DURMS
Durham Undergraduate
Research in Music & Science

# Using Personality to Predict the Content of 'Feel Good' Playlists

Paige Denning
*Durham University*

## ABSTRACT

Given the wealth of literature on the links between personality and music preference, it is surprising that there is a gap in looking at how this link can vary under specific listening contexts. This study aims to bridge part of that gap, participants (*N* = 73) completed the BFI personality questionnaire with the results from which then analysed against nine audio features retrieved from their Spotify 'feel good' playlists. Extraversion was found to be the most robust predictor of these audio features. Implications are discussed with regards to personality-targeted advertising.

## 1. INTRODUCTION

Examining the role of personality in music preference is a long-established area of interest in music psychology (e.g. Cattell & Anderson, 1953) and often measures personality using the big five factors: openness, conscientiousness, extraversion, agreeableness, and neuroticism (Goldberg, 1990). One of the most notable papers on such determined correlates between the big five personality factors and four dimensions of music that they established: reflective-complex (jazz, blues, classical, and folk), intense-rebellious (rock, alternative, and heavy metal), upbeat-conventional (country, pop, sound tracks, and religious), and energetic-rhythmic (rap/hip-hop, soul-funk, and electronica/dance) (Rentfrow & Gosling, 2003). They found positive correlations between the reflective-complex dimension and openness; the intense-rebellious dimension and openness; the upbeat-conventional dimension and extraversion, agreeableness, and conscientiousness; and the energetic-rhythmic dimension and extraversion and agreeableness. The positive correlations between openness and the reflective-complex and intense-rebellious dimensions, as well as between extraversion and the energetic-rhythmic and upbeat-conventional dimensions have seen replicated results in more recent years (Vella & Mills, 2016). However, both studies rely on the use of a self-report inventory, the Short Test of Musical Preference (STOMP) (Rentfrow & Gosling, 2003), a method which has been critiqued as self-report measures are known to be affected by response biases (Podsakoff & Organ, 1986) and can produce incomplete data (Hongpanarak & Mongkolnavin, 2021) which hinders the validity of the experiment. Combatting this issue, a recent study obtained the full listening history of users on the music streaming platform Last.fm who also completed a five-factor personality questionnaire through Facebook, a popular social media platform (Melchiorre & Schedl, 2020). They acquired data on the acoustic features of users' tracks through Spotify API, finding many correlations between these features and personality though some of the most relevant include extraversion's positive correlation with danceability and negative correlation with instrumentalness, as these findings were later replicated in a Brazilian sample (Júnior et al., 2021) where data on musical preference was obtained by requesting Spotify users' top 100 tracks. Overall, it is apparent that personality can correlate with musical preference, from the level of acoustic features up to broader musical dimensions, however there is a clear need for research to depart from the use of self-report measures for an activity as personal as music-listening.

In addition to personality correlating with our musical preferences, the way that we use music also correlates with personality. One study found that those high in openness tend to prefer listening to music for rational or cognitive appreciation and those high in neuroticism tended to use music for emotion regulation; it was also hypothesised that those high in extraversion would prefer to use music in the background of other activities as a means of increasing arousal, though this was not supported (Chamorro-Premuzic & Furnham, 2007). However, a later replication in a Spanish sample supported the hypothesised correlation between extraversion and background uses (Chamorro-Premuzic et al., 2009). Further to personality relating to our uses of music, uses of music have also been found to correlate with musical preference: those who listen to music for emotion regulation tend to listen to sad music, those who listen for cognitive appreciation tend to listen to more complex music, and those who use music as a background tend to listen to happy music (Chamorro-Premuzic et al., 2010). The links described above between personality, music preference, and how we use music may indicate a predictive mediation relationship, whereby how we use music mediates the link between personality and music preference. Exploring the directions of these relationships, one study that found cognitive appreciation of music partially mediates the link between openness and a preference for the reflective-complex dimension, whilst emotion regulation partially mediates the link between openness and a preference for the intense-rebellious dimension of music (Vella & Mills, 2017). Though, the assumed direction of personality influencing music-listening behaviour may not be the full picture, with one longitudinal study finding that the different ways adolescents utilise music as a coping method can influence their neuroticism levels later in life (Miranda et al., 2010). Hence, these relationships must be bidirectional. However, all studies previously mentioned measure both music preference and how we use music as fixed units and fail to consider how people may listen differently across different contexts, such as activity, mood, and reason for listening (North et al., 2004). Therefore, a need for investigation into musical preferences across contexts is highlighted.

Given the rise of mobile phone usage and their capabilities for music streaming and organisation, we are now able to easily create playlists that allow us to listen to a larger variety of genres and artists than in previous times, when listening was limited to pre-determined albums or laboriously creating mixtapes and 'burning' CDs. Investigating how users curate playlists on music-streaming platforms has revealed that peoples' playlists can show high context sensitivity, where they can act as soundtracks for different activities or affects (Hagen, 2015).

Despite the wealth of literature in the area, there have been no studies thus far on how personality influences music preference in specific listening contexts. As previously mentioned, mediation effects are present in the relationship between preference, reasons for listening, and personality (Vella & Mills, 2017) and that people can vary in their preference as their reasons for listening may vary (North et al., 2004). Hence, the present study will aim to explore whether personality can be predictive of the musical content of context-specific playlists. Though, due to the limited scope of this study, the focus will be on 'feel good' playlists, as they have been reported as the most popular category of playlist, with 91% of participants in one study having one (Pichl et al., 2016), characterised by high energy, valence, and danceability values, similar to that of the happy music category from Chamorro-Premuzic, and colleagues (2010). Measuring music preference by genre or dimension can be reductive and can even give inconsistent results (Schäfer & Mehlhorn, 2017), hence the present study will analyse music preference with regards to defined audio features from Spotify API through multiple linear regressions. Nine audio features (danceability, energy, loudness, speechiness, acousticness, instrumentalness, liveness, valence, and tempo) (see Appendix A for definitions from Spotify API) were selected due to the data being continuous, a requirement for linear regression. Participants' personalities will be measured using the Big Five Inventory (BFI) which has greater reliability than the popular NEO-FFI (John & Srivastava, 1999), as well as having a briefer completion time and items that are easier to understand (Benet-Martinez & John, 1998). This data will then be analysed to determine whether personality can predict the values of the audio features in Spotify users' 'feel good' playlists.

As previously mentioned, those high in extraversion tend to listen to music in the background of other activities (Chamorro-Premuzic et al., 2009), which in turn typically means an increased likelihood in listening to happy music (Chamorro-Premuzic et al., 2010) which is synonymous with a 'feel good' playlist. Hence, results for those high in extraversion may reflect the acoustic features seen in the 'feel good' playlist category as described by Pichl and colleagues (2016).

It is, therefore, hypothesised that extraversion will predict a positive relationship to energy, valence, and danceability audio features in 'feel good' playlists.

No other hypotheses will be made with regards to the other personality factors as they did not have correlations with uses of music and preference that would be consistent with the that of a 'feel good' playlist, instead an exploratory approach will be taken.

## 2. METHOD

This study was approved by Durham University Department of Music Ethics Committee and all participants provided informed consent.

*Participants.* Participants were required to be over 18 and have a personal Spotify account and were recruited through opportunity sampling, whereby the study was advertised through the researcher's social media, as well as shared with friends and family. A total of 73 participants took part, with all meeting the requirements for the study and no eliminations required. The age of those who took part ranged from 18 to 25 years ($M$ = 20.3, $SD$ = 1.2) and the cohort was 38.4% male ($N$ = 28) and 61.6% female ($N$ = 45).

*Materials.* The Big Five Inventory (BFI) (John & Srivastava, 1999), a 44-item questionnaire that allows for responses on a 5-point Likert scale from 'Disagree Strongly' to 'Agree Strongly', measures the Big Five Factors of personality and was administered to participants. Most questions were coded such that 1 = Disagree Strongly and 5 = Agree Strongly, though the following were coded for the inverse: Q2, Q6, Q8, Q9, Q12, Q18, Q21, Q23, Q24, Q27, Q31, Q34, Q35, Q37, Q41, and Q43. Ten of the questions were reflective of the openness dimension, nine questions for conscientiousness, eight for extraversion, nine for agreeableness, and eight for neuroticism. All questions start with "I see myself as someone who…" to then be followed by each item. Example items from the BFI include "… Values artistic, aesthetic experiences" and "… Is full of energy". A full copy of the BFI can be found in Appendix B.

*Design.* To measure the effects of personality on the audio features of 'feel good' playlists, a within-subjects repeated measures design was implemented. The independent variables were the scores from the five personality factors: openness, conscientiousness, extraversion, agreeableness, and neuroticism. The dependant variables were the nine mean acoustical features taken for each playlist which consisted of: danceability, energy, loudness, speechiness, acousticness, instrumentalness, liveness, valence, and tempo.

*Procedure.* Participants were scheduled to take part in the study in-person and were met in a public space. Upon arrival, participants were presented with the information letter and then provided informed consent. Following this, demographic data was obtained and participants were instructed to complete the BFI questionnaire. A link to the participant's 'feel good' playlist was then requested, with requirements being that the playlist was created by themselves, it consisted of at least 30 songs, and its primary utility was to be the preferred playlist to listen to for increasing positive affect. If participants had more than one playlist that fitted these requirements, the playlist that they used most frequently was taken. If participants did not have a playlist that they felt fitted these requirements, then they were to be thanked for their time and informed that they do not meet the requirements for the study, though no participants in this study warranted this. Participants were only told prior to the study that a specific Spotify playlist would be requested, not that it would be a 'feel good' playlist, this was to reduce the likelihood that participants would edit their playlist before the data was retrieved. Following the retrieval of a 'feel good' playlist, participants were thanked for taking part and shortly debriefed on the study.

*Data Analysis.* BFI data was recorded and then calculated as a mean across each factor to account for differences in the number of questions allocated to each personality factor, with scores ranging from one to five. Acoustical features were obtained using Spotify Web API (https://developer.spotify.com/documentation/web-api), where data can be manually obtained on one track at a time. To expedite this process, a Python script (Appendix C) was written, enabling data acquisition for up to 100 tracks per playlist which was consolidated into a CSV file, ready for data analyses. Limitations on computer capabilities unfortunately did not allow for pagination in the code so the data acquired for each playlist was capped at the first 100 tracks, though few playlists exceeded this number ($N = 8$). Mean values were then calculated for each acoustical feature in each participant's playlist and recorded as the final measurements of the dependant variables. Data was analysed using JASP software where nine multiple linear regressions were run using the forced entry method of entering the predictors to determine whether the five personality factors were suitable predictors for each acoustical feature. A further Pearson's correlation analysis was run to determine if any of the dependant variables correlated with one another.

## 3. RESULTS

*Descriptive statistics.* Descriptive statistics were produced for scores on the BFI as well as for the mean acoustical features and can be seen in Table 1 and Table 2, respectively.

Table 1. *Descriptive Statistics for BFI Scores Across Participants*

| Personality Factor | Openness | Conscientiousness | Extraversion | Agreeableness | Neuroticism |
|---|---|---|---|---|---|
| *M* | 2.990 | 2.745 | 2.751 | 2.707 | 2.508 |
| *SD* | 1.046 | 0.995 | 1.035 | 1.021 | 0.934 |

Table 2. *Descriptive Statistics for Measurements of Acoustical Features Across Participants*

| Acoustic Feature | Danceability | Energy | Loudness | Speechiness | Acousticness |
|---|---|---|---|---|---|
| *M* | .629 | .524 | -9.439 | .100 | .187 |
| *SD* | .108 | .185 | 2.676 | .053 | .093 |
| Min. | .419 | .173 | -14.990 | .008 | .043 |
| Max. | .920 | .867 | -4.173 | .194 | .415 |

*Table 2 Continued*

| Acoustic Feature | Instrumentalness | Liveness | Valence | Tempo |
|---|---|---|---|---|
| *M* | .076 | .138 | .611 | 118.057 |
| *SD* | .050 | .060 | .138 | 8.977 |
| Min. | .005 | .002 | .383 | 100.487 |
| Max. | .184 | .243 | .910 | 135.297 |

*Inferential Statistics.* Nine separate multiple linear regressions were run to test the predictability of the five personality factors against each acoustical feature.

Plots of standardised residuals against predicted values were used to test for linearity and homoscedasticity, which all multiple regressions met the assumptions for. Histograms for all multiple regressions showed approximately normally distributed errors, as did the standardised residuals Q-Q plot. Pearson's correlations were used to test for the collinearity assumption, which found that multicollinearity of the predictors was not a concern for all multiple regressions. Lastly, no outliers were found. Hence, all assumptions were met across all tests.

All tests report the standardised β and adjusted $R^2$ value for variance unless this resulted in a negative value in which case the $R^2$ value is used and stated as such.

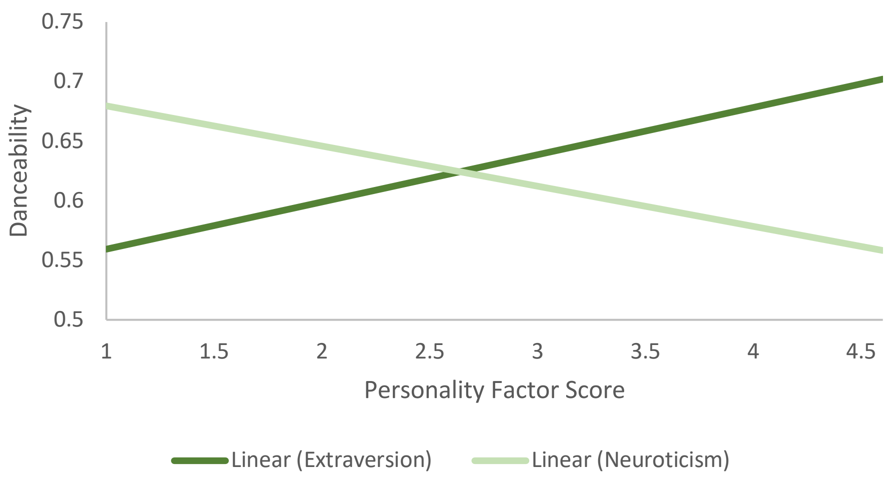


Figure 1. *Line Graph Demonstrating the Relationship Between Danceability and Extraversion and Neuroticism.*

D*anceability.* The regression model explained 16.8% of the variance in danceability values which was significant amount of explained variance ($F(5, 67) = 3.904$, $p = .004$) and so fits better than the model without predictors. With regards to the individual predictors, extraversion was a significant predictor for a positive relationship with danceability (β = 0.349, $t = 3.187$, $p = .002$), whilst neuroticism significantly predicted a negative relationship with danceability (β = -0.283, $t = -2.558$, $p = .012$), these predictors can be seen clearer in Figure 1. Extraversion had a greater effect size than neuroticism and so was the more influential predictor. No other personality factors were significant predictors.

*Energy.* The regression model explained 10.3% of the variance in energy values which was a significant amount of explained variance ($F(5, 67) = 2.661$, $p = .030$) and so fits better than without any predictors. Extraversion was a significant predictor for a positive relationship with energy ($\beta = 0.293$, $t = 2.581$, $p = .012$) (see Figure 2). No other personality factors were significant predictors.

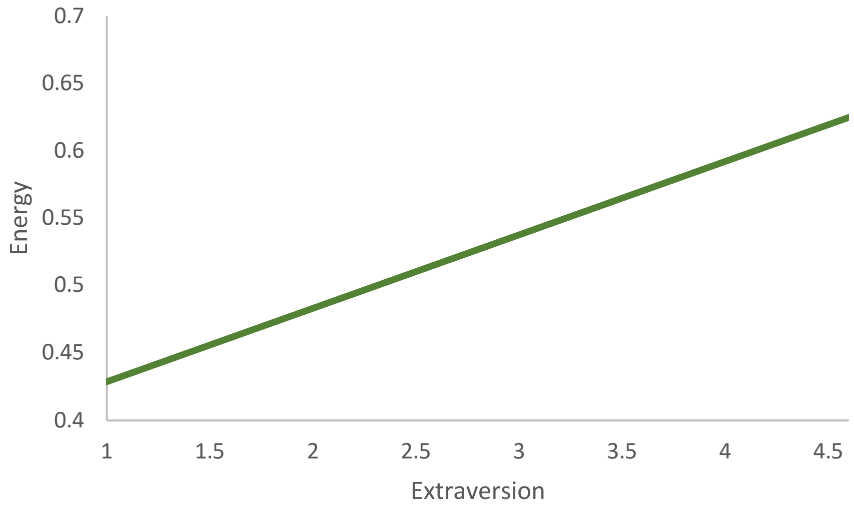


Figure 2. *Line Graph of the Relationship Between Extraversion and Energy.*

*Loudness.* The regression model explained 5.4% of variance in loudness values using the $R^2$ value, which was found to not be a significant amount of explained variance ($F(5, 67) = 0.759$, $p = .582$), meaning the model without the predictors fits best for loudness. No personality factors were found to be significant individual predictors.

*Speechiness.* The regression model explained 6.1% of variance in speechiness values using the $R^2$ value, which was not significant ($F(5, 67) = 0.870$, $p = .506$), so the model without any predictors fits best for speechiness. No personality factors were found to be significant individual predictors.

*Acousticness.* The regression model explained 19% of the variance in acousticness values which was significant ($F(5, 67) = 4.386$, $p = .002$), seen in Figure 3, fitting better than the model without any predictors. Agreeableness was the only personality factor found to be a significant individual predictor, with a positive relationship to acousticness ($\beta = 0.482$, $t = 4.482$, $p < .001$).

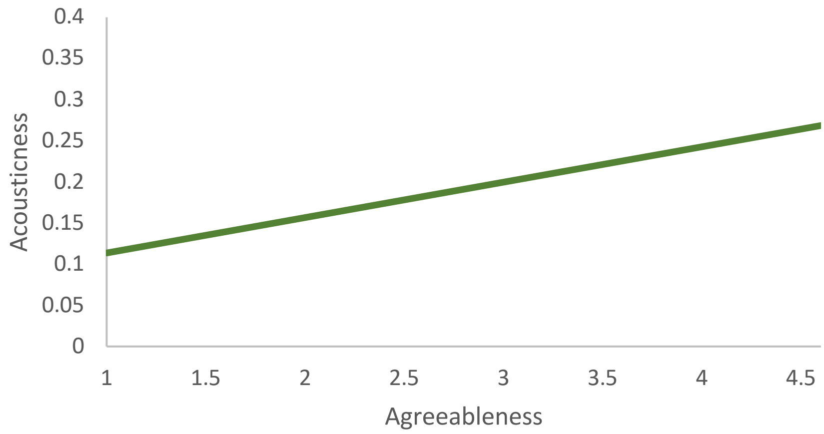


Figure 3. *Line Graph of the Relationship Between Agreeableness and Acousticness.*

*Instrumentalness.* The regression model explained 16.3% of the variance in instrumentalness values which was significant ($F(5, 67) = 3.804$, $p = .004$), seen in Figure 4, fitting better than the model without any predictors. Agreeableness was the only personality factor to be a significant individual predictor, with a negative relationship to instrumentalness ($\beta = -0.435$, $t = -3.973$, $p < .001$).

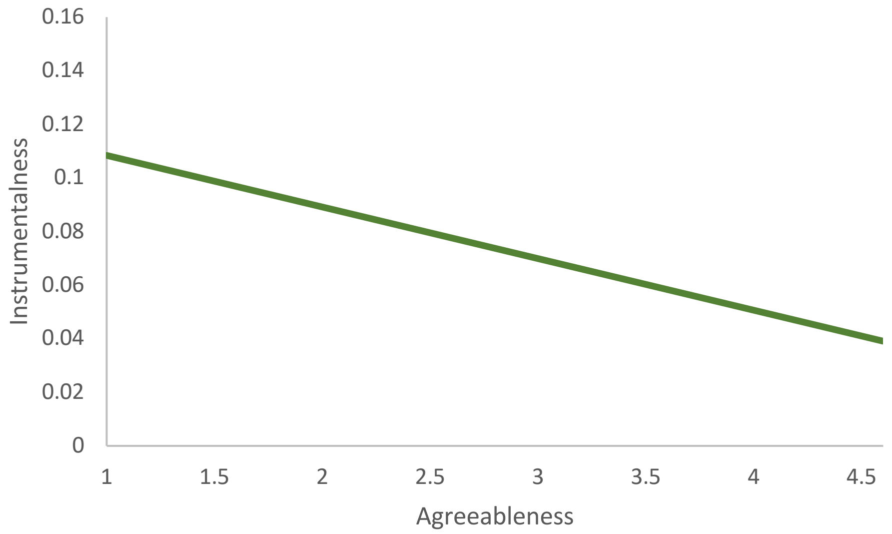


Figure 4. *Line Graph of the Relationship Between Agreeableness and Instrumentalness*

*Liveness.* The regression model explains 8.6% of the variance in liveness values which was not a significant amount ($F$(5, 67) = 1.261, $p$ = .291), meaning the model without any predictors fits best. However, extraversion was still found to be a significant individual predictor for a negative relationship with liveness (β = -0.250, $t$ = -2.104, $p$ = .039), seen in Figure 5. No other personality factors were found to be significant individual predictors.

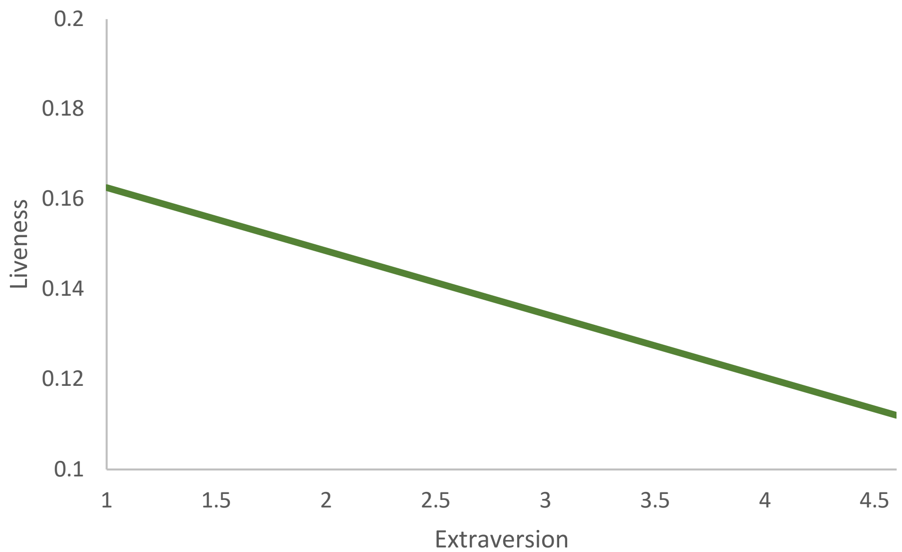


Figure 5. *Line Graph of the Relationship Between Extraversion and Liveness.*

*Valence.* The regression model explained 20.7% of variance in valence values which was significant ($F$(5, 67) = 4.751, $p$ < .001), fitting better than the model without any predictors. Extraversion was the only personality factor found to be a significant individual predictor of valence, predicting a positive relationship (β = 0.474, $t$ = 4.433, $p$ < .001), see Figure 6.

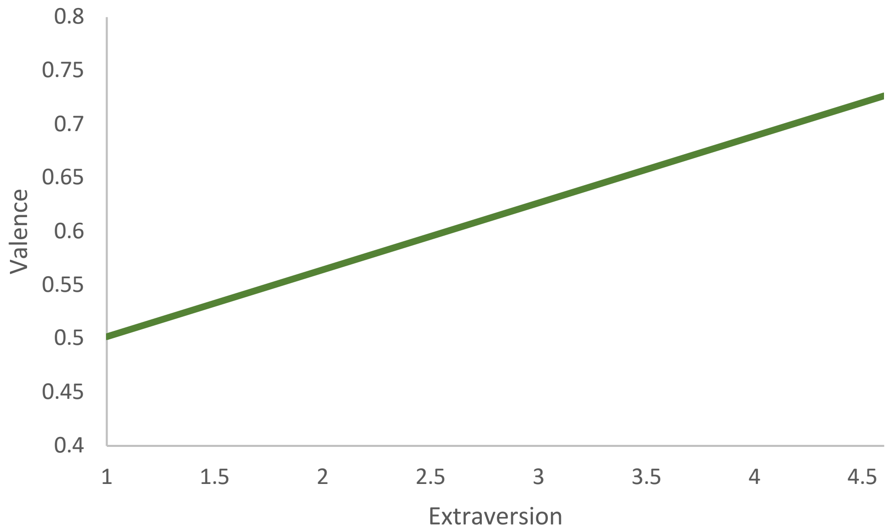


Figure 6. *Line Graph of the Relationship Between Extraversion and Valence.*

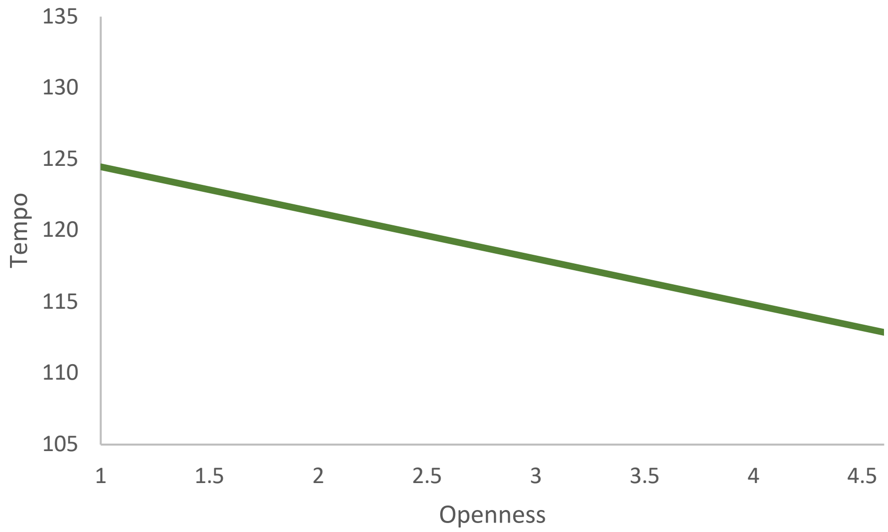


Figure 7. *Line Graph of the Relationship Between Openness and Tempo.*

*Correlations Between Acoustic Features.* Pearson's correlation test was run to establish any correlations between the nine acoustic features. Danceability and energy were significantly and positively correlated with one another, with a small effect size ($r(71) = .257$, $p = .028$). Additionally, danceability and valence were significantly and positively correlated with each other, with a medium effect size ($r(71) = .353$, $p = .002$). No other correlations were found between acoustic features.

## 4. DISCUSSION

The present study explored whether personality (as measured by the BFI) was able to predict the acoustic features of 'feel good' playlists, where the hypotheses of extraversion predicting a positive relationship to the typical features of a 'feel good' playlist of danceability, energy, and valence (Pichl et al., 2016) were supported. This demonstrates that extraverted people have similar music preferences for their 'feel good' playlists as they do in previous findings of their overall music taste, where they have been found to have a preference for songs with high danceability (e.g. Melchiorre & Schedl, 2020) , as well as songs that fall under the upbeat-conventional and energetic-rhythmic dimensions (Rentfrow & Gosling, 2003), which high valence and high energy songs naturally fall under, respectively. This correlation between their preference under this playlist category and overall music preference further supports the previously discussed link whereby extraverted people tend to listen to music as a background to other activities (Chamorro-Premuzic et al., 2009), which in turn tends to lead to listening to happy music (Chamorro-Premuzic et al., 2010).

The negative relationship between openness and tempo was initially unexpected, as it was discussed earlier that emotional uses of music partially mediates the link between high openness and a preference for intense-rebellious music (Vella & Mills, 2016), a dimension that is associated with higher tempo but is also low in positive effect and high in negative affect (Rentfrow & Gosling, 2003). This indicates that the emotional use of music that mediates the link between openness and intense-rebellious music may be, more specifically, listening to up-regulate negative affect. This would also explain why those high in openness would prefer slower tempo music for a playlist that can act both as downregulating negative affect and upregulating positive affect, if positive and negative affect are seen as opposites of one another. Hence, a need for future research to consider and specify different types of emotional uses of music is recommended to enable investigation into how music preferences may fluctuate to match with our own emotional states, as interactionist theorists would argue it does (Rentfrow et al., 2011). Similarly, interactionist theories support the negative relationship found between neuroticism and danceability, as those who are more prone to negative affect would tend to seek out more sombre songs, rather than those with high danceability which was shown to correlate with valence.

The negative relationship between agreeableness and instrumentalness indicates that those high in agreeableness prefer tracks that contain a higher level of vocals which may relate to prosocial behaviour, something which agreeableness has been seen as the primary personality trait to influence positively (Caprara et al., 2012). Music containing the highest level of vocals, and hence attracting those highest in agreeableness, tend to be from choirs or vocal ensembles which are typically prosocial (Kirschner & Tomasello, 2010; Cohen, 2019), potentially due to being one of the most community-based forms of music. Further, those high in agreeableness see increased wellbeing when experiencing social cohesion (Reizer et al., 2023), therefore seeking out 'social-sounding' music is a logical route for highly agreeable people seeking to increase positive affect. Incorporating the relationship between high agreeableness and high acousticness only further promotes the concept of seeking music with a social sound to it, as choirs and vocal ensembles are typically primarily acoustic. This also aligns with previous findings that highly agreeable people tend to dislike intense electric music (Upadhyay & Chakraborty, 2016) and prefer more gentle and mellow music (Flannery & Woolhouse, 2021). Taken together, these acoustic features reflect the 'unpretentious' category of music outlined by Rentfrow et al. (2011), of which agreeableness has been found to correlate with (Schäfer & Melhorn, 2017) though with only a small effect size. It is proposed that this effect would increase when considering individuals' purposes for listening to music, as highly agreeable people may listen to more music of this type when seeking to increase positive affect via the feeling of social 'togetherness', though further investigation is required to confirm this theory.

In addition to music-streaming services being able to apply these insights internally to their recommendation algorithms, this data can also be used by external companies to improve personality-targeted advertising. The effectiveness of tailoring persuasive messages to people's personality has been well-cited (e.g. Hirsh et al., 2012), with social media advertising particularly making use of this method, largely thanks to the wealth of data that they collect on their users' activities. Companies such as Facebook gather the opinions of users, who they follow, and even their activity on other apps and websites outside of Facebook itself (Singer, 2018). Such a wealth of data enables highly accurate inferences to be made on users, with some computer-based personality judgements even able to predict a user's personality better than their own spouse (Youyou et al., 2015). Utilising accurate profiling in personality-targeted social media adverts can, compared to industry baselines, lead to twice the number of clicks on an advert (LaMontagne, 2015) and up to 50% more sales (Matz et al., 2017). With Spotify automatically setting people's playlists to public, a wealth of data can be retrieved, including the content of 'feel good' playlists which the findings from this study can then be used to infer personality attributes of users. Social media advertising is a market that is projected to be worth US$207.1bn globally by the end of 2023 (Statista, 2022), hence improving such personality profiling systems can lead to increases in companies' profits through the improved effectiveness of social media advertising on a tremendous scale.

*Limitations and Future Directions.* One key limitation of this study is the small sample size ($N$ = 73), especially given the number of predictor variables that were used ($N$ = 5). This research can, therefore, act as preliminary findings to be replicated in a much larger sample. Given the popularity of Spotify, there is a large sample size to work with in future research.

Further, the limitation of 100 songs per playlist does reduce the validity of the data, though few ($N$ = 8) playlists exceeded this limit. Regardless, future considerations should include suitable computer access to enable pagination in the computer code and allow for data retrieval for all songs in a given playlist.

Lastly, facets of the five factors of personality were not measured or considered in this study. Some studies have shown that these facets can correlate with different music dimensions, even if their relevant overall factor does not (Zweigenhaft, 2008). Hence, future research should consider using the NEO-PI instead, which measures all 30 facets of the big five personality factors, giving a more in-depth look at what aspects of personality may be more important.

*Conclusion.* To conclude, this study investigated whether the five factors of personality can be used to predict the content of 'feel good' playlists. Extraversion resulted in being the most robust predictor for this type of playlist, likely due to its already established links with positive music and hypotheses relating to such were met. Findings that were not hypothesised highlight a need for greater clarity in what emotional uses of music can mean in literature, with recommendations that future literature specifies whether the reported emotional uses relate to positive or negative affect. Large-scale implications for social media advertising are discussed, with recommendations that companies use the data presented in this paper to make inferences on Spotify users' personality through access to public playlists. Future research should endeavour to replicate this study across other types of playlist categories and with much larger sample sizes.

## REFERENCES

Benet-Martínez, V., & John, O. P. (1998). Los Cinco Grandes across cultures and ethnic groups: Multitrait multimethod analyses of the Big Five in Spanish and English. *Journal of personality and social psychology*, *75*(3), 729.

Caprara, G. V., Alessandri, G., & Eisenberg, N. (2012). Prosociality: the contribution of traits, values, and self efficacy beliefs. *Journal of personality and social psychology*, *102*(6), 1289.

Cattell, R. B., & Anderson, J. C. (1953). The measurement of personality and behavior disorders by the IPAT Music Preference Test. *Journal of Applied Psychology*, *37*(6), 446.

Chamorro-Premuzic, T., & Furnham, A. (2007). Personality and music: Can traits explain how people use music in everyday life?. *British journal of psychology*, *98*(2), 175-185.

Chamorro-Premuzic, T., Gomà-i-Freixanet, M., Furnham, A., & Muro, A. (2009). Personality, self-estimated intelligence, and uses of music: A Spanish replication and extension using structural equation modeling. *Psychology of Aesthetics, Creativity, and the Arts*, *3*(3), 149.

Chamorro-Premuzic, T., Fagan, P., & Furnham, A. (2010). Personality and uses of music as predictors of preferences for music consensually classified as happy, sad, complex, and social. *Psychology of Aesthetics, Creativity, and the Arts*, *4*(4), 205.

Flannery, M. B., & Woolhouse, M. H. (2021). Musical preference: Role of personality and music-related acoustic features. *Music & Science*, *4*, 20592043211014014.

Goldberg, L. R. (1990). An alternative" description of personality": the big-five factor structure. *Journal of personality and social psychology*, *59*(6), 1216.

Hagen, A. N. (2015). The playlist experience: Personal playlists in music streaming services. *Popular Music and Society*, *38*(5), 625-645.

Hirsh, J. B., Kang, S. K., & Bodenhausen, G. V. (2012). Personalized persuasion: Tailoring persuasive appeals to recipients' personality traits. *Psychological science*, *23*(6), 578-581.

Hongpanarak, T., & Mongkolnavin, J. (2021, June). A Study of Relationship Between Music Streaming Behavior and Big Five Personality Traits of Spotify Users. In *The 12th International Conference on Advances in Information Technology* (pp. 1-5).

John, O. P., & Srivastava, S. (1999). The Big-Five trait taxonomy: History, measurement, and theoretical perspectives. In L. A. Pervin & O. P. John (Eds.), *Handbook of personality: Theory and research* (Vol. 2, pp. 102–138). New York: Guilford Press.

Júnior, L. D. S. M., Cabral, G. R. E., & Cabral, G. R. E. (2021, October). Correlating Big Five Primary Personality Dimensions with Musical Preferences. In *Anais do XVIII Simpósio Brasileiro de Computação Musical* (pp. 103 -108). SBC.

Kirschner, S., & Tomasello, M. (2010). Joint music making promotes prosocial behavior in 4-year-old children. *Evolution and human behavior*, *31*(5), 354-364.

LaMontagne, L. (2017). Personality-matched ads: How Hilton worldwide effectively personalized its marketing messages.

Matz, S. C., Kosinski, M., Nave, G., & Stillwell, D. J. (2017). Psychological targeting as an effective approach to digital mass persuasion. *Proceedings of the national academy of sciences*, *114*(48), 12714-12719.

Melchiorre, A. B., & Schedl, M. (2020, July). Personality correlates of music audio preferences for modelling music listeners. In *Proceedings of the 28th ACM conference on user modeling, adaptation and personalization* (pp. 313 -317).

Miranda, D., Gaudreau, P., & Morizot, J. (2010). Blue notes: Coping by music listening predicts neuroticism changes in adolescence. *Psychology of Aesthetics, Creativity, and the Arts*, *4*(4), 247.

North, A. C., Hargreaves, D. J., & Hargreaves, J. J. (2004). Uses of music in everyday life. *Music perception*, *22*(1), 41-77.

Pichl, M., Zangerle, E., & Specht, G. (2016, December). Understanding playlist creation on music streaming platforms. In *2016 IEEE International Symposium on Multimedia (ISM)*(pp. 475-480). IEEE.

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. *Journal of management*, *12*(4), 531-544.

Reizer, A., Harel, T., & Ben-Shalom, U. (2023). Helping others results in helping yourself: How well-being is shaped by agreeableness and perceived team cohesion. *Behavioral Sciences*, *13*(2), 150.

Rentfrow, P. J., & Gosling, S. D. (2003). The do re mi's of everyday life: the structure and personality correlates of music preferences. *Journal of personality and social psychology*, *84*(6), 1236.

Rentfrow, P. J., Goldberg, L. R., & Levitin, D. J. (2011). The structure of musical preferences: a five-factor model. *Journal of personality and social psychology*, *100*(6), 1139.

Schäfer, T., & Mehlhorn, C. (2017). Can personality traits predict musical style preferences? A meta analysis. *Personality and Individual Differences*, *116*, 265-273.

Singer, N. (2018). What you don’t know about how Facebook uses your data. *The New York Times*, *11*.

Statista. (2022). Social Media Advertising - Worldwide. (n.d.). Retrieved May 16, 2023, from https://www.statista.com/outlook/dmo/digital-advertising/social-media-advertising/worldwide

Upadhyay, D., Shukla, R., & Chakraborty, A. (2016). Factor structure of music preference scale and its relation to personality. *Journal of Indian Academy of Applied Psychology*, *43*(1), 104-113.)

Vella, E. J., & Mills, G. (2017). Personality, uses of music, and music preference: The influence of openness to experience and extraversion. *Psychology of Music*, *45*(3), 338-354.

Youyou, W., Kosinski, M., & Stillwell, D. (2015). Computer-based personality judgments are more accurate than those made by humans. *Proceedings of the National Academy of Sciences*, *112*(4), 1036-1040.

Zweigenhaft, R. L. (2008). A do re mi encore: A closer look at the personality correlates of music preferences. *Journal of individual differences*, *29*(1), 45-55.

# APPENDICES

## Appendix A
## **Definitions of Spotify API Acoustic Features**

**Acousticness** - A confidence measure from 0.0 to 1.0 of whether the track is acoustic.1.0 represents high confidence the track is acoustic

**Danceability** - Danceability describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 0.0 is least danceable and 1.0 is most danceable.

**Energy** - Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. For example, death metal has high energy, while a Bach prelude scores low on the scale. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy.

**Instrumentalness** - Predicts whether a track contains no vocals. "Ooh" and "aah" sounds are treated as instrumental in this context. Rap or spoken word tracks are clearly "vocal". The closer the instrumentalness value is to 1.0, the greater likelihood the track contains no vocal content. Values above 0.5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.0.

**Liveness** - Detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live. A value above 0.8 provides strong likelihood that the track is live.

**Loudness** - The overall loudness of a track in decibels (dB). Loudness values are averaged across the entire track and are useful for comparing relative loudness of tracks. Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). Values typically range between 60 and 0 db.

**Speechiness** - Speechiness detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g., talk show, audio book, poetry), the closer to 1.0 the attribute value. Values above 0.66 describe tracks that are probably made entirely of spoken words. Values between 0.33 and 0.66 describe tracks that may contain both music and speech, either in sections or layered, including such cases as rap music. Values below 0.33 most likely represent music and other non-speech-like tracks.

**Valence** - A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g., happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g., sad, depressed, angry).

## Appendix B
## **The Big Five Inventory (BFI)**

Here are a number of characteristics that may or may not apply to you. For example, do you agree that you are someone who likes to spend time with others? Please write a number next to each statement to indicate the extent to which you agree or disagree with that statement.

I see Myself as Someone Who...

___1. Is talkative

___2. Tends to find fault with others

___3. Does a thorough job

___4. Is depressed, blue

___5. Is original, comes up with new ideas

___6. Is reserved

___7. Is helpful and unselfish with others

___8. Can be somewhat careless

___9. Is relaxed, handles stress well

___10. Is curious about many different things

____11. Is full of energy

____12. Starts quarrels with others

____13. Is a reliable worker

____14. Can be tense

____15. Is ingenious, a deep thinker

____16. Generates a lot of enthusiasm

____17. Has a forgiving nature

____18. Tends to be disorganized

____19. Worries a lot

____20. Has an active imagination

____21. Tends to be quiet

____22. Is generally trusting

____23. Tends to be lazy

____24. Is emotionally stable, not easily upset

____25. Is inventive

____26. Has an assertive personality

____27. Can be cold and aloof

____28. Perseveres until the task is finished

____29. Can be moody

____30. Values artistic, aesthetic experiences

____31. Is sometimes shy, inhibited

____32. Is considerate and kind to almost everyone

____33. Does things efficiently

____34. Remains calm in tense situations

____35. Prefers work that is routine

____36. Is outgoing, sociable

____37. Is sometimes rude to others

____38. Makes plans and follows through with them

____39. Gets nervous easily

____40. Likes to reflect, play with ideas

____41. Has few artistic interests

____42. Likes to cooperate with others

____43. Is easily distracted

____44. Is sophisticated in art, music, or literature

## Appendix C

## Python Code

```
import csv

import os

import re

import spotipy

from dotenv import load_dotenv

from spotipy.oauth2 import SpotifyClientCredentials

load_dotenv()

CLIENT_ID = os.getenv("CLIENT_ID", "")
```

```
CLIENT_SECRET = os.getenv("CLIENT_SECRET", "")

OUTPUT_FILE_NAME = "pop_trial.csv"

# change inside “ “ for each playlist

PLAYLIST_LINK =
"https://open.spotify.com/playlist/37i9dQZF1EQncLwOalG3K7?si=41c81e8b328a4
4d9"

client_credentials_manager = SpotifyClientCredentials(

      client_id=CLIENT_ID, client_secret=CLIENT_SECRET

)

session =
spotipy.Spotify(client_credentials_manager=client_credentials_manager)

if match := re.match(r"https://open.spotify.com/playlist/(.*)\?",
PLAYLIST_LINK):

      playlist_uri = match.groups()[0]

else:

      raise ValueError("Expected format:
https://open.spotify.com/playlist/...")

tracks = session.playlist_tracks(playlist_uri)["items"]

with open(OUTPUT_FILE_NAME, "w", encoding="utf-8") as file:

      writer = csv.writer(file)

      writer.writerow(["track", "artist", "danceability", "energy",
      "loudness", "speechiness", "acousticness", "instrumentalness",
      "liveness", "valence", "tempo"])

      for track in tracks:

            name = track["track"]["name"]

            artists = ", ".join([artist["name"] for artist in
      track["track"]["artists"]])

            audio_features= session.audio_features(track["track"]["id"])[0]

            danceability = audio_features["danceability"]

            energy = audio_features["energy"]

            loudness = audio_features["loudness"]

            speechiness = audio_features["speechiness"]

            acousticness = audio_features["acousticness"]
```

```
        instrumentalness = audio_features["instrumentalness"]

        liveness = audio_features["liveness"]

        valence = audio_features["valence"]

        tempo = audio_features["tempo"]

        writer.writerow([name, artists, danceability, energy, loudness, speechiness, acousticness, instrumentalness, liveness, valence, tempo])
```