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The Influence of the Facets of Openness to Experience on Music Preference

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Listening to music is a widespread activity. Openness to experience in particular has been found to be one of the personality dimensions that most consistently predicts music preference. However, the singular facets of openness to experience have never been looked at in depth. This study tried to uncover the impact that openness to experience facets of both the five factor model (FFM) and HEXACO model of personality have on music preference. A total of 478 undergraduate Psychology students enrolled at Illinois State University participated in the study by accessing a Qualtrics survey. Participants completed two openness to experience measures (FFM and HEXACO) and two music preference measures, one using music genre-labels to measure music preference and the other using musical excerpts ratings to measure music preference. Similarly to Rentfrow and colleagues (2011), five dimensions of music preference were observed for the musical excerpts measure. All of the openness facets were significantly positively correlated with all of the music preference dimensions aside from the *unpretentious* one. Latent profile analysis (LPA) revealed three latent profiles of music preference. This study shows that openness to experience facets may predict music preference in a more specific way compared to general openness to experience, suggesting attention when using openness to experience to predict music preference. Further, meaningful patterns of music reference were uncovered by LPA, which might have important implications both for the field of music preference research and the commercial distribution of music.

KEYWORDS: Music preference; openness to experience; dominance analysis; latent profile analysis

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F. S.

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CHAPTER I: LITERATURE REVIEW

Introduction to Music Preference Research

There certainly are not many activities that almost every person engages in, yet listening to music might be one. There is evidence that even Neanderthals engaged in musical activities even thousands of years ago (Mithen, 2011). Furthermore, Rentfrow and Gosling (2003) report that out of nine leisure activities, music was rated as the second most important. Finally, according to the Industrial Federation of the Phonographic Industry (IFPI, 2019), on average people listened to music 2.6 hours per day. The ubiquity of music in our daily life is truly undeniable. However, music cannot be conceived as a monolithic entity, as it can be divided in genres that are widely different from each other both in sounds and themes (i.e., metal versus classical, religious music versus rap). Additionally, it is also quite clear that individuals like different kinds of music (e.g., Cattell & Sounders, 1954). Then, given the importance of music in our daily life, it becomes rather intriguing to investigate the issue of *music preference*, or more simply put, the kind of music that people prefer. Accordingly, under the assumption that music preference should be explainable by psychological dimensions across which people differ, the research has been focusing on uncovering individual differences that may account for the variance in music preference in the general population.

Cattell and Saunders (1954) were among the first researchers to investigate music preference; they posited that music preferences could be conceptualized as a manifestation of unconscious dispositions. Surprisingly, for about 50 years after Cattell and Saunders's (1954) paper, the research on music preference was somewhat scarce, with only few sporadic instances of researchers trying to tackle the topic (e.g., Daoussis & McKelvie, 1986; Dollinger, 1993). Although some of the basic theoretical ideas regarding music preference, such as personality being a possible predictor of what kind of music people like (e.g., Rawlings & Ciancarelli, 1997), had been hinted at, there appeared to be no solid and well-validated measure of music preference, making the topic quite difficult to properly study.

Renfrow and Gosling (2003), surprised by the paucity of literature regarding music preference, crafted one of the most robust and more widely utilized measure of music preference, the Short Test Of Music Preference (STOMP). In the field of modern music preference research, Rentfrow and Gosling's (2003) research is regarded as the seminal work that informs the vast majority of the music preference research that follows (Delsing et al., 2008; Dunn et al., 2012). Then, after 2003, the research on music preference became increasingly popular, and, although it still holds a niche status in the literature, it has attracted a good deal of research. As more and more researchers became intrigued with the topic, music preference research has become more and more interdisciplinary, spanning many fields of psychology (e.g., Adamos et al., 2016; Dyrlund & Winiger, 2008; Jiang et al., 2016).

Measuring Music Preference

As the topic of music preference is by no means a well-known field of research, it is useful to first explain how music preference is measured. Proper measurement is probably one of the most pivotal prerequisites when studying constructs that are not directly observable, and music preference clearly is one such construct.

An absence of tools measuring music preference has probably been the most likely cause of much of the delays in music preference research. Before Rentfrow and Gosling (2003), there was no agreed upon method of measuring music preference. The first attempt at developing a comprehensive tool for measuring music preference was by Cattell and Sounders, who developed the I.P.A.T. music preference test of personality (I.PA.T., 1953); this tool was dubbed a “test of personality” because Cattell and Sounders (1954) believed that music preference was so strongly related to personality that it could even predict the latter. The I.P.A.T is comprised of a series of 120 music excerpts of about 20 s each that every respondent listens to and then answer questions about. Among these is a question that specifically asks about the preference towards certain excerpts (Cattell & Sounders, 1954). Although this test is the first recorded attempt to create a comprehensive music preference measure, it is not used nowadays, and it is very seldom mentioned in the literature. I speculate that this test is not very relevant to music preference anymore, as it presented mainly jazz and classical music excerpts, two genres that clearly do not capture the breadth of the contemporary music scene. Similarly, in the following decades, other attempts to create a comprehensive and valid music preference have been sporadic and unsuccessful, as the tools developed were scarcely used and not very popular in the literature (e.g., Litle & Zuckerman, 1986; Sikkema, 1999).

At the turn of the century, the field of music preference research was still very much in an embryonic state, with research being scarce and fragmented, with no systematic way of measuring music preference; these issues made it unfeasible to compare the few findings on the subject. It is in 2003 that Rentfrow and Gosling, surprised by the dearth of research regarding the ubiquitous phenomenon of music preference, decided to take up the task of creating a comprehensive and valid measure of music preference. In a series of rigorous studies, Rentfrow and Gosling (2003) developed the Short Test Of Musical Preference (STOMP). To develop this tool, the researchers first identified 14 music genres and 66 subgenres; then, they asked a group of 30 participants to rate their familiarity with each of them. Interestingly enough only 7% of the participants were familiar with all the subgenres, whereas 97% of the participants were familiar with all of the 14 music genres. Thus, the final version of the STOMP is quite the simple tool to administer as it presents 14 items, each of which is the name of a music genre (e.g., pop, rock, jazz), and a 7-point Likert scale to measure the preference for each item (1 = *not at all*, 7 = *a great deal*).

Later on, Rentfrow and colleagues (2011) expanded the STOMP by including nine additional music genres, thus creating the STOMP-Revised (STOMP-R; Rentfrow et al., 2011). The STOMP-R functions in very much the same way as the STOMP, with the only difference that it measures preference for 23 music genres rather than 14.

The Structure of Music Preference

When discussing measurement of constructs such as music preference , it is relevant to answer a question that suggests itself: is there a structure of music preference? Or in other words, can music preference be conceptualized in terms of dimensions or factors? To give a better idea of what "structure" means in this case, it is useful to draw a parallel to personality and its structure. One of the most popular models of personality is the five-factor model (FFM; McCrae & John, 1992). This model maintains that personality and its various aspects can be summarized by five major dimensions. Dimensions of personality emerge because sets of narrower aspects of personality have something in common. Similarly, It is reasonable to assume that people who like a certain music genre (e.g., punk rock), will tend to like music genres that have a similar style (e.g., alternative rock).

Aside from creating a proper measure of music preference, identifying a structure of music preference was one of the main aims of Rentfrow and Gosling (2003). Interestingly enough, they were essentially the first researchers to clearly articulate the hypothesis of the existence of a music preference structure; their 2003 paper was very much an exploratory analysis in this regard. To answer their exploratory question, Renfrow and Gosling (2003) administered the STOMP to two large samples of undergraduate students. Once exploratory factor analysis (EFA) was applied to participants' self-reported liking of the 14 music genres in the STOMP, it transpired that music preference tended to cluster into four dimensions. Accordingly, the four dimensions of music preference identified were respectively named *Reflective and Complex* (blues, jazz, classical, folk), *Intense and Rebellious* (rock, alternative, heavy metal), *Upbeat and Conventional* (country, soundtracks, religious, pop), and *Energetic and Rhythmic* (rap/hip-hop, soul/funk, electronic/dance). Participants who liked a genre in a given dimension tended to like all of the other genres in the same dimension.

In the same paper, Rentfrow and Gosling (2003) shed light on why music genres tend to cluster and create different factors; crucially, the researchers had seven judges rate 140 songs representative of the 14 well-known music genres according to musical attributes (e.g., fast, slow, emotional, sad). It turned out that the four music dimensions were significantly different across all but one musical attribute. Although Rentfrow and Gosling (2003) did not dwell too much on this finding, it appears that factors of music preference, and consequently the genres within them, present musical attributes that are quantitatively distinct between music preference dimensions. For instance, music genres in the *Reflective and Complex* dimension were, as the label suggests, significantly more complex than other music genres belonging to other dimensions. Likewise, genres in the *Intense and Rebellious* dimensions were significantly higher in negative affect compared to other music genres.

In 2011, with the intention of including a higher number of music genres, Rentfrow and colleagues (2011) measured preference for 23 music genres with the STOMP-R instead of the 14 music genres of the STOMP in a large sample. Once EFA was conducted on the reported music preference for each genre, instead of four dimensions of music preference, five emerged: *Mellow* (electronica/dance, new age, world), *Unpretentious* (pop, country, religious), *Sophisticated* (blues, jazz, bluegrass, folk, classical, gospel, opera), *Intense* (rock, punk, alternative, heavy metal), and *Contemporary* (rap, soul/R&B, funk, reggae).

Although these findings might seem to suggest a conflict between the Rentfrow and Gosling (2003) and Rentfrow and colleagues (2011) findings, it is not necessarily so. The issue regarding how many basic dimensions of music preference actually exist is somewhat of a contentious topic, with some finding four (Rentfrow & Gosling, 2003), five (Colley, 2008; Gardikiotis & Baltzis, 2012), or even eight (George et al., 2007). However, it is very likely that the number of dimensions of music preference that emerges might hinge upon the number of genres that researchers elect to study. A recent study by Brisson and Bianchi (2020) did in fact find that the structure of music preference is very much dependent on the number of items observed, with even a subtle variation in the number of genres presented resulting in a different number of dimensions.

What can be gathered from the research on the structure of music preference is that (a) there are clusters/dimensions of music preference; if a person likes a music genre in a certain cluster, they are likely to also like the other music genres present in that cluster/dimension. For instance, a person who likes punk rock, a music genre that belongs to the *intense* dimension according to Renfrow and colleagues (2011), will also tend to like heavy metal, rock, and alternative rock, three other music genres also belonging to the *intense* dimension. Additionally, (b) This phenomenon happens because music genres in a certain dimension have similar musical attributes, or more simply put, sound similar (Renfrow & Gosling, 2003). Finally, (c) as music can take so many forms and can be divided into so many diverse genres, it is almost impossible to create an exhaustive taxonomy of dimensions of music preference. Still, taxonomies such as the one created by Renfrow and colleagues (2011), whereas by no means exhaustive, are still practically useful when talking about music preference.

Genre-based Measures of Music Preference versus Musical Excerpts Rating

Although the STOMP, a genre-based measure of music preference, sparked renewed interest in the music preference research, issues have rightfully been raised as to whether it is the most appropriate tool to measure music preference. The main problem that is generally brought up with genre-based measures of music preference such as the STOMP is that it merely asks people to report their preference for a list of genres (Ferrer et al., 2013; Greenberg et al., 2015). As I will discuss later, genre labels are charged with social meaning and stereotypes (North & Hargreaves, 1999; Rentfrow & Gosling, 2006). Furthermore, the classification of music genres is a rather debated issue itself in the literature (see Sturm, 2013), and there does not appear to be any agreed upon taxonomy of music genres. For instance, labels such as “pop” or “rock” are clearly too broad and fail to encapsulate the diversity of music styles that they attempt to describe (Oramas et al., 2018). Hence, genre labels can very well present a strong subjective interpretation of what kind of music they describe (McKay & Fujinaga, 2006), which is a reason to doubt that genre-based measures of music preference are comparable across individuals.

The STOMP and the STOMP-R are easy-to-administer measure of music preference, but there have been many concerns for the ecological validity of genre-based measure, concerns that have been echoed even by the authors of the STOMP themselves (Rentfrow et al., 2011; Rentfrow et al., 2012). Cattell and Sounders (1954) had intuited that the best possible way of testing music preference was that of using actual musical excerpts, but, probably for some of the reasons discussed earlier, their I.P.A.T. never caught on. Rentfrow and colleagues (2011), very much aware of the need for an ecologically valid measure of music preference, decided to collect

94, 15 s long, musical excerpts that included 26 different music genres and subgenres. Crucially, these music excerpts were selected by five expert judges that worked independently to form a varied pool of music genres. Furthermore, the judges reached a consensus on whether each musical excerpt fit a certain genre out of all of the 26 music genres. Finally, all of the musical excerpts came from songs that were either unreleased or mostly unknown to the public. This was done to avoid any familiarity with the stimuli presented, as familiarity has been reported to increase music preference (Madison & Schiölde, 2017; Fischinger et al., 2020). These excepts were randomly presented to respondents who rated their liking of each of excerpt from 1 (*not at all*) to 9 (*very much*). The musical excerpts selected by Rentfrow and colleagues (2011) are considered by many to be a representative and ecologically valid set of stimuli in music preference research; as such, they have been used in many other research studies investigating music preference (e.g., Güçlütürk & Van Lier, 2019; Greenberg et al., 2016).

Although using musical excerpts as a measure of music preference is probably the best course of action (Brisson & Bianchi, 2020), there is also a sizable body of evidence that attests for the usefulness of the STOMP and STOMP-R. Interestingly enough, the same five-factor structure of the STOMP-R emerges when participants are asked to report their liking for genres and when they are asked to rate their liking for music excerpts (Rentfrow et al. 2011). Similarly, Langmeyer and colleagues (2012) found that self-reported preference for genres on the STOMP correlated to preference for musical excerpts of the same genre. Hence, despite the fact that genre-based measures of music preference may not be the most ecologically valid measure of music preference, they still seem to have some practical value as they can provide a quick and reasonably accurate measure of music preference.

On the Predictors of Music Preference

After about 20 years of research, we now know a lot about what predicts the music people prefer. The predictors that influence music preference span from the properties of music itself to broader dynamics such as the social and cultural context and the functions that music serves for the individual. In this section, I will provide a look at the various approaches in music preference research.

Intuitively, people might listen to music for different purposes; for instance, someone interesting in relaxing will probably choose to listen to classical music over heavy metal. Likewise, football players may listen to energizing music before a game instead of relaxing music. Chamorro-Premuzic and Furnham (2007) point out that people tend to listen to music for different reasons. Namely, they observed that music is generally used in three different ways: emotional use, which entails utilizing music to elicit or inhibit certain emotions; cognitive use, which entails listening to music and focus in the more complex aspects of a music piece such as the performance of single instruments and the overall structure of the piece; and background use, which involves listening to music while being engaged in a different activity such as working or studying. Incidentally, the way in which people utilize music predicts music preference, with background use of music being related to preference for music with a social and happy valence, and emotional use of music predicting preference for sad music (Chamorro- Premuzic & Furnham, 2010).

Music, however, cannot be relegated within the individual, as music listening often becomes a social activity that entails interaction with other individuals (O’Hara & Brown, 2006). Accordingly, in a study on an adolescent sample, North and Hargreaves (1999) report that participants held stereotypes about the normative characteristics of fans of a certain music style;

for instance, individuals who preferred classical music were perceived as more sophisticated and well-educated compared to fans of other music styles. Additionally, even genres themselves were considered to have some sort of intrinsic status, with British pop being rated as more prestigious than heavy metal. The authors explain that individuals seemed to prefer music styles of which the stereotypical fan matches their own self-concept, a psychological construct that involves the perception of the self and perception of oneself in relation to other individuals (North & Hargreaves, 1999; Rogers, 1951). This notion is supported by the finding that music preference correlates to how much people feel that a certain genre expresses their identity and values (Schäfer, 2009) and that music serves identity enhancing functions (King, 2017). A recent study puts further emphasis on the importance that identity has in regard to music preference as it reports that people are more likely to prefer artists whose personality or public "persona" resembles their own, a phenomenon known as the "self-congruity effect." This phenomenon causes a consumer to be more likely to support a product that conveys a congruous image to the consumer's self-concept (Greenberg et al., 2020; Japutra et al., 2019).

Very much related to the notion that music is a vehicle to express one's identity, Boer and colleagues (2013) surveyed six different cultures and found that strong national identity was invariantly associated with a preference for national music styles. Along the same lines, in a study on racial identity and music preference, it was found that Black participants lower in racial centrality, which refers to the extent to which race is considered an important determinant on one's identity Sellers et al., 1998), tended to have more positive rating for music associated with white American culture compared to Black participants higher in racial centrality (Marshall & Naumann, 2018). Similarly, music experience seems to differ to some degree across cultures. For instance, in a study comparing German participants, an example of individuals belonging to an individualistic culture, and Indian participants, who belong to a collectivistic culture, it was found that Indian participants put a higher value on music that emphasizes social connectedness and societal integration (Schäfer et al., 2012). Similarly, the preference for certain genres appears to be also culturally dependent, as, for example, Germans do not value folk/national music as much as Turkish people do (Tekman & Hortacsu, 2002).

Finally, there is a growing body of evidence documenting that music preference is influenced by age, as it appears to change across the lifespan (Greasley & Lamont, 2006; Hemming, 2013). In a study observing how music preference changes as a function of age it was found that music with contemporary styles and more intense sounds is liked less as age increases. Additionally, preference for jazz and "unpretentious" music styles such as country and pop increases with age (Bonneville-Roussy & Stillwell, 2017). Although normative changes in personality, psychosocial development, and changes in hearing have been proposed as a possible cause of music preference changes throughout adulthood (Bonneville-Roussy et al., 2013), there does not appear to be enough research to clearly understand how age influences music preference.

Another approach is that of analyzing the complexity of music excerpts, an approach that has also been applied in art preference research by measuring the complexity of an artistic display (Güçlütürk et al., 2016). The notion that complexity relates to preference of a certain stimulus was first proposed by Berlyne (1971), who noted that there seemed to be an "inverted U-shaped" relationship between complexity of an aesthetic display and reported liking such that liking would be positively correlated with complexity up to a certain level of complexity and then liking would eventually become negatively correlated with complexity if complexity kept increasing beyond a certain level. Although this inverted U-shaped relation between complexity and liking has been reported in some studies (Burke & Gridley,1990; Hunter & Schellenberg, 2011), there are at least an equivalent number of studies that report a different relation or even no relation at all between preference and complexity (North & Hargreaves, 1997; Russell 1987). A plausible reason for the conflicting findings in this line of research is that an objective and well-defined measure of complexity in music is almost impossible to obtain due to its elusive definition, and, as such, many researchers have utilized different measures (Güçlütürk & Van Lier, 2019).

A more reasonable approach that has been used to measure music complexity is that of a subjective aggregate rating provided by a large number of individuals (e.g., Madison and Schiölde, 2017). Utilizing this notion, Güçlütürk and Van Lier (2019) had 40 independent raters evaluate the complexity of several musical excerpts and then asked 353 participants to report their liking for each of the musical excerpts. At first, it transpired that liking had an inverted U-shaped relationship to complexity; however, after further analysis it became clear that participants could be divided into two groups: those who liked complexity and presented a positive correlation between preference and complexity, and those who disliked complexity and presented a negative correlation between preference and complexity. Although the researchers speculated on the possible individual differences that could account for this finding, they only put forward tentative explanation. Thus, complexity of a given music excerpt seems to have effects on preference, but this relation is still not well understood.

Personality and Music Preference

Personality is arguably the most researched predictor of music preference. In particular, the most popular model of personality used in music preference research is the FFM, which maintains that most of the breadth of personality is captured by five dimensions or traits:

Openness to experience (O), conscientiousness (C), extraversion (E), agreeableness (A), and neuroticism (N) (McCrae & Costa, 2008). Once again, the first tentative step in linking personality to music preference was taken by Cattel and Sounders (1954), who found that extraversion predicted preference for music with strong rhythm and fast tempo. Leading up to the turn of the century, only some sporadic attempts at uncovering a link between music preference and personality are recorded in the literature (e.g., Daoussis & McKelvie, 1986; Payne, 1980). It is only towards the late 1990s that this type of research started to gain popularity. Unfortunately, the research trying to link personality to music preference has produced lukewarm results at times, with most of the personality traits turning out to have a weak or nonsignificant relation with music preference (Schäfer & Mehlhorn, 2017). For example, neuroticism was found to be positively weakly related to preference for classical music in a handful of studies (Dunn et al. 2011; Delsing et al. 2008); yet, just as many studies found nonsignificant correlations between classical music and neuroticism (e.g., Zweigenhaft, 2008; Ferwerda et al., 2017). Similarly, conscientiousness and agreeableness make for negligible predictors of music preference (Schäfer & Mehlhorn, 2017).

The two most influential dimensions of personality in regard to music preference generally tend to be extraversion and openness to experience. For instance, Rawlings and Ciancarelli (1997) found that extraversion was positively correlated to preference for popular music (e.g., pop, pop rock, popular soundtracks). Sensation seeking or excitement seeking, a facet of the extraversion personality trait that has many names but is essentially the same construct with different labels (Zuckerman, 2010), has been found to consistently predict preference for arousing and intense music such as heavy metal (McNamara & Ballard, 1999). Still, it is not clear whether sensation seeking is what links extraversion to music preference as another research study could only find an indirect link between sensation seeking and music preference (Nater et al., 2005).

Openness to experience has been the most promising personality trait in the music preference research. Openness to experience, very much in line with what the label would suggest, is linked to preference for a wider array of musical genres (Rawlings & Cianciarelli, 1997), and it reached a .44 correlation to preference for genres such as classical, jazz, blues, and folk in Rentfrow and Gosling's (2003) study. Indeed, openness to experience is maybe the only personality trait that consistently yields significant correlations with music preferences for certain music styles (e.g., Vella & Millis, 2017; Dunn et al. 2012). An approach that surprisingly has not been very common is that of observing the different facets, which are specific, lower-level components of a personality trait (McCrea & Costa, 2003). Brown (2012) investigated the relation between music preference and the facets of openness and found significant correlations for almost all the facets of openness to preference for gospel, jazz, and opera music. However, Brown's (2012) study was conducted in a Japanese sample and used the HEXACO model of personality (Lee & Ashton, 2004), a model of personality that captures somewhat different aspects of personality compared to the FFM (Ashton & Lee, 2007; Christiansen et al. 2019). Zweigenhaft (2008) also examined the facets of openness to experience, yet the measure of music preference that he used was a self-report measure of music preference. Such measures, as I have explained, are sometimes not considered an ecologically valid measure of music preference. I am not aware of any study that has looked at facets of openness to experience as predictors of music preference measured by excerpts ratings. Hence, openness to experience certainly has promise as a possible important predictor of music preference and warrants a much closer look.

Openness to Experience

Openness to experience has been defined as the "breadth, depth, and permeability of consciousness, and in the recurrent need to enlarge and examine experience" (McCrae & Costa, 1997, p. 826). Although this definition is not very clear intuitively, openness to experience is a personality trait that is believed to encompass a staggering variety of aspects and characteristics. People high in openness to experience have been thought to be sensitive to aesthetic beauty, attracted by novelty, more accepting of cultural differences, intellectually curious, imaginative, and much more (Connelly et al., 2014).

Just like the long list of characteristics attributed to it, the trait openness to experience has a long history. Before it became widely recognized as fundamental component of the FFM (McCrae & John, 1992), many researchers had already observed it. As early as 1949, Fiske (1949) observed four stable components of personality, among which was one identified as Inquiring Intellect, an aspect of personality that is strongly related to openness to experience (DeYoung et al., 2014). Likewise, Norman (1963) identified five stable factors of personality while trying to create a taxonomy of personality and called one of them Culture, which, similarly to openness to experience, encompassed qualities such as artistic sensitiveness and reflectiveness. It was not until 1976 that two of the pioneers of the FFM, Costa and McCrae (1976), found that four scales of the Sixteen Personality Questionnaire (16PF; Cattell, Eber, & Tatsuoka, 1970)—intelligence (B), tender-mindedness (I), imagination (M), and liberal thinking (Q1)—tended to cluster together in some age groups (Costa & McRae, 1976). Informed by this observation, the authors went on to further research this cluster, ending up including the trait "openness to experience" in their revised version of the NEO personality inventory, a personality inventory that measures personality from a FFM point of view (NEO-PI-R; Costa & McCrae, 1992a).

Although openness to experience is better known as the factor O of the Big Five personality model, there are different questionnaires that measure openness to experience. However, whereas all these questionnaires purport to measure openness to experience, they all measure somewhat different dimensions of the openness to experience personality trait (Christensen et al., 2019).

Openness to experience in the Five Factor Model (FFM)

In the FFM, as in most models of personality, personality factors are characterized by facets, mutually exclusive covarying elements within of a domain (Costa & McCrae, 1995). Facets of personality traits emerge when factor analysis is applied to the questionnaire items that measure that personality factor. Accordingly, Costa and McCrae (1995) identified six facets of openness to experience when applying factor analysis to their measure of the five-factor model. It emerged that openness to experience could be divided into *fantasy* (O1), the tendency to have a prolific imagination; *aesthetics* (O2), the tendency to appreciate art and beauty; *feelings* (O3), the tendency to be empathic and value feelings; *actions* (O4), the tendency of seeking novel experiences; *ideas* (O5), the tendency of being interested in abstract ideas or concepts; and *values* (O6), which is related to political views and moral principles. A person who is high in openness to experience will score, on average, high on these six facets in a personality questionnaire.

Openness to experience in the HEXACO

The HEXACO model (Lee & Ashton, 2004) is a model of personality that, unlike the FFM, conceptualizes personality as six different dimensions rather than five. Although somewhat similar to the five-factor model, the HEXACO model includes honesty-humility (H), a factor that is mostly independent to any of the Big Five factor and that adds incremental predictivity validity over FFM personality measures in certain situations (e.g., Ashton & Lee, 2008). The questionnaire that measures personality according to the HEXACO model is called the HEXACO-PI (HEXACO-PI; Lee & Ashton, 2004).

The HEXACO model, and more specifically the HEXACO-PI, is particularly relevant because it includes its own conception of openness to experience (O). To be sure, openness to experience measured by the HEXACO-PI and by the NEO-PI are conceptually similar, having high reported correlations such as .76 (Gaughan et al., 2012) and .75 (Vries et al., 2009). Yet, the two measures of openness to experience appear to capture somewhat different aspects of personality; Christensen and colleagues (2019) analyzed four different inventories that measure openness to experience and identified 10 distinct “subdimensions” of openness to experience. The HEXACO version of openness to experience was related to narrower aspects such as intellectual interest and aesthetic appreciation, whereas the NEO-PI measure of openness to experience tended to have a broader yet different coverage of openness to experience compared to the HEXACO model (Christiansen et al., 2019).

The HEXACO version of openness to experience is made up of four facets: *Aesthetic appreciation*, one’s tendency to enjoy beauty and art; *Inquisitiveness*, one’s tendency to spontaneously seek information about the world; *Creativity*, one’s preference for innovation and experimenting; and *Unconventionality*, one’s tendency to accept or be attracted by the unusual.

The Present Study

Music preference research is a very diverse field, and it would be impossible to account for every predictor of music preference in a single study. Still, openness to experience appears to be a very promising predictor of music preference. Although there are studies that have empirically tested this link between music preference and openness to experience (e.g., Rentfrow & Gosling, 2003; Vella & Millis, 2017), specific facets of openness have been rarely looked at. Ashton and colleagues (2014) argue that facet-level scales can have increased predictive validity over factor-level scales when there is a strong conceptual link between the factor-level scale and the criterion variable. Given the empirical evidence reviewed, it seems very reasonable to assume that the link between openness to experience and music preference is a theoretically solid one; facets could then tell us much more about what informs this consistently reported link between openness to experience and preference for certain kinds of music.

Knowing more about music preference is inherently intriguing given that music listening is such a ubiquitous activity; as previously discussed in the introduction, many people listens to music daily. More narrowly, understanding how personality influences consumption of music has very clear commercial implications which could be employed by music streaming platforms to better tailor music experience toward consumers' personalities. Finally, knowing in what way openness to experience predicts music preference could broaden our understanding of openness to experience itself, a personality trait that encompasses a staggering number of aspects.

CHAPTER II: METHOD

Participants

I recruited participants through the psychology department pool using the Sona recruitment platform. Participants who took part in the study were required to be 18 years old or older and enrolled at Illinois State University (ISU). Participants received extra course credit for taking part in the study.

A total of 478 ISU students completed the study. As 104 participants either failed an attention check placed in one of the blocks of the survey (see *Procedure* section) or did not answer to a considerable amount of items (i.e., over 50% of the total items), only N = 374 participants were considered for data analysis. The mean age of the participants was M = 19.40 (SD = 1.56), ranging from 18 years of age to 34 years of age. A total of 327 (87%) participants identified as female, 42 (11%) identified as male, 2 (0.05%) responded with "other", and 3 (0.08%) declined to answer. Finally, 271 (72%) participants identified as White, 45 (12%) identified as Hispanic, 33 (9%) identified as African American, 7 (2%) identified as Eastern Asian, 4 (1%) identified as Indian Asian, 1 (0.30%) identified as Native American, 12 (3%) identified as "other", and 1 (0.30%) declined to answer.

Materials

Openness to Experience Facets

The facets of openness to experience according to the FFM were measured through the openness to experience subscale of the International Personality Item Pool (IPIP) measure of the FFM (60 items; Goldberg, 1990), a copyright-free measure of personality tailor made to resemble as closely as possible the NEO-PI-R (NEO-PI-R; Costa & McRae, 1992), one of the most popular personality measures of the FFM. Correlations between the IPIP and the NEO-PI-R are extremely high, reaching .94 once correlations are corrected for unreliability. Thus, the two tools are virtually parallel. The openness facets according to the FFM are measured with six subscales containing 10 items each: imagination ($\alpha = .83$), artistic interest ($\alpha = .84$), emotionality ($\alpha = .81$), adventurousness ($\alpha = .80$), intellect ($\alpha = .83$), and liberalism ($\alpha = .84$). The observed reliability for this measure of global openness to experience according to the FFM was $\alpha = .91$.

The HEXACO version of openness to experience was measured by the openness to experience subscale of the IPIP measure of the HEXACO personality model (40 items; Goldberg, 1990). Once again, the correlation between the IPIP measure of the HEXACO model and the HEXACO-PI (HEXACO-PI; Lee & Ashton, 2004), the measure created by the authors of the HEXACO model themselves, is extremely high. Even Ashton and colleagues (2007) themselves endorse the use of the IPIP version of the HEXACO-PI as an alternative to the HEXACO-PI. The openness to experience facets according to the HEXACO model are measured through four subscales containing 10 items each: aesthetic appreciation ($\alpha = .80$), inquisitiveness ($\alpha = .78$), creativity ($\alpha = .84$), and unconventionality ($\alpha = .78$). The observed reliability for this measure of global openness to experience according to the HEXACO model was $\alpha = .90$.

Music Preference Measures

The first measure of music preference was the STOMP-R (23 items; Rentfrow et al., 2011). As previously explained, the STOMP-R has been used in multiple studies and still remains a very popular and reasonably viable, although not perfect, measure of music preference. The STOMP-R utilizes a 7-point Likert scale to measure the preference for each of the 23 music genres presented (1 = *not at all*, 7 = *a great deal*). I expected to observe the same factor structure found by Renfrow and colleagues (2011): *Mellow* (electronica/dance, new age, world), *Unpretentious* (pop, country, religious), *Sophisticated* (blues, jazz, bluegrass, folk, classical, gospel, opera), *Intense* (rock, punk, alternative, heavy metal), and *Contemporary* (rap, soul/R&B, funk, reggae). The observed reliability for this measure was α = .84.

It is also important to include a more ecologically valid measure of music preference; as such, music preference was also measured by having participants listen to and report preference from 1 (*do not like at all*) to 7 (*like a great deal*) for twenty 15-s long musical excerpts used in Renfrow and colleagues (2011). The first four excerpts in term of factor loadings were selected for each music preference dimension (four excerpts for each dimension). I thought that using the four most representative musical excerpts of each dimension of music preference should have allow for an accurate re-creation of the five dimensions of music preference among respondents. The genre of these music excerpts has been categorized by 10 professionals in the music industry; furthermore, these musical excerpts are commonly used in other studies measuring music preference through musical excerpts rating (e.g., Güçlütürk & Van Lier, 2019). The observed reliability for this measure was α = .86.

Procedure

Students who participated in the study accessed a Qualtrics survey by clicking a link that was made available to all ISU students registered on Sona through the Department of Psychology. First, participants read the informed consent form and decided whether to accept it. If participants decided not to accept the informed consent, the survey ended immediately. Once the consent form was accepted, participants were asked to report their age, gender, and ethnicity. Then, participants were asked to complete the four blocks; these blocks were presented in a random order to prevent any order effect (4! possible orders). The first two blocks of questions involved completing the 60-item measure of openness to experience and its facets according to the FFM (block 1) and the 40-item measure of openness to experience according to the HEXACO model (block 2). The third block involved participants completing the STOMP-R to self-report their music preference (block 3). Finally, the fourth block involved participants listening to 20 musical excerpts utilized in Renfrow and colleagues (2011) and rating their preference for each of them from 1 (*Do not like at all*) to 7 (*Like a great deal*). Music excerpts from block 4 were presented in random order to every participant. At the end of these four blocks, participants were thanked for their participation in the study and informed about the study's purpose.

To increase the quality of collected data, an attention check was inserted in block 4, the music excerpts section. The attention check consisted of a 15 s audio clip instructing participants to select a specific number on the 1 to 7 Likert scale. Data from participants who failed to select the appropriate response required by the audio clip were discarded.

CHAPTER III: RESULTS

Factor Analysis

I conducted actor analysis was conducted to ascertain that the music factors for both the musical excerpts and the STOMP-R would replicate. I made this decision for two reasons. Firstly, as discussed above, the structure of music preference tends to be somewhat inconsistent, with researchers finding different numbers of music preference dimensions depending on the sample and the number of music genres observed. Additionally, music evolves over time, with new musical styles and genres constantly emerging; so it could be the case that, although Rentfrow and colleagues (2011) found five factors of music preference utilizing the same tools, music preference structure could have changed in the last 10 years.

Factors of both the musical excerpts and the STOMP-R were extracted utilizing principal-axis factoring (PAF). This factor analytic technique analyzes only the common variance among variables, as opposed to principal component analysis (PCA), which analyzes all of the variance among variables, common and not. Although Rentfrow and colleagues (2011) reported factors extracted by PCA, they also mentioned that the results were very similar to those extracted by PAF, so the two methods should not yield significantly different results. Similarly, Farbrigar and colleagues (1999) report that when the assumptions for PCA are met appropriately, PAF tends to perform just as well. To further clarify the factor structure of the data, a Promax rotation was utilized on the initial unrotated solution. Promax rotation is a type of oblique rotation that, unlike Varimax ration, does not assume that the extracted factors are orthogonal. Still, should the extracted factors be orthogonal, the Promax rotated factors will remain orthogonal and produce similar results to Varimax rotated ones (Finch, 2006).

To decide the number of factors to extract, parallel analysis (PA; Horn, 1965) was used first. PA generates a random sample that mimics the observed data both in number of observations and number of variables, and compares the eigenvalues of the correlation matrix of the two samples, original and randomly generated. According to PA's logic, only a number of factors equal to the number of larger eigenvalues in the observed data correlation matrix compared to the corresponding eigenvalues generated by the random data correlation matrix should be extracted. PA suggested to extract four components for the musical excerpts measure of music preference and five components for the STOMP-R. However, the factor pattern coefficients and the factor structures coefficients for both measures of music preference did not appear very interpretable and were far from what previously observed in the literature (Bonaville-Roussy et al., 2013; Rentforw et al., 2011). On the other hand, a more interpretable factor pattern was observed for both measures of music preference when five factors were extracted for the musical excerpts and six factors were extracted for the STOMP-R; this was suggested by Kaiser's criterion (Kaiser, 1960), which advises to extract factors equal to the number of eigenvalues larger than 1 in the data correlation matrix. Kaiser's criterion is generally considered inferior to PA (Breaken et al., 2017); yet, in this instance, Kaiser's criterion's decision appeared more appropriate. The factor analyses for the musical excerpts and the STOMP-R are displayed in Table 1 and Table 2 respectively.

PAF of the 20 musical excerpts revealed a rather clear five-factor structure of music preference (initial eigenvalues: 5.52, 2.57, 2.04, 1.72, 1.03), with only a few musical excerpts loading somewhat weakly on their dimension of music preference (i.e., Mountain Trek by Frank Joseph, and Braunschweig Polka by The Evergreen Production Music Library). Still, even the weakest loading excerpts remain the highest for their hypothesized dimension of music preference. It is fair to say that the results of Rentfrow and colleagues (2011) in regards to the dimensions of music preference measured by musical excerpts were replicated.

Table 1

Principal-axis Factoring Pattern Matrix for Each Factor for the Musical Excerpts

			Factors				
Artist	Piece	Genre	S	U	I	C	M
Ljova	Seltzer, Do I Drink Too Much?	Avant-garde classical	**.77**	.02	-.03	-.01	-.03
Various artists	La Trapera	Latin	**.71**	-.02	-.01	.02	.13
Various artists	Polka From Tving	Polka	**.69**	.16	.03	-.02	-.07
The Evergreen Production Music Library	Braunschweig Polka	Polka	**.46**	-.23	.07	.01	.33
James E. Burns	I'm Already Over You	New Country	-.11	**.80**	-.05	-.03	.06
Bob Delevante	Penny Black	New Country	.08	**.76**	-.04	.02	-.07
Babe Gurr	Newsreel Panoramica	Bluegrass	.16	**.64**	.04	.10	-.05
Five Foot Nine	Lana Marie	Country rock	-.04	**.65**	.05	-.11	.17
Squint	Michigan	Punk	.30	-.01	**.56**	-.01	-.14
The Tomatoes	Johnny Fly	Classic Rock	-.07	.03	**.79**	-.01	.06

(Table continues)

Table 1, continued

Artist	Piece	Genre	Factors				
			S	U	I	C	M
The Stand In	Frequency of a Heartbeat	Punk	-.09	-.02	**.82**	.04	.06
Five Finger Death Punch	Death Before Dishonor	Heavy Metal	.03	-.02	**.92**	-.05	-.07
Ciph	Brooklyn Swagger	Rap	-.06	.02	-.01	**.74**	-.08
Sammy Smash	Get the Party Started	Rap	.06	.06	-.03	**.73**	-.09
Mykill Miers	Immaculate	Rap	.16	-.02	-.02	**.40**	.13
Robert LaRow	Sexy	Europop	-.06	-.10	0.01	**.67**	.11
Walter Rodriguez	Safety	Electronica	.11	-.04	-.11	-.08	**.72**
Frank Joseph	Mountain Trek	Quiet storm	-.10	.22	.16	.12	**.39**
Taryn Murphy	Love Along the Way	Soft rock	.07	.14	-.02	-.04	**.59**
Bruce Smith	Children of Spring	Adult contemporary	-.04	.07	.04	.10	**.50**

Note. S = Sophisticate; U = Unpretentious; I = Intense; C = Contemporary; M = Mellow. These are the same labels used in Rentfrow and colleagues (2011)

The six factors extracted for the STOMP-R (initial eigenvalues: 5.92, 2.08, 1.72, 1.46, 1.37, 1.05) did not present the expected structure. Unlike the musical excerpts, the factor analysis of the STOMP-R did not replicate as well as the musical excerpts. This finding was extremely peculiar, as the extracted factors were rather different compared to those found by Bonneville-Roussy and colleagues (2013). Even though Bonneville-Roussy and colleagues opted for exploratory structural equation modeling (ESEM) instead of an exploratory factor analysis (EFA) such as PAF, it is unexpected that the factor structure would differ this much. Although more interpretable than the five-factor structure initially suggested by PA, the factor loadings of the STOMP-R factor analysis of this study are still quite different from the expected structure described in the method section. For instance, Factor IV very clearly captures preference for *gospel* and *religious* music exclusively, but these two items loaded onto two separate factors in Bonneville-Roussy and colleagues (2013). Similarly, Factor III only includes *bluegrass* and *folk*. These two genres were considered belong to the *sophisticated* dimension, yet here they loaded onto a factor of their own. Finally Factor I, which is the closest factor to the *sophisticated* dimension of music preference, includes *world* and *funk,* two items that should load onto other factors according to the previous research.

Table 2

Principal-axis Factoring Pattern Matrix for Each Factor for the STOMP-R

Genre	Factors					
	I	II	III	IV	V	VI
Alternative	-.07	**.48**	.25	-.15	.11	.02
Bluegrass	-.11	-.01	**.88**	.06	.00	-.11
Blues	**.50**	-.16	.40	.03	.12	-.03
Classical	**.90**	-.06	-.12	.02	-.23	.11

(table continues)

Table 2, continued

Genre	Factors					
	I	II	III	IV	V	VI
Rap/Hip-Hop	-.29	.00	-.19	.06	**.67**	.24
Country	-.40	-.05	.32	.09	-.13	**.43**
Dance/Electronica	.32	-.01	.01	-.06	.09	**.53**
Folk	.09	.03	**.69**	-.02	-.21	.08
Funk	**.46**	.19	.20	.00	.00	.14
Gospel	.13	.02	-.04	**.81**	.17	-.05
Heavy Metal	-.04	**.82**	-.05	.16	-.13	-.03
World	**.43**	.17	.18	.07	.06	.05
Jazz	**.65**	-.06	.10	.00	.18	-.06
New Age	.13	.19	.03	.07	.16	.07
Opera	**.77**	.05	-.07	.03	-.19	.03
Pop	.07	-.01	-.21	-.05	.28	**.52**
Punk	.12	**.79**	-.08	-.06	.04	-.01
Reggae	.09	.08	.31	-.11	**.41**	-.06
Religious	-.02	.01	.07	**.86**	.00	-.01
Rock	-.08	**.80**	.01	-.02	-.02	-.02
Soul/R&B	.00	-.04	.00	.09	**.63**	.04

Note. The “oldies” and “soundtrack” items were removed from the analyses because the authors of the STOMP-R suggested they did not load onto any factor.

Openness to Experience Predicting Music Preference

One of the main goals of this study was to observe the relation between both the openness to experience facets of the FFM and the HEXACO model of personality and music preference. Table 3 presents the descriptive statistics and correlations between the five dimensions of music preference measured by musical excerpt and the facets of openness to experience for both the FFM and the HEXACO openness to experience facets. In general, ratings of the *sophisticated*, *intense, contemporary,* and *mellow* dimensions of music preference were positively correlated with all of the openness to experience facets of the big-five model of personality. The HEXACO's openness facets showed a similar pattern, with aesthetic appreciation, inquisitiveness, and creativity also positively correlating with the *sophisticated*, *intense*, *contemporary*, and *mellow* dimensions of music preference. The HEXACO's unconventionality facet was positively correlated with only the *sophisticated*, *intense*, and *contemporary* dimensions of music preference. Finally, the *unpretentious* dimension of music preferences was uncorrelated with all the facets of openness to experience. The dimensions of music preference measured by the STOMP-R were not considered for this part of the analysis, as the factor structure that was extracted did not resemble the five-factor structure reported in the literature (e.g., Bonneville-Roussy et al., 2013; Rentfrow et al., 2011).

Table 3

Means, Standard Deviations, and Correlations Among the Five Dimensions of Music Preference Measured by Musical Excerpts and Openness to Experience Facets.

Variable	*M*	*SD*	1	2	3	4	5
1. Sophisticated	2.70	1.29					

(Table continues)

Table 3, continued

Variable	M	SD	1	2	3	4	5
2. Unpretentious	3.18	1.38	.16**				
3. Intense	3.45	1.61	.43**	.19**			
4. Contemporary	3.98	1.25	.26**	.03	.21**		
5. Mellow	3.57	1.21	.48**	.43**	.30**	.27**	
6. Imagination NEO	3.82	0.64	.14**	-.04	.21**	.18**	.13*
7. Artistic interest NEO	4.19	0.58	.20**	.02	.21**	.19**	.25**
8. Emotionality NEO	4.01	0.47	.14**	-.03	.19**	.20**	.18**
9. Adventurousness NEO	3.82	0.42	.14**	-.02	.24**	.23**	.15**
10. Intellect NEO	3.74	0.42	.17**	-.01	.27**	.25**	.17**
11. Liberalism NEO	3.65	0.39	.22**	-.06	.30**	.27**	.18**
12. Aesthetic Appreciation HEX	3.88	0.57	.24**	.03	.26**	.19**	.30**
13. Inquisitiveness HEX	3.42	0.60	.24**	.01	.26**	.22**	.16**
14. Creativity HEX	3.79	0.59	.10*	.00	.12*	.17**	.12*
15. Unconventionality HEX	3.13	0.59	.23**	-.06	.31**	.26**	.00

Note. M and SD are used to represent mean and standard deviation, respectively. * indicates p < .05. ** indicates p < .01. Big-five model of personality openness facets are marked as "NEO" and HEXACO model of personality openness facets are marked as "HEX".

The initial intent of the study was to run five multiple-regressions analyses with the five dimensions of music preference as the criterion variable and the 10 facets of openness to experience as the predictor variables for each regression. Unfortunately, the results of the multiple regressions presented beta coefficients with opposite signs compared to zero-order correlations (e.g., a negative slope between the criterion and the predictor variable even though the zero-order correlation between the two variables is positive). This is considered a red flag in multiple regression, and it generally indicates high correlation between the predictor variables (Daoud, 2017). This is condition that is generally referred to as multicollinearity and can cause and artificial inflation of the variance explained by the model (Alin, 2010).

To explore a possibility of multicollinearity between predictors, the tolerance was calculated for each of the predictor variables. The tolerance is calculated with the following formula $Tol = 1 - \mathrm{R}^2$, where R^2 represents the total variance that the other predictor variables explain in one predictor variable. Then, "Tol_j is a measure of the independence of X_i from the other regressors" (Darlington & Hayes, 2017, p. 109). Low tolerance implies that much of a variable's variance is already explained by other predictor variables, rendering low-tolerance variables redundant. Indeed, the tolerance for each of the predictor variables shown in Table 4 suggest strong multicollinearity. For instance, the *intellect NEO* facet of openness to experience has a tolerance of 0.03, meaning that only 3% of its variance is not already explained by other predictor variables. Unfortunately, strong collinearity between independent variables makes classical OLS regression techniques not suited for the analysis.

Table 4

Tolerance for the Intended Predictor Variables

Predictor Variable	**Tolerance**
1. Imagination NEO	.20
2. Artistic interest NEO	.15

(Table continues)

Table 4, continued

Predictor Variable	Tolerance
3. Emotionality NEO	.06
4. Adventurousness NEO	.03
5. Intellect NEO	.02
6. Liberalism NEO	.07
7. Aesthetic Appreciation HEX	.22
8. Inquisitiveness HEX	.40
9. Creativity HEX	.41
10. Unconventionality HEX	.68

Note. Big-five model of personality openness facets are marked as "NEO" and HEXACO model of personality openness facets are marked as "HEX".

Due to the collinearity among the 10 predictor variables, regression coefficients are not well suited to interpret the relative importance of each predictor (Graham, 2003). An analysis that has been popular in the organizational literature to evaluate the relative importance of predictor variables is Dominance Analysis (DA; Budescu, 1993). DA examines the unique contribution in variance explained by each predictor variable in a regression. This process is carried out by calculating the squared semi partial correlation that each predictor would add to any possible subset of regressions including any number of X_i predictors. For instance, if we had three predictors (X_1, X_2, X_3), DA would calculate the additional variance explained that each X_i predictor adds for each possible regression model with either 0, 1, or 2 of the other predictor variables as regressors, which would be any subset model with k-1 predictors. Then, according to Azen and Budescu (2003), three levels of dominance between any two sets of predictor variables can be established. *Complete dominance* of X_i over X_j is established when X_i's additional contribution to all subset models is greater than that of X_j. *Conditional dominance* of X_i over X_j is established when the average additional contribution of X_i across all models with *k* predictors is greater than that of X_j. Finally, *general dominance* of X_i over X_j is established when the average additional contribution of X_i across all possible subset models is greater than that of X_j. It is useful to note that complete dominance implies conditional dominance, which in turn implies general dominance. Therefore, one can view these three levels of dominance as being an ordinal scale of dominance strength, with complete dominance being the strongest dominance level. Although these three levels of dominance are central notions to DA, the applications and nuances of DA extend way beyond what discussed here. For additional information on how different levels of dominance are established, refer to Azen and Budescu (2006).

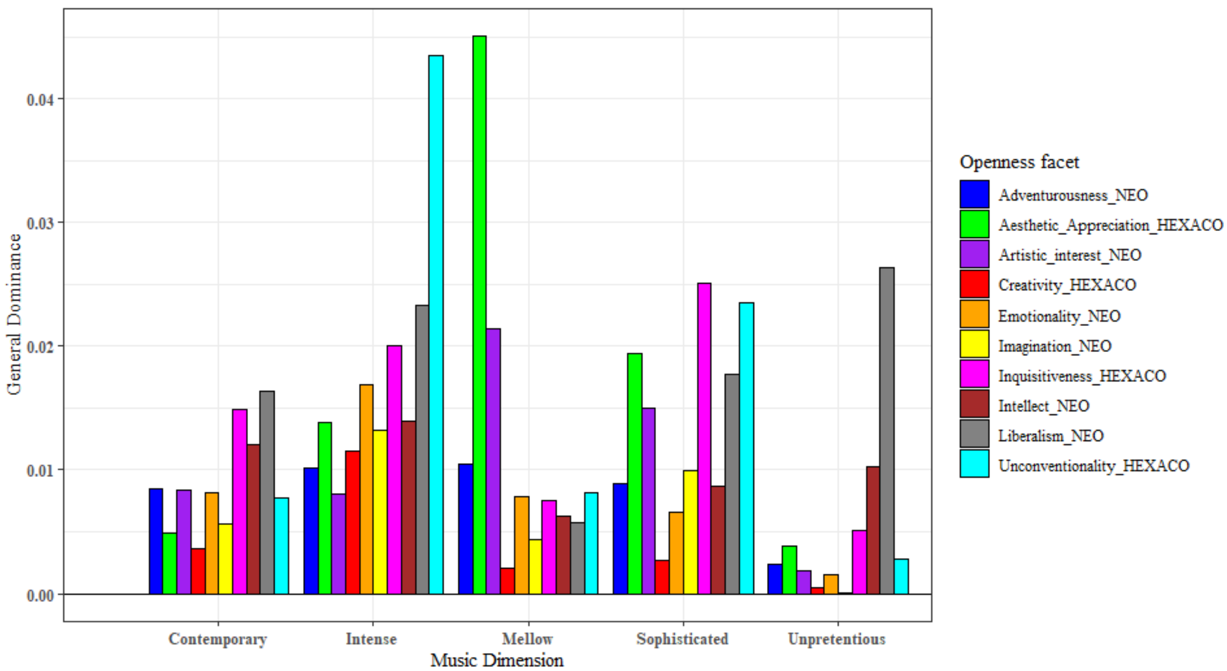
Figure 1 presents the general dominance indexes for the 10 openness to experience facets for each dimension of music preference measured by musical excerpts. As it can be seen, the most relevant predictor for the *intense* ($R^2 = .17$[1]) dimension appears to be the HEXACO's unconventionality facet. Not only did HEXACO's unconventionality show general dominance over the other openness facets in predicting preference for intense, but it also showed conditional dominance over the other facets. Similarly, HEXACO's aesthetic appreciation facet turned out to both generally dominate and conditionally dominate all other predictors for the *mellow* ($R^2 = .12$; see footnote 1) dimension. The liberalism facet of the FFM generally dominated all of the other facets and conditionally dominated all of the other facets except for HEXACO's unconventionality for the *unpretentious* ($R^2 = .05$; see footnote 1) dimension. HEXACO's inquisitiveness generally dominated all of the other facets for the *sophisticated* ($R^2 = .14$; see footnote 1) dimension, and conditionally dominated all of the other facets aside from FFM's

[1] Represents the total variance in liking for the music dimension explained by the multiple regression with all of the 10 openness facets as predictors.

imagination and HEXACO's unconventionality. Finally, the FFM liberalism facet generally dominated the other openness facets for the *contemporary* (R^2 = .09; see footnote 1) dimension, but no clear conditional dominance pattern could be established.

Figure 1

General Dominance Index of Each Openness Facet for Each Music Preference Dimension



Note. The Y-axis represents the facet general dominance index, which is the average R^2 increase that each facet contributes across all subset models with $k - 1$ predictors. The X-axis represents the openness facets clustered according to the five dimensions of music preference. Big-five model of personality openness facets are marked as "NEO" and HEXACO model of personality openness facets are marked as "HEXACO".

Latent Profile Analysis

The second purpose of this study was to explore whether latent profiles of music preference based on the five dimensions of music preference could be extracted from the data. Latent Profile Analysis (LPA) is a clustering technique that falls under the family of latent variable analysis techniques known as mixture modeling. The idea behind mixture modeling is that the distribution of one or more variables can be expressed as a finite subset of not-observed, latent distributions that are generally easier to understand (Masyn, 2013). In similar fashion, LPA starts from a dataset containing a number of variables for a given number of people and attempts to uncover a number of “profiles”. These profiles are based on common patterns that participants display on the variables under observation. Then, based on the observed patterns, LPA estimates both how many of these common patterns, or profiles, are likely to exist and the probability of each participant to belong to each of the estimated profiles (Spurk et al., 2020). These profiles are referred to as “latent” because they are not directly observable and have to be inferred through LPA.

The LPA was carried out using `tidyLPA` (Rosenberg at al., 2018), a freely available R package the serves as a front end for the more popular latent variable clustering R package `mclust` (Scrucca et al., 2016). The first step in LPA is to specify the nature of the variances and covariances of the latent profiles to be estimated. The estimated variances for the profiles can either be specified to be equal across all profiles or to be varying across all profiles. The covariances can either be specified to be 0 across all profiles, meaning that the estimated profiles should be independent from one another, or varying across all profiles, meaning that the profiles are allowed to covary. Since there is no previous literature on LPA applied to music preference, meaning that there is no information on the nature of the latent profiles, the variances and covariances of the estimated profiles were allowed to vary freely for all the profiles. This is considered the least restrictive specification for profile’s variances and covariances (Masyn, 2013). Then, models having between 1 and 10 latent profiles were estimated. Although, the optimal model could conceivably contain more than 10 latent profiles, the ease of interpretation and usefulness of such a model seems somewhat questionable, hence the more parsimonious approach was chosen.

As with the vast majority of analyses dealing with latent variables, it is important to test how well the extracted latent variables fit the data, a process that is generally carried out by evaluating various fit statistics. A fit statistic is a statistic that essentially tests how well the chosen model describes the data it was derived from. In the case of this LPA, the fit statistics that had the highest weight in the decision of the appropriate latent profile model were the Bayesian information criterion (BIC; Schwarz, 1978), the sample adjusted Bayesian information criterion (SABIC; Sclove, 1987), and the bootstrapped likelihood ratio (BLRT; McLachlan, 1987). Both the BIC and the SABIC are fit statistics that consider the overall fit of the model to the data while emphasizing parsimony over pure model fit. These two statistics are useful because they apply a penalty for each parameter, or in this case profile, that is added to the model. Because model fit virtually always increases when a parameter is added, the BIC and the SABIC attempt to discourage the additions of parameters that would only yield a marginal increment in model fit (Masyn, 2013). Lower BIC and SABIC indicate better fit to the data; however, the difference between the BIC and the SABIC is that they apply a different penalty based on the number of parameters, with that of the BIC being more restrictive than the SABIC (Kenny, 2015). The BLRT is a statistic that compares the overall fit of a model with a k number of latent profiles to the model with $k - 1$ latent profiles; if the model with k latent profiles presents a significant improvement in fit over the model with $k - 1$ latent profiles, the BLRT p value will be significant. The BLRT is calculated by comparing the log-likelihood (LL) of a model, which is a general measure of model fit, to that of another model. Although higher LL implies better model fit, the BLRT evaluates whether the LL increase is significant enough to warrant the inclusion of an additional parameter, or in this case profile. This process has to be done because the LL by itself cannot be interpret, as the inclusion of an additional parameter always yields a better LL compared to the model with one less parameter. It is important to note that there is a wide range of fit statistics utilized for model selection in LPA, and there is no consensus on which ones are the most reliable for model selection (Grimm et al., 2017). The three fit statistics that were used for model selection in this paper were suggested by Tein and colleagues (2013), who noted that BIC, SABIC, and BLRT tend to select the appropriate number of profiles more reliably than other widely utilized fit statistic in the majority of circumstances. Entropy is also reported in Table 5; this measure indicates the a posteriori probability that each individual was correctly assigned to the profile they were assigned to. This measure ranges from 0 to 1, with 1 meaning complete confidence that participants were assigned to the correct profiles. However, entropy has been found to be a poor predictor of the appropriate number of profiles (Tein et al., 2013), and should only be strongly considered as a red flag if its value is close to 0 (Masyn, 2013). Therefore, entropy is purely reported to better describe the nature of the latent profiles.

Table 5

Fit Indices for Latent Profile Analysis of the Five Dimensions of Music Preference Measured by Musical Excerpts

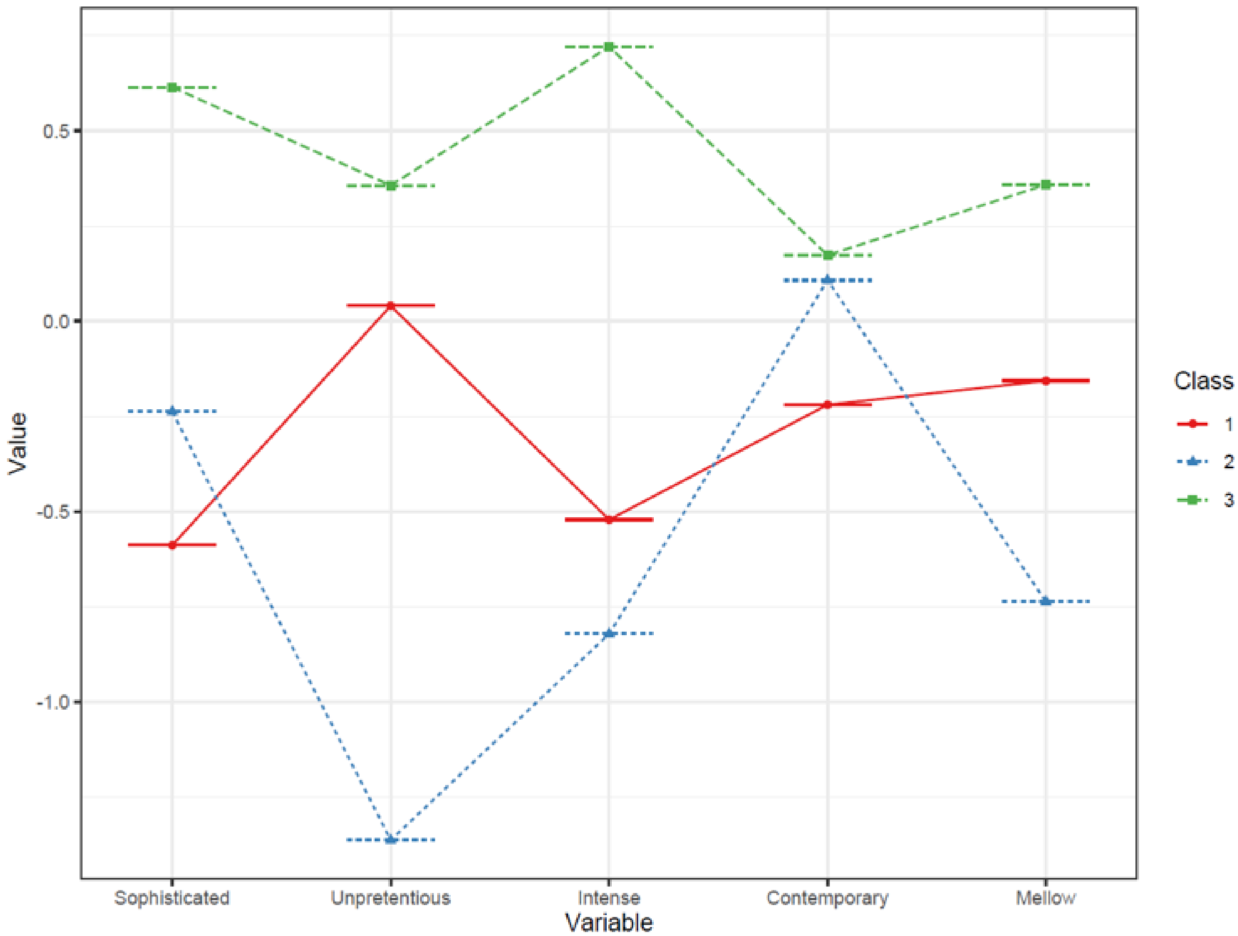
Number of Profiles	LL	BIC	SABIC	BLRT val	BLRT p	entropy
One	-2497.10	5112.69	5049.23	N/A	N/A	1
Two	-2447.88	5138.65	5008.57	98.45	<.01	0.86
Three	-2401.13	5171.56	4974.85	91.5	<.01	0.74
Four	-2380.82	5253.35	4990.01	42.62	0.32	0.76
Five	-2354.82	5325.76	4995.80	52	0.29	0.79

Note. LL = log likelihood; BIC = Bayesian information criterion; SABIC = sample adjusted Bayesian information criterion; BLRT val = bootstrapped likelihood ratio value; BLRT *p* = bootstrapped likelihood ratio *p* value.

The model that was selected was the one with three latent profiles. The fit statistics for models with 1 to 5 profiles are shown in Table 5. Fit statistics for models with 6 to 10 profiles are not displayed due to no significant improvement over models with a smaller number of profiles. As shown in Table 5, the BLRT suggests that the model with three latent profiles shows an improvement over both the models with one and two latent profiles. However, the model with four latent profiles does not improve over the model with three latent profiles. On the other hand, the BIC suggests a one-latent-profile model, whereas the SABIC suggests a three-latent-profile model. Still, the model with three latent profiles was favored for two reasons. Firstly, the BIC can be extremely restrictive and underestimate the appropriate number of latent profiles (Yang, 2006). More practically, a model with a single latent profile, aside from likely being uninteresting, would have no practical use. Then, I decided to value the SABIC's suggestion, which generally appears to perform similarly to the BIC (e.g., Tein et al., 2013; Yang, 2006). The estimated profiles and the estimated number of each participants for each latent profile are displayed in Figure 2.

Figure 2

Standardized Profiles for the Three Latent-Profile Solution



Profile 1: 161 **Profile 2:** 54 **Profile 3:** 159

Note. Dimensions of music preference are displayed on the X-axis, which is labeled as "Variable". The Standardized preference ratings for each dimension of music preference are displayed on the Y-axis, which is labeled as "Value". The estimated number of participants for each profile is displayed right below the graph.

After profile estimation, LPA computes the probability of each participant to be in each profile and assign profile membership accordingly. As a result, 161 (43%) participants were assigned to Profile 1; 54 (14%) participants were assigned to Profile 2; and 159 (43%) participants were assigned to Profile 3. Participants belonging to Profile 1 had a preference for the *Unpretentious* music dimension, somewhat dislike music from the *Contemporary* and *Mellow* dimensions, and dislike music from the *Sophisticated* and *Intense* dimensions.

Participants belonging to Profile 2 liked music from the *Contemporary* dimension, somewhat dislike music from the *Sophisticated* dimensions, dislike music from the *Mellow* and *Intense* dimension, and strongly dislike music from the *Unpretentious* dimension. Finally, participants belonging to Profile 3 presented higher general liking of all the music dimensions compared to the other two profiles, with *Sophisticated* and *Intense* being the two preferred music dimensions. To test whether the estimated latent profile differed in music preference across music dimensions, a multivariate analysis of variance (MANOVA) was computed. The mean preferences for music dimensions differed highly significantly across the three profiles, Wilk's $\Lambda = .25$, $F(10, 732) = 73.89$, $p < .001$. I tested whether the latent profiles differed significantly in general openness to experience measured by the FFM and the HEXACO. Only differences in openness to experience as a whole were tested, as it would be cumbersome to present pairwise comparisons between profiles for all of the 10 openness facets. The three profiles were highly significantly different in openness measures, Wilk's $\Lambda = .92$, $F(4, 726) = 7.39$, $p < .001$. Bonferroni pairwise comparisons for FFM's openness to experience across the 3 profiles show that participants assigned to Profile 3 ($M_{\text{FFM}} = 3.95$, $SD_{\text{FFM}} = 0.45$) were significantly higher in openness than participants assigned to Profile 1 ($M_{\text{FFM}} = 3.80$, $SD_{\text{FFM}} = 0.43$), $\Delta M_{\text{FFM}} = 0.15$, $p = .007$, 95% CI [0.03; 0.27]. On the other hand, neither Profile 1 nor Profile 3 mean FFM openness to experience was significantly different than that of participants assigned to Profile 2 ($M_{\text{FFM}} = 3.84$, $SD_{\text{FFM}} = 0.43$). Bonferroni pairwise comparisons for HEXACO'S openness to experience yielded similar results; participants assigned to Profile 3 ($M_{\text{HEXACO}} = 3.66$, $SD_{\text{HEXACO}} = 0.42$) were significantly higher in HEXACO openness to experience than participants in profile 1 ($M_{\text{HEXACO}} = 3.42$, $SD_{\text{HEXACO}} = 0.42$), $\Delta M_{\text{HEXACO}} = 0.25$, $p < .001$, 95% CI [0.12; 0.36]. Just like with FFM's openness, participants assigned to Profile 2 ($M_{\text{HEXACO}} = 3.54$, $SD_{\text{HEXACO}} = 0.44$) did not significantly different in mean HEXACO's openness to experience compared to participants assigned to Profile 1 or Profile 3. It is no surprise that general openness measured by the FFM and the HEXACO yielded similar results in this case, because the two inventories were highly correlated, $r = .81$.

To further explore the nature of the profiles, a χ^2 test of association was computed to test whether there was an association between profile membership and ethnicity. Only participants who reported "White," "Hispanic," and "African American" as the ethnicity they identified with were observed. I chose not to include participants who identified with other ethnicities due to low representation in the sample (i.e., fewer than 10 participants per ethnicity). Table 6 displays the cross tabulation of observed proportions for profile membership and ethnicity. Among the participants who identified as "White", 49% were in Profile 1, 7% were in Profile 2, and 44% were in Profile 3. Among the participants who identified as "Hispanic", 27% were in Profile 1, 24% were in Profile 2, and 49% were in Profile 3. Among the participants who identified as "African American", 33% were in Profile 1, 58% were in Profile 2, and 9% were in Profile 3. These frequencies presented a highly significant association between profile membership and ethnicity, χ^2 (4, N = 349) = 70.03, $p < .001$.

Table 6

Cross Tabulation of Profile Membership and Ethnicity

Profile	**Ethnicity**			
	White	Hispanic	African American	Total
1	132 (85.16%)	12 (7.74%)	11 (7.1%)	155
2	20 (40%)	11 (22%)	19 (38%)	50
3	119 (82.64%)	22 (15.28%)	3 (2.08%)	144

(Table continues)

Table 6, continued

Profile	**Ethnicity**			
	White	Hispanic	African American	Total
Total	271	45	33	349

Note. Numbers in parentheses represent the percentage of the ethnicity in each profile.

CHAPTER IV: DISCUSSION

Summary of Findings

The primary objective of this study was to explore the relation between openness to experience facets measured by both the FFM and the HEXACO model of personality and music preference measured by musical excerpts ratings and the STOMP-R. The reported 5-factor structure of music preference was not replicated by the STOMP-R, so only musical excerpts ratings were considered to be a valid measure of music preference for the analysis. This means that measuring music preference through musical expert ratings may be more appropriate. The correlation matrix between music preference dimensions and openness to experience facets revealed that all of FFM openness to experience were positively correlated with preference for the *sophisticated*, *intense*, *contemporary,* and *mellow* dimensions of music preference. The HEXACO openness to experience facets also tended to show the same correlation pattern with music preference dimensions (i.e., positive correlations with *sophisticated*, *intense*, *contemporary,* and *mellow*). Due to multicollinearity among the 10 openness facets, DA was used to interpret the importance of the single openness facets as predictors of the five dimensions of music preference. HEXACO's unconventionality conditionally dominated all the other openness facets when predicting preference for *intense* music, suggesting that HEXACO's unconventionality might be the best predictor of preference for *intense* music. HEXACO'S aesthetic appreciation conditionally dominated all of the other openness facets when predicting *mellow* music, maybe suggesting that artistically receptive individual prefer more relaxing music. FFM's liberalism conditionally dominated all of the other facets aside from HEXACO's unconventionality when predicting preference for *unpretentious* music. However, FFM's liberalism appeared to be much higher in general dominance compared to HEXACO'S conventionality. Then, it may be that FFM's liberalism is the most important openness facet in explaining variance in preference for *unpretentious* music. No definitive conditional dominance relation among the openness facets could be established when predicting *contemporary* and *sophisticated* music. However, the openness facets as a whole explained more variance in preference for *sophisticated* music (R^2 = .14) than in *contemporary* music (R^2 = .09), implying that openness to experience better predicts preference for *sophisticated* music compared to preference for *contemporary* music.

The second objective of this study was to uncover latent profiles of music preference through LPA. The latent profile solution that was chosen was a three-profile one, with model specifications of varying variances and varying covariances across profiles. This choice was informed by the BIC, SABIC, and BLRT, three fit statistics that are used to evaluate how well the model fits the data. To test the mean differences in music preference dimensions across profiles, a MANOVA was computed. The profiles turned out to be highly significantly different across mean preference for the five music preference dimensions, implying that the three profiles described distinct patterns of music preference. To test the effect of profile on openness to experience levels, a MANOVA was computed to test whether the three profiles significantly differed in general openness measured by the FFM and the HEXACO. Profile 3 was significantly higher in both measures of openness to experience compared to Profile 1. This finding could imply that openness to experience levels could be tied to patterns of music preference. Finally, the χ^2 test of association that was computed revealed a highly significant association between profile membership and ethnicity. This implies that ethnicity, probably through the cultural experience that are tied to ethnicity, can shape one's patterns of music preference.

General Discussion

The five dimensions of music preference reported in Rentfrow and colleagues (2011) were recreated only for music preference measured through musical excerpts. Surprisingly, PAF applied to the STOMP-R did not extract a cohesive five-factor solution like the one of Bonneville-Roussy and colleagues (2013). This specific finding could hold really important implications for the field of music preference as a whole. Namely, the STOMP-R not being able to recreate the expected dimensions of music preference bolsters the arguments of those who maintain that genre-based measures of music preference lack in ecological validity (e.g., Brisson & Bianchi, 2020). Although unexpected, this finding could make sense if one takes into account the subjectivity that comes with music genre labels. It is possible that participants at the time of this study (2021), have different conceptions of what the music genres of the STOMP-R represent compared to the participants in Renfrow and colleagues (2011) and Bonneville-Roussy and colleagues (2013). For instance, in the Bonneville-Roussy and colleagues (2013) study, the *gospel* item was considered to belong to the *sophisticated* factor and the *religious* item was considered to belong to the *unpretentious* factor. On the other hand, the PAF of the STOMP-R in this study (Table 2) revealed a really clear factor that encapsulated the *gospel* item and the *religious* item exclusively. Then, it seems that participants in Bonneville-Roussy and colleagues (2013) viewed gospel and religious music as being distinct musical styles, whereas participants in this study view them as being very similar musical styles. Although factor analysis can present some subjectivity in the choice of the number of factors to be retained (Horn, 1967), the Promax rotated loading of the *gospel* item and the *religious* item were respectively .81 and .86 on Factor IV; the extraction of such a strong and clear factor hints at a qualitatively different factor solutions than what was previously observed in the literature.

Aside from the possibility of a different subjective interpretation of music genre labels, it is also possible that some of the participants did not recognize some of the genres presented in the STOMP-R. For instance, it seems intuitively possible that genres such as *world music* and *new age* may not be as familiar to participant as something like *pop* or *rock*. If that was the case, ratings of music genres that participants are not very familiar with may not be meaningful. This possibility is clearly not present when music preference is measured by musical excerpts ratings as participants merely report how much they like the music excerpt they listened to, which is something that does not require knowledge about the genre of the musical excerpt.

In contrast to these possible issues with the STOMP-R, the factor analysis of the musical excerpts extracted 5 reasonably clear factors. The musical excerpts that were used to measure these factors were among the same one used by Renfrow and colleagues in 2011; even after 10 years, the same musical excerpts seemed to retain their validity in measuring music preference. Then, the results of these two factor analyses present a stark contrast between genre-based measures of music preference and musical excerpts ratings measures of music preference, with musical excerpt measures appearing to be the most appropriate one. This finding corroborates some of the concerns about the use of genre-based measures of music preference (Brisson & Bianchi, 2020; Oramas et al., 2018).

As previously mentioned, all of the openness to experience facets of the FFM model had significant positive correlations with all of the dimensions of music preference but the *unpretentious* one. HEXACO's openness to experience facets showed an extremely similar pattern. These similarities across openness facets are probably due to the sizeable degree of multicollinearity among the variables. Although it is probably unreasonable to maintain that DA solves the issue of multicollinearity between predictor variables altogether, there are researchers who consider it a reasonable method to explore the relative importance of variables when multicollinearity is present (e.g., Gluschkoff et al., 2022; Tighe & Schatschneider, 2014), as DA tends to de-emphasize the effect of redundant predictors (Kraha et al., 2012). Thus, the results of the DA aid in interpreting the relation between the dimensions of music preference and the facets of openness to experience. For, instance the liberalism facet of the FFM showed both general and conditional dominance over other predictors for the *unpretentious* dimension. This means that liberalism was the predictor that explained the most variance in preference for *unpretentious* music by a reasonable margin. Although DA does not show the direction of the relation between a predictor and a criterion because all of the values it generates are squared semi-partial correlations, it is more likely than not that the liberalism facet of openness negatively predicts liking for unpretentious music when other openness facets are controlled for. Indeed, in the literature it is often reported that openness to experience is negatively correlated with preference for *unpretentious* music (e.g., Langmayer et al. 2012; Rentfrow & Gosling, 2003). Likewise, liking of *unpretentious* music was also negatively correlated with liberal political views in Rentfrow and Gosling (2003). Then, a possible interpretation of what the DA for *unpretentious* shows is that the liberalism facet of openness to experience might be the driving facet behind the relation between openness to experience and *unpretentious* music that is observed in the literature.

Another interesting result of the DA was the conditional dominance of HEXACO's unconventionality over the other predictors for *intense* music. This finding makes sense if one looks at the literature that associates preference for rock music and heavy metal music, two genres represented in the *intense* dimension measured in this study, to rebelliousness and negative attitudes toward authority (Bleich et al., 1991; Swami et al., 2013). Indeed, some of the items that measured HEXACO's unconventionality were "I rebel against authority," and "I swim against the current," which seem to tap into rebelliousness and authority defiance. This finding is also rather interesting because it might show that HEXACO's openness to experience, or more specifically the unconventionality facet, relates to music preference in a way that FFM's openness does not. In fact, HEXACO's unconventionality may be the most unique of all the openness to experience facets in predicting music preference as its tolerance was the highest in Table 4.

The DA also suggested that preference for the *mellow* dimensions is mostly predicted by HEXACO's aesthetic appreciation. This finding is harder to interpret, but it could be that people who are artistically receptive may prefer more calming and relaxing music, which is captured by the *mellow* dimension. Literature that examines the possible link between aesthetic appreciation and liking for relaxing music is very scarce, but a recent study by Baltazar and Västfjäll (2020) could provide some insight on this matter. The two researchers reported that participants consistently rated relaxing music much higher in perceived aesthetic value/beauty compared to non-relaxing music. So, it seems possible that participants who are higher in aesthetic appreciation tend to prefer relaxing music, as its perceived features are more congruous with participant's personality.

Finally, it was not possible to establish clear conditional dominance for any of the openness facets predicting preference for the *sophisticated* and *contemporary* dimensions. However, the key difference is that the 10 openness facets appear to explain a sizably larger proportion of variance in the *sophisticated* dimension (R^2 = .14) than in the *contemporary* dimension (R^2 = .09). Then, it appears that openness facets as a whole, which would be general openness to experience, are better at predicting preference for the *sophisticated* dimension. On the other hand, it may be that openness facets in general are not good predictors of preference for the *contemporary* dimension. This is also the case in the literature, where openness to experience is reported to correlate to preference for *sophisticated* music much more reliably than preference for *contemporary* music (e.g., Dunn et al., 2011; Rentfrow and Gosling, 2003; Vella & Mills, 2017). One of the proposed mechanisms by which openness to experience relates to higher preference for *sophisticated* music could be the use that people make of music. Vella and Mills (2017) reported that the relation between openness to experience and liking of *sophisticated* music was mediated by cognitive use of music, the act of listening to music to appreciate composition complexity and technical execution. The *sophisticated* dimension of music preference encompasses music that tends to be a good deal more complex than other music dimensions, making it well suited for cognitive use. On the other hand, *contemporary* music might not lend itself to cognitive use as well as *sophisticated* music. This comparison of the DA results for the *sophisticated* dimension and *intense* dimension would be in line with previous findings.

The highly significant difference of the three profiles in mean music dimension preference lends support to the notion that the three estimated profile are meaningfully different from each other. This result is important, as it would be of little practical usefulness to estimate profiles that are not significantly different from each other. The three profiles estimated by the LPA provided some interesting results. The majority of the sample was estimated to be either in Profile 1 or Profile 3, with Profile 2 presenting the lower number of participants. Aside from the between differences in music preference for the three profiles, it can be seen that participants belonging to Profile 3 tend to be higher in liking for every music preference dimension than both of the other latent profiles. This could be interpreted as participants of Profile 3 being more interested in music and appreciative of music as a whole, no matter the genre. On the other hand, participants in Profile 1, given their average or below average liking scores for every music preference dimensions, could be thought as more “casual” listeners. Given the preference for unpretentious music, which in this study was comprised of country music and derivative genres, and more pronounced distaste for sophisticated and intense music, participants belonging to Profile 1 may prefer to listen to something simple (unlike classical music) or more neutral sounding (unlike heavy metal).

The most unique pattern of music preference was captured by Profile 2. Participants in Profile 2 expressed a clear preference for the contemporary music dimension, which in this study was mostly rap and *R&B* music, and a general dislike for other music dimensions, with the unpretentious dimension being strongly disliked. The pairwise comparisons for openness to experience showed that participants in Profile 3 were higher in mean openness to experience than participants in Profile 1. Incidentally, participants in Profile 3 were consistently higher in liking for all of the music dimensions. This can probably be interpreted as participants higher in general openness to experience being more appreciative of music as a whole. In support of these interpretation, it has been observed that people higher in openness to experience are more likely to experience awe-like feelings when listening to music (Silvia et al., 2015), rate unfamiliar pieces of music higher than people lower in openness to experience (Hunter & Schellenberg, 2011), and tend to appreciate a wider range of musical styles (Rawlings & Cincarelli, 1997). The association between profile membership and ethnicity was another very intriguing finding. As shown by Table 6 and by the χ^2 test of association, a significant proportions of participants in Profile 2 were African American. Similarly, a good proportion of the Hispanic participants were assigned to Profile 3. Then, ethnicity seems to have some connection to music preference patterns. However, this finding should not be interpreted as ethnicity itself shaping music preference patterns; rather, it would be much more logical to maintain that the cultural experience that is inevitably tied to ethnicity (Worrell, 2015) should be considered the main agent by which music preference is shaped. One possible issue with this assumption is that I did not measure “culture” directly, but rather asked participants to report their “ethnicity”. Still, I believe it reasonable to assume that there should be a good degree of overlap between the two constructs for most of the participants in this study, meaning that “ethnicity” should serve as a reasonably good, yet not perfect, proxy measure for “culture”. Finally, Although many studies already reported this link between culture and music preference (e.g., Marshall & Naumann, 2018; McDermott et al., 2016), the findings of this study are slightly different. So far, the literature on music preference has shown that there is a solid connection between culture and music preference measured either by musical excerpts, music labels, or music dimensions; however, this study goes beyond that, and suggests that distinct patterns of music preference (i.e., latent profiles), and not preference for a single music dimension or a genre alone, could be tied to culture.

To conclude this section, I believe it relevant to comment on the nature of statistical models. As George Box famously wrote, “all models are wrong, some are useful” (1976, p. 792). This quote perfectly illustrate how it is virtually impossible, especially in Psychology, to construct a model that perfectly captures and predicts a phenomenon or behavior. Yet, interesting insight can still be gained from a “wrong” model. Along the same lines, the three latent-profile model of music preference shown in this study is most certainly “wrong” in the sense that is not the perfect model, and there surely is a set of latent profiles that better describe music preference patterns. Still, the results remain interesting in virtue of the significant differences in music preference dimensions across profiles, the differences in general openness to experience, and the significant association between profile membership and ethnicity (i.e., culture).

Limitations

The findings of this study come with many limitations. Firstly, the sample utilized was fully made up of undergraduate Psychology college students. A sample of undergraduate college students is very likely mostly Western, educated, industrialized, rich, and democratic, a type of convenience sample that is known in the psychological literature as the WEIRD sample. The sample used in this study clearly presents some of these features, as 72% of the participants were "white" and the entirety of the sample was made up of educated college students. Some researchers rightfully point out how it is generally unreasonable to generalize studies who only focus on a WEIRD (Henrich et al., 2010). Personally, I echo these concerns. There is no guarantee that the findings of this study will generalize to populations who present different characteristics compared to a WEIRD sample.

Another potential issue related to the sample is the strong prevalence of White participants and the underrepresentation of other ethnicities. Although it was reported that a significant association between ethnicity and profile membership had been observed, this finding could possibly be due to the low number of participants holding minoritized identities in the study. More specifically, participants holding minoritized identities may have presented some specific music preference patterns that are not actually representative of the ethnic group they belong to. As it is generally the case in psychology, a large sample is always advised to increase the chances of reasonably represent a population's characteristics. This may not be the case for the population holding minoritized identities in this study, which was rather small. A more racially and ethnically diverse and balanced sample, or even a sample comprised mostly of a specific race and ethnicity, would be needed to further support the relation between ethnicity and musical preference patterns that was observed in this study.

As discussed in the *Introduction* section, the number of observed dimensions of music preference often varies depending on the diversity of the measurement used. In this case, the excerpts that were used included a somewhat limited group of music genres. Then, every time that music preference is mentioned in this study, one has to keep in mind that what was actually measured was preference for 20 musical excerpts. There clearly are inherent limitations that come with the attempt to measure something as broad as music preference. The 20 excerpts used in this study could never be fully representative of the *true* structure of music preference, a music preference structure that would have to take into account and keep up with all the possible music genres that exist and will be developed in the future.

DA analysis is a very useful tool to look at the relative importance of predictors. Still, one of the limitations of DA for this particular study is that it is not possible to use it to establish the direction of the relation between predictor and criterion. This direction can be hypothesized through scrutiny of the previous literature, but this method is still somewhat inferior to actually having some interpretable regression coefficients. Unfortunately, due to predictor multicollinearity, this was not possible.

The results of the LPA also need to be interpreted with caution. It is important to keep in mind that, in general, the implementation of such mixture modeling approaches tends to be a purely exploratory procedure. This happens for many reasons, one of them being the complex post-hoc fine tuning required to properly implement mixture modeling on a set of data and another being the lack of use of mixture modeling approaches in the research area. Indeed, researchers who utilize techniques such as LPA, for example, are seldom able to reasonably hypothesize a priori how many latent profiles they expect to observe. The main decision on the number of profiles is based on the observations of fit statistics and theoretical implications, two practices that involve a reasonable degree of subjectivity. Then, mixture modeling approaches could be exacerbating the issue of “researcher degrees of freedom” mentioned by Simmons and colleagues (2011), where scientific results are hard to replicate due to excessive freedom in data collection, data analysis, and reporting. Given the lack of agreed-upon guidelines on how to approach LPA, this might be a case where a replication study could be extremely useful. Observing a similar latent profile solution for music preference patterns in a different sample would probably be the best way to corroborate the findings of this study.

Theoretical and Practical Implications

The results of this study have some important implications for the music preference research field. The most important finding that transpired from the factor analyses is that researchers should be wary of deciding to measure music preference with genre-based measures. On the other hand, measuring music preference with musical excerpts appeared to be a very solid way to measure music preference, as the same factor structure observed 10 years ago in Rentfrow and colleagues (2011) was replicated. In line with other researchers (i.e., Brisson & Bianchi, 2020), it is urged that future music preference researchers measure music preference through musical excerpts rather than genre labels.

Although the original intent of predicting music preference with the 10 openness facets with a multiple regression was not possible due to multicollinearity, DA offered some interesting insights that should not be overlooked. Researchers interested in music preference and openness to experience should take into account the relative importance that every openness facet had in this study. Additionally, this study also shows that FFM’s openness to experience and

HEXACO's openness to experience are somewhat different in predicting music preference, and future research should take that into account when choosing openness to experience measures in the field of music preference.

The LPA in this study, just like most LPAs in other studies, was a purely exploratory procedure. However, if similar results were replicated in other samples, the theoretical and practical implications would be rather far reaching. From a theoretical perspective, the LPA results would indicate an effect of openness to experience and culture on music preference. Namely, researchers should carefully keep in mind how a certain sample might be more likely to display a certain music preference pattern depending on its personality or demographic characteristics. More practically, these results may be very important for companies who offer music streaming services such as Spotify or Apple Music. Knowing that there are discernable latent profiles of music preference could help a great deal in recommending appropriate music to suit users' taste. Additionally, latent profiles of music preference could be useful to musicians and music producers to predict the kind of music that a certain audience might prefer. For instance, musician and producers could decide what music style to incorporate in their music depending on the music preference profiles of their listeners.

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