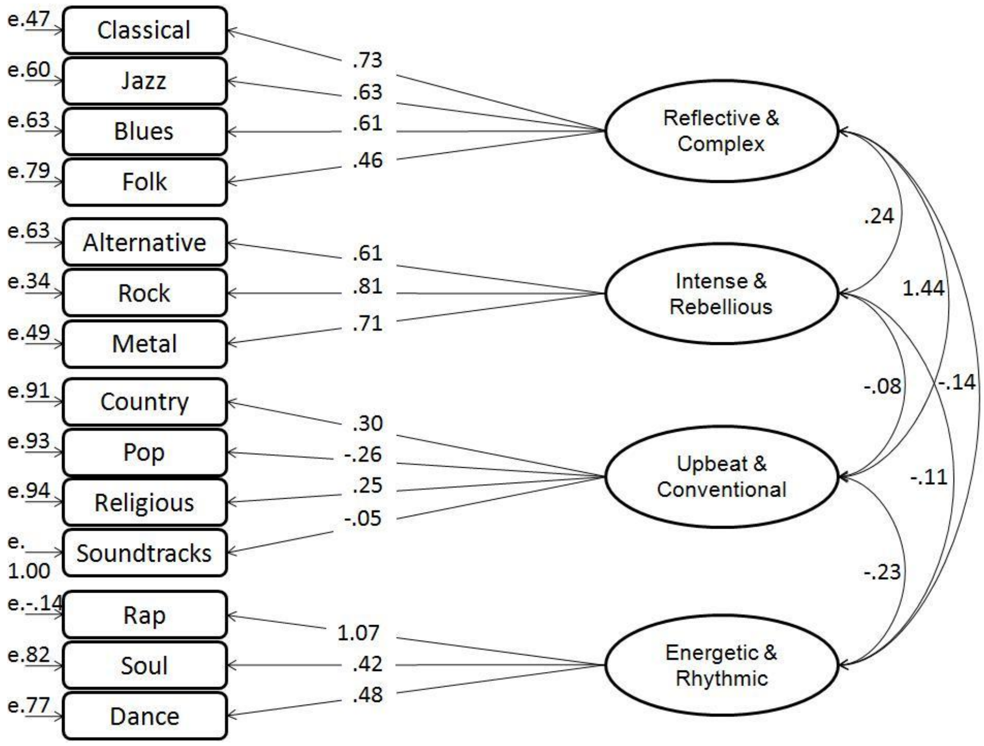



*Figure 4.7*. Standardized parameter estimates of the CFA STOMP model for the Dutch/Belgian data. $\chi^2$ (91, $N$ = 133) = 249.09, $p$ < .001 (GFI = .79, AGFI = .69, RMSEA = .14, SRMR = .12). Values shown on the far right denote correlations between latent factors. Path coefficients shown down the middle of the diagram are the estimated effect sizes between latent factors on the right and measured, explanatory variables on the left. Error variance (e) values shown on the far left denote the proportion of variance in the explanatory variables that is not accounted for by the latent variables.

participants often gave high preference ratings to music clips that were from the same genre categories for which they had given a high genre preference score (all $p$ < .01). Furthermore, for any given column in Table 4.7, the correlations between STOMP scores and preference ratings were strongest for matching genre categories. Also similar to Online Study 1, positive correlations were often found between participants' STOMP scores and their preference ratings for genre categories that could be grouped according to the preference dimensions described by Rentfrow and Gosling (2003; all $p$ < .01), but this was not always the case. For example, while combinations

*Table 4.7*
Correlation coefficients between Dutch/Belgian participants' STOMP scores and their music preference ratings.

| | Music Preference Genre | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| STOMP Genre | Blues | Classical | Country | Dance | Heavy Metal | Jazz | Pop | R'n'B | Rap | Rock |
| Blues | **.75**** | .28** | .40** | -.05 | .11 | .57** | -.06 | .26** | -.01 | .16 |
| Classical | .31** | **.76**** | .20* | -.01 | .01 | .52** | -.17* | -.02 | -.17 | -.04 |
| Country | .26** | .23** | **.75**** | -.12 | -.04 | .16 | .13 | .19* | -.07 | .11 |
| Dance | -.10 | -.08 | -.08 | **.62**** | .02 | -.03 | .19* | .23** | .49** | .02 |
| Heavy Metal | .10 | .00 | -.14 | -.01 | **.72**** | -.05 | -.39** | -.26** | -.12 | .11 |
| Jazz | .46** | .38** | .16 | .05 | .05 | **.74**** | -.18* | .21* | .05 | .11 |
| Pop | -.10 | -.23** | .10 | .15 | -.06 | -.25** | **.63**** | .35** | .29** | .19* |
| Soul (R'n'B) | .33** | .09 | .08 | .29** | -.07 | .42** | .12 | **.52**** | .48** | .26** |
| Rap | .05 | -.07 | -.03 | .36** | -.04 | .08 | .25** | .48** | **.81**** | .06 |
| Rock | .27** | .03 | -.01 | .18* | .69** | .08 | -.06 | .03 | .00 | **.43**** |

*Note*. $N = 133$. Correlations indicated in **bold** represent same genre correlations.
* $p < .05$, ** $p < .01$.

for Blues, Classical, and Jazz between participants' STOMP scores and their preference ratings were all consistently correlated, possible combinations between Pop and Country were uncorrelated in this manner. Last, there were fewer significant correlations in total compared to the results shown in Table 4.3 from Online Study 1.

*Confirmatory Factor Analysis of Music Stimuli Preferences Model*

Since Online Study 1 was able to build a preliminary model of music preferences, Online Study 2 evaluated the validity of this model. Evaluation of the model began by testing Hypothesis 3 (H3), which was done by conducting a Confirmatory Factor Analysis (CFA) using the Dutch/Belgian sample song preference ratings. Unfortunately, the size of the Dutch/Belgian sample was not large enough to properly conduct a CFA using all 120 music clip items originally used in the Principal Components Analysis from Online Study 1. To overcome this issue, the CFA used only the top three music clips that provided the strongest magnitude loading from the PCA. These top three music clips within each music component from the original PCA are provided in the Pattern Matrix table shown in Appendix E (Table E1). For the purposes of this CFA analysis, these music clips represent the prototypical representation for each of these nine music components. The CFA indices showed a reasonable fit to the data, $\chi^2$ (288, $N$ = 133) = 466.19, $p < .001$; CFI = .94, RMSEA = .068, SRMR = .077, GFI = .79, AGFI = .73. Figure 4.8 provides the standardized parameter estimates from this CFA.

*Confirming Relations between Music Preference Components and Personality Facets*

Once this CFA had confirmed the music preferences components identified in Online Study 1, it was now time to confirm the predictive equations found to relate music preferences to personality facets. This analysis would test hypotheses H4 through H12. As with the analyses done in the Online Study 1, gender, age, and music training were considered prior to looking at this relation between participants' predicted music preferences and their personality. Again, these factors influenced participants' predicted scores toward the nine music preference components after conducting a 2 (gender) × 9 (component) mixed ANCOVA with participants' predicted component scores as the DV, and age and years of music training as covariates. Tests of within-subjects effects showed participants' predicted scores for each of the nine preference categories had significant interaction effects with gender

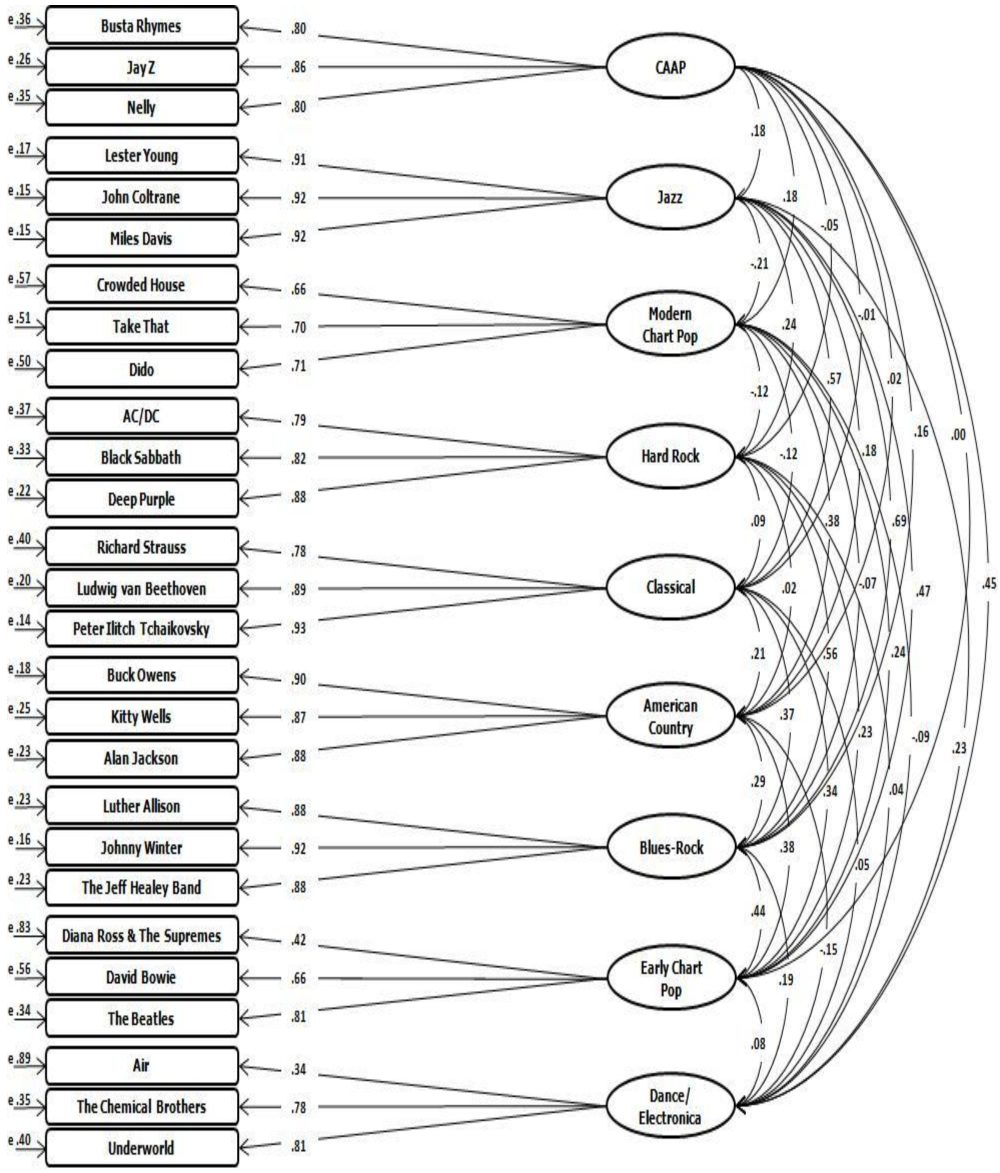



*Figure 4.8.* Standardized parameter estimates from the CFA conducted for music preference ratings using the Dutch/Belgian sample. $\chi^2$ (288, $N$ = 133) = 466.19, $p$ < .001; CFI = .94, RMSEA = .068, SRMR = .077, GFI = .79, AGFI = .73. e = error variance. Values down the centre of the figure indicate standardized parameter estimates between the measured DV (music clip preference ratings) and the latent variables (music preference components). Values to the right of the latent variables indicate correlations between latent variables beginning with latent variables next to each other (leftmost) to latent variables located furthest away from each other (rightmost).

($F$ (8, 1,032) = 4.11, $p < .001$, partial $\eta^2 = .03$), age ($F$ (8, 1,032) = 11.95, $p < .001$, partial $\eta^2 = .09$), and music training ($F = 4.60$ (8, 1,032), $p < .001$, partial $\eta^2 = .03$). Given these results, variance in participants' predicted music preference scores accounted for by gender, age, and music training was partitioned out. So, further statistical testing used the residual scores of participants' predicted preference scores.

Using the residual scores, nine linear regressions were done to confirm the nine predictive regression equations found during the analysis for Online Study 1. These linear regressions revealed that only some of the facets from the previous predictive equations were significant when predicting participants' music preference. Certainly, it is possible and even likely that there are some unique culturally defined personality characteristics that are attached to certain music preferences. So, to explore this issue, further regressions were performed between participants' music preference scores and their personality facet scores. Specifically, the personality facets found to be significant in the confirmatory step were retained. After retaining these personality facets, further stepwise regressions on participants' music preference components given their personality facet scores were done to explore culturally specific personality facets, which potentially predict Dutch/Belgian music preferences. Table 4.8 provides the complete results from the music preference modelling using the Dutch/Belgian sample. As with Table 4.5, the top row identifies each of the music preference components (categories), along with its associated coefficient of determination ($R^2$). The personality facets found to significantly predict a proportion of variance in any one these music preference components are listed down the first column. The standardized regression coefficients (β) per music preference component given personality facets are indicated in each of the cells, when applicable. Unique to Table 4.8, these β values are indicated in bold when findings between Online Study 1 and Online Study 2 have been confirmed. All $R^2$ and β values were significant at $p < .05$. Interestingly, similar to the findings with the International sample, no personality facets were found to be stable predictors of music preferences toward American Country music.

### 4.4.3 Online Study 2: Discussion

The primary objective of the second online study was to confirm the model of music preferences and its relation to personality found in the first online study. This model was confirmed in the last two sub-sections of the Results

*Table 4.8*
Standardized regression coefficients (β) per music preference component given personality facets.

| | Component ($R^2$ = ) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Personality Facet | CAAP (.20) | Jazz (.30) | Modern Chart Pop (.20) | Hard Rock (.12) | Classical (.09) | American Country (N/A) | Blues-Rock (.12) | Early Chart Pop (.17) | Dance/ Electronica (.06) |
| N4: Self-Consciousness | | | .21 | | | | | | |
| N5: Impulsiveness | | .19 | | | | | | .22 | |
| E1: Warmth | **.24** | | | | | | | | |
| E5: Excitement-Seeking | **.21** | | | **.32** | | | | | |
| E6: Positive Emotions | -.20 | | | | | | | | |
| O2: Aesthetics | | **.33** | **-.18** | | **.30** | | **.20** | .23 | **.21** |
| O4: Actions | | **.12** | | | | | | | |
| O5: Ideas | | | | **.15** | | | | | |
| O6: Values | | .20 | | | | | | **.17** | |
| A4: Compliance | | | | .23 | | | | | |
| C2: Order | | | .31 | | | | -.26 | | |
| C3: Dutifulness | -.28 | | | | | | | | -.19 |
| C5: Self-Discipline | .29 | | **.12** | | | | | -.20 | **-.10** |
| C6: Deliberation | | | | | | | .20 | -.20 | |

*Note*. $N = 133$. Cells represent standardized regression coefficient (β). β values presented in **bold** indicate confirmed values between International and Dutch/Belgian samples. All values shown are significant at $p < .05$.

by: (1) conducting a Confirmatory Factor Analysis (CFA) on the music preference categories found from Online Study 1 using participants' preference ratings for the music stimuli, and (2) conducting regression analyses that related participants' predicted preferences to their personality facet scores. Results from the CFA confirmed the 9-component model of music preferences found in Online Study 1. Also, some personality facets were reliably able to predict music preferences both in Online Study 1 and confirmed in Online Study 2. Nevertheless, this was not the rule and there were many personality facets that remained unconfirmed. There were also new and different facets derived from this Dutch/Belgian sample, which were able to predict music preferences. These confirmatory results will be specifically addressed nearing the end of this section. The current discussion will begin by addressing the results for the hypotheses in the order specified at the beginning of this section.

*STOMP Confirmatory Factor Analysis*

The first hypothesis asserted for Online Study 2 again tried to confirm Rentfrow and Gosling's (2003) model via participants' music preference scores obtained from the STOMP. It was hoped that a more homogeneous sample with respect to nationality might provide data capable of confirming this model of music preferences. Nonetheless, similar to previous attempts to confirm this model, the Confirmatory Factor Analysis (CFA) that was done with the Dutch/Belgian sample was not able to reject the null hypothesis and did not replicate Rentfrow and Gosling's model. Just as with the previous attempts, the data appeared to fit for the model's Reflective and Complex and Intense and Rebellious dimensions, while the remaining two dimensions gave problematic results. Again, Pop and Soundtracks proved to be two variables that did not fit as expected into the Upbeat and Conventional dimension of this model, while Rap seemed to be unrelated to Dance and Soul within the Energetic and Rhythmic dimension

While the sample size was sufficient to conduct a CFA using the current data, it is arguable that the relatively small sample size ($N = 133$) might be a reason why the data obtained in this study was unable to confirm Rentfrow and Gosling's model. Nonetheless, the consistency of the results among the last three CFA attempts to confirm this model and with a total of nearly 900 participants ($N = 882$) suggests that there are problems with the latter two dimensions in this model (i.e., Upbeat and Conventional and Energetic and Rhythmic). Given these results, it is clear that there are at least cultural differences with respect to nationality that limit how much Rentfrow and

Gosling's model of music preferences can be generalized. These results also support the necessary changes that Delsing et al. (2008) and George et al. (2007) had done to accommodate this model to their respective samples. Therefore, these results support the argument that music preference data obtained from preference scores toward genres or dimensions broadly describing genre preferences are limited in their ability to generalize music preferences across cultural boundaries. Other means must be used to obtain music preferences, such as directly from preferences toward specific music stimuli to provide more accurate, valid, and reliable data that is less affected by cultural differences regarding genre stereotypes.

*Reported Genre Preference versus Song Scores*

The second hypothesis addressed whether participants' STOMP scores for each genre would be positively correlated with their music clip preference ratings categorized according to the same industry-referred genre categories (e.g., AMG, 2007). The results obtained in this study were remarkably similar to Online Study 1, and so this hypothesis was confirmed. There were strong positive correlations found between participants' STOMP scores and their music clip preference ratings for the same genre. Again, preference ratings for music clips from any given genre were shown to have the strongest correlations with the STOMP preference scores for the same genre. The average among these matched genre correlations was $r$ = .67, and with the exception of the Rock genre, no correlation fell below $r$ = .50. As in Online Study 1, this validates the music clips that were selected for this study, showing that participants' like or dislike for music from a given genre, such as Blues or Rock, was also reflected in their preference ratings for the music clips that were selected from the same genre.

As in Online Study 1, the pattern of correlations found in this study helped to further explain why Rentfrow and Gosling's model of music preferences remained unconfirmed. Specifically, STOMP preference scores for Blues, Classical, and Jazz generally had the strongest positive correlations with music clips taken from these genres, which support the consistent and robust findings for the Reflective and Complex dimension. These genres were also consistently categorized by participants in a highly similar manner to how these clips were initially categorized according to industry standards (e.g., Amazon.com, 2007; AMG, 2007; Last.fm, 2007).

The Intense and Rebellious dimension also provided results that were highly similar to Online Study 1. Thus, this study further supports the argument taken from Online Study 1; this dimension is simply re-asserting how the music industry currently groups Rock, Heavy Metal, and Alternative (Rock) music under one broad genre category, which is often referred to simply as Rock (AMG, 2007). It would appear that participants view Heavy Metal music as a style within Rock, which is in agreement with current music genre hierarchies (e.g., AMG, 2007) and is also reflected by the current correlation results. Nonetheless, the pattern of correlations between preference scores and music clip preference ratings for these two genres indicated that participants who liked either Heavy Metal or Rock tended to prefer the Heavy Metal over the Rock music. Given this, it is possible that the Rock clips used in these two studies were more mainstream Rock found in top hit charts compared to participants' conception of Rock.

Overall, there seemed to be fewer significant correlations in this analysis than in Online Study 1. This finding was reflected with respect to music from the Upbeat and Conventional. Compared to Online Study 1, the correlations between Pop and Country music were not significant. This is a strong indicator why this music dimension was not supported in the previous Confirmatory Factor Analysis for Rentfrow and Gosling's model of music preferences. In fact, preference scores and preference ratings for Pop music tended to be correlated with ratings and scores for music from the Intense and Energetic dimension (i.e., Dance, R'n'B, and Rap). This provides further evidence that Pop music is a mismatch for the Upbeat and Conventional dimension and supports Delsing et al.'s (2008) research and their reassignment of Pop into a preference dimension with Dance music. Given that Delsing et al.'s sample and the present one are from roughly the same geographic region, these findings are clear indications of cultural differences in music preferences around the world.

*Confirmatory Factor Analysis of Music Stimuli Preferences Model*

The third hypothesis addressed the first part of the main objective for this study, which was to confirm the model of music preferences that had been found from the Principal Components Analysis completed in Online Study 1. The hypothesis was tested by doing a Confirmatory Factor Analysis (CFA) using participants' preference ratings toward the three music stimuli that had independently loaded strongest on each of the nine music components found in the initial PCA. For the purposes of this CFA then, these music clips were prototypical representations for each of these music components. This CFA provided a good fit to the data, which supported the assertion of the third hypothesis. Moreover, the standardized parameter estimates obtained from the CFA indicated very strong correlations between the measured variables (i.e., music stimuli) and the latent variables that they had been associated with given this model. Given the consistency of these results across both online studies, it is fair to say that these music samples are good estimates of an intangible prototypical or ideal representation of music from the nine prescribed preference categories. Due to the diversity among nationalities represented in the samples from both online studies, it is further argued that these representations are less impacted by cultural differences that have previously been found to influence music preference dimensions according to genre (e.g., Delsing et al., 2008; George et al., 2007). Therefore, the geographically diverse samples obtained in the two online studies presented in the current chapter give the greatest chance of accurately measuring music preferences that reflect essential personality characteristics that can be broadly found among audiences regardless of cultural boundaries. As a result, the samples also provide the opportunity for greater insight into the specific nature of music preferences and, in turn, improving music recommender accuracy by incorporating personality.

*Confirming Relations between Music Preference Components and Personality Facets*

The remaining nine hypotheses asserted in the introduction to the present section (H4 through H12) addressed the second part of the main objective for this second online study. Specifically, the second part was to confirm the predictive relations between the modelled music preferences and personality found in Online Study 1. Each hypothesis stated the predicted relations between a given music preference category (e.g., Classical, or Blues-Rock) and personality. None of the hypotheses was fully supported by the results, but there were consistencies found for the two studies with respect to personality facets that were significantly predictive of music preferences. For instance, the Aesthetics facet of Openness to Experience was consistently predictive of preferences for Classical, Jazz, and Blues-Rock. Given the definition of the Aesthetics facet, the finding suggests that individuals who enjoy the theatre, arts, and literature are more likely to also enjoy music that represents these music preference categories. This finding replicates previous findings that have linked preference scores toward these genres to Aesthetics or Openess to Experience (e.g., Delsing et al., 2008; George et al., 2007; Rentfrow & Gosling, 2003; Zweigenhaft, 2008). Also consistent with previous research was the relation between the Excitement-Seeking facet of Extraversion and music preference toward music identified in the Contemporary African American Popular (CAAP) category (e.g., Delsing et al., 2008; Rentfrow & Gosling, 2003; Zweigenhaft, 2008). CAAP was predominantly comprised of music that would be identified as Rap and R'n'B. This relation suggests that individuals who look for exciting and stimulating environments also enjoy the music that has been identified to be associated with the CAAP category. Curiously, just as in Online Study 1, there were no consistent relations found between preference ratings for American Country music clips and personality.

Given these results, it is argued that the replicated relations between the music preference categories and personality are likely fundamental relations between music preference and personality. These replicated relations are consistent and robust descriptions of individuals who are attracted to music of the type that is specified in these relations. Linking these relations to specific music stimuli has allowed a certain precision that is unavailable when measuring music preferences according to genre. As a result, it is believed that inconsistencies among previous results that related music preferences with personality, which are summarized in Chapter 1 of this thesis are avoided. Other relations found between music preferences and personality that were not replicated between the two studies are likely reflections of cultural differences among social groups that listen to these music clips for each given music category. Nonetheless, it is further argued that these fundamental relations between music preference and personality are likely also reflected in extracted music characteristics or features, which describe such things as the tempo, rhythm, beat, and tonality of the music. If this is the case, then linking personality to specific music features will give an even greater understanding and accurate knowledge of the relation between music preferences and personality. This will be the objective for the next chapter of this thesis.

### 4.4.4 Online Study 2: Summary and Conclusions

The main objective for Online Study 2 was to confirm the model of music preferences based on stimuli and related to personality that was generated in Online Study 1. This study achieved this objective and found a consistent and reliable structure of preferences using music stimuli. Not all the relations between music preference categories and personality facets were confirmed. Still, there were several consistent relations between music preferences and personality found in this regard. This supports the notion that there are essential features in music that attract individuals with certain personality characteristics. It is further argued that other relations that were not found to be consistent across both online studies reflect cultural differences in music preferences. Finally, given the reliability and strength of the relations from the present findings, it is concluded that these findings now confirmed the model of music preferences and provide the highest chance of success for recommending music based on personality.

## 4.5 General Summary and Conclusions

This chapter aimed to model preferences according to music stimuli and subsequently relate these preferences to personality. This involved a three-step process in which: (1) suitable stimuli were found that were used to model music preferences; (2) a preliminary structure of music preferences was built using these stimuli, which was then related to personality; (3) this preliminary structure of music preferences was confirmed along with its relations to personality facets. Subsequently, this chapter was divided into three sections that were devoted to each of these steps. The first section described a detailed process that was used to select music stimuli utilized for structuring music preferences. During this process, some indications of how music features differed according to genre were provided. These indications perhaps provide some initial hints with respect to how preferences according to specific features extracted from music might be related to personality. Nevertheless, this issue is dealt with in further detail in the next chapter. So, the remaining portion of this discussion will focus on some conclusions derived from the second and third sections of this chapter.

The second section focused on building a preliminary structure of music preferences by performing a Principal Components Analysis (PCA) to group participants' music preferences according to their ratings for the music stimuli. The resultant music preference categories were then related to personality facets. The first online study also further validated the music stimuli by correlating music stimuli selected according to genre to participants' reported preference scores for the same genres. Finally, this study also attempted to confirm Rentfrow and Gosling's (2003) model of music preferences based on genre. Overall, the results suggested that the music stimuli were valid examples of their respective music genres, and that genres are accurate to the extent that they provide a conceptual description of music preferences. Nonetheless, Rentfrow and Gosling's model of music preferences was not confirmed, which was attributed to a lack of fit for the Upbeat and Conventional, and Energetic and Rhythmic dimensions in their model. The music preference categories derived from the preliminary PCA structure exemplified how some music examples can be viewed as prototypically representative of preference for one genre enjoyed by a specific audience, but other music examples are able to bridge preferences across multiple audiences. For example, Limp Bizkit's Nookie is able to appeal to audiences who generally enjoy Rap, as well as appeal to audiences who enjoy Hard Rock. Therefore, this supported the argument that structuring a model of music preferences based on specific stimuli improves the accuracy of this model, and ultimately, a music recommender that would be based on this model. Accurate prediction of these music preferences given personality was gained by measuring specific personality facets, which also supported what appear to be robust findings in the research literature that have related music preferences and personality (e.g., Delsing et al., 2008; George et al., 2007; Rentfrow & Gosling, 2003; Zweigenhaft, 2008). For example, preference ratings for music from Blues-Rock, Classical, and Jazz appear to be consistently related to Openness to Experience, and specifically to the Aesthetic facet of this trait dimension.

The third and final section of this chapter attempted to confirm or verify the results from the previous section. This initially meant trying to confirm Rentfrow and Gosling's (2003) model of music preferences based on genre and further verify the song stimuli as representative of the genres they were selected from. Following these analyses, this section also attempted to confirm the preliminary structure of music preferences by doing a Confirmatory Factor Analysis (CFA) on the music preference categories according to participants' music preferences ratings for the music stimuli. Finally, attempts to confirm the relations found between these music preference categories and personality facets was also done in this section. Overall, the results from this section supported the results from the first online study. Specifically, the music stimuli were again found to be valid examples of their respective genres, while a lack of fit for Rentfrow and Gosling's model of music preferences was attributed to the Upbeat and Conventional, and Energetic and Rhythmic dimensions. These results again demonstrated that genres are limited in their accuracy to describe music preferences. Confirmation of the model of music preferences based on music stimuli further supported this argument. Lastly, while some relations between music preferences and personality were confirmed in this study, other relations remained unconfirmed. As a result, it was argued that the confirmed relations reflect essential relations that describe universal personality characteristics of audiences attracted to certain varieties of music.

# 5

## Discriminating among Music Preference Categories using Extracted Audio Features

Much of the research that has investigated music preferences and its relation to personality has asked participants to rate their music preference using given genre labels (e.g., Arnett, 1992; Delsing, Ter Bogt, Engels, & Meeus, 2008; George, Stickle, Rachid, & Wopnford, 2007; Litle & Zuckerman, 1986; McNamara & Ballard, 1999; Rentfrow & Gosling, 2003; Zweigenhaft, 2008). At first, this appears to make sense; individuals often arbitrarily use genre labels in conversation to describe their music preferences (Rentfrow & Gosling, 2006). These labels are also often used in various areas of research to describe music or music preferences (e.g., Juslin & Sloboda, 2008; Levitin, 2006; North & Hargreaves, 1999). Simply put, genre labels are a convenient and effective way to describe various styles of music playing on the whole.

Despite the convenience and common use of genre labels, there are several reasons to suggest that genre labels might not be the most accurate method to measure music preferences. First, sociologists have pointed out that genre labels are used as a tool by the music industry as part of its strategy to sell music to various audiences (e.g., Longhurst, 1995; Negus, 1996). As a result, individuals can have different conceptual ideas of the content that is represented by a given genre label. For example, is the Beatles' music considered to be Rock or Pop? Depending on who you ask and what specific song they have in mind, you might get two different answers. This would suggest that genre labels are ultimately somewhat subjective in nature. Perhaps it is this reason that people have often used several genre labels to describe their musical taste because one label is often not enough to fully describe their taste.

Second, our everyday experience suggests that genre labels are neither fully descriptive of individuals' music preferences, nor are these labels intended to mean that all music contained therein would be similarly enjoyed by a given individual. For example, an individual, let us call her Katrina, may describe her music preferences to include music from Rock, Heavy Metal, and Blues genres. And while Katrina might love the Rock band, U2, she might abhor another Rock band like Coldplay. Granted, there could be many inter-related reasons for Katrina to like one Rock band (in this case, U2), and not like another (Coldplay). These reasons could include, but are not limited to:

- how a given music artist or group has been marketed by the music industry (Negus, 1996);
- the social status attached to given music artists and bands for a given social group (North & Hargreaves, 1999; Rentfrow & Gosling, 2006);
- the emotional response that can be instigated by certain music or songs (Juslin & Sloboda, 2008);
- (emotionally significant) memories that are linked to certain songs (Levitin, 2006).

Despite these reasons, however, previous research has shown that genre labels have been sufficiently accurate to show measureable trends in music preferences (e.g., Delsing et al., 2008; George et al., 2007; Rentfrow & Gosling, 2003). Using our example again, let us say Katrina has indicated using some self-report measure that she likes Rock, Heavy Metal, and Blues music. This description gives a conceptual idea of the type of music she likes, but perhaps greater descriptive accuracy would be gained if there were specific audio features that were common among all the music that Katrina listens to within those three genres. For instance, if Katrina liked all music within these genres that emphasized melodies that were played in minor key, then this would give greater descriptive accuracy to the kind of music that Katrina likes. Perhaps one of the reasons why the previous research mentioned above has generally used genre labels rather than more descriptive musical properties is because it might be difficult for many individuals to describe their music preferences in terms of objective musical properties. For instance, Katrina might find it easier to subjectively describe her music preferences with the genre labels Rock, Heavy Metal, and Blues, but she might have no idea that all of the specific songs that she likes within these genres are often played in minor key. Therefore, while genre labels might give a good subjective interpretation and description of one's music preferences, a more accurate description might be obtained by using objective features linked to the music content, which could be difficult for people to explicitly describe.

Third, certain objective and measureable audio features might give greater descriptive accuracy of individuals' music preferences compared to genre labels. As stated earlier in Chapter 1 of the present thesis, Pachet and Cazaly (2000) conducted a study that showed different genre taxonomies employed by various music resources representing the music industry were inconsistent in their approach to music categorization. This finding prompted Aucouturier and Pachet to investigate other approaches to music categorization, which included audio feature extraction.

Audio features contained in music have been shown to communicate emotion to the listener (e.g., Juslin, 2000), and the relation between music and emotion has been intensely studied (cf. Juslin & Sloboda, 2008). Consider that personality traits, such as the Big Five, predispose individuals to experiencing certain emotional states (Rusting, 1998). Given this, it should not be surprising that individuals with specified personality traits are shown to have preferences to music with an empirically-defined set of audio features. Audio feature extraction has the potential to build on previous research that has investigated the relation between personality and music preferences by providing an objective and measureable description of music preferences that relates to personality traits. The present chapter introduces a first foray into this area of research, and shows an approach to investigating the relation between personality and music preferences using audio feature extraction.

## 5.1 Chapter Objectives

The present chapter has only one objective with no hypotheses stated. The objective of this chapter is to describe the extracted audio features that can accurately discriminate between the music preference categories that have been determined in Chapter 4. In doing so, it is argued that by describing music preference categories according to audio features, this chapter will give further insight into the relation between personality and music preferences. Specifically, it will provide some initial ideas about what are the essential audio features in music that attract individuals with specific personality characteristics.

## 5.2 Method

Rather than using human participants to explore or test relations between personality and music preferences, this chapter is focused on discriminating among music preference categories defined in Chapter 4 by using extracted audio features. Thus, this section describes the method used to further investigate extracted audio data using sampled music clips.

*Music Samples*

The music samples used in this analysis were taken directly from the 120 music clips that were identified and used in Chapter 4 to define nine music preference categories based on these stimuli. These music clips each lasted approximately 20 s. It was necessary to filter the 120 music clips to ensure that only those clips that were clearly representative of only one music preference category were selected. Filtering the data in this way would provide the best opportunity to discriminate among the music preference categories. The Principal Components Analysis (PCA) reported in Chapter 4 was used to filter these data. Stated objectively, the selection criterion meant that music clips must have had a pattern matrix factor loading with a magnitude greater than |.400| on only one of the nine PCA components to be included in this analysis. Music clips that did not meet this criterion were excluded. As a result, 16 of the original 120 music clips did not attain this minimum criterion and were not included in this analysis. Therefore, there were 104 music clips that were included in this analysis.

*Software*

The AFX3 software tool used for the analysis has been developed within Philips Research and is confidential in nature. This software extracted 85 audio features from music approximately every 743 ms and resulted in 21 observations per 20 s music clip. These 85 audio features are divided into four general categories: (1) spectro-temporal signal properties, (2) percussive event properties, (3) tonal properties, and (4) rhythmic properties. Due to the confidential nature of this software, a precise description cannot be provided here. Generally speaking, however, the nature of this tool is similar to other software dedicated to audio feature extraction, such as Marsyas (Tzanetakis & Cook, 2000), MA toolbox for MatLab (Pampalk, 2004), and MIR toolbox (Lartillot, 2008; Lartillot & Toiviainen, 2007).

To assist future replication of the current analysis, Table 5.1 summarizes similarities between the audio features extracted by all four software tools. The first column in this table lists the software tool and its author(s), while the last column indicates the total number of features extracted by each of these tools. The remaining five columns indicate what audio features are extracted by each software tool by musicological category. Timbre category includes features describing spectral and cepstral properties found in the music, such as spectral centroid, brightness, roughness, Mel Frequency Cepstral Coefficients (MFCCs), and Linear Prediction Cepstral Coefficients. This category matches closely with the first AFX3 category, spectro-temporal signal properties. Percussive category describes features estimating such things as the frequency and consistency of percussive events found in the music and is representative of the second AFX3 category, percussive events properties. Pitch/Chroma category includes features that describe the musical chroma or pitches and key (major vs. minor) estimates extracted from music. The Pitch/Chroma category is represented by the third AFX3 category, tonal properties. Rhythm category includes estimates of tempo and note onset, and is represented by the last AFX3 category, Rhythm properties. Lastly, Loudness category describes the energy found in the music. In this case, the AFX3 tool includes a measurement of the energy (loudness), which is included as part of its identified spectro-temporal signal properties.

The number of features extracted per musicological category and in total by each of the software tools has not been explicitly stated by its authors (e.g., Lartillot, 2008; Pampalk, 2004; Tzanetakis & Cook, 2000). For this reason, the numbers provided in Table 5.1 are based on the investigation conducted by Novello (2009) and communication with one of the authors of the AFX3 software, J. Skowronek (personal communication, November 19, 2009), on the referenced software tools.

*Analysis Procedure*

As mentioned in the previous section, the AFX3 software tool extracts the 85 audio features from music every 743 ms. Audio features were not extracted from the first and last 2 s of each music clip because the audio for these clips was faded in and out. In this manner, the consistency of the audio features was maintained as much as possible. As a result, this meant that there were 21 observations or times that audio features had been extracted for each of the 20 s music clips.

*Table 5.1*
Summary of the Audio Features Extracted by Software Tools.

| Software Tool (Authors) | Extracted Features (#) Timbre | Percussive | Pitch/ Chroma | Rhythm | Loudness | # of Features |
|---|---|---|---|---|---|---|
| AFX3 (Breebaart, McKinney, Skowronek, & van de Par) | Yes (20) | Yes (21) | Yes (26) | Yes (16) | Yes (2) | 85 |
| Marysas (Tzanetakis & Cook) | Yes (376) | No | No | No | No | 376 |
| MA toolbox (Pampalk) | Yes (206) | No | No | Yes (4) | Yes (2) | 212 |
| MIR toolbox (Lartillot & Toiviainen) | Yes (105) | No | Yes (22) | Yes (8) | Yes (2) | 137 |

*Note*. Number of extracted features provided is based on investigation by Novello (2009).

## 5.3 Results

Once the 85 audio features had been extracted for all music clips, the values obtained from the audio feature extraction were transformed into z-scores. This transformation was done to ensure that each extracted audio feature would have relatively equal weighting for the analysis that discriminate these music clips based on their assigned music preference categories. The audio feature data was analysed by conducting a stepwise Multiple Discriminant Analysis (MDA). Due to redundancy among the audio features, the stepwise MDA allowed for the elimination of 53 audio features that did not appreciably add to the accuracy of this analysis to correctly discriminate the music according to the preference categories. The 53 audio features that were eliminated were found to be highly correlated to the remaining 32 audio features and did not appreciably add to the explained variance in the MDA model. In turn, this elimination would help maintain robust MDA results and prevent over-fitting of the data.

An MDA was conducted on the remaining 32 audio features that were left after the data set had been filtered and redundant audio features had been removed. Eight functions discriminated between the music contained in each of the nine music preference categories. A chi-square test of Wilks' Lambda (Λ) was used to evaluate the overall significance of the MDA. The result was $\Lambda = .009$, $\chi^2$ (256, $N$ = 2,184) = 10,081, $p < .001$, partial $\eta^2 = .44$ with 95% confidence limits from .40 to .46. Further tests of $\Lambda$ indicated that each function added significantly to the discriminant ability of the MDA. This was shown by a chi-square test of $\Lambda$ for the last and weakest discriminant function, $\Lambda = .845$, $\chi^2$ (25, $N$ = 2, 184) = 364.20, $p < .001$, partial $\eta^2 = .02$ with 95% confidence limits from .00 to .02. Furthermore, cross-validated classification is used to indicate the accuracy of the discriminant model. The cross-validated classification showed that roughly 80% of the data points in this analysis were correctly classified, which indicates that the discriminant model is fairly accurate. The first four discriminant functions accounted for a total of 85.5% of the between-group variability amongst the music preference components, with each function separately accounting for at least 10% of this total variance. For this reason, only results for these four functions are described in further detail.

A canonical $R^2$ was used for each of the four discriminant functions to express the relation between the extracted audio features and the nine music preference components first shown in Table 4.4 on pp. 73-74. From the first to the fourth discriminant function, these canonical $R^2$ values were $R^2{}_1 = .77$, $R^2{}_2 = .61$, $R^2{}_3 = .51$, $R^2{}_4 = .45$, respectively. Similar to the $\Lambda$ values expressed above, each of these values was significant at $p < .001$. Figure 5.1 and Figure 5.2 give two visual representations of the first two discriminant functions that used extracted audio features to discriminate music clips according to each of the components. Figure 5.1 indicates how the extracted audio feature data points are distributed on the first two discriminant functions. The data points in Figure 5.1 are separated by colour based on their music preference category. Figure 5.2 gives a visual interpretation of how the music preference categories are distributed in Figure 5.1. Only the first two functions are shown in both Figures because these functions provided the best visual distinction between the music contained in each of the nine components. Furthermore, Table 5.2 provides the group means (i.e., group centroids) for each of the discriminant functions.

Using Figure 5.1, Figure 5.2, and Table 5.2, two extremes are seen from the means in the first discriminant function. The negative extreme had Contemporary African Amercian Popular (CAAP) music ($M$ = -2.42, $SD$ = 0.76) and Dance/Electronica music ($M$ = -2.55, $SD$ = 1.18). The positive extreme had music from Jazz ($M$ = 1.56, $SD$ = 1.19), American Country ($M$ = 1.07, $SD$ = 0.85), and at its most extreme, Classical music ($M$ = 3.76, $SD$ = 1.40). Further tests indicated that the differences between means at these extremes were significant ($p < .001$). Using the function loadings

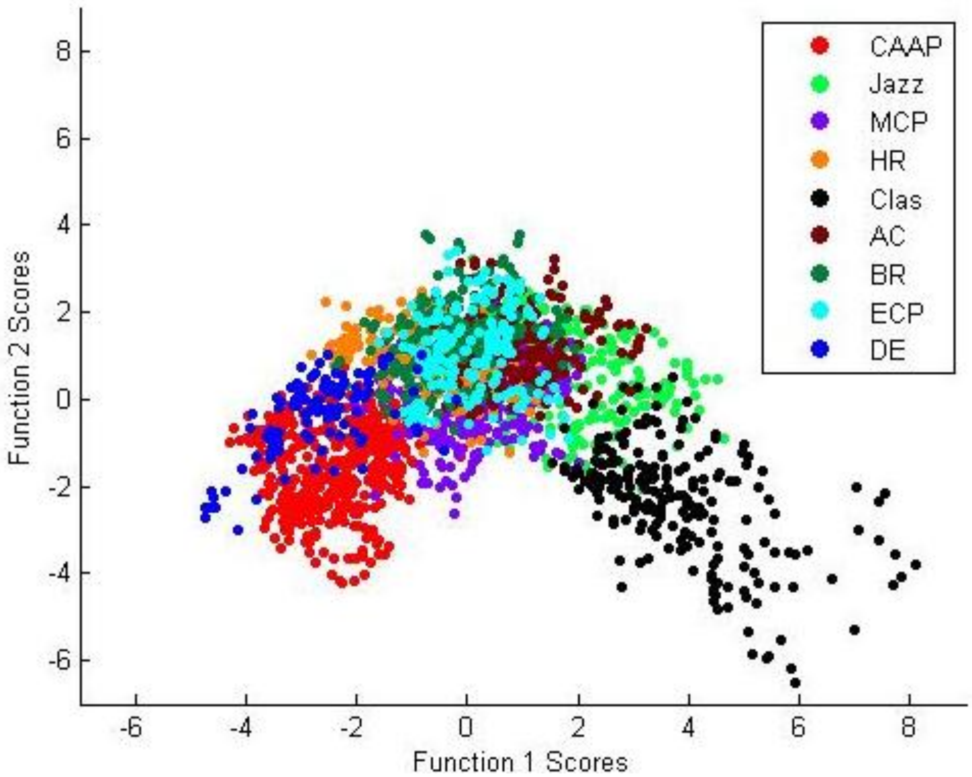



*Figure 5.1*. Visual representation of the first two discriminant functions that used extracted audio features to discriminate music clips according to the nine music preference categories indicated in the legend. CAAP = Contemporary African American Popular; Jazz = Jazz; MCP = Modern Chart Pop; HR = Hard Rock; Clas = Classical; AC = American Country; BR = Blues-Rock; ECP = Early Chart Pop; DE = Dance/Electronica.

provided by the MDA, the best predictors for discriminating between these extreme groups included audio features related to percussive event properties. These loadings indicated that music from the negative extreme tended to have more percussive events with shorter intervals between these events compared to music from the positive extreme.

Interpretation of the function loadings provided by the MDA indicated that percussive events were also important when discriminating between extremes along the second discriminant function. At the second function's most negative extreme was Classical music ($M$ = -2.34, $SD$ = 1.31), and CAAP music ($M$ = -1.56, $SD$ = 0.95). At its positive extreme was Hard Rock ($M$ = 0.98, $SD$ = 0.70), American Country ($M$ = 1.24, $SD$ = 0.78),

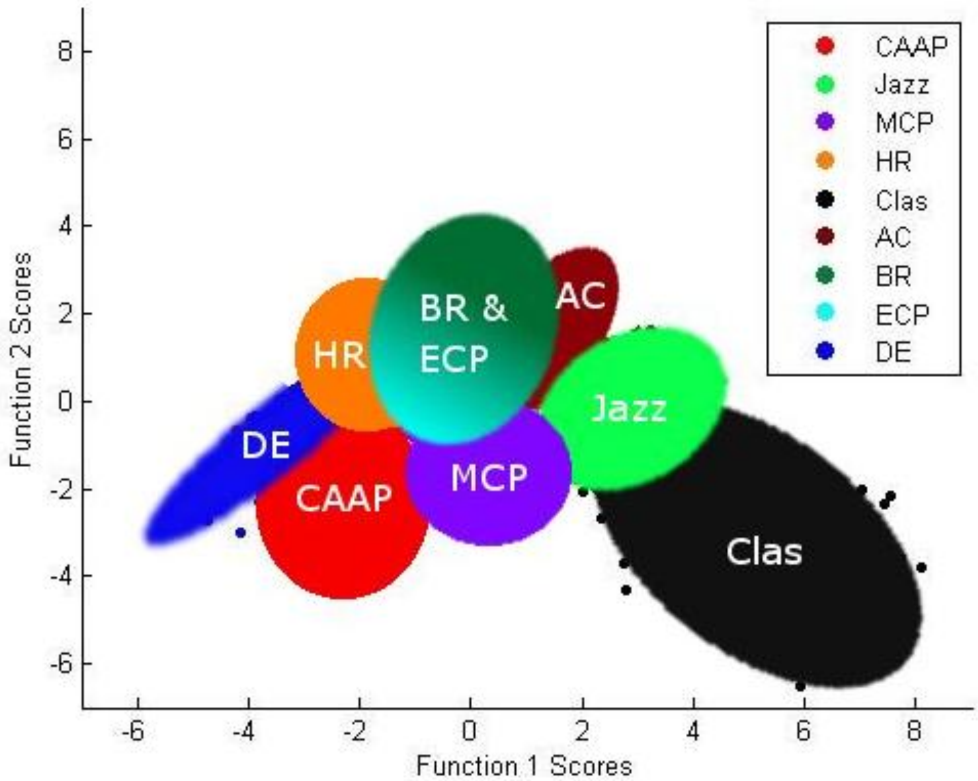



*Figure 5.2*. Visual interpretation of how music preference categories are distributed in conceptual space along the first two discriminant functions illustrated in Figure 5.1. CAAP = Contemporary African American Popular; Jazz = Jazz; MCP = Modern Chart Pop; HR = Hard Rock; Clas = Classical; AC = American Country; BR = Blues-Rock; ECP = Early Chart Pop; DE = Dance/Electronica.

Blues-Rock ($M$ = 1.30, $SD$ = 0.89), and Early Chart Pop music ($M$ = 1.05, $SD$ = 0.96). Again, further tests indicated that the differences between means at these two extremes were significant ($p < .001$). The function loadings indicated that music taken from the negative extreme tended to have greater variation in the timing between percussive events compared to music from the positive extreme.

For the third discriminant function, the negative extreme had Jazz ($M$ = -1.51, $SD$ = 1.07) and Blues-Rock music ($M$ = -1.23, $SD$ = 0.93). The positive extreme had Modern Chart Pop music ($M$ = 1.52, $SD$ = 0.90). Further tests indicated that the differences between means at these two

*Table 5.2*
Means per Group (Centroids) taken from MDA.

| Music Preference Component | Discriminant Function | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| CAAP | -2.424 | -1.562 | -0.569 | 0.487 |
| Jazz | 1.558 | 0.645 | -1.515 | 0.491 |
| Modern Chart Pop | 0.157 | 0.017 | 1.517 | 1.102 |
| Hard Rock | -0.647 | 0.975 | 0.767 | -1.325 |
| Classical | 3.756 | -2.339 | 0.152 | -0.929 |
| American Country | 1.065 | 1.235 | 0.781 | 0.763 |
| Blues-Rock | -0.372 | 1.300 | -1.233 | -0.388 |
| Early Chart Pop | 0.017 | 1.052 | -0.320 | 0.021 |
| Dance/Electronica | -2.549 | -0.274 | 0.607 | -1.811 |

*Note*. $N$ = 2,184. Cells represent group means ($M$). CAAP = Contemporary African American Popular.

extremes were significant ($p < .001$). The loadings provided by the MDA indicated that the best predictors for discriminating between these extreme groups included audio features related to tonal properties. These loadings indicated that music from the negative extreme tended to be played more often in minor key and also tended to have a more complex tonal structure compared to music from the positive extreme.

The negative extreme of the fourth discriminant function had Hard Rock ($M$ = -1.33, $SD$ = 0.86) and Dance/Electronica music ($M$ = -1.81, $SD$ = 0.82). At its positive extreme was Modern Chart Pop ($M$ = 1.10, $SD$ = 0.84) and American Country music ($M$ = 0.76, $SD$ = 0.83). Further tests indicated that the differences between means at these two extremes were significant ($p < .001$). Similar to the third discriminant function, the loadings provided for the fourth function showed that the best predictors for distinguishing between these extreme groups included audio features related to tonal complexity in the music. Also similar to the third discriminant function, these loadings were related to tonal structure and showed that music from the negative extreme tended to have more tonal complexity compared to music from the positive extreme.

## 5.4 Discussion

To accomplish the aim set for this chapter, a Multiple Discriminant Analysis (MDA) used extracted audio features to discriminate music clips according to the nine music preference components. Four discriminant functions accounted for the lion's share in the variability among the audio feature data points. These functions also seemed to give the best insight into how audio features could express music preferences more accurately, and how these features could be linked to personality. The following discussion considers the MDA results in combination with the results from Chapter 4 that described the relation between music preferences and personality. After considering the combination of these results, two examples have been highlighted, which illustrate how audio features can be used to express music preferences and its link to personality more accurately.

The first function from the MDA provides a clear distinction between Contemporary African American Popular (CAAP) music on the one hand, and Classical music on the other hand. Given the function loadings, it was clear that one of the features used by the first function was related to the amount of percussive sounds and bass in the audio. For instance, music clips that scored low on the first function were songs like Dirt off your Shoulder, by Jay Z, and Don't Phunk with my Heart, by the Black-Eyed Peas. Music clips that scored high on the first function, however, were Classical pieces like Beethoven's Eroica, and Bach's Matthaus Passion. Comparing the MDA results to the results relating music preferences with personality, it seems that Excitement-Seeking tends to be negatively related to scores along this function. That is, music that had more percussive events like that found in CAAP tended to be enjoyed by participants who were higher in Excitement-Seeking. While those participants who were lower in Excitement-Seeking tended to enjoy music with fewer percussive events, like Classical. This might help further explain the results from McCown et al. (1997), who found that Extraversion was positively related to preference for music with enhanced bass. That is, the Excitement-Seeking facet in the Extraversion dimension seems to be positively related to individuals' preferences for music that emphasizes frequencies at least below 200 Hz, which tend to emanate from percussive events.

The third function provides a clear distinction between Jazz music on the one hand, and Pop music on the other hand. Given the function loadings, it was clear that tonal complexity was a key feature used by this function to discriminate these groups according to extracted audio features. Examples of music clips that scored high on the third function were Crazy by Seal, and Back for Good by Take That. Examples of music clips that scored low on the third function were Wynton Marsalis' The End of a Love Affair, and Louis Armstrong's What a Wonderful World. Further comparisons between the MDA results and results relating music preferences with personality indicated that Aesthetics seems important in this distinction. In this case, lower function scores tended to come from music like Jazz, which tended to be enjoyed by participants' who were higher in their openness to aesthetic experiences, like attending the ballet or an art show. Higher function scores tended to come from music like Pop, which tends to have a simpler tonal complexity and is enjoyed more by participants who were lower in Aesthetics.

These results provide some good preliminary examples that result from considering the role that audio features play in the relation between music preferences and personality. As part of the conclusion it is argued that this research demonstrates how extracted audio features can provide a more accurate description of music preferences compared to genre labels, and so, helps provide greater insight into the relation between music preferences and personality.

## 5.5 Conclusion

This chapter addressed the genre ambiguity problem by exploring how extracted audio features can be used to distinguish among music preference categories identified in Chapter 4. Results revealed how music preference categories can be discriminated by using extracted audio features, which can then be interpreted and connected to personality descriptions. Therefore, the present results suggest that audio features can improve our understanding of the relation between personality and music preferences compared to reported music preferences using genre labels. Consequently, the present results also suggest predicting music preferences using audio features would be more accurate compared to using genre labels.

In a similar vein, the technique demonstrated in this paper provides the opportunity to achieve greater insight into what audio features could be specifically preferred by people with certain personality traits. In turn, this could improve our understanding of what music we like and why. From an applied perspective, this might also be used to improve technologies, such as recommender systems or similar intelligent systems.

# 6

## Applying Music Recommendation based on Personality

The introduction of the computer, and ultimately, the Internet has also expanded our access to a limitless amount of digital information that is a clichéd fact of life for individuals living in a digital society. Equally cliché is the term, information overload, which has often been used to express the situation wherein too much access to information is provided to individuals. As a result, individuals are left *satisficing* their search criteria. Newell and Simon (1972) use the term, satisficing, to describe a decision-making strategy wherein individuals attempt to satisfy their search criteria rather than find the optimal solution. To help individuals in their information search, various software tools have been devised to deal with information overload, such as search engines and retrieval systems. Included among these tools are recommender technologies. Recommender technologies are often used to help resolve information overload linked to various commercial media, including digital music information search and retrieval (e.g., Li, Myaeng, & Kim, 2007; Pauws, 2000; Yoshii, Goto, Komatani, Ogata, & Okuno, 2008). Despite its success, recommender technologies are challenged by what is often referred to as the *cold start* problem (Lam, Vu, Le, & Duong, 2008; Rashid et al., 2002; Schein, Popescul, Ungar, & Pennock, 2002). Cold start is defined as the initial problems for recommender algorithms when trying to recommend material when a new item or new user is added to its system (Schein et al.).

To address cold start and information overload concurrently, Lam, Vu, Le, and Duong (2008) have suggested measuring characteristics designed to better understand the individual or user who is listening to the music. Lam et al. found that inclusion of non-descript user demographic information provided some improvement to current recommender technologies, but argued that further improvements could be gained by using more specific user information. Personality information would qualify as more specific information, but more research was necessary to improve our understanding of its relation to music preferences. The majority of the current thesis has been dedicated to learning about and modelling the relation between personality and music preferences. The work undertaken in the present thesis to this point has contributed to previous research (e.g., Delsing, Ter Bogt, Engels, & Meeus, 2008; George, Stickle, Rachid, & Wopnford, 2007; Rentfrow & Gosling, 2003), and so has been valuable in its own right. Nonetheless, one potential application granted by the research provided so far in the present thesis is that it could be used to help improve the cold start problem.

If personality can be used to better predict music preferences and help improve cold start, then two comparisons must be made. First, the modelled relation between music preferences and personality provided in the present thesis must show that it is better than random prediction of music preferences to show at least some potential. Second, the modelled relation provided in the present thesis must be compared to current recommender technologies to see if using individuals' personality information can already help reduce problems associated with cold start and information overload. In the current chapter, the relation between personality and music preferences modelled in the present thesis is compared to another recommendation system. In this way, the modelling approach taken in the present thesis is tested in an applied manner to answer if music recommendation based on personality can be a practical solution to the cold start problem. To this end, the remainder of the introduction discusses information overload, reviews approaches often used by recommendation technologies to help resolve information overload, and expands on how cold start is a problem that is encountered by these recommendation technologies.

## 6.1 Information Overload, Recommenders, and Cold Start

Among the researchers investigating information overload, this term is often used to suggest that there is an overwhelming amount of digital information that is now accessible to users, particularly when surfing the Internet (e.g., Anand, Kearney, & Shapcott, 2007; Herlocker, Konstan, Terveen, & Riedl, 2004; Lekakos & Giaglis, 2006; Middleton, Shadbolt, & de Roure, 2004; Montaner, López, & de la Rosa, 2003). Nevertheless, the meaning of information has been left implicit by most of these researchers. Perhaps the closest definition of information overload is provided by Blair (1980), who has described this situation for the user by proposing two *futility points*, which can be summarized as:

1. The point at which the amount of displayed information exceeds the amount of information that the user is willing to begin scanning or browsing through.
2. The point at which the amount of information that users are willing to scan or browse through is exceeded.

Should either of these points be exceeded, then users have experienced information overload and abandon their information search.

Information overload is a problem that can be applied to any type of content (e.g., news, movies, literature, research papers), and so various software tools have been developed to deal with information overload (e.g., search engines, retrieval systems). The remainder of the introduction concentrates only on research dealing with software tools used to improve information overload related to music; namely recommender technologies.

Often referred to simply as recommenders, recommender technologies typically fall into one of three essential approaches described by Adomavicius and Tuzhilin, 2005:

1. *Content-Based (CB)*: recommended items are provided based on similarities to previous items preferred by the user.
2. *Collaborative Filtering (CF)*: recommended items are provided based on reported preferences from other users found to have similar tastes to the user in question.
3. *Hybrid*: combines CB and CF approaches.

These three approaches have been consistently used throughout the literature on recommender systems, though additional approaches have also been described (cf. Burke, 2002; Montaner et al., 2003). Among these approaches, Collaborative Filtering (CF) has been the most predominantly used (Bertin-Mahieux, Eck, Maillet, & Lamere, 2008; Deshpande & Karypis, 2004; Herlocker et al., 2004). The success of CF approaches is partly due to its imitation of the social techniques individuals use to get informed about novel experiences, commonly known as word-of-mouth (Resnick & Varian, 1997; Shardanand & Maes, 1995).

Collaborative Filtering (CF) approaches recommend items based on the similarity of preferences between users. In order to recommend items, CF algorithms begin by calculating the *Pearson Product-Moment Correlation* ($r$) between the target user ($a$) and all users ($i$) given their preference scores ($\upsilon$) on all rated items ($j$; Breese, Heckermman, & Kadie, 1998; Resnick, Iacovou, Suchack, Bergstrom, & Riedl, 1994; Shardanand & Maes, 1995). Thus, the calculation is represented by the following formula:

$$r_{a,i} = \frac{\Sigma_j(\upsilon_{a,j} - \bar{\upsilon}_a)(\upsilon_{i,j} - \bar{\upsilon}_i)}{\sqrt{\Sigma_j(\upsilon_{a,j} - \bar{\upsilon}_a)^2 \Sigma_j(\upsilon_{i,j} - \bar{\upsilon}_i)^2}}$$

A minimum positive $r$ is specified to identify users with similar tastes. Once users with similar tastes are identified, then a weighted average proportional to $r$ is used to estimate the target user's preference ratings and recommend items to the target user.

Despite its success, the formula above indicates a well-known issue for CF approaches known as cold start and more specifically, the new user problem (Lam, Vu, Le, & Duong, 2008; Rashid et al., 2002; Schein, Popescul, Ungar, & Pennock, 2002). For the formula to work, the target user must have rated a number of items to compare preferences with all users. Often, new users to CF systems have not rated any items and so their preferences cannot be compared to other users. As a result, items recommended to the target user are less accurate than after the target user has had a chance to provide preference ratings to a number of items.

In an attempt to provide one possible solution for the new user problem, Lam et al. (2008) have suggested incorporating user characteristics as part of the CF approach (i.e., various demographic characteristics). Initial research that incorporates user characteristics into CF systems to deal with the new user problem has shown promise (e.g., Lam et al., 2008; Lekakos & Giaglis, 2006; Nguyen, Denos, & Berrut, 2007). As previously mentioned, that research has only looked at surface-level characteristics at this point (e.g., gender, age), but further improvements in addressing the new user problem are expected to be gained by measuring more detailed user characteristics (Lam et al.). Personality traits constitute a more detailed measurement of user characteristics that have been shown to give stable and reliable estimates of individuals' habits and behaviours (Gosling, 2008; John & Srivastava, 1999; Rentfrow & Gosling, 2003).

Up to this point, the present thesis has investigated the relation between personality and music preference in order to provide some predictive capability to estimate individuals' music preference given their personality. Still, the resultant personality algorithms predicting music preferences must be compared to a traditional CF algorithm in order to gauge how well the personality algorithms work in an applied setting and how well these algorithms address the new user problem. The personality algorithms used for estimating music preferences are based on a linear regression formula provided below. The formula estimates preference (*P*) for each user (*i*) and for each one of eight music preference categories (*j*) identified in Chapter 4.[1] The estimated preference for a given user and music category is equal to the sum of the standardized regression coefficients (β) for each personality trait (*t*) in the equation, multiplied by the user's standardized score (z) for that personality trait. The number of personality traits in the eight music categories can range from 1 to *n* depending on the personality traits found to be significant to the specified music category reported in Chapter 4.

$$P_{i,j} = \sum_{t=1}^{n} (\beta_1 \times z_{i,1} + \ldots + \beta_n \times z_{i,n})$$

The objective for the present chapter is to assess the predictive ability of the personality and music preferences model developed in Chapter 4 and Chapter 5. To accomplish this, the Mean Average Error (MAE) between standardized estimated preference scores and standardized actual preference scores will be compared among random prediction, prediction using the CF algorithm described above, and the personality and music preferences algorithm described above. MAE is typically used in research on recommender technologies to evaluate and compare the performance of recommender systems (e.g, Herlocker et al., 2004; Lam et al., 2008; Shardanand & Maes, 1995). Given the literature on recommender technologies (e.g, Herlocker et al., 2004; Lam et al., 2008; Rashid et al., 2002; Resnick et al., 1994; Schein et al., 2002; Shardanand & Maes, 1995), it is expected that the CF algorithms will perform better than random. If the personality and music preferences model is able to predict preferences, then it should be at least better than random prediction. To show its feasibility compared to current CF algorithms, however, estimated preferences by the personality and music preferences model should be at least equivalent, if not better than, CF estimated preferences. Therefore, the hypotheses are summarized as:

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[1]These algorithms excluded a formula for the American Country music preference category since there had been no significant personality traits consistently related to this category.

H1. Estimated music preferences using CF algorithms will provide a significantly lower MAE compared to randomly estimated music preferences.

H2. Estimated preferences obtained using the personality and music preferences model will provide a significantly lower MAE compared to randomly estimated music preferences.

H3. Estimated preferences obtained using the personality and music preferences model will provide an equivalent MAE compared to estimated music preferences using CF algorithms.

## 6.2 Method

*Participants*

Participants ($N$ = 30; 21 males) volunteered following a recruitment email sent to those who had previously participated in one of the experiments described in Chapter 2 or in Chapter 3, and had completed the NEO personality measure provided in these previous experiments (NEO PI-R; Costa & McCrae, 1992). All participants were employees of Royal Philips Electronics. Ages ranged from 26 to 54 years ($M$ = 38.5, $SD$ = 8.81). Reported nationalities included Dutch ($n$ = 18), Belgian ($n$ = 4), US ($n$ = 2), Italian ($n$ = 2), Other ($n$ = 4).

*Materials*

Participants listened to 80 different audio recordings streamed over the Intranet and played from their own computer. Participants were able to play each recording in its entirety, or long enough to gauge and respond the music preference items provided below. Participants answered the following items on a Likert scale using an interface provided with each audio recording (scale anchors are provided in brackets):

1) In your opinion, how much do you like this song? (1 = *Strongly Dislike*, 2 = *Dislike*, 3 = *Neutral*, 4 = *Like*, 5 = *Strongly Like*)

2) Are you familiar with this song? (1 = *Not at all*, 2 = *Maybe a little*, 3 = *I know I've heard it before*, 4 = *I'm very familiar with the song*, 5 = *I'm a big fan*)

3) In your opinion, would you like to have this song and songs similar to this (from the same artist, etc.) recommended to you in the future? (1 = *Certainly not*, 2 = *Unlikely*, 3 = *Maybe, I don't care either way*, 4 = *Probably*, 5 = *Definitely*)

4) Would you consider adding this song to your music collection (e.g., any form of downloading, CD purchase)? (1 = *Never*, 2 = *Unlikely*, 3 = *Maybe, I don't care either way*, 4 = *Probably*, 5 = *Definitely or already have it in my collection*)

As in the experiments described in Chapter 4, questions 1, 3, and 4 were summed and used a measure of participants' music preference per song, which values ranged from 3 to 15. A screenshot of the interface is provided in Appendix B.

The audio recordings used in the present experiment were played from the same music database described in Chapter 2, and allowed participants to listened to and complete the experiment via Royal Philip Electronics' Intranet. The music database contained over 70,000 audio recordings, which were tagged according to an industry standard (All Music Guide (AMG), 2007). Random selection of recordings was done separately for each participant with a minimum music representation requirement. The representation requirement stipulated that a minimum of five recordings were required to come from eight of the music preference groups identified in Chapter 4. The representation requirement excluded the American Country preference group and was carried out by implementing the discriminant algorithms obtained in Chapter 5. The representation requirement accounted for 40 of the recordings that were randomly selected, while the remaining 40 recordings were selected completely at random. The described procedure for selecting these recordings at random was followed to ensure that there was no experimental bias toward either the personality prediction algorithms or the collaborative filtering prediction algorithms.

*Procedure*

After viewing an Informed Consent page, participants started the experiment by providing their demographic information. Subsequently, participants listened to each of their randomly selected audio recordings and responded to the music preference and familiarity questions presented with each recording. Participants were thanked for their participation once they had listened to and responded to questions for all 80 audio recordings. On average, the experiment took 45 minutes to complete.

*Data Analyses*

The collected data went through two processes to prepare these data for the results analyses. First, the data was screened and missing data and data obtained for items that reportedly did not play were removed from the analyses. This shrunk the data set from 2,400 data points (30 participants × 80 music pieces) to 2,368 data points.

Second, it was necessary to convert the CF estimated preference scores and actual preference scores to standard scores based on parameter estimates. The conversion was done for two reasons. First, the estimated preference scores obtained using the personality and music preferences model used standardized parameter estimates obtained from the Online Study 1 done in Chapter 4. Second, the CF algorithm used preference scores taken from the users of the experimental music database and ranged between scores of 1 and 5, while the personality and music preference model estimates and actual preference scores were taken by the three music preference questions listed in the Method section and ranged between scores of 3 and 15. To standardize scores for the CF algorithm, the parameter estimates were taken from the mean ($M$ = 3.48) and standard deviation ($SD$ = 1.33) of all the users' who provided preference scores while using the experimental music database ($N$ = 119,994). As described in the introduction of the present chapter, the estimates made by the personality and music preferences model provided in the current thesis should be at least better than random estimates of music preferences to show some external validity for this model. To test the music preference estimates made by the personality and music preferences model against random estimates, SPSS' (2006) random number creation function provided random estimates of participants' music preferences with a $M$ = 0 and $SD$ = 1.0. Therefore, the conversions and data generation using SPSS made all estimated and actual preference scores comparable.

## 6.3 Results

The stated objective for this chapter was to assess the predictive ability of the personality and music preferences model developed in Chapters 4 and 5. The objective was evaluated by comparing the Mean Average Error (MAE) of the estimated music preferences achieved by the personality and music preferences model, the Collaborative Filtering (CF) algorithm, and random estimates. To calculate the MAE, the observed error between estimated and actual music preference needed to be calculated first. For each case in the dataset, the observed error was calculated by subtracting the obtained standardized algorithm estimate from the standardized actual preference score for each observation. Taking the observed errors for each case, the MAE was calculated separately for the personality and music preference model estimates, the Collaborative Filtering (CF) estimates, and the random estimates. How the MAE was calculated is shown by the formula provided below. The formula shows that the MAE ($|\overline{E}|$) for each estimation method ($i$) was the sum of the absolute observed errors ($|\varepsilon|$) divided by the number of observations for that method ($N = 2{,}368$).

$$|\overline{E}|_i = \frac{\sum_{k=1}^{N} |\varepsilon_i|}{N_i}$$

The error and MAE for each algorithm provided the dependent measure to compare the performance of the personality and music preferences model to random preference estimation and the CF algorithm. The comparison tested all hypotheses for the present experiment and was done by using a one-way repeated ANOVA with the three levels of estimation method (i.e., personality and music preferences model, CF algorithm, and random) as levels of the independent variable and error as the dependent measure. Results from this ANOVA indicated a main effect of estimation method for MAE, $F(1, 2{,}367) = 446.15$, $p < .001$. Post-hoc (Bonferroni) tests indicated that random estimation had the highest MAE = 1.078 ($SE$ = .016, $CI_{95}$ = 1.046, 1.110), which was higher than the MAE obtained for both the personality and music preferences model estimations (MAE = 0.890, $SE$ = .012, $CI_{95}$ = 0.865, 0.914, $p < .001$), and the CF algorithm estimations (MAE = 0.699, $SE$ = .011, $CI_{95}$ = 0.678, 0.720, $p < .001$). Furthermore, the MAE obtained from the personality and music preferences model estimations were significantly higher the MAE obtained from the CF algorithm estimations ($p < .001$).

In sum, these results indicated that the CF algorithm gave significantly lower error estimates compared to both random and the personality and music preferences model estimates. The personality and music preferences model estimates followed the performance of the CF algorithms and gave significantly lower error estimates compared to random estimates.

## 6.4 Discussion

The experiment conducted in the present chapter assessed the personality and music preferences model that had been built in the previous chapters. Unsurprisingly, random estimation provided the highest Mean Average Error (MAE) compared to both estimation by the personality and music preferences model and estimation by the Collaborative Filtering (CF) algorithms. These comparisons confirmed Hypothesis 1 and Hypothesis 2, and provided some validation for the personality and music preferences model. Nonetheless, Hypothesis 3 was not confirmed and so, there was no indication that music preference estimation performed by the personality and music preferences model was as good as or better than estimation by the CF algorithms. In fact, results indicated that the CF algorithms significantly outperformed the personality and music preferences model with respect to music preference estimation MAE.

These results indicate that although there is some evidence for the predictive validity of the personality and music preferences model, it is not yet an effective option for current recommender technologies. Thus, although Lam et al. (2008) have suggested that CF recommender systems could be improved by measuring more detailed user characteristics to address the new user, the results of the current experiment show that still more work needs to be done in order to make this a feasible option.

There are two reasons why the personality and music preferences model has not shown itself to be a feasible alternative for addressing cold start. First, the model itself could still be improved. Though many of the findings were confirmed during the various steps taken to build the model, many of these steps were completed separately from previous steps. For example, personality variables were related to music preference groups only after these groups had been constructed, and the personality variables were never directly related to the extracted audio features. Thus, future research could attempt to directly relate personality variables to extracted audio features now that the foundation for this research has been laid here in the current thesis.

Second, the present experiment tested the personality and music preferences model against CF algorithms in order to assess this model's effectiveness for predicting music preferences. Despite indications that this model is not a viable alternative to CF algorithms, future research could consider whether personality variables could be used in conjunction with CF algorithms. Merging CF algorithms with detailed user data was originally what Lam et al. (2008) had suggested, but this was not tested here. Furthermore, future research could consider a correlational approach to personality, whereby the CF algorithms match users based on how well their personality profiles match up with other users, in addition to correlating music preferences. This would be instead of the model-based approach taken in this thesis.

It could be argued that by introducing personality acquisition to music recommendation systems, another cold start problem is introduced. Namely, users must now enter in their personality information. Though this is a possibility, there is also evidence that there are implicit or passive means to gather personality data about the user (e.g., Dunn, Wiersema, Ham, & Aroyo, 2009). Introducing personality into recommender systems also offers an additional advantage. Personality has the potential of being applicable to many situations and contexts. As a result, user's personality information could be applied to many different recommender-type systems and other applications. Imagine for instance, a living space that can automatically adjust lighting and music conditions when a user enters after a long day of work, and she is provided with movie recommendations for relaxing and watching the television in the evening. This becomes a single solution possibility when using personality.

# 7

## Conclusion

The present thesis has worked toward modelling music preferences using audio stimuli, and relating the modelled music preferences to detailed personality characteristics. In doing so, the thesis has contributed to previous research that has investigated the relation between personality and music preferences. Furthermore, the present thesis applied the modelled music preferences and its relation to personality to introduce a potential solution to cold start, and specifically, the new user problem found in the information technology literature dealing with recommender systems.

In Chapters 2 and 3 of the present thesis, an earlier model of music preference was tested and the relations between personality, reported music preference, and listening behaviour were investigated in a manner that advanced our understanding of these relations. In Chapters 4 and 5, extensive work detailing the construction of a model of music preferences based on audio stimuli was given. Using various univariate and multivariate statistical methods, the music preference factors within the constructed model were subsequently related to detailed personality traits, known as personality facets (cf. Costa & McCrae, 1992), and extracted audio features were used to describe how the music contained within the various factors can be discriminated from each other. Finally, in Chapter 6, the personality and music preferences model that was constructed in Chapters 4 and 5 was applied and then compared to current Collaborative Filtering (CF) recommender algorithms to ascertain how accurate the model is at predicting music preferences to various musical pieces and songs. The remainder of this chapter summarizes the findings of the present thesis in the next three sections. Finally, the present chapter is concluded with a fourth section providing some final thoughts about the thesis and directions for future work.

## 7.1 Personality, Reported Music Preferences, and Listening Behaviour

The research presented in Chapter 2 built on previous research relating personality and music preferences by investigating the relation between these two variables and their relation to listening behaviour. To accomplish that goal, participants' personality and reported music preferences were measured, and their listening behaviour using an online music database was also tracked for a minimum period of three months.

In the experiment presented in Chapter 2, participants ($N$ = 395) had completed the STOMP questionnaire (Rentfrow & Gosling, 2003), which indicated their reported music preferences. This presented the opportunity to test Rentfrow and Gosling's model of music preferences. Results obtained from a Confirmatory Factor Analysis (CFA) showed that Rentfrow and Gosling's model could not be confirmed using the data from the current participant sample. Given the results, a Principal Components Analysis (PCA) was done to explore potential factors of music preferences using the obtained music preference scores in the current sample. The PCA indicated a six-factor solution was suitable to describe participants' music preferences, instead of the four-factor solution proposed by Rentfrow and Gosling. All in all, the results from the CFA and PCA analyses indicated that broad genres, like Pop, or hybrid genres, like Soundtracks, presented the largest problems when trying to represent music preferences in the four-factor model. Consequently, it was argued that the problems presented by such genres likely result from the constantly evolving nature of these genres. The evolving nature of genre makes it difficult to pin down the type of content that is supposed to be described by genre labels. The findings provided in Chapter 2 were part of the motivation to pursue modelling music preferences using audio stimuli later in the present thesis, instead of reported music preferences.

The experiment presented in Chapter 2 also investigated the relation between reported music preferences and listening behaviour, and compared the correlations between personality and reported music preferences, and personality and listening behaviour. In so doing, the experiment built on previous research looking at personality and music preferences by including a direct measure of observed music listening behaviour. As expected from the hypotheses, reported music preferences for a given genre were positively correlated with listening behaviour for the same genre. Despite this consistency, however, these correlations were not high enough to provide reliable results when comparing the Big Five personality dimensions and reported music preferences correlations to the personality dimensions and listening behaviour correlations. The latter comparisons indicated that only two correlations reliably provided significant results. Specifically, these were positive correlations between Neuroticism and either reported music preferences or listening behaviour for Classical music, and between Openness to Experience and either reported music preferences or listening behaviour for Jazz music. Considering the previous literature researching the relation between personality and music preferences (e.g., Delsing, Ter Bogt, Engels, & Meeus, 2008; George, Stickle, Rachid, & Wopnford, 2007; Rentfrow & Gosling, 2006; Zweigenhaft, 2008), the results clearly show that the relation between Openness to Experience and preference for Jazz music is a very robust relation. Nonetheless, the lack of consistency described for these results in general raised two suggestions for the following chapters. Specifically, the lack of correlation results and consistency of significant correlation results reinforced the argument to make attempts to reduce measurement error when constructing a model of personality and music preference by: (1) using audio stimuli instead of potentially ill-conceived genre label descriptors, and (2) using personality facets to obtain a more detailed analysis of personality traits, as suggested in previous research (e.g., Rentfrow & Gosling, 2003; Zweigenhaft, 2008).

The experiment in Chapter 3 built on the results from Chapter 2 by exploring how more detailed personality measurements via facets relate to music preferences measured using audio stimuli. Results from the experiment showed that preference for specific songs labelled under the same genre can vary quite drastically. This was especially seen for Pop music. As a result, these findings gave further support to the notion of building a model of music preferences using audio stimuli, rather than genre labels that can potentially describe multiple varieties of music preference. The genres which provided songs with correlated measured preference were related to broad personality dimensions and finer personality facets. This statistical investigation evaluated whether the use of personality facets gave an improved relation to music preferences, which would be evidenced by significant increases of the predicted variance in music preferences using the personality facets compared to personality dimensions. The results from this investigation showed that personality facets nearly always provided an improved predictive relation with music preferences compared to personality dimensions and this improvement was significant in half of the cases. Given the relatively small sample size of 36 participants for the experiment, the significant results indicate a medium to large effect size for improving the predictive relation when using personality facets versus dimensions. Based on the literature and the results obtained in Chapter 2 and Chapter 3, it was decided that using audio stimuli to measure music preferences and relating these preferences to measured personality facets offered the greatest possibility to create an accurate predictive model of music preferences using personality.

## 7.2 Modelling Personality with Music Preferences

The research presented in Chapter 4 began by describing a detailed process for identifying the music stimuli that would be used for modelling preferences. Based on the research literature, the music stimuli identified in this process were taken from 10 different genres and were subsequently used to build and test a model of music preferences. The preliminary model had shown that the 120 music stimuli used to measure music preferences fell into nine factors that generally described participants' preferences. This model was later confirmed in Chapter 4 by conducting a Confirmatory Factor Analysis using a second sample. Interestingly, some of the music preferences factors, such as the Classical and Jazz factors, accurately reflected the content from genres of the same name. At other times, however, music preference factors were made up of a hybrid of stimuli taken from several genres. For instance, Contemporary African American Popular (CAAP) music was made up of audio stimuli taken from Rap and contemporary R'n'B genres. Furthermore, audio stimuli taken from genres, such as Pop and Rock, tended to be segmented across several music preference factors, which in this example were Early Chart Pop, Modern Chart Pop, and Hard Rock. These results echo the findings taken earlier in the thesis, providing further evidence that genres with a broad array of content, like Pop and Rock, can potentially represent essentially different types of music preferences.

Once the nine music preference factors had been determined, preference for the music contained in these factors was related to personality facets. The analysis done in this instance was performed by conducting linear regression on participants' predicted scores for each music preference factor given their personality facet scores. The predictive relations were obtained in a preliminary sample and then confirmed in a secondary sample. Looking at the confirmed predictive relations, there were several interesting relations that build on the research literature concerning personality and music preference. For instance, preference for CAAP and Hard Rock music was significantly and positively related to Excitement-Seeking. Excitement-Seeking is a facet contained under the Extraversion personality dimension. Extraversion has previously been found to be positively related to Rap music (e.g., Delsing et al., 2008; Rentfrow & Gosling, 2006; Zweigenhaft, 2008), which is one of the constituent styles of music that is contained in CAAP music. Extraversion has also previously been found to be positively related to Hard Rock music (e.g., Arnett, 1992; Litle & Zuckerman, 1986; McCown, Keiser, Mulhearn, & Williamson, 1997). The findings taken from Chapter 4 not only support the previous research findings, but also improve our understanding of what particular aspect of Extraversion tends to be influential in preferences for CAAP and Hard Rock styles of music. Similar observations can be deduced from the relations between the Aesthetics personality facet and preference for Blues-Rock, Classical, and Jazz music. Aesthetics is a personality facet that is contained within the Openness to Experience dimension and expresses an individual's love for the dramatic and fine arts. Openness to Experience has previously been found to be positively correlated with preference for Blues, Classical, and Jazz music (e.g., Delsing et al., 2008; George et al., 2007; Rentfrow & Gosling, 2006; Zweigenhaft, 2008). Consequently, the consistent positive relations found in Chapter 4 enhance our predictive and descriptive understanding of the relation between Openness to Experience and preference for Blues, Classical, and Jazz by showing that it is specifically individuals who are open to the dramatic and fine arts that are more likely to enjoy music from these genres. If people who do love the dramatic and fine arts tend to enjoy Blues, Classical, and Jazz as suggested, then this suggestion also provides some further explanation as to why preference for these genres has been so robustly related to Openness to Experience in previous research (e.g., Delsing et al., 2008; George et al., 2007; Rentfrow & Gosling, 2006). Taken together, the results from Chapter 4 substantially improved the predictive and descriptive understanding of the relation between personality and music preferences by narrowing in on personality facets.

The results from Chapter 4 also provided the motivation for investigating what audio features might be involved that could also improve our understanding of the relation between personality and music preferences from a musicological perspective. To investigate how music preferences might be described better by audio features, the research presented in Chapter 5 attempted to give a deeper understanding of the audio properties that characterize the music preference factors. Toward this end, audio features were extracted from the music contained among the nine music preference factors and these extracted audio features were used in a Multiple Discriminant Analysis (MDA). The MDA provides a description of the discriminating audio features that characterize the differences in music contained within each of the nine music preference factors. Results from the MDA indicated that the four discriminant functions accounted for 85.5% of the variance in extracted audio feature measurements. Furthermore, cross-validation of the MDA algorithm showed that the music pieces were correctly classified into their preference factors nearly 80% of the time when using the discriminant functions.

Percussive features were important descriptors when discriminating between the music contained within each of the nine preference factors established in Chapter 4. Tonal features were also important descriptors for this purpose. Interpretation of the results from the first discriminant function showed that Contemporary African American Popular (CAAP) and Dance/Electronica music contained significantly more percussive events with a higher repetition frequency compared to music from Blues-Rock, Classical, and Jazz. The preference factors began to group themselves into two extremes based on extracted audio features, particularly along the first MDA function. The two constituent extreme groups along the first MDA function were very similar to the genres that are part of two of Rentfrow and Gosling's (2003) four music preference dimensions; namely, Reflective and Complex for Blues-Rock, Classical, and Jazz music, and Energetic and Rhythmic for CAAP and Dance/Electronica. Furthermore, results from Chapter 4 and previous research has found that music, like CAAP or Dance/Electronica is often correlated with personality measures of Extraversion, or specifically, Excitement-Seeking (e.g., Delsing et al., 2008; McCown et al., 1997; Rentfrow & Gosling, 2006; Zweigenhaft, 2008). Classical music also showed itself to be negatively related to Excitement-Seeking. For this reason, it was argued that perhaps the first MDA function can be directly negatively correlated to Excitement-Seeking.

Interpretation of the results from the third discriminant function showed that Blues-Rock and Jazz music had significantly more complex tonal structures and were more often played in minor key compared to Modern Pop music. Preference measured for Modern Pop music in Chapter 4 showed that this factor was negatively related to the Aesthetics facet under the Openness to Experience personality dimension. Furthermore, previous research has robustly shown a preference for Jazz music to be positively related to either Aesthetics or Openness to Experience (e.g., Delsing et al., 2008; George et al., 1997; Rentfrow & Gosling, 2006; Zweigenhaft, 2008). Given this information, it is argued that the complexity of the tonal structure in music is positively related to Aesthetics under the Openness to Experience personality dimension.

## 7.3 Assessment of the Constructed Model

Finally, Chapter 6 presented research that was designed to assess the algorithms obtained in Chapters 4 and 5, which predicted music preferences given personality facets measured within the Big Five. The feasibility of the personality and music preference algorithms was assessed by comparing the accuracy for music preference estimations versus estimations generated randomly and generated using Collaborative Filtering (CF) algorithms. The accuracy for each method of estimation was measured using the standardized Mean Average Error (MAE) taken from each method. The results from these comparisons indicated that, although the personality and music preference model algorithms estimated participants' music preference scores better than random estimation, its performance was still inferior to CF estimation. In turn, the results indicated that the constructed model of music preferences given personality had shown itself to validly predict music preferences to some extent, but its performance was not as strong as current technologies found in CF recommender systems. Therefore, more research is necessary to improve the personality and music preferences model if it were to be used as a viable alternative to or used with modern recommender technologies.

## 7.4 Future Work and Final Conclusions

The work presented in the current thesis has improved our understanding of music preferences and its relation to personality. This work has shown how reported music preferences are related to listening behaviour, investigated previous models of reported music preference, and built a model of music preferences based on music stimuli. Factors within the built model of music preferences were related to personality and discriminated amongst each other using extracted audio features to produce algorithms capable of automatically estimating music preferences given personality traits. Finally, these algorithms were tested against random music preference estimation and estimation using Collaborative Filtering (CF) algorithms.

Rentfrow and Gosling's (2003) model of music preference and its relation to personality traits had been the most thorough investigation in the area to date. Ultimately, the results from this thesis provided only partial support for their model of music preferences based on reported preference for genres. At a broad genre level, preferences for Blues, Classical, and Jazz, as well as for Rap and Dance, and Alternative, Heavy Metal, and some styles of Rock, all seem to fit reasonably well in a descriptive model of music preferences. This fit supports three of the four music preferences dimensions in their model, which are Reflective and Complex, Intense and Rebellious, and Energetic and Rhythmic, respectively. Nonetheless, the model did not fit adequately well on the whole. The results presented in this thesis showed that preference for some genres, like Pop and Rock, were enjoyed by individuals who enjoyed nearly any other type of music, while other genres, like Soundtracks and Religious, did not seem to fit in any model. In the end, a model of music preferences based on audio stimuli (i.e., music pieces or songs) appeared to capture the nature of music preferences within and across the genres that were used. The model of music preferences based on audio stimuli showed nine music preference factors, which were labelled as: Contemporary African American Popular, Jazz, Modern Chart Pop, Hard Rock, Classical, American Country, Blues-Rock, Early Chart Pop, and Dance/Electronica. In contrast to Rentfrow and Gosling's model of music preferences based on genre labels, the model of music preferences based on audio stimuli indicated music from factors such as Blues-Rock, Classical, and Jazz were separated, but the correlation between these factors remained positive and strong. More important, however, was that the model of music preferences based on audio stimuli identified three factors of music preferences within the broad genres for Rock and Pop music. These three factors were a preference for a harder and edgier Rock (Hard Rock), which included Heavy Metal music, a preference for mainstream Rock and Pop music that had an older sound (Early Chart Pop), and a preference for mainstream Rock and Pop music that had a newer sound (Modern Chart Pop). The audio features from the music used to build the model were identified to produce a predictive model of music preferences based on audio stimuli and related to personality.

The predictive model of personality and music preferences performed better than random estimation of music preferences as expected, but not as well as CF algorithm estimation. These results provided some validation for the predictive accuracy of our model, but also leave room for future research and improvement. For instance, despite the large number of music clips researched in the current thesis, this sample of clips is small compared to the amount of music that exists. Future research would need to include more music that broadens the artistic musical styles to further verify whether the relations between music preferences and personality exist across musical and geographical boundaries. In particular, the majority of this research dealt with music and participants from Western world countries. Whether these same relations exist for the non-Westernized world has yet to be confirmed. Furthermore, while the Multiple Discriminant Analysis (MDA) presented in Chapter 5 is a suitable statistical method to determine what audio features can be used to discriminate between music contained in each of the nine music preference categories; its limitation is that it is primarily exploratory in nature. Additional data should be applied to the discriminant model derived in the present thesis to test whether this model is robust and other music can be explained by this model reliably.

Another limitation related to the audio feature work presented in the current thesis was that it was not possible to directly relate personality to music preferences according to audio properties. The work presented in this thesis began from a foundation of using genre to describe music preferences because this would allow for comparison with previous research and no known previous research had constructed a model of music preferences related to personality using audio characteristics. Now that this work is done, there are several potential relations between personality and music preferences according to audio properties that have been revealed. For instance, Openness to Experience (Aesthetics) is positively related with preference for tonal complexity in music. Also, Extraversion (Excitement-Seeking) is positively related with preference for percussive or “thumping” music. These are asserted relations based on the results obtained in this thesis. Still, future work could take up the challenge of confirming these relations and perhaps use this as a start to building a model of personality and music preferences solely defined according to music properties. It is suggested here that such a model would likely provide stronger predictive accuracy.

Improved music prediction might also be possible by incorporating personality as part of a Hybrid music recommendation system, instead of as an alternative to a Collaborative Filtering (CF) recommendation system. The current thesis only explored how well the developed personality and music preferences model compared against a CF recommendation system, though it is possible that this model could be successfully incorporated into a Hybrid recommendation system. Incorporating personality into a hybrid system was not explored in the current thesis because of the many possible ways that such a Hybrid recommendation system could be developed and tested. Still, future research could investigate how such a hybrid could be constructed and tested to see if the personality and music preferences model developed in this thesis could provide some additional improvement to a Hybrid music recommendation system.

Finally, future research could also attempt to provide a more complete model of music preferences by including situation variables, such as emotions. The model of music preferences presented in this thesis was related to personality based on an interactionist perspective, which proposes that understanding individuals' personality provides insight into their propensity for certain attitudes, emotions, and behaviours. Still, individuals are likely to have variations in music preferences, just as they have variations in attitudes, emotions, and behaviours. Understanding the role of situational variables, such as emotions, into a predictive model of music preferences is likely to increase the effectiveness for predicting music preferences. In doing so, we could finally obtain a complete understanding of music preferences and possibly be able to estimate preferences as well as CF technologies.

In conclusion, the current thesis has advanced our understanding of the relation between personality and music preferences. The work presented in this thesis has demonstrated how music stimuli can lead to a more detailed model of music preferences, which is arguably more accurate than similar models developed using genre labels. The current thesis also provides work that demonstrates how music can be more accurately linked to detailed personality traits known as facets, and to specific audio features inherent in this music. For instance, Jay Z's Dirt off your Shoulder contains a lot of energy in the frequency signals below 500 Hz, like many songs that come from the Rap, R'n'B, or Dance genres. All of these songs tend to be enjoyed by individuals who measure high on the personality trait, Excitement-Seeking. Conversely, individuals who measure low on Excitement-Seeking tend to be attracted to music that contains substantially less energy in the frequency signals below 500 Hz, which is typical of many Classical music pieces. This is just one example of the relation between personality and preference to audio features in music that can be derived from the results that have been described in the present thesis. Perhaps somehow, these audio characteristics strike certain chords in individuals that act as keys to their personality. In this way, it is argued that music is not only entertaining, but is uniquely suited to describe aspects of who we are.

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# Appendix A
# Questionnaire Screenshots

The following figures show screenshots of the various questionnaires implemented in the studies presented in this thesis. These questionnaires include a demographics questionnaire, the Short Test of Musical Preference (STOMP; Rentfrow & Gosling, 2003), a music genre preference questionnaire, and the Revised NEO Personality Inventory (NEO PI-R; Costa & McCrae, 1992). There were minor differences in the presentation of these questionnaires across the various studies. These differences were mainly aesthetic in nature (i.e., font, font size, layout, colour scheme) or expected differences when translating content between English and Dutch. Given these minor differences and to maintain brevity, one screenshot is provided to sufficiently represent each of the questionnaire interfaces. The caption below each figure indicates in which studies each questionnaire was used.

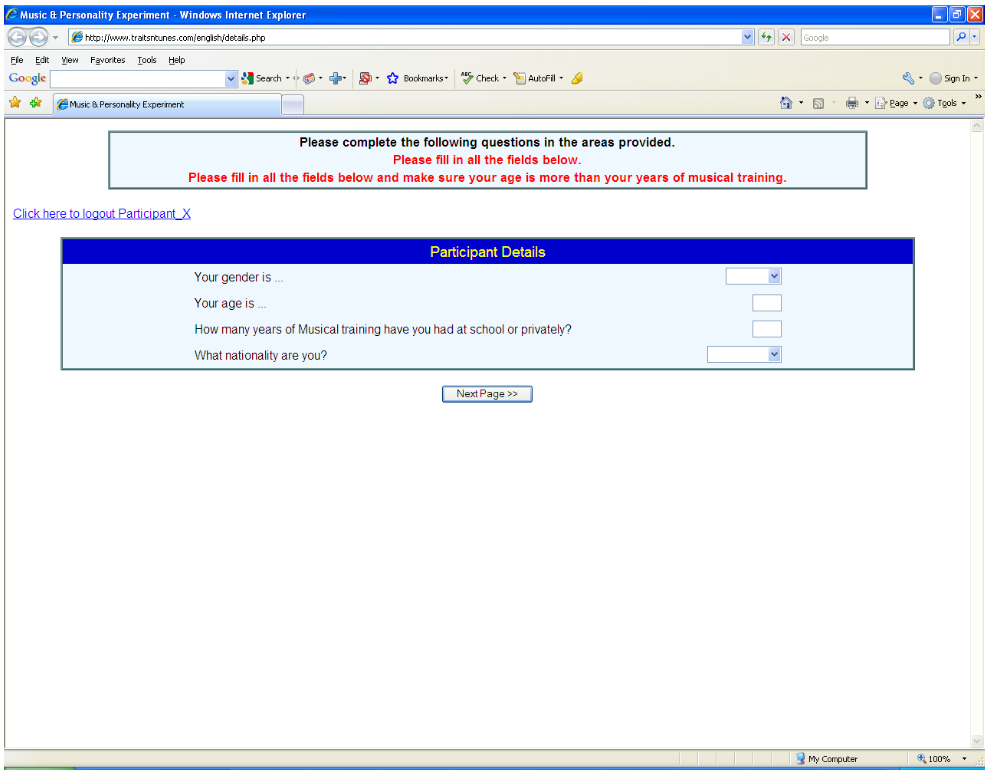



*Figure A1.* Screenshot of the demographics questionnaire used in the studies presented in Chapters 2, 3, 4 (sections 4.3 and 4.4), and 6.

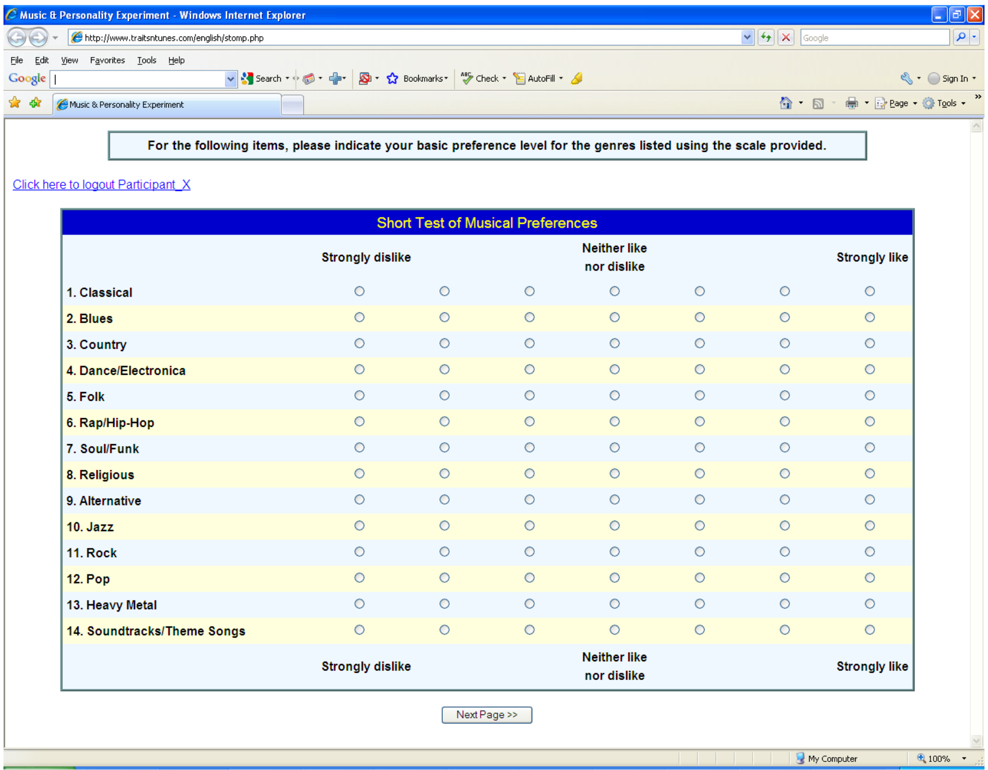
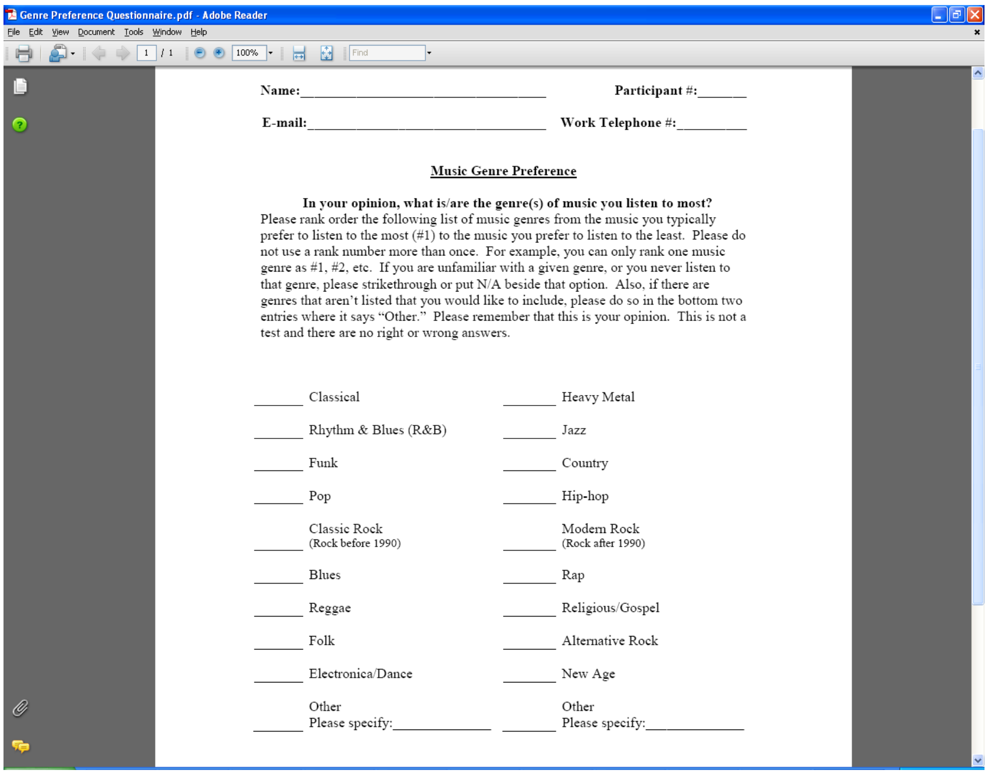



*Figure A2.* Screenshot of the STOMP questionnaire used in the studies presented in Chapters 2 and 4 (sections 4.3 and 4.4).




**Name:**_____________________________ **Participant #:**______

**E-mail:**____________________________ **Work Telephone #:**_________

**Music Genre Preference**

**In your opinion, what is/are the genre(s) of music you listen to most?**
Please rank order the following list of music genres from the music you typically prefer to listen to the most (#1) to the music you prefer to listen to the least. Please do not use a rank number more than once. For example, you can only rank one music genre as #1, #2, etc. If you are unfamiliar with a given genre, or you never listen to that genre, please strikethrough or put N/A beside that option. Also, if there are genres that aren't listed that you would like to include, please do so in the bottom two entries where it says "Other." Please remember that this is your opinion. This is not a test and there are no right or wrong answers.

______ Classical ______ Heavy Metal

______ Rhythm & Blues (R&B) ______ Jazz

______ Funk ______ Country

______ Pop ______ Hip-hop

______ Classic Rock (Rock before 1990) ______ Modern Rock (Rock after 1990)

______ Blues ______ Rap

______ Reggae ______ Religious/Gospel

______ Folk ______ Alternative Rock

______ Electronica/Dance ______ New Age

______ Other Please specify:____________ ______ Other Please specify:____________

*Figure A3.* Screenshot of the Music Genre Preference questionnaire used in the study presented in Chapter 3.

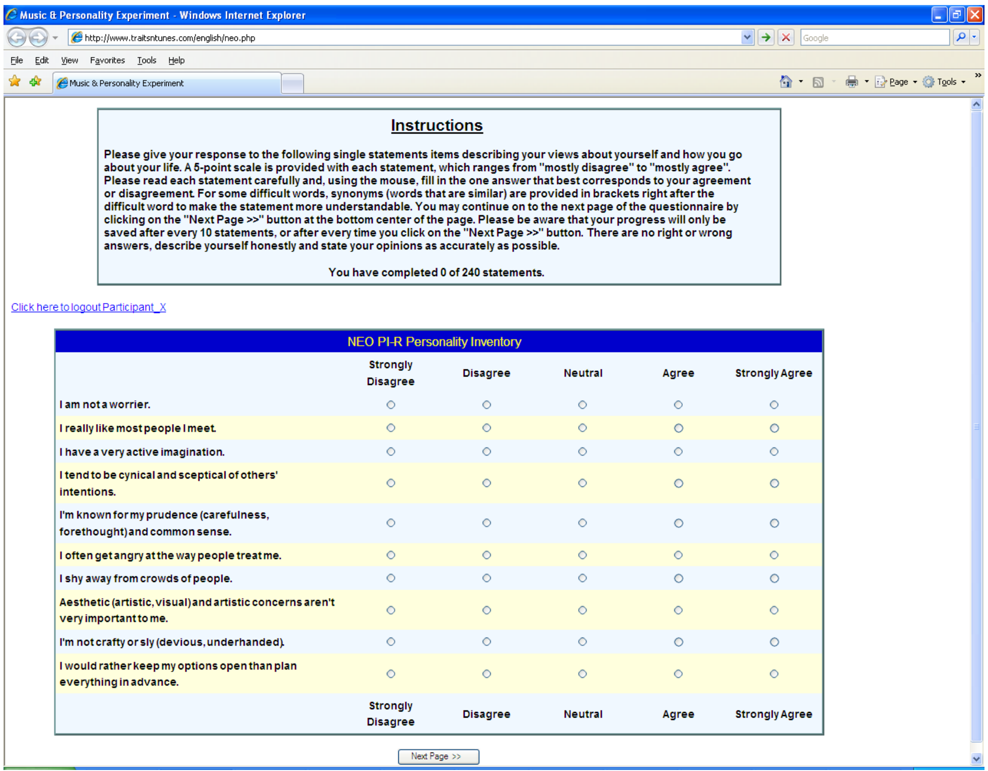



*Figure A4.* Screenshot of the NEO PI-R questionnaire used in the studies presented in Chapter 2, 3, and 4 (sections 4.3 and 4.4).

# Appendix B
# Music Interface Screenshots

The following figures show screenshots of the various music interfaces that were implemented in the studies presented in this thesis. The caption below each figure indicates in which studies each music interface was used.

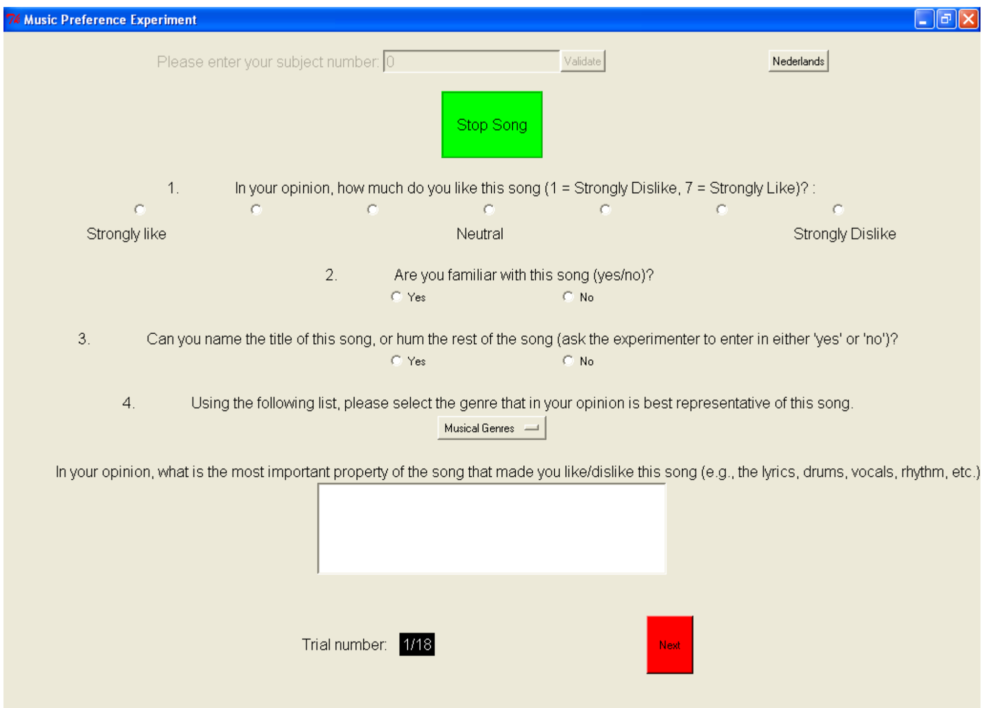



*Figure B1*. Screenshot of the music player and questionnaire interface used in the study presented in Chapter 3.

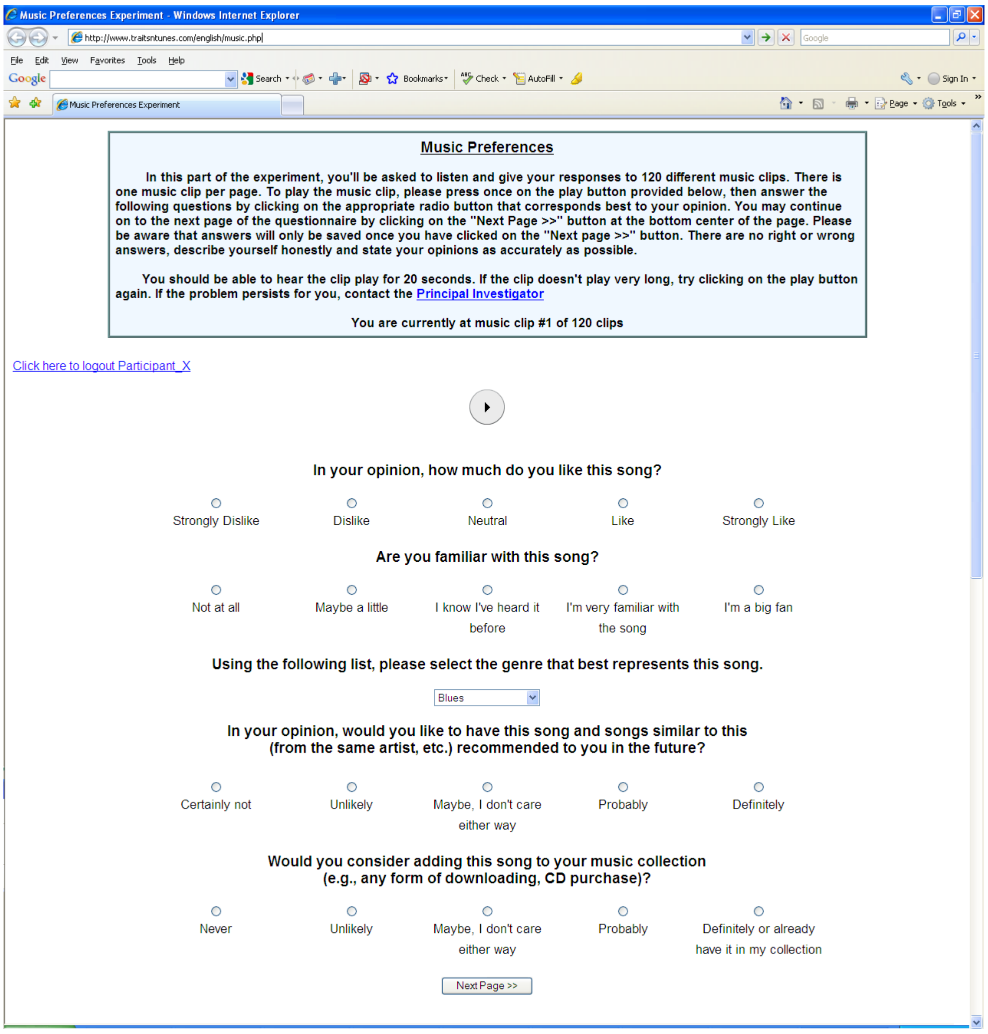



*Figure B2.* Screenshot of the music player and questionnaire interface used in the studies presented in Chapter 4 (sections 4.3 and 4.4).

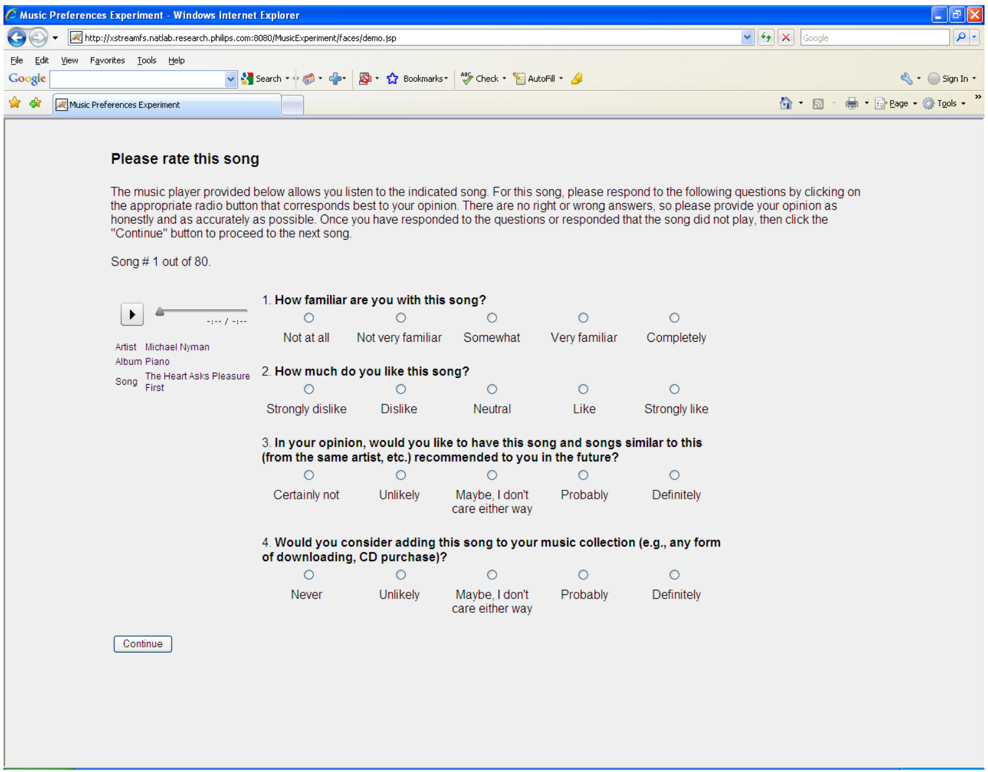



*Figure B3.* Screenshot of the music player and questionnaire interface used in the study presented in Chapter 6.

# Appendix C
# Music Sampling Frequency Distributions by Genre for Spectral Frequency Centroids and Relative Bass

The following frequency distributions were collected during the music selection process described in Chapter 4.2. The frequency distributions are divided by genre. There is one frequency distribution provided for Spectral Frequency Centroid and one for the relative bass for each genre. Relative bass was calculated by subtracting the energy present in frequencies below 500 Hz from to the energy present across the entire frequency spectrum in a music clip, measured in dB. Axes for the frequency distributions are uniformly fixed to facilitate comparisons between the different genres.

**Blues**

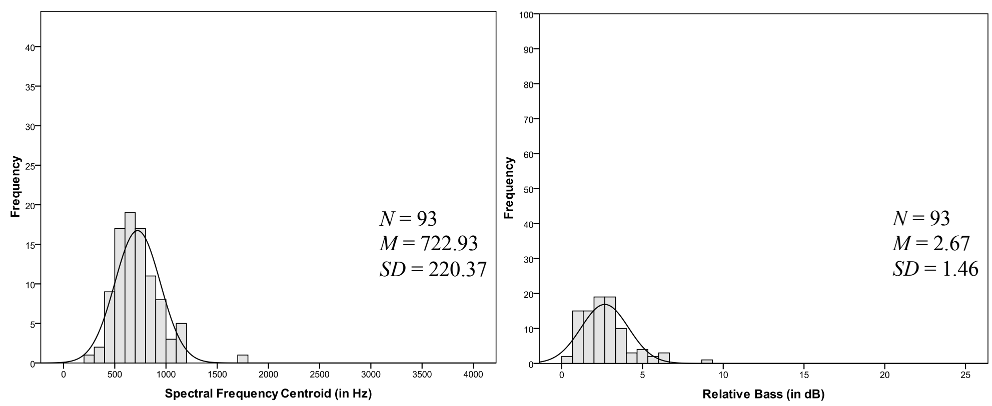



*Figure C1*. Frequency distributions for Spectral Frequency Centroid (in Hz) and relative bass (in dB), respectively, given Blues genre songs.

## Classical

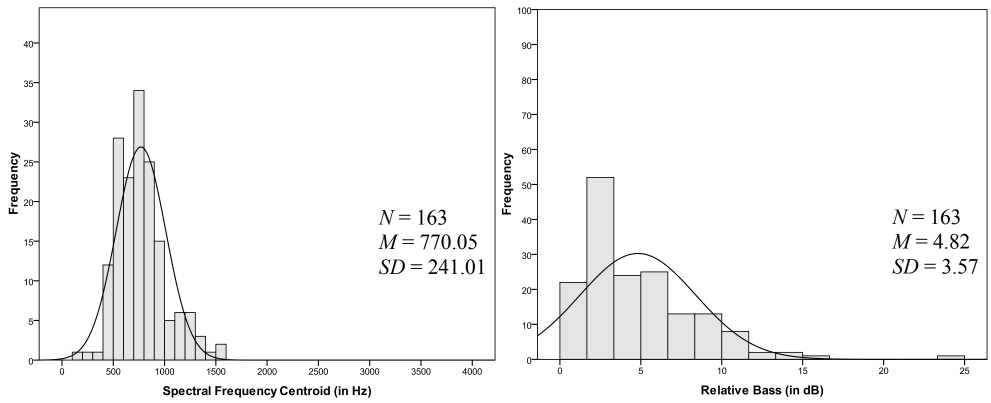



*Figure C2*. Frequency distributions for Spectral Frequency Centroid (in Hz) and relative bass (in dB), respectively, given Classical genre songs.

## Country

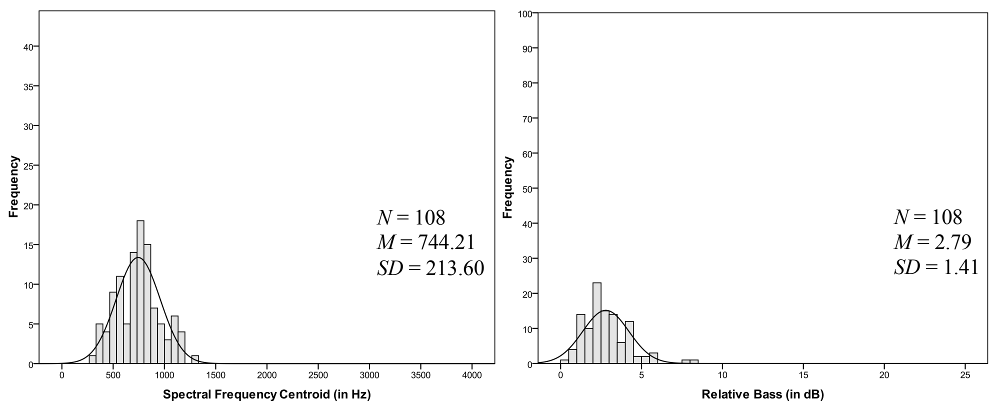



*Figure C3*. Frequency distributions for Spectral Frequency Centroid (in Hz) and relative bass (in dB), respectively, given Country genre songs.

**Dance**

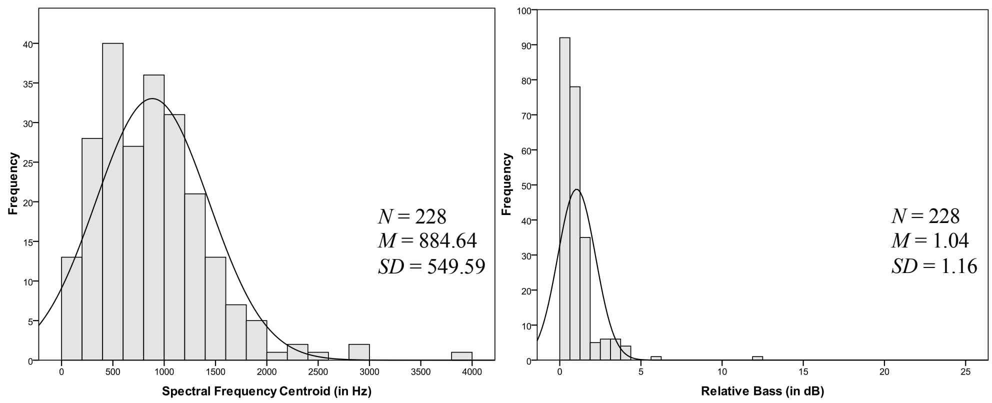



*Figure C4*. Frequency distributions for Spectral Frequency Centroid (in Hz) and relative bass (in dB), respectively, given Dance genre songs.

**Heavy Metal**

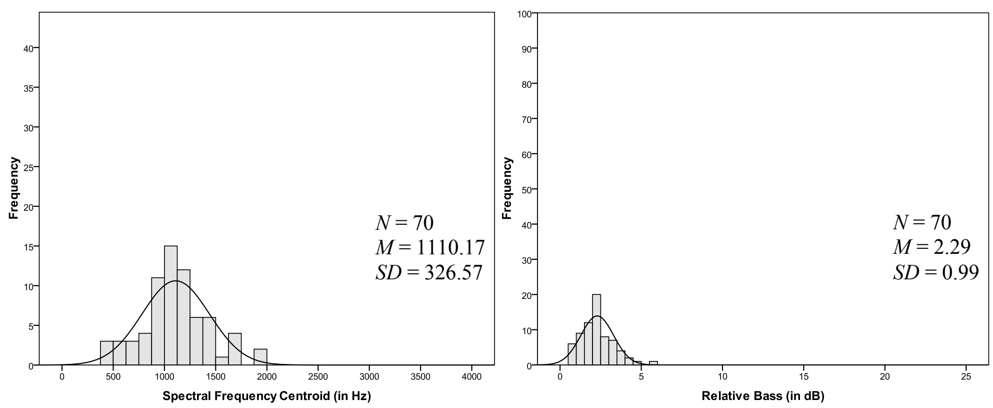



*Figure C5*. Frequency distributions for Spectral Frequency Centroid (in Hz) and relative bass (in dB), respectively, given Heavy Metal genre songs.

**Jazz**

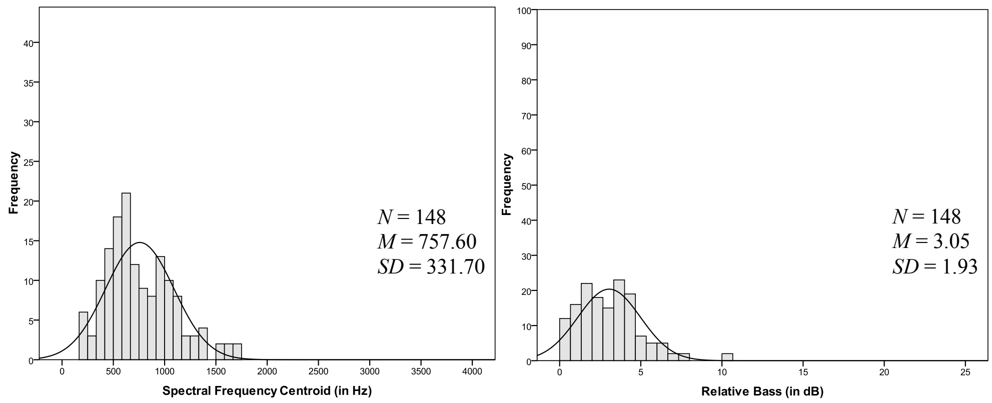



*Figure C6*. Frequency distributions for Spectral Frequency Centroid (in Hz) and relative bass (in dB), respectively, given Jazz genre songs.

**Pop**

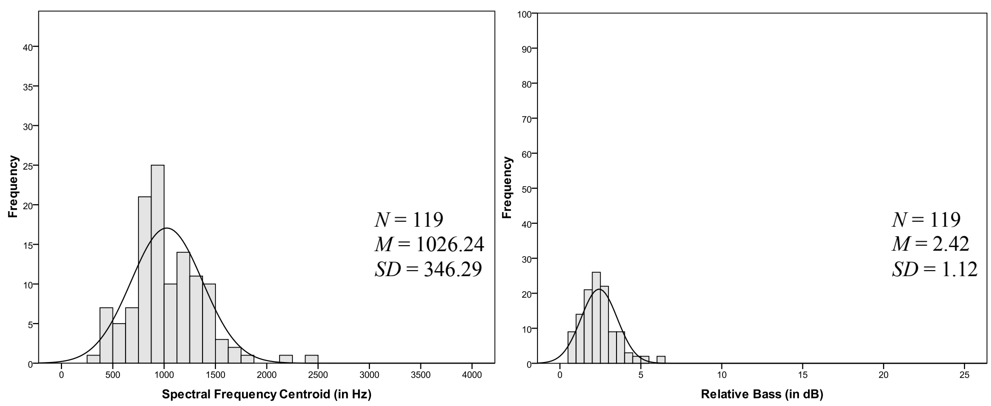



*Figure C7*. Frequency distributions for Spectral Frequency Centroid (in Hz) and relative (in dB), respectively, given Pop genre songs.

**R'n'B**

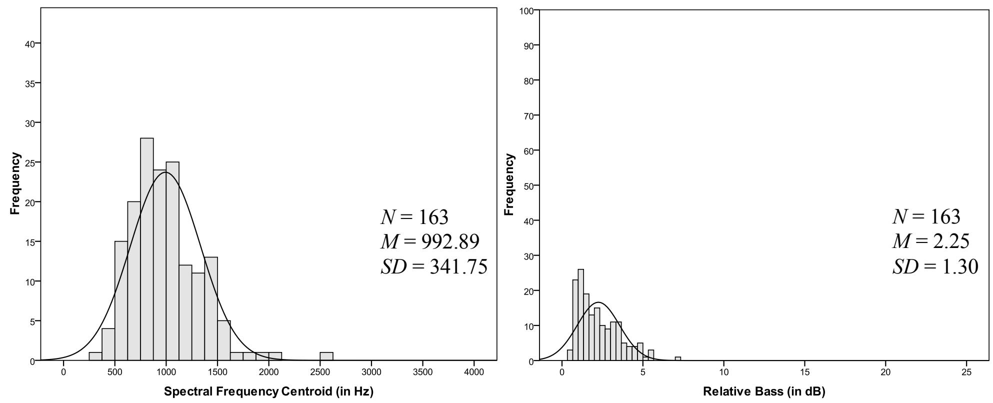



*Figure C8*. Frequency distributions for Spectral Frequency Centroid (in Hz) and relative bass (in dB), respectively, given R'n'B genre songs.

**Rap**

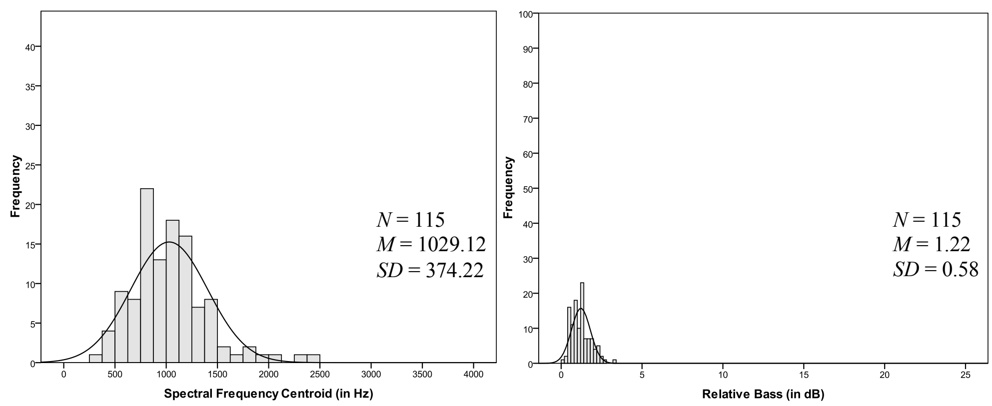



*Figure C9*. Frequency distributions for Spectral Frequency Centroid (in Hz) and relative bass (in dB), respectively, given Rap genre songs.

**Rock**

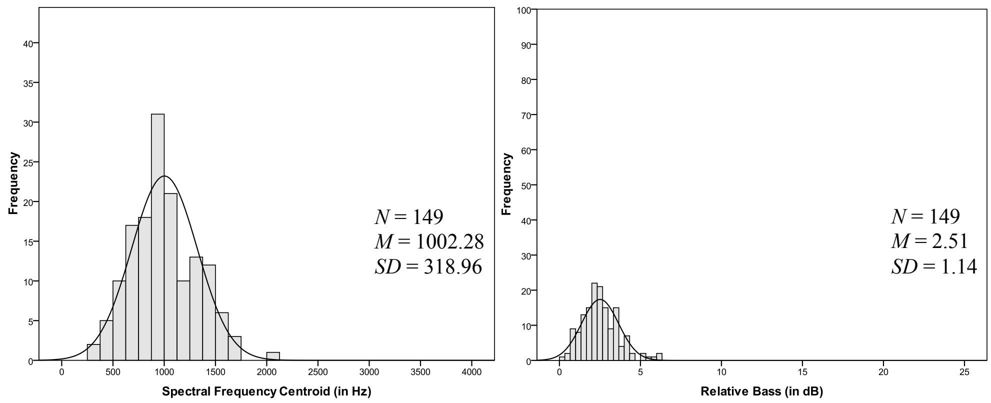



*Figure C10*. Frequency distributions for Spectral Frequency Centroid (in Hz) and relative bass (in dB), respectively, given Rock genre songs.

# Appendix D
# Song Sampling Frequency Distributions by Genre for Spectral Frequency Centroids and Bass

The following table lists the music clips that were used in the online studies described in Chapter 4. The left-most column in this table, labelled Category, divides the music clips according to their assignment across the three Independent Variables (IVs). The first IV used in this segmentation was level of Genre (Blues, Classical, Country, Dance, Heavy Metal, Jazz, Pop, R'n'B, Rap, and Rock). The second IV used in this segmentation was SFC (low, mid, and high), and the third IV used was bass enhancement (no bass enhancement and bass enhancement).

Following the first column, the second column gives the experiment number assigned to each music clip used for the purposes of counter balancing music clip order. The third and fourth columns indicate the title and artist/composer, respectively, for each music clip. Finally, the last two columns give the measured SFC (in Hz) and the relative bass (Bass; in dB),[1] which had been obtained from each music clip.

[1] A different measure for bass was originally used to decide what music clips would receive bass enhancement. It was later determined that the relative bass measure would be more accurate and more robust for replication in later experiments. Small differences between these measures of bass led to 4 instances (out of a possible 120), where a non bass enhanced clip had more relative bass than a bass enhanced clip. This occurred for music clips 21, 64, and 48 (×2).

*Table D1*
Final music selection by genre, spectral frequency centroid, and bass with music number assignment and statistics.

| Category | Music Clip # | Title | Artist/ Composer | SFC (in Hz) | Bass (in dB) |
|---|---|---|---|---|---|
| Blues | | | | | |
| Low SFC | | | | | |
| No bass enhancement | 1 | Lonesome Graveyard | Lightnin' Hopkins | 433.86 | 3.04 |
| | 21 | At Last | Etta James | 562.78 | 2.72 |
| Bass enhancement | 11 | I Need You So | B.B. King | 477.08 | 0.46 |
| | 31 | M&O Blues | Lucille Bogan | 576.94 | 2.83 |
| Mid SFC | | | | | |
| No bass enhancement | 41 | Mustang Sally | Buddy Guy | 727.18 | 1.39 |
| | 71 | Pride and Joy | Stevie Ray Vaughan | 952.04 | 1.62 |
| Bass enhancement | 51 | Nice Problem to Have | The Jeff Healey Band | 727.49 | 0.33 |
| | 61 | Mail Order Mystics | John Mayall | 884.80 | 0.64 |
| High SFC | | | | | |
| No bass enhancement | 81 | Pitiful | Big Maybelle | 1,113.65 | 3.87 |
| | 91 | Lights are on but Nobody's Home | Albert Collins | 1,126.79 | 2.93 |
| Bass enhancement | 101 | All the King's Horses | Luther Allison | 1,135.36 | 1.74 |
| | 111 | I Smell Trouble | Johnny Winter | 1,160.13 | 2.09 |
| Classical | | | | | |
| Low SFC | | | | | |
| No bass enhancement | 2 | Kyrie | Arvo Part | 541.54 | 3.65 |
| | 22 | Symphony No. 3 "Eroica" | Ludwig van Beethoven | 557.91 | 2.15 |
| Bass enhancement | 12 | Rhapsody in Blue | George Gershwin | 548.78 | 1.48 |
| | 32 | Piano Concerto No. 1 | Peter I. Tchaikovsky | 585.54 | 1.70 |
| Mid SFC | | | | | |
| No bass enhancement | 62 | Rite of Spring | Igor Stravinsky | 859.09 | 2.27 |
| | 72 | Matthaus Passion 1 | Johann Sebastian Bach | 985.80 | 6.44 |

*Table D1* (*continued*)
Final music selection by genre, spectral frequency centroid, and bass with music number assignment and statistics.

| Category | Music Clip # | Title | Artist/ Composer | SFC (in Hz) | Bass (in dB) |
|---|---|---|---|---|---|
| Classical | | | | | |
| Mid SFC | | | | | |
| Bass enhancement | 42 | Requiem | Wolfgang A. Mozart | 708.53 | 2.13 |
| | 52 | Canto Della Terra | Andrea Bocelli | 790.60 | 2.09 |
| High SFC | | | | | |
| No bass enhancement | 82 | Solo Allah Es Vencedor | Eduardo Paniagua | 1,109.54 | 8.47 |
| | 92 | Till Eulenspiegels Lustige Streiche | Richard Strauss | 1,117.23 | 5.84 |
| Bass enhancement | 102 | Gassenhauer | Kaiser Heinrich II | 1,255.15 | 3.95 |
| | 112 | Destiny | Vanessa-Mae | 1,381.85 | .99 |
| Country | | | | | |
| Low SFC | | | | | |
| No bass enhancement | 3 | Crazy | Patsy Cline | 476.53 | 1.83 |
| | 23 | Coat of Many Colors | Dolly Parton | 528.34 | 2.40 |
| Bass enhancement | 13 | I Walk the Line | Johnny Cash | 504.25 | 1.68 |
| | 33 | Always on my Mind | Willie Nelson | 532.90 | 1.27 |
| Mid SFC | | | | | |
| No bass enhancement | 53 | Forever and Ever, Amen | Randy Travis | 742.90 | 2.06 |
| | 63 | Stand by your Man | Tammy Wynette | 771.87 | 2.88 |
| Bass enhancement | 43 | A Better Man | Clint Black | 715.52 | 0.61 |
| | 73 | Don't Rock the Jukebox | Alan Jackson | 876.16 | 1.42 |
| High SFC | | | | | |
| No bass enhancement | 83 | It wasn't God who made Honky Tonk Angels | Kitty Wells | 1,109.32 | 3.09 |
| | 103 | Any Man of Mine | Shania Twain | 1,123.86 | 4.37 |

*Table D1* (*continued*)
Final music selection by genre, spectral frequency centroid, and bass with music number assignment and statistics.

| Category | Music Clip # | Title | Artist/ Composer | SFC (in Hz) | Bass (in dB) |
|---|---|---|---|---|---|
| Country | | | | | |
| High SFC | | | | | |
| Bass enhancement | 93 | My Heart Skips a Beat | Buck Owens | 1,117.70 | 2.31 |
| | 113 | The Great Escape | Ilse de Lange | 1,147.24 | 2.26 |
| Dance | | | | | |
| Low SFC | | | | | |
| No bass enhancement | 14 | Divano | Era | 478.25 | 0.97 |
| | 34 | Next Heap With | Aphex Twin | 561.79 | 3.36 |
| Bass enhancement | 4 | Talisman | Air | 362.54 | 0.24 |
| | 24 | Push Upstairs | Underworld | 523.47 | 0.12 |
| Mid SFC | | | | | |
| No bass enhancement | 54 | Praise you | Fatboy Slim | 860.98 | 2.13 |
| | 64 | Dreaming | DJ Dado | 915.41 | 0.73 |
| Bass enhancement | 44 | South Side | Moby | 702.09 | 0.56 |
| | 74 | Enjoy the Silence | Depeche Mode | 940.85 | 0.76 |
| High SFC | | | | | |
| No bass enhancement | 94 | Twilight Zone | 2 Unlimited | 1,166.01 | 1.81 |
| | 114 | One More Time | Daft Punk | 1,919.38 | 1.20 |
| Bass enhancement | 84 | It Began in Africa | The Chemical Brothers | 1,137.99 | 0.43 |
| | 104 | Firestarter | The Prodigy | 1,171.74 | 0.53 |
| Heavy Metal | | | | | |
| Low SFC | | | | | |
| No bass enhancement | 15 | Smoke on the Water | Deep Purple | 521.57 | 1.58 |
| | 35 | Stairway to Heaven | Led Zeppelin | 598.89 | 1.16 |
| Bass enhancement | 5 | Paranoid | Black Sabbath | 387.76 | 0.24 |
| | 25 | No One Knows | Queens of the Stone Age | 549.36 | 0.52 |
| Mid SFC | | | | | |
| No bass enhancement | 45 | My Immortal | Evanescence | 703.54 | 3.67 |
| | 75 | Here to Stay | Korn | 994.49 | 1.74 |
| Bass enhancement | 55 | Nookie | Limp Bizkit | 732.80 | 0.33 |
| | 65 | Until it Sleeps | Metallica | 795.44 | 0.42 |

*Table D1* (*continued*)
Final music selection by genre, spectral frequency centroid, and bass with music number assignment and statistics.

| Category | Music Clip # | Title | Artist/ Composer | SFC (in Hz) | Bass (in dB) |
|---|---|---|---|---|---|
| Heavy Metal | | | | | |
| High SFC | | | | | |
| No bass enhancement | 95 | Back in Black | AC/DC | 1,428.67 | 4.72 |
| | 105 | Jump | Van Halen | 1,456.12 | 2.49 |
| Bass enhancement | 85 | Sweet Child O' Mine | Guns n' Roses | 1,123.90 | 1.42 |
| | 115 | Du Hast | Rammstein | 1,473.07 | 0.63 |
| Jazz | | | | | |
| Low SFC | | | | | |
| No bass enhancement | 26 | What a Wonderful World | Louis Armstrong | 529.93 | 1.47 |
| | 36 | Night in Tunisia | Dizzy Gillespie | 570.71 | 3.81 |
| Bass enhancement | 6 | „S Wonderful | Diana Krall | 419.46 | 0.62 |
| | 16 | God Bless the Child | Billie Holiday | 445.93 | 0.85 |
| Mid SFC | | | | | |
| No bass enhancement | 56 | The End of a Love Affair | Wynton Marsalis | 880.69 | 10.29 |
| | 76 | Lester Swings | Lester Young | 960.89 | 5.34 |
| Bass enhancement | 46 | Sinnerman | Nina Simone | 791.02 | 2.08 |
| | 66 | Summer Wind | Frank Sinatra | 936.42 | 0.80 |
| High SFC | | | | | |
| No bass | 96 | Take the "A" Train | Duke Ellington | 1,411.60 | 10.42 |
| enhancement | 116 | All Blues | Miles Davis | 1,637.74 | 6.03 |
| Bass enhancement | 86 | Locomotion | John Coltrane | 1,365.83 | 1.96 |
| | 106 | Mack the Knife | Ella Fitzgerald | 1,608.99 | 2.92 |
| Pop | | | | | |
| Low SFC | | | | | |
| No bass enhancement | 17 | Fall at your Feet | Crowded House | 498.72 | 1.42 |
| | 37 | Sacrifice | Elton John | 581.67 | 2.02 |
| Bass enhancement | 7 | Misunderstood | Robbie Williams | 488.84 | 0.30 |
| | 27 | Life for Rent | Dido | 558.11 | 0.59 |

*Table D1* (*continued*)
Final music selection by genre, spectral frequency centroid, and bass with music number assignment and statistics.

| Category | Music Clip # | Title | Artist/ Composer | SFC (in Hz) | Bass (in dB) |
|---|---|---|---|---|---|
| Pop | | | | | |
| Mid SFC | | | | | |
| No bass enhancement | 47 | Crazy | Seal | 774.67 | 2.12 |
| | 57 | My Heart will go on | Céline Dion | 787.07 | 4.39 |
| Bass enhancement | 67 | Turn off the Light | Nelly Furtado | 865.32 | 0.53 |
| | 77 | Back for Good | Take That | 933.25 | 1.19 |
| High SFC | | | | | |
| No bass enhancement | 107 | Like a Prayer | Madonna | 1,500.82 | 2.24 |
| | 117 | Dancing Queen | ABBA | 1,798.07 | 5.41 |
| Bass enhancement | 87 | Thriller | Michael Jackson | 1,272.45 | 0.83 |
| | 97 | Baby One More Time | Britney Spears | 1,480.50 | 1.32 |
| R'n'B | | | | | |
| Low SFC | | | | | |
| No bass enhancement | 20 | Let's Stay Together | Al Green | 479.92 | 1.19 |
| | 30 | Just My Imagination | The Temptations | 517.42 | 0.79 |
| Bass enhancement | 10 | Blueberry Hill | Fats Domino | 479.24 | 0.61 |
| | 40 | Used to Love U | John Legend | 517.00 | 0.35 |
| Mid SFC | | | | | |
| No bass enhancement | 50 | Georgia on my Mind | Ray Charles | 718.34 | 3.78 |
| | 60 | Respect | Aretha Franklin | 735.72 | 4.04 |
| Bass enhancement | 70 | Crazy in Love | Beyoncé | 856.98 | 0.46 |
| | 80 | Family Affair | Mary J. Blige | 992.35 | 0.41 |
| High SFC | | | | | |
| No bass enhancement | 100 | I Heard it Through the Grapevine | Marvin Gaye | 1,211.14 | 3.19 |
| | 120 | You Keep me Hangin' on | Diana Ross & the Supremes | 1,478.54 | 4.34 |
| Bass enhancement | 90 | What's Love got to do with it | Tina Turner | 1,124.14 | 1.68 |
| | 110 | Yeah! | Usher | 1,398.80 | 0.58 |

*Table D1* (*continued*)
Final music selection by genre, spectral frequency centroid, and bass with music number assignment and statistics.

| Category | Music Clip # | Title | Artist/ Composer | SFC (in Hz) | Bass (in dB) |
|---|---|---|---|---|---|
| Rap | | | | | |
| Low SFC | | | | | |
| No bass enhancement | 8 | Country Grammar (Hot Shit) | Nelly | 581.98 | 0.81 |
| | 18 | C.R.E.A.M. | Wu Tang Clan | 465.26 | 0.51 |
| Bass enhancement | 28 | Dirt off your Shoulder | Jay Z | 484.01 | 0.19 |
| | 38 | Stan | Eminem (feat. Dido) | 487.14 | 0.16 |
| Mid SFC | | | | | |
| No bass enhancement | 48 | I Need Love | LL Cool J | 833.76 | 0.47 |
| | 58 | Who Am I (What's my Name) | Snoop Doggy Dogg | 903.99 | 1.24 |
| Bass enhancement | 68 | California Love | 2Pac | 832.26 | 0.54 |
| | 78 | Get Ur Freak On | Missy Elliot | 733.95 | 0.49 |
| High SFC | | | | | |
| No bass enhancement | 88 | Gettin Jiggy Wit It | Will Smith | 1,232.05 | 1.71 |
| | 108 | Straight Outta Compton | N.W.A. | 1,391.40 | 2.52 |
| Bass enhancement | 98 | Don't Phunk with my Heart | Black-Eyed Peas | 1,275.97 | 0.62 |
| | 118 | Dangerous | Busta Rhymes | 1,485.88 | 0.21 |
| Rock | | | | | |
| Low SFC | | | | | |
| No bass enhancement | 19 | Don't Give Up | Peter Gabriel (feat. Kate Bush) | 411.57 | 0.89 |
| | 39 | White Rabbit | Jefferson Airplane | 485.65 | 0.90 |
| Bass enhancement | 9 | Every Breath You Take | The Police | 333.42 | 0.18 |
| | 29 | Something | The Beatles | 459.15 | 0.40 |

*Table D1* (*continued*)
Final music selection by genre, spectral frequency centroid, and bass with music number assignment and statistics.

| Category | Music Clip # | Title | Artist/ Composer | SFC (in Hz) | Bass (in dB) |
|---|---|---|---|---|---|
| Rock | | | | | |
| Mid SFC | | | | | |
| No bass enhancement | 49 | Space Oddity | David Bowie | 716.80 | 2.20 |
| | 59 | Jumpin Jack Flash | The Rolling Stones | 771.51 | 1.44 |
| Bass enhancement | 69 | Speed of Sound | Coldplay | 842.96 | 0.77 |
| | 79 | With or Without You | U2 | 899.48 | 0.79 |
| High SFC | | | | | |
| No bass enhancement | 99 | Smells Like Teen Spirit | Nirvana | 1,542.17 | 3.13 |
| | 119 | Born in the U.S.A. | Bruce Springsteen | 1,659.63 | 3.47 |
| Bass enhancement | 89 | I Love Rock „n' Roll | Joan Jett | 1,277.62 | 1.83 |
| | 109 | Dani California | Red Hot Chili Peppers | 1,635.54 | 1.30 |

# Appendix E
# Pattern & Structure Matrices

The following tables provide the Pattern and Structure Matrices that resulted from the Principal Components Analysis (PCA) reported in Chapter 4, Section 4.3. The first two columns in these tables list the music clip titles and their affiliated artist or composer, respectively. The remaining columns provide the loadings for each of the nine components labelled at the top of each column.

*Table E1*

Factor loadings from the pattern matrix for the 9-component Promax-rotated PCA solution.

| Music Clip Title | Artist/ Composer | CAAP | Jazz | Modern Chart Pop | Hard Rock | Classical | American Country | Blues - Rock | Early Chart Pop | Dance/ Electronica |
|---|---|---|---|---|---|---|---|---|---|---|
| Dangerous | Busta Rhymes | ***.907*** | -.081 | -.282 | -.063 | .063 | .086 | .096 | .098 | .028 |
| Dirt Off Your Shoulder | Jay Z | ***.895*** | -.057 | -.249 | .039 | .030 | .118 | .011 | -.056 | -.050 |
| Country Grammar (Hot Shit) | Nelly | ***.884*** | -.048 | -.075 | -.021 | -.014 | .037 | .044 | -.056 | -.087 |
| Who Am I - What's My Name | Snoop Doggy Dogg | ***.825*** | -.085 | -.243 | .077 | -.025 | .032 | .050 | .085 | .053 |
| Get Ur Freak On | Missy Elliot | ***.795*** | .080 | -.116 | -.050 | -.019 | -.015 | -.127 | .009 | .172 |
| Yeah! | Usher | ***.774*** | .001 | .209 | -.029 | .007 | .014 | -.071 | -.070 | -.058 |
| Family Affair | Mary J. Blige | ***.727*** | .019 | .205 | -.054 | -.068 | .021 | .033 | -.039 | .063 |
| Gettin Jiggy wit it | Will Smith | ***.724*** | .034 | .079 | .107 | .064 | -.082 | -.043 | -.006 | -.095 |
| C.R.E.A.M. | Wu Tang Clan | ***.722*** | .071 | -.336 | -.130 | -.066 | .138 | .112 | .077 | .175 |
| Straight Outta Compton | N.W.A. | ***.702*** | -.024 | -.396 | .041 | .022 | .129 | -.026 | .202 | .206 |
| Stan | Eminem (feat. Dido) | ***.689*** | .031 | -.049 | .175 | .077 | .014 | -.088 | -.031 | .038 |
| Used to Love U | John Legend | ***.669*** | -.035 | .284 | -.181 | -.005 | -.144 | .282 | .043 | .006 |
| I Need Love | LL Cool J | ***.647*** | -.210 | .115 | -.304 | .080 | .024 | .251 | .170 | .214 |
| Don't Phunk with My Heart | Black-Eyed Peas | ***.644*** | .063 | .291 | .038 | -.005 | -.095 | -.022 | -.237 | .034 |
| California Love | 2Pac | ***.594*** | .022 | .102 | .156 | -.085 | .004 | .042 | -.053 | .099 |
| Crazy in Love | Beyoneé | ***.566*** | .168 | .328 | .024 | -.074 | -.048 | -.149 | -.094 | -.040 |
| Turn off the Light | Nelly Furtado | ***.446*** | .142 | .339 | .055 | -.144 | -.105 | -.100 | -.007 | .063 |

*Note*. $N = 354$. All factor loadings |.400| or larger are provided in *italics*; the highest factor loadings within each component are in **bold**. CAAP = Contemporary African American Popular; Modern Chart Pop = 80s to current Chart Pop; Early Chart Pop = 60s and 70s Chart Pop.

*Table E1* (*continued*)
Factor loadings from the pattern matrix for the 9-component Promax-rotated PCA solution.

| Music Clip Title | Artist/ Composer | CAAP | Jazz | Modern Chart Pop | Hard Rock | Classical | American Country | Blues - Rock | Early Chart Pop | Dance/ Electronica |
|---|---|---|---|---|---|---|---|---|---|---|
| Michael Jackson | Thriller | ***.417*** | .014 | .196 | .214 | .042 | .043 | -.074 | .241 | -.129 |
| Twilight Zone | 2 Unlimited | ***.402*** | -.175 | .397 | .064 | .097 | -.051 | -.039 | -.007 | .283 |
| One More Time | Daft Punk | **.389** | -.048 | .341 | .034 | -.108 | -.124 | -.047 | -.093 | .297 |
| Lester Swings | Lester Young | -.046 | ***.797*** | -.101 | -.043 | .136 | -.015 | .157 | -.091 | .073 |
| Locomotion | John Coltrane | -.048 | ***.788*** | -.195 | .023 | .138 | .013 | .092 | -.109 | .061 |
| All Blues | Miles Davis | -.107 | ***.777*** | -.133 | -.067 | .095 | -.029 | .114 | -.038 | .072 |
| Take the A Train | Duke Ellington | -.003 | ***.772*** | -.094 | -.079 | .283 | .039 | -.043 | .003 | -.030 |
| Mack the Knife | Ella Fitzgerald | .023 | ***.757*** | -.058 | -.112 | .076 | .067 | .128 | -.025 | .017 |
| Night in Tunisia | Dizzy Gillespie | -.004 | ***.740*** | -.190 | -.023 | .260 | -.029 | .088 | -.044 | .047 |
| The End of a Love Affair | Wynton Marsalis | -.146 | ***.728*** | .089 | -.130 | .186 | -.032 | .182 | -.091 | .038 |
| God Bless the Child | Billie Holiday | .045 | ***.681*** | -.170 | -.169 | .057 | .041 | .123 | .178 | .010 |
| Summer Wind | Frank Sinatra | .078 | ***.630*** | .060 | .065 | .197 | .099 | .003 | -.077 | -.200 |
| At Last | Etta James | .074 | ***.590*** | .170 | -.051 | .015 | .057 | -.078 | .226 | -.166 |
| What a Wonderful World | Louis Armstrong | .037 | ***.566*** | .069 | .075 | .126 | .054 | -.066 | .126 | -.180 |
| „S Wonderful | Diana Krall | -.090 | ***.519*** | .386 | -.188 | .084 | -.027 | .286 | -.138 | .040 |
| Georgia on my Mind | Ray Charles | .080 | ***.511*** | .087 | -.046 | .092 | .009 | .116 | .240 | -.219 |
| Crazy | Patsy Cline | -.053 | ***.479*** | .191 | -.126 | -.015 | .314 | -.093 | .206 | .018 |
| Sinnerman | Nina Simone | .087 | **.308** | -.144 | .048 | -.008 | -.013 | .194 | .223 | .205 |

*Note*. $N$ = 354. All factor loadings |.400| or larger are provided in *italics*; the highest factor loadings within each component are in **bold**. CAAP = Contemporary African American Popular; Modern Chart Pop = 80s to current Chart Pop; Early Chart Pop = 60s and 70s Chart Pop.

*Table E1* (*continued*)
Factor loadings from the pattern matrix for the 9-component Promax-rotated PCA solution.

| Music Clip Title | Artist/ Composer | CAAP | Jazz | Modern Chart Pop | Hard Rock | Classical | American Country | Blues - Rock | Early Chart Pop | Dance/ Electronica |
|---|---|---|---|---|---|---|---|---|---|---|
| Fall at Your Feet | Crowded House | -.174 | -.087 | ***.784*** | -.164 | -.123 | .078 | .153 | .111 | .163 |
| Back for Good | Take That | .034 | -.106 | ***.750*** | -.137 | .022 | .036 | .018 | .050 | -.096 |
| Life for Rent | Dido | -.158 | .246 | ***.733*** | .004 | -.100 | .031 | -.040 | -.047 | .192 |
| Sacrifice | Elton John | -.072 | -.177 | ***.726*** | -.150 | .060 | .099 | .105 | .217 | .000 |
| Misunderstood | Robbie Williams | -.110 | -.036 | ***.688*** | -.039 | .044 | .121 | .191 | -.087 | .128 |
| Divano | Era | -.170 | -.150 | ***.686*** | -.057 | .347 | .001 | .103 | -.032 | .294 |
| The Great Escape | Ilse de Lange | -.043 | .174 | ***.616*** | -.025 | -.099 | .297 | .200 | -.296 | .069 |
| My Heart will go on | Céline Dion | .136 | -.102 | ***.614*** | -.086 | .167 | .203 | .002 | -.280 | -.185 |
| Don’t Give Up | Peter Gabriel (feat. Kate Bush) | -.192 | .046 | ***.607*** | -.149 | -.041 | -.008 | .044 | .376 | .256 |
| Dreaming | DJ Dado | .109 | -.241 | ***.601*** | -.056 | .098 | -.064 | .088 | .017 | .523 |
| Like a Prayer | Madonna | .234 | -.066 | ***.572*** | -.008 | .008 | .069 | -.235 | .229 | .056 |
| What’s Love got to do with it | Tina Turner | .173 | -.087 | ***.571*** | -.064 | -.004 | .024 | .108 | .338 | -.069 |
| My Immortal | Evanescence | -.018 | .112 | ***.568*** | .230 | -.003 | .116 | .033 | *-.469* | -.020 |
| Crazy | Seal | .118 | .136 | ***.554*** | -.018 | -.183 | -.101 | -.022 | .192 | .157 |
| Canto Della Terra | Andrea Bocelli | -.024 | -.069 | ***.549*** | .014 | *.487* | -.040 | .053 | -.048 | .024 |
| Dancing Queen | ABBA | .064 | -.026 | ***.538*** | -.041 | .154 | .095 | -.307 | .272 | -.038 |
| Baby One More Time | Britney Spears | *.430* | -.025 | ***.509*** | -.113 | .098 | .080 | -.179 | -.043 | -.056 |

*Note*. $N$ = 354. All factor loadings |.400| or larger are provided in *italics*; the highest factor loadings within each component are in **bold**. CAAP = Contemporary African American Popular; Modern Chart Pop = 80s to current Chart Pop; Early Chart Pop = 60s and 70s Chart Pop.

*Table E1* (*continued*)

Factor loadings from the pattern matrix for the 9-component Promax-rotated PCA solution.

| Music Clip Title | Artist/ Composer | CAAP | Jazz | Modern Chart Pop | Hard Rock | Classical | American Country | Blues - Rock | Early Chart Pop | Dance/ Electronica |
|---|---|---|---|---|---|---|---|---|---|---|
| Every Breath You Take | The Police | -.031 | -.097 | ***.511*** | .216 | .098 | -.072 | .054 | .244 | -.080 |
| Speed of Sound | Coldplay | -.093 | .298 | ***.470*** | .181 | -.363 | -.033 | -.131 | .030 | .164 |
| With or Without You | U2 | -.159 | .095 | ***.487*** | .320 | -.134 | -.079 | -.069 | .320 | .058 |
| Back in Black | AC/DC | .055 | -.112 | -.198 | ***.783*** | .022 | .079 | .127 | .055 | -.031 |
| Paranoid | Black Sabbath | -.076 | -.153 | -.164 | ***.756*** | .076 | .058 | .169 | .226 | .029 |
| Smoke on the Water | Deep Purple | -.075 | -.104 | -.033 | ***.755*** | .139 | -.066 | .260 | .172 | -.182 |
| Sweet Child O' Mine | Guns n' Roses | .093 | -.093 | .011 | ***.736*** | .033 | .045 | .064 | .146 | -.146 |
| Until it Sleeps | Metallica | -.045 | -.155 | -.047 | ***.728*** | .058 | .052 | .248 | -.094 | .201 |
| Smells Like Teen Spirit | Nirvana | .017 | .095 | -.101 | ***.700*** | -.100 | -.017 | -.065 | .052 | .196 |
| No One Knows | Queens of the Stone Age | .024 | .124 | -.114 | ***.698*** | -.118 | .015 | .040 | -.067 | .178 |
| Here to Stay | Korn | .101 | -.068 | -.096 | ***.675*** | .084 | .062 | .136 | -.237 | .234 |
| Stairway to Heaven | Led Zeppelin | -.197 | -.124 | .035 | ***.611*** | .117 | .022 | .125 | .342 | -.001 |
| Dani California | Red Hot Chili Peppers | .084 | .069 | .159 | ***.538*** | -.201 | -.047 | .080 | -.242 | .075 |
| South Side | Moby | .177 | .126 | .073 | ***.524*** | .027 | -.129 | -.174 | .103 | .131 |
| Jump | Van Halen | -.039 | -.171 | .305 | ***.521*** | .126 | -.012 | .080 | .263 | -.078 |

*Note*. $N = 354$. All factor loadings |.400| or larger are provided in *italics*; the highest factor loadings within each component are in **bold**. CAAP = Contemporary African American Popular; Modern Chart Pop = 80s to current Chart Pop; Early Chart Pop = 60s and 70s Chart Pop.

*Table E1* (*continued*)
Factor loadings from the pattern matrix for the 9-component Promax-rotated PCA solution.

| Music Clip Title | Artist/ Composer | CAAP | Jazz | Modern Chart Pop | Hard Rock | Classical | American Country | Blues - Rock | Early Chart Pop | Dance/ Electronica |
|---|---|---|---|---|---|---|---|---|---|---|
| Nookie | Limp Bizkit | *.442* | -.044 | -.213 | ***.518*** | .140 | .034 | .042 | -.269 | .117 |
| I Love Rock „N' Roll | Joan Jett | .149 | -.040 | .210 | ***.464*** | .013 | .105 | -.030 | .227 | -.133 |
| Born in the U.S.A. | Bruce Springsteen | -.036 | -.245 | .272 | ***.455*** | .066 | .074 | .123 | .291 | -.125 |
| Praise You | Fatboy Slim | .182 | .246 | .049 | **.314** | -.167 | -.109 | -.111 | .145 | .289 |
| Till Eulenspiegels lustige Streiche | Richard Strauss | .008 | .204 | .064 | .112 | ***.856*** | .004 | -.132 | .018 | -.059 |
| Symphony No. 3, "Eroica" | Ludwig van Beethoven | .019 | .193 | .019 | .038 | ***.845*** | -.055 | -.015 | .027 | -.094 |
| Piano Concerto No. 1 | Peter Ilitch Tchaikovsky | .036 | .238 | .053 | .052 | ***.840*** | -.061 | -.045 | -.023 | -.108 |
| Requiem | Wolfgang A. Mozart | -.054 | .103 | .018 | .057 | ***.823*** | -.015 | -.030 | .008 | .060 |
| Matthaus Passioin 1 | Johann Sebastian Bach | -.029 | .079 | .027 | .003 | ***.816*** | -.020 | .029 | .003 | -.007 |
| Kyrie | Arvo Part | -.027 | .119 | .081 | -.017 | ***.759*** | .005 | -.056 | -.018 | .088 |
| Rite of Spring | Igor Stravinsky | .116 | .266 | -.214 | .074 | ***.726*** | -.039 | -.012 | -.038 | .033 |
| Next Heap With | Aphex Twin | -.067 | .196 | .103 | .090 | ***.683*** | -.025 | -.096 | -.023 | .222 |
| Rhapsody in Blue | George Gershwin | -.032 | .395 | .070 | .011 | ***.626*** | -.070 | -.170 | .067 | .019 |
| Gassenhauer | Kaiser Heinrich II | .054 | .129 | .009 | -.080 | ***.483*** | .147 | -.034 | .084 | .210 |

*Note*. $N$ = 354. All factor loadings |.400| or larger are provided in *italics*; the highest factor loadings within each component are in **bold**. CAAP = Contemporary African American Popular; Modern Chart Pop = 80s to current Chart Pop; Early Chart Pop = 60s and 70s Chart Pop.

*Table E1* (*continued*)
Factor loadings from the pattern matrix for the 9-component Promax-rotated PCA solution.

| Music Clip Title | Artist/ Composer | CAAP | Jazz | Modern Chart Pop | Hard Rock | Classical | American Country | Blues - Rock | Early Chart Pop | Dance/ Electronica |
|---|---|---|---|---|---|---|---|---|---|---|
| My Heart Skips a Beat | Buck Owens | -.096 | .020 | .100 | .041 | .032 | ***.809*** | .011 | .078 | .097 |
| It Wasn't God Who Made Honky Tonk Angels | Kitty Wells | -.006 | .157 | -.076 | -.081 | -.011 | ***.807*** | -.033 | .141 | .202 |
| I Don't Rock the Jukebox | Alan Jackson | .104 | .060 | .082 | .103 | -.106 | ***.786*** | .070 | -.238 | -.138 |
| A Better Man | Clint Black | .087 | -.023 | .183 | .106 | -.029 | ***.762*** | .066 | -.255 | -.068 |
| Coat of Many Colors | Dolly Parton | .036 | -.060 | .165 | -.067 | .099 | ***.755*** | -.075 | .220 | .081 |
| Forever and Ever, Amen | Randy Travis | .074 | -.042 | .189 | .062 | -.077 | ***.749*** | .051 | -.139 | -.090 |
| Stand By Your Man | Tammy Wynette | -.065 | .152 | .020 | -.006 | -.022 | ***.721*** | -.170 | .316 | .087 |
| Any Man of Mine | Shania Twain | .169 | .054 | .304 | .012 | -.042 | ***.655*** | -.009 | -.198 | -.112 |
| Always on my Mind | Willie Nelson | -.203 | .047 | .387 | .066 | .046 | ***.464*** | -.049 | .242 | -.041 |
| All the King's Horses | Luther Allison | -.019 | .043 | .028 | .243 | .010 | -.051 | ***.778*** | .069 | .048 |
| I Smell Trouble | Johnny Winter | .032 | .208 | -.042 | .123 | -.093 | -.041 | ***.777*** | .013 | .055 |
| Nice Problem to Have | The Jeff Healey Band | .058 | .183 | -.032 | .154 | -.011 | -.086 | ***.727*** | -.005 | .047 |

*Note*. $N$ = 354. All factor loadings |.400| or larger are provided in *italics*; the highest factor loadings within each component are in **bold**. CAAP = Contemporary African American Popular; Modern Chart Pop = 80s to current Chart Pop; Early Chart Pop = 60s and 70s Chart Pop.

*Table E1* (*continued*)
Factor loadings from the pattern matrix for the 9-component Promax-rotated PCA solution.

| Music Clip Title | Artist/ Composer | CAAP | Jazz | Modern Chart Pop | Hard Rock | Classical | American Country | Blues - Rock | Early Chart Pop | Dance/ Electronica |
|---|---|---|---|---|---|---|---|---|---|---|
| I Need You So | B.B. King | -.069 | .343 | .148 | .037 | -.046 | -.041 | ***.668*** | .013 | .017 |
| Lights are on but Nobody's Home | Albert Collins | .003 | .311 | .139 | .056 | -.059 | .001 | ***.655*** | .022 | -.050 |
| Mail Order Mystics | John Mayall | -.053 | -.033 | .186 | .252 | -.015 | .104 | ***.596*** | -.091 | .050 |
| Lonesome Graveyard | Lightnin' Hopkins | .020 | .269 | -.131 | .013 | -.056 | .056 | ***.563*** | .197 | .121 |
| Pride and Joy | Stevie Ray Vaughan | -.011 | .180 | .027 | .313 | -.173 | .002 | ***.561*** | .096 | -.193 |
| M&O Blues | Lucille Bogan | -.064 | .348 | .084 | -.017 | -.095 | .138 | ***.556*** | .029 | .055 |
| Pitiful | Big Maybelle | .053 | *.473* | -.031 | -.011 | -.109 | -.044 | ***.552*** | .085 | .039 |
| Mustang Sally | Buddy Guy | .182 | .082 | .071 | .193 | .027 | -.058 | ***.473*** | .234 | -.246 |
| You Keep Me Hangin' On | Diana Ross & the Supremes | .216 | -.095 | .277 | -.075 | .025 | -.104 | -.067 | ***.659*** | .014 |
| Space Oddity | David Bowie | -.264 | .015 | .053 | .161 | .002 | .068 | .007 | ***.623*** | .209 |
| Something | The Beatles | -.117 | .097 | .144 | .116 | .053 | -.084 | .068 | ***.606*** | -.087 |
| I Heard it Through the Grapevine | Marvin Gaye | .172 | .223 | .088 | .020 | -.076 | -.058 | .115 | ***.553*** | -.134 |
| Jumpin Jack Flash | Rolling Stones | -.055 | -.052 | -.098 | *.462* | .075 | -.025 | .099 | ***.543*** | -.058 |
| I Walk the Line | Johnny Cash | .044 | .058 | -.203 | .168 | -.157 | *.478* | -.120 | ***.499*** | .039 |
| White Rabbit | Jefferson Airplane | -.237 | .074 | -.093 | .228 | .051 | .008 | .055 | ***.492*** | .331 |

*Note*. $N = 354$. All factor loadings |.400| or larger are provided in *italics*; the highest factor loadings within each component are in **bold**. CAAP = Contemporary African American Popular; Modern Chart Pop = 80s to current Chart Pop; Early Chart Pop = 60s and 70s Chart Pop.

*Table E1* (*continued*)
Factor loadings from the pattern matrix for the 9-component Promax-rotated PCA solution.

| Music Clip Title | Artist/ Composer | CAAP | Jazz | Modern Chart Pop | Hard Rock | Classical | American Country | Blues - Rock | Early Chart Pop | Dance/ Electronica |
|---|---|---|---|---|---|---|---|---|---|---|
| Blueberry Hill | Fats Domino | .110 | .061 | .054 | .009 | .033 | .204 | .142 | ***.492*** | .025 |
| Let's Stay Together | Al Green | .296 | .310 | .121 | -.117 | -.134 | -.143 | .141 | ***.437*** | -.097 |
| Just My Imagination | The Temptations | .172 | .101 | .255 | -.043 | .006 | .044 | .141 | **.388** | -.162 |
| Respect | Aretha Franklin | .298 | .325 | .115 | .018 | -.059 | -.151 | .091 | **.333** | -.209 |
| Talisman | Air | -.086 | .039 | .189 | .013 | -.034 | .117 | -.010 | .038 | ***.730*** |
| It Began in Africa | The Chemical Brothers | .208 | -.024 | .104 | -.014 | .042 | -.021 | .107 | .076 | ***.701*** |
| Push Upstairs | Underworld | .277 | -.027 | .091 | .012 | .051 | -.054 | .005 | -.019 | ***.662*** |
| Destiny | Vanessa-Mae | .075 | -.254 | *.506* | .027 | .185 | -.031 | .148 | -.099 | ***.590*** |
| Firestarter | The Prodigy | .233 | .177 | -.145 | .271 | -.044 | -.029 | -.094 | -.009 | ***.542*** |
| Du Hast | Rammstein | .095 | -.106 | -.057 | *.434* | .129 | .047 | -.028 | -.095 | ***.522*** |
| Enjoy the Silence | Depeche Mode | -.102 | .047 | .386 | .159 | -.063 | -.057 | -.226 | .394 | ***.417*** |
| Solo Allah Es Vencedor | Eduardo Paniagua | .122 | .130 | -.082 | -.200 | .192 | .077 | .168 | .223 | **.372** |

*Note*. $N = 354$. All factor loadings |.400| or larger are provided in *italics*; the highest factor loadings within each component are in **bold**. CAAP = Contemporary African American Popular; Modern Chart Pop = 80s to current Chart Pop; Early Chart Pop = 60s and 70s Chart Pop.

*Table E2*
Factor loadings from the structure matrix for the 9-component Promax-rotated PCA solution.

| Music Clip Title | Artist/ Composer | CAAP | Jazz | Modern Chart Pop | Hard Rock | Classical | American Country | Blues - Rock | Early Chart Pop | Dance/ Electronica |
|---|---|---|---|---|---|---|---|---|---|---|
| Country Grammar (Hot Shit) | Nelly | ***.836*** | .037 | .232 | .292 | -.328 | .108 | .034 | .092 | -.026 |
| Yeah! | Usher | ***.814*** | .061 | *.466* | .317 | -.305 | .097 | -.070 | .079 | -.035 |
| Dirt Off Your Shoulder | Jay Z | ***.803*** | .034 | .087 | .291 | -.294 | .138 | .040 | .083 | .030 |
| Family Affair | Mary J. Blige | ***.802*** | .118 | *.433* | .325 | -.303 | .102 | .025 | .127 | .072 |
| Who Am I - What's My Name | Snoop Doggy Dogg | ***.793*** | .071 | .069 | .357 | -.312 | .055 | .078 | .189 | .136 |
| Dangerous | Busta Rhymes | ***.788*** | .125 | .013 | .230 | -.184 | .119 | .159 | .223 | .201 |
| Get Ur Freak On | Missy Elliot | ***.763*** | .150 | .121 | .260 | -.283 | -.049 | -.097 | .103 | .259 |
| Gettin Jiggy wit it | Will Smith | ***.760*** | .130 | .357 | .394 | -.250 | .008 | -.011 | .151 | -.007 |
| California Love | 2Pac | ***.724*** | .114 | .338 | *.458* | -.320 | .038 | .036 | .108 | .143 |
| Don't Phunk with My Heart | Black-Eyed Peas | ***.721*** | .060 | *.469* | .357 | -.286 | -.046 | -.094 | -.071 | .086 |
| Stan | Eminem (feat. Dido) | ***.716*** | .124 | .231 | *.411* | -.228 | .023 | -.029 | .111 | .131 |
| Crazy in Love | Beyoneé | ***.710*** | .158 | *.532* | .357 | -.322 | .015 | -.144 | .071 | -.010 |
| Used to Love U | John Legend | ***.694*** | .158 | *.435* | .210 | -.145 | .061 | .241 | .226 | .014 |
| Turn off the Light | Nelly Furtado | ***.648*** | .168 | *.498* | .393 | -.336 | -.051 | -.112 | .122 | .083 |
| Straight Outta Compton | N.W.A. | ***.633*** | .169 | -.121 | .249 | -.170 | .087 | .097 | .275 | .284 |
| C.R.E.A.M. | Wu Tang Clan | ***.627*** | .213 | -.103 | .127 | -.174 | .136 | .183 | .218 | .231 |
| Michael Jackson | Thriller | ***.593*** | .201 | *.469* | *.450* | -.172 | .178 | .076 | .385 | -.117 |

*Note*. $N = 354$. All factor loadings |.400| or larger are provided in *italics*; the highest factor loadings within each component are in **bold**. CAAP = Contemporary African American Popular; Modern Chart Pop = 80s to current Chart Pop; Early Chart Pop = 60s and 70s Chart Pop.

*Table E2* (*continued*)
Factor loadings from the structure matrix for the 9-component Promax-rotated PCA solution.

| Music Clip Title | Artist/ Composer | CAAP | Jazz | Modern Chart Pop | Hard Rock | Classical | American Country | Blues - Rock | Early Chart Pop | Dance/ Electronica |
|---|---|---|---|---|---|---|---|---|---|---|
| I Need Love | LL Cool J | ***.562*** | .066 | .219 | .024 | -.008 | .154 | .257 | .245 | .168 |
| One More Time | Daft Punk | ***.546*** | -.013 | .399 | .335 | -.295 | -.149 | -.153 | -.058 | .294 |
| Twilight Zone | 2 Unlimited | **.522** | -.028 | *.475* | .330 | -.119 | -.030 | -.068 | .029 | .257 |
| Lester Swings | Lester Young | -.048 | ***.829*** | -.083 | -.019 | *.416* | .070 | *.416* | .313 | .216 |
| Take the A Train | Duke Ellington | -.063 | ***.812*** | -.043 | -.094 | *.496* | .128 | .301 | .362 | .106 |
| Mack the Knife | Ella Fitzgerald | .038 | ***.800*** | -.003 | -.036 | .339 | .176 | *.400* | .370 | .115 |
| Night in Tunisia | Dizzy Gillespie | -.076 | ***.796*** | -.157 | -.051 | *.490* | .045 | .380 | .320 | .216 |
| God Bless the Child | Billie Holiday | .028 | ***.792*** | -.104 | -.088 | .334 | .164 | *.422* | *.505* | .103 |
| All Blues | Miles Davis | -.110 | ***.792*** | -.138 | -.064 | .391 | .038 | .365 | .314 | .207 |
| Locomotion | John Coltrane | -.061 | ***.790*** | -.155 | .004 | .383 | .055 | .357 | .271 | .221 |
| The End of a Love Affair | Wynton Marsalis | -.147 | ***.769*** | .039 | -.112 | *.498* | .101 | *.420* | .290 | .132 |
| At Last | Etta James | .216 | ***.676*** | .310 | .111 | .138 | .228 | .219 | *.526* | -.131 |
| Georgia on my Mind | Ray Charles | .157 | ***.667*** | .222 | .079 | .245 | .240 | *.400* | *.562* | -.164 |
| Summer Wind | Frank Sinatra | .118 | ***.652*** | .199 | .101 | .293 | .237 | .284 | .307 | -.104 |
| What a Wonderful World | Louis Armstrong | .134 | ***.636*** | .213 | .141 | .218 | .193 | .230 | *.433* | -.103 |
| „S Wonderful | Diana Krall | -.011 | ***.577*** | .316 | -.054 | .348 | .161 | *.409* | .216 | .044 |
| Crazy | Patsy Cline | .093 | ***.572*** | .276 | -.002 | .183 | *.411* | .218 | *.459* | -.050 |
| Sinnerman | Nina Simone | .160 | ***.505*** | -.066 | .165 | .140 | .052 | .371 | *.423* | .274 |

*Note*. $N$ = 354. All factor loadings |.400| or larger are provided in *italics*; the highest factor loadings within each component are in **bold**. CAAP = Contemporary African American Popular; Modern Chart Pop = 80s to current Chart Pop; Early Chart Pop = 60s and 70s Chart Pop.

*Table E2* (*continued*)
Factor loadings from the structure matrix for the 9-component Promax-rotated PCA solution.

| Music Clip Title | Artist/ Composer | CAAP | Jazz | Modern Chart Pop | Hard Rock | Classical | American Country | Blues - Rock | Early Chart Pop | Dance/ Electronica |
|---|---|---|---|---|---|---|---|---|---|---|
| Solo Allah Es Vencedor | Eduardo Paniagua | .041 | **.382** | -.104 | -.110 | .363 | .118 | .349 | .338 | .376 |
| Back for Good | Take That | .219 | -.018 | ***.738*** | .084 | -.016 | .226 | .016 | .119 | -.253 |
| Sacrifice | Elton John | .122 | .029 | ***.690*** | .051 | .109 | .314 | .164 | .273 | -.195 |
| Fall at Your Feet | Crowded House | .103 | .050 | ***.681*** | .079 | .002 | .236 | .138 | .178 | -.045 |
| Like a Prayer | Madonna | *.461* | .069 | ***.680*** | .273 | -.150 | .163 | -.141 | .257 | -.052 |
| Life for Rent | Dido | .172 | .270 | ***.679*** | .232 | -.018 | .113 | .008 | .123 | .085 |
| What's Love got to do with it | Tina Turner | .394 | .171 | ***.672*** | .232 | -.033 | .270 | .210 | *.452* | -.191 |
| My Heart will go on | Céline Dion | .191 | -.125 | ***.643*** | .022 | .052 | .335 | -.014 | -.149 | -.315 |
| Baby One More Time | Britney Spears | *.512* | .016 | ***.631*** | .152 | -.115 | .178 | -.142 | .050 | -.127 |
| Misunderstood | Robbie Williams | .098 | .078 | ***.625*** | .126 | .120 | .264 | .199 | .067 | -.022 |
| The Great Escape | Ilse de Lange | .197 | .171 | ***.623*** | .163 | -.001 | *.407* | .218 | -.014 | -.079 |
| Dancing Queen | ABBA | .221 | .101 | ***.600*** | .115 | .054 | .200 | -.139 | .280 | -.145 |
| My Immortal | Evanescence | .210 | -.002 | ***.599*** | .326 | -.096 | .151 | -.031 | -.255 | -.071 |
| Crazy | Seal | *.422* | .254 | ***.596*** | .317 | -.194 | .012 | .011 | .299 | .092 |
| Every Breath You Take | The Police | .217 | .115 | ***.587*** | .361 | .028 | .116 | .143 | .329 | -.136 |
| With or Without You | U2 | .251 | .255 | ***.570*** | *.510* | -.150 | .030 | .044 | *.407* | .013 |

*Note*. $N$ = 354. All factor loadings |.400| or larger are provided in *italics*; the highest factor loadings within each component are in **bold**. CAAP = Contemporary African American Popular; Modern Chart Pop = 80s to current Chart Pop; Early Chart Pop = 60s and 70s Chart Pop.

*Table E2* (*continued*)
Factor loadings from the structure matrix for the 9-component Promax-rotated PCA solution.

| Music Clip Title | Artist/ Composer | CAAP | Jazz | Modern Chart Pop | Hard Rock | Classical | American Country | Blues - Rock | Early Chart Pop | Dance/ Electronica |
|---|---|---|---|---|---|---|---|---|---|---|
| Divano | Era | -.081 | .041 | ***.527*** | .014 | *.404* | .106 | .143 | .027 | .180 |
| Don't Give Up | Peter Gabriel (feat. Kate Bush) | .066 | .278 | ***.519*** | .079 | .128 | .137 | .162 | *.426* | .112 |
| Speed of Sound | Coldplay | .323 | .254 | ***.514*** | *.434* | -.350 | -.033 | -.122 | .150 | .119 |
| Dreaming | DJ Dado | .266 | -.041 | ***.500*** | .192 | .054 | -.043 | .024 | .010 | *.418* |
| Canto Della Terra | Andrea Bocelli | -.021 | .104 | ***.492*** | .034 | *.452* | .119 | .155 | .070 | -.012 |
| Enjoy the Silence | Depeche Mode | .216 | .240 | **.388** | .359 | -.062 | -.078 | -.094 | .364 | .365 |
| Sweet Child O' Mine | Guns n' Roses | .389 | .094 | .311 | ***.770*** | -.192 | .121 | .185 | .296 | -.079 |
| Smells Like Teen Spirit | Nirvana | .333 | .179 | .106 | ***.742*** | -.256 | -.110 | .016 | .159 | .306 |
| Back in Black | AC/DC | .295 | .051 | .078 | ***.741*** | -.171 | .075 | .217 | .187 | .064 |
| No One Knows | Queens of the Stone Age | .328 | .183 | .092 | ***.734*** | -.250 | -.068 | .093 | .095 | .289 |
| Smoke on the Water | Deep Purple | .171 | .145 | .198 | ***.700*** | .014 | .072 | .382 | .342 | -.085 |
| Paranoid | Black Sabbath | .176 | .106 | .065 | ***.696*** | -.040 | .089 | .310 | .330 | .101 |
| Until it Sleeps | Metallica | .198 | .013 | .108 | ***.692*** | -.066 | .021 | .266 | .044 | .268 |
| Dani California | Red Hot Chili Peppers | .395 | .033 | .312 | ***.657*** | -.367 | -.082 | -.001 | -.085 | .136 |
| Here to Stay | Korn | .284 | .017 | .074 | ***.655*** | -.100 | -.029 | .140 | -.086 | .334 |
| South Side | Moby | *.435* | .227 | .272 | ***.646*** | -.187 | -.159 | -.072 | .205 | .247 |

*Note*. $N$ = 354. All factor loadings |.400| or larger are provided in *italics*; the highest factor loadings within each component are in **bold**. CAAP = Contemporary African American Popular; Modern Chart Pop = 80s to current Chart Pop; Early Chart Pop = 60s and 70s Chart Pop.

*Table E2* (*continued*)
Factor loadings from the structure matrix for the 9-component Promax-rotated PCA solution.

| Music Clip Title | Artist/ Composer | CAAP | Jazz | Modern Chart Pop | Hard Rock | Classical | American Country | Blues - Rock | Early Chart Pop | Dance/ Electronica |
|---|---|---|---|---|---|---|---|---|---|---|
| I Love Rock „N' Roll | Joan Jett | *.436* | .150 | *.475* | ***.598*** | -.167 | .220 | .126 | .370 | -.139 |
| Jump | Van Halen | .250 | .089 | *.477* | ***.589*** | -.012 | .134 | .206 | .360 | -.087 |
| Stairway to Heaven | Led Zeppelin | .069 | .162 | .193 | ***.568*** | .073 | .114 | .303 | *.426* | .025 |
| Nookie | Limp Bizkit | *.486* | .004 | .033 | ***.559*** | -.158 | -.049 | .043 | -.118 | .261 |
| Praise You | Fatboy Slim | *.454* | .333 | .194 | ***.530*** | -.253 | -.159 | -.030 | .257 | .374 |
| Born in the U.S.A. | Bruce Springsteen | .236 | .017 | *.451* | ***.522*** | -.051 | .231 | .237 | .367 | -.177 |
| Symphony No. 3, "Eroica" | Ludwig van Beethoven | -.240 | *.407* | .018 | -.155 | ***.860*** | .090 | .301 | .220 | .036 |
| Matthaus Passioin 1 | Johann Sebastian Bach | -.298 | .295 | -.021 | -.204 | ***.851*** | .096 | .296 | .145 | .086 |
| Requiem | Wolfgang A. Mozart | -.299 | .316 | -.029 | -.158 | ***.849*** | .065 | .254 | .142 | .163 |
| Piano Concerto No. 1 | Peter Ilitch Tchaikovsky | -.209 | *.422* | .060 | -.130 | ***.837*** | .079 | .267 | .190 | .030 |
| Till Eulenspiegels lustige Streiche | Richard Strauss | -.205 | *.402* | .086 | -.083 | ***.829*** | .112 | .213 | .205 | .061 |
| Kyrie | Arvo Part | -.257 | .302 | .021 | -.187 | ***.789*** | .076 | .205 | .111 | .166 |
| Rite of Spring | Igor Stravinsky | -.157 | *.434* | -.183 | -.106 | ***.735*** | .015 | .276 | .161 | .209 |
| Next Heap With | Aphex Twin | -.203 | .371 | .045 | -.047 | ***.716*** | -.002 | .165 | .120 | .318 |

*Note*. $N$ = 354. All factor loadings |.400| or larger are provided in *italics*; the highest factor loadings within each component are in **bold**. CAAP = Contemporary African American Popular; Modern Chart Pop = 80s to current Chart Pop; Early Chart Pop = 60s and 70s Chart Pop.

*Table E2* (*continued*)

Factor loadings from the structure matrix for the 9-component Promax-rotated PCA solution.

| Music Clip Title | Artist/ Composer | CAAP | Jazz | Modern Chart Pop | Hard Rock | Classical | American Country | Blues - Rock | Early Chart Pop | Dance/ Electronica |
|---|---|---|---|---|---|---|---|---|---|---|
| Rhapsody in Blue | George Gershwin | -.168 | *.530* | .059 | -.097 | ***.683*** | .011 | .152 | .258 | .143 |
| Gassenhauer | Kaiser Heinrich II | -.087 | .324 | -.001 | -.133 | ***.556*** | .179 | .220 | .209 | .231 |
| My Heart Skips a Beat | Buck Owens | .032 | .168 | .243 | .037 | .169 | ***.823*** | .306 | .271 | -.118 |
| I Don't Rock the Jukebox | Alan Jackson | .229 | .042 | .308 | .136 | -.092 | ***.807*** | .231 | .030 | -.314 |
| Coat of Many Colors | Dolly Parton | .125 | .146 | .320 | -.011 | .178 | ***.803*** | .241 | .358 | -.146 |
| Forever and Ever, Amen | Randy Travis | .213 | -.008 | .380 | .117 | -.066 | ***.787*** | .207 | .071 | -.298 |
| A Better Man | Clint Black | .215 | -.001 | .378 | .143 | -.032 | ***.786*** | .220 | .016 | -.260 |
| It Wasn't God Who Made Honky Tonk Angels | Kitty Wells | .064 | .303 | .069 | -.054 | .176 | ***.778*** | .302 | .339 | .020 |
| Stand By Your Man | Tammy Wynette | .084 | .317 | .193 | .033 | .119 | ***.728*** | .204 | *.467* | -.094 |
| Any Man of Mine | Shania Twain | .308 | .055 | *.496* | .127 | -.072 | ***.713*** | .138 | .046 | -.294 |
| Always on my Mind | Willie Nelson | .022 | .218 | *.477* | .119 | .155 | ***.583*** | .215 | .390 | -.223 |

*Note*. $N$ = 354. All factor loadings |.400| or larger are provided in *italics*; the highest factor loadings within each component are in **bold**. CAAP = Contemporary African American Popular; Modern Chart Pop = 80s to current Chart Pop; Early Chart Pop = 60s and 70s Chart Pop.

*Table E2* (*continued*)
Factor loadings from the structure matrix for the 9-component Promax-rotated PCA solution.

| Music Clip Title | Artist/ Composer | CAAP | Jazz | Modern Chart Pop | Hard Rock | Classical | American Country | Blues - Rock | Early Chart Pop | Dance/ Electronica |
|---|---|---|---|---|---|---|---|---|---|---|
| All the King's Horses | Luther Allison | .121 | .366 | .102 | .343 | .204 | .196 | ***.827*** | .395 | .081 |
| I Smell Trouble | Johnny Winter | .149 | *.465* | .027 | .260 | .155 | .190 | ***.821*** | .381 | .102 |
| Nice Problem to Have | The Jeff Healey Band | .150 | *.439* | .038 | .273 | .190 | .138 | ***.771*** | .346 | .115 |
| I Need You So | B.B. King | .075 | *.566* | .172 | .181 | .248 | .218 | ***.763*** | *.410* | .040 |
| Lights are on but Nobody's Home | Albert Collins | .152 | *.537* | .212 | .217 | .193 | .273 | ***.756*** | *.425* | -.034 |
| Lonesome Graveyard | Lightnin' Hopkins | .099 | *.546* | -.060 | .134 | .222 | .238 | ***.720*** | *.506* | .149 |
| M&O Blues | Lucille Bogan | .072 | *.540* | .129 | .116 | .209 | .340 | ***.692*** | *.400* | .034 |
| Pitiful | Big Maybelle | .168 | *.670* | .043 | .165 | .173 | .170 | ***.691*** | *.477* | .105 |
| Pride and Joy | Stevie Ray Vaughan | .225 | .378 | .199 | *.434* | -.046 | .240 | ***.635*** | *.424* | -.162 |
| Mail Order Mystics | John Mayall | .123 | .179 | .249 | .334 | .104 | .279 | ***.606*** | .186 | .015 |
| Mustang Sally | Buddy Guy | .315 | .368 | .268 | .350 | .068 | .235 | ***.599*** | *.520* | -.207 |
| I Heard it Through the Grapevine | Marvin Gaye | .354 | *.508* | .276 | .258 | -.008 | .177 | .351 | ***.731*** | -.123 |
| Something | The Beatles | .070 | *.407* | .236 | .216 | .157 | .124 | .315 | ***.689*** | -.095 |

*Note*. $N = 354$. All factor loadings |.400| or larger are provided in *italics*; the highest factor loadings within each component are in **bold**. CAAP = Contemporary African American Popular; Modern Chart Pop = 80s to current Chart Pop; Early Chart Pop = 60s and 70s Chart Pop.

*Table E2* (*continued*)
Factor loadings from the structure matrix for the 9-component Promax-rotated PCA solution.

| Music Clip Title | Artist/ Composer | CAAP | Jazz | Modern Chart Pop | Hard Rock | Classical | American Country | Blues - Rock | Early Chart Pop | Dance/ Electronica |
|---|---|---|---|---|---|---|---|---|---|---|
| Blueberry Hill | Fats Domino | .239 | .391 | .215 | .169 | .132 | .378 | *.412* | ***.647*** | -.038 |
| Let's Stay Together | Al Green | *.443* | *.534* | .280 | .196 | -.066 | .086 | .310 | ***.640*** | -.065 |
| You Keep Me Hangin' On | Diana Ross & the Supremes | .370 | .234 | .394 | .191 | -.022 | .083 | .110 | ***.639*** | -.041 |
| Space Oddity | David Bowie | -.047 | .335 | .089 | .208 | .161 | .143 | .261 | ***.626*** | .154 |
| Jumpin Jack Flash | Rolling Stones | .157 | .282 | .103 | *.483* | .051 | .107 | .332 | ***.617*** | -.011 |
| I Walk the Line | Johnny Cash | .233 | .272 | .045 | .244 | -.108 | *.486* | .190 | ***.573*** | -.054 |
| Just My Imagination | The Temptations | .317 | .354 | *.407* | .176 | .047 | .289 | .331 | ***.565*** | -.211 |
| Respect | Aretha Franklin | *.444* | *.502* | .313 | .275 | -.064 | .074 | .263 | ***.561*** | -.141 |
| White Rabbit | Jefferson Airplane | -.070 | .370 | -.074 | .234 | .209 | .021 | .283 | ***.521*** | .344 |
| It Began in Africa | The Chemical Brothers | .288 | .193 | .065 | .198 | .070 | -.104 | .130 | .119 | ***.699*** |
| Push Upstairs | Underworld | .334 | .117 | .066 | .214 | -.002 | -.177 | -.010 | -.003 | ***.686*** |
| Talisman | Air | .073 | .172 | .084 | .144 | .082 | -.025 | .037 | .053 | ***.667*** |
| Firestarter | The Prodigy | .366 | .257 | -.056 | *.411* | -.123 | -.197 | -.036 | .069 | ***.646*** |
| Du Hast | Rammstein | .216 | .016 | .003 | *.452* | -.005 | -.120 | -.004 | -.069 | ***.583*** |
| Destiny | Vanessa-Mae | .188 | -.057 | .391 | .201 | .147 | -.048 | .080 | -.083 | ***.513*** |

*Note*. $N$ = 354. All factor loadings |.400| or larger are provided in *italics*; the highest factor loadings within each component are in **bold**. CAAP = Contemporary African American Popular; Modern Chart Pop = 80s to current Chart Pop; Early Chart Pop = 60s and 70s Chart Pop.

# The Music in You:
# Investigating Personality-Based Recommendation

## Summary

As much as music is a form of entertainment that keeps our feet tapping, it also helps each of us express our own personality to others in our social environment. Much of the previous research relating personality and music preferences has measured reported preferences by genre before relating these preferences to the Big Five model personality. The research presented in the current thesis builds on previous research by investigating how reported music preferences by genre is related to music listening behaviour and how both of these variables are related to personality according to the Big Five. The presented research also extends previous knowledge concerning the relation between personality and music preferences by building a model of music preferences using music stimuli (i.e., songs). Subsequently, music preferences derived from this model are related to detailed personality traits within the Big Five model, known as facets, and to extracted audio features. As one potential application, the presented research describes an attempt to use algorithms for music preference prediction, based on knowledge concerning the relation between personality and music preference factors discriminated by audio features. If successful, the music preference algorithms could be applied to music recommender technologies to help achieve better music recommendation when faced with an overwhelming amount of digital music information available to users.

The research presented in the current thesis describes seven studies with a total of nearly 1,000 participants and thousands of music stimuli that were used to investigate the relation between personality and music preferences. While music preferences were measured in several different ways and these respective measurements were compared, all of the studies presented in the thesis measured personality according to the Big Five model. Several studies presented in the thesis measured reported music preferences according to genre, and compared the structure of these reported music preferences to Rentfrow and Gosling's (2003) model of music preferences. One study presented in the thesis also compared participants' reported music preferences to their music listening behaviour,

which was tracked when using an online database containing thousands of music stimuli (*n* = 138). After a thorough data study to obtain 120 prototypical music clips from 10 different genres, these music clips were listened to over the Internet and rated according to preference by an international sample (*n* = 354, mainly from the US, UK, and Canada) and a Dutch/Flemish sample (*n* = 136). The international sample was used to construct a model of music preferences using the music stimuli, after which the dimensions of music preferences derived from this model were related to personality facets. Subsequently, the Dutch/Flemish sample tested the model and its relations to personality to confirm the findings taken from the international sample results. Audio feature extraction was used to computationally analyse and discriminate among the modelled music preference dimensions. The last study used the algorithms derived from the constructed music preference model and its relation to personality and extracted audio features. These algorithms tested the potential for applying personality to predict music preference versus Collaborative Filtering (CF) algorithms often used in current recommender technologies.

Main results from the thesis confirmed that reported music preference behaviour is often significantly and positively related to music listening behaviour for the same genre. Nonetheless, the main results were unable to confirm Rentfrow and Gosling's (2003) earlier model of music preferences based on reported preferences by genre. Instead, the model constructed in the current thesis broadly grouped music preferences into nine dimensions based on the 120 music clips. The nine dimensions were found and confirmed across the international and Dutch/Flemish samples and were labelled as: Contemporary African American Popular (CAAP), Jazz, Modern Chart Pop, Hard Rock, Classical, American Country, Blues-Rock, Early Chart Pop, and Dance/Electronica. Also, several personality facets were individually found to be related to preferences for music contained within the nine dimensions. For instance, preference for CAAP music was related to a personality facet that expresses a predisposition for exciting or stimulating environments. Similarly, Jazz music was related to a predisposition for finding pleasure in visual and dramatic arts. When related to the extracted audio features, preference for CAAP music was related to fast and steady beats in music, while preference for Jazz music was related to complex tonal structures. These are just two examples of the several complex relations found between participants' personality, their preferences toward music clips, and the audio features that described the music clip preference factors. Despite the promising results from the constructed model, comparison with current CF algorithms suggested that there is still further work needed if the model is to be used in applied settings.

# Acknowledgements

Those who know me also know that I am somewhat prone to ramble in my speech and in my prose, but I will keep this short. For those who were responsible for my supervision and progression through to the conclusion of my Ph.D., I am thankful for your guidance and support. Furthermore, I am eternally grateful to be fortunate enough to be surrounded by many family members and friends who have supported me throughout the years of my life. There are, in fact, too many to be able to mention them all here. For the sake of brevity, what follows is a list of people whom I would like to acknowledge by name because they have gone to extra lengths in these past four years to support me in my work and in my life: My parents, Rob and Tilly; my brother, Matt, and my sister, Janina, and their families (Michelle, Nicholas, Katrina, Paolo, and Olivia); my Oma and the rest of my family living in the Netherlands, Canada, and abroad; Thomson, on whom I could always count; my Marie Curie companions, Alberto, Marco C., and Marco T.; my friends in the DSP group, Janto, Tobias, and Steven; my SigScalers, Jan, Jettie, Janneke, and Nele; my roommates, Bram, Javed, Evelein, Gijs, Marjolein, Joris, Maurits; my student, Jurgen; and a special thanks to two very special friends who I will treasure forever, Dragan and Will. For all those whom I did not mention here, but were part of my life while at Philips in Eindhoven, please trust that I have valued your friendship and will I always remember you with a smile. I love you all and have nothing but the fondest memories of my last four years with you.

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# Curriculum Vitae

Peter Gregory Dunn ("Greg") was born on December 16, 1974, in Ottawa, Canada. He was born with a medical condition that destroyed the entire function of his left kidney and about half of the function of his right kidney. He had a left nephrectomy (left kidney removal) when he was three. His health has had a substantial impact on his philosophy and his education.

Greg graduated from Sir Robert Borden High School in Ottawa, Canada, in June of 1994. He had been fortunate to maintain a satisfactory health condition up to that point in time and had never needed to receive dialysis for his condition. On November 24, 1995, he received a kidney transplant due to the declining function of his right kidney. The kidney was donated by his mother, Tilly Dunn.

Subsequent to his recovery from the transplant operation, Greg began studying psychology at Carleton University in Ottawa, Canada, in September, 1996. Greg concentrated in personality psychology and graduated from Carleton University with a Bachelor of Arts, Highest Honours in the Fall of 2000. After taking a year off, Greg continued studying psychology for his Master's at Carleton University, but changed his focus to investigate the relation between psychology and technology; a field known as Human-Computer Interaction (HCI). In July 2005 he started his Ph.D. as a Marie Curie Research Fellow at the Philips Research Laboratories in Eindhoven, The Netherlands, under the auspices of the Eindhoven University of Technology.

In his recreation time, Greg enjoys sports and gaming. In particular, Greg has played in the competitive curling circuit in Canada, winning various tournaments and prize money. In the Netherlands, Greg offered some of his time to coach the National Dutch Men's team and played on that team from January 2006 to September 2007. Greg currently lives with his wife, Vanja, in Eindhoven, The Netherlands.