Personality Correlates of Music Audio Preferences for Modelling Music Listeners

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ABSTRACT

Past studies have shown that personality has a significant association with user behaviour and preferences, not least towards music. This makes personality information a promising aspect for user modelling in personalised recommender systems and similar domains. In contrast to existing studies, which investigate personality correlates of music preferences via genres or styles, we study such correlates by modelling music preferences at a finer-grained content level, using audio features of the music users listen to. Leveraging listening and personality information of more than 1,300 Last.fm users, we identify several significant medium and weak correlations between music audio features and personality traits, the latter defined by the five-factor model. Our results provide useful insights into the relationship between personality and music preference, which can be valuable for music recommender systems in terms of more personalised recommendations.

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1 INTRODUCTION

Personality has been identified as a stable psychological aspect of human life [4, 20, 21, 24]. It has a significant association with many life aspects, including well-being, self-identity, quality of social relationships, and occupational satisfaction, conveying behaviour and preferences of the individual [22]. Relationships between media preferences and personality, in particular, has been widely explored in various domains including TV programmes [14, 29], movies [33], and music [8, 10, 25, 26]. As a consequence of these findings, personality information reveals to be an excellent candidate for user profiling in personalised recommender systems and has been shown to improve the quality of recommended items, e.g. [6, 11, 18].

Among the various domains investigated so far, music is particularly noteworthy since it strongly intertwines with people's life [28], and since music recommender systems [27] have nowadays become more ubiquitous than ever following the increasing popularity of numerous music streaming platforms such as Pandora, Spotify, and Deezer. Therefore, *understanding the relationship between music preferences and personality* is a timely research topic and an important asset for music recommender systems, especially in a cold-start scenario where nothing or little is known of the target user.

This relationship has been explored in the past in different works, e.g. [8, 25, 26], however, the majority of these studies categorise music preferences into broad and debatable genres and styles, even providing inconsistent results [26]. In contrast to this loosely-defined music categorisation, we explore music preferences in terms of a defined set of audio features, including tempo, loudness, and energy (cf. Section 4), which are not tied to a specific genre or subgenre. More precisely, we study to what extent personality traits, defined by the five-factor model [12], correlate with music preference profiles created from such finer content-based features of the music people listen to. To this end, we analyse the music listening data and personalities traits of more than 1,300 users who shared over 35 million listening events on the music streaming platform Last.fm. Against this background we formulate the following research question:

RQ: Are there significant correlations between listeners' personality traits and music preferences in terms of audio features of the music they listen to? And if so, how strong are these correlations?

2 RELATED WORK

Understanding what differentiates individuals' music preferences has been widely studied in the past decade. Researchers surveyed several factors that could explain such differences, including age [3, 7, 10], gender [10, 19], cognitive style [9], and personality [8, 10, 25, 26]. The latter, in particular, is considered as an indicator for personal preferences and, hence, an appropriate factor for studying music inclinations [10]. The well-established five-factor model [12] (also know as OCEAN model) offers a generally accepted method to measure such a personality along five dimensions or traits: openness to experience, consciousness, extraversion, agreeableness, and neuroticism.

Among the several studies that explore the connection between personality and music preferences [3, 5, 8, 10, 16, 25, 26], many of them consider music preferences in terms of genres, styles, or high-level music dimensions [3, 5, 8, 16, 25, 26]. In one of the first works on the topic, Rentfrow et al. [25] consider four music preference dimensions (Reflective & Complex, Intense & Rebellious, Upbeat & Conventional, Energetic & Rhythmic) enclosing 14 different genres. They show, e.g., that openness is highly correlated with reflective

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and complex genres such as jazz and classical music, and that high agreeableness indicates a generally higher preference for upbeat and conventional music such as pop and country. Their work influenced several following studies, e.g. [3, 5, 16], which employed different music styles and dimensions. A meta-analysis of these (and other similar) studies can be found in [26]. Schäfer et al. [26] also suggest to use a finer categorisation of music preferences based on musical attributes instead of genres since the concept of genre may not fully capture the musical tastes of the users.

Such a fine-grained categorisation concerning musical attributes is considered by Greenberg et al. in [10], where they identify three main musical dimensions, namely arousal (e.g., intense, forceful, thrilling), depth (e.g., complex, deep, dreamy), and valence (e.g, happy, lively, amusing). They find, for example, that agreeableness is negatively correlated with affectively negative and aggressive music (arousal), or that openness is positively correlated with complex and intelligent musical pieces (depth).

While the above-mentioned works rely on the explicit feedback of study participants on their music preferences, Ferwerda et al. [8], instead, study the relationship between personality and genre preferences by analysing user-generated data from the music streaming platform Last.fm. Given the entire music listening history of the users, they find significant correlations between 18 genres and personality traits.

Addressing the topic from a different perspective, Lu et al. [18] explore the issue of diversity in music recommender systems. In their pilot study, the authors investigate the correlations between personality and diversity degrees concerning various music attributes (e.g. number of artists, key, genre). The significant correlations are then used to tune a recommendation algorithm according to the personalised diversity needs, showing an increase in user satisfaction and user-perceived recommendation quality.

The study at hand differs from the mentioned works for the following reasons: (1) it models music preferences in terms of a wide spectrum of music audio features which are not tied to a specific genre or style, (2) it is based on the analysis of user-generated data created by more than 1,300 users who shared over 35 million listening events, and (3) it investigates three statistical moments (mean, standard deviation, and skewness) to model audio features in the creation of users' music preference profiles.

3 DATA ACQUISITION AND PROCESSING

Since we aim at uncovering hidden relationships between music listeners' personality traits and audio features of the music they listen to, we use a subset of the MyPersonality dataset [30]. MyPersonality was a popular application on Facebook where users were able to take psychometric questionnaires to assess their personality according to the five-factor model. Since our study focuses on music preferences, we only consider users of MyPersonality who provided their user names for the music streaming platform Last.fm.[1] We filter out careless users through long-string analysis [13]; i.e., for each user, we count the maximum number of consecutive duplicate answers and drop users above the 99% percentile. After manual inspection, we also remove users whose names most certainly hint at a fake account, e.g., "Last.FM" or "901". We then query the Last.fm API[2] for the full listening history of each remaining user (until November 28, 2019), excluding private or deleted accounts. A user's listening history comprises various listening events, each of which is defined by a user name, track name, artist name, album name, and the MusicBrainz[3] track identifier (when available). Users without listening events are filtered out. These processing steps eventually result in a dataset of 1,487 users, who shared a total of 48,829,949 listening events on Last.fm (covering 4,854,393 unique tracks).

[1] https://www.last.fm

			Full	Refined
		# Users	1,470	1,346
		# List. Events	34,692,227	34,690,978
		# Tracks	2,391,096	2,390,924
Per user	**List. Events**	mean	23,600	25,773
		std	37,958	38,957
		min	1	30
		max	366,565	366,565
		median	8,168	10,521
	Tracks	mean	4,724	5,159
		std	7,756	7,967
		min	1	16
		max	158,873	158,873
		median	2,108	2,519

Table 1: Basic statistical properties of the dataset.

In order to complement the listening events with content-based information of the music tracks, we fetch the respective audio features from Spotify.[4] In detail, we use a conjunction of track name, artist name, and album name to retrieve the corresponding Spotify URIs.[5] The gathered URIs are then used to query the Spotify Audio Features API,[6] retrieving a set of 12 features per track (cf. Section 4). As a result, we acquire content-based features for 1,908,594 unique tracks (39%), covering 28,997,721 listening events (59%). The remaining tracks could not be resolved to a Spotify URI, foremost because of missing or noisy information.[7] Besides, Spotify does not provide the audio features for all tracks in their library.

To improve coverage of listening events in the presence of such noisy and/or incomplete data, we adopt a URI propagation approach as follows. In case of an unresolved track with missing album name, we rely on the resolved tracks with the same MusicBrainz track identifier,[8] if there are any. If a single resolved track with the same MusicBrainz identifier exists, we propagate its URI to the unresolved track under consideration. If multiple resolved tracks with the same MusicBrainz identifier exist, we propagate the URI of the most popular resolved track according to Spotify's popularity measure (cf. Section 4). This URI propagation process grants us *audio features for 2,391,096 tracks and 34,692,227 listening events*, which account for 49% and 71% of all tracks and listening events, respectively. The remaining, unresolved tracks and listening events are discarded

[2] https://www.last.fm/api/show/user.getRecentTracks
[3] https://www.musicbrainz.org
[4] https://www.spotify.com
[5] https://api.spotify.com/v1/search
[6] https://api.spotify.com/v1/audio-features
[7] Last.fm music metadata is predominantly maintained by their community and is therefore prone to noisy or ambiguous text as names for tracks, albums, and artists.
[8] For more details, please consider https://musicbrainz.org/doc/Track.

from the dataset. We also drop users that do not have tracks with audio features, leaving us with *1,470 users*.

Statistics of the final dataset are shown in Table 1 (column "Full"). For reproducibility, we make both the code and the data publicly available. [9]

4 METHODOLOGY

The goal of this study is to gain insights into the relatedness of music content preferences and personality traits of users. To this end, for each user, we construct a music preference profile by aggregating the audio features of all the tracks they listened to and then compute rank-order correlations between these preference profiles and personality traits.

The music preference profile is modelled through a set of 12 track features (11 audio-related and 1 popularity measure), provided by Spotify: *Acousticness* (probability that a track is acoustic); *Danceability* (how suitable a track is for dancing); *Duration* (of the track in milliseconds); *Energy* (perception of intensity and activity in a track); *Instrumentalness* (probability a track does not contain vocals); *Liveness* (confidence value that indicates whether the track has been performed in presence of an audience); *Loudness* (average loudness of the track in decibel); *Speechiness* (presence of spoken words); *Tempo* (pace of the track in beats per minute); *Valence* (probability that the track conveys positiveness); *Mode* (major or minor); *Popularity* (Spotify's popularity value).

Given these features for each track in our collection, we construct per-user *music preference profiles* in the following way: we aggregate the audio features of all the listening events (not unique tracks) the target user listened to and compute the mean, standard deviation, and skewness. Tracks listened to multiple times will, therefore, contribute more to a user's profile than tracks listened only once. Since *mode* is a binary attribute, we compute the percentage of tracks in minor mode in the listening history of each user and use this percentage as a continuous feature (the percentage of major mode is complementary). As additional features, we consider the total number of listening events and the total number of tracks the user listened to on Last.fm.

Finally, we compute Spearman's rank-order correlation coefficients ρ [32] and test their statistical significance using the two-tailed t-test at different confidence levels (α = 5%, 1%, and 0.1%). We opt for a rank-correlation measure since we are interested in monotonic relationship between our attributes instead of plain linear relationship [23]. Moreover, in order to control for the number of false discoveries in our study, we opt for the False Discovery Rate method [2] with a q-value of 5%.

Our final music preference profile is defined in terms of statistics (arithmetic mean, standard deviation, and skewness) whose quality depends on the number of listening events we aggregate on a per-user-basis. Therefore, to ensure the meaningfulness of our results, we refine our dataset by selecting only the users that have a number of listening events above or equal to a certain threshold. We explore different values for the threshold, ranging from 0 (threshold not enforced) to 100, with increments of tens. Computing the average of the absolute correlation values (correlations between all personality traits and all music preference attributes), we notice that they approach a local maximum and stabilise when the threshold reaches the value of 30. We, therefore, drop all users that have fewer than 30 listening events. The statistics of this refined dataset are shown in Table 1 (column "Refined").

[9]https://gitlab.cp.jku.at/alessandro/pers-corr

5 RESULTS AND DISCUSSION

The strength of our correlations and their respective significance are shown in Figure 1. The overall correlations are low to moderate, with the most accentuated effects for the openness trait. Below we discuss and describe our significant results for each trait.

Openness is positively correlated with the number of tracks ($\rho = 0.095$) and negatively with track popularity (*popularity mean* $\rho = -0.133$, *skew* $\rho = 0.102$). Therefore, people scoring high on this trait, and hence more likely to try new things, listen to a higher number of unique tracks with a higher preference for niche tracks. Moreover, we also notice that openness is almost always positively correlated with the standard deviation of all audio features (*acousticness std* $\rho = 0.297$; *danceability std* $\rho = 0.215$; *duration std* $\rho = 0.205$; *energy std* $\rho = 0.281$; *instrumentalness std* $\rho = 0.182$; *loudness std* $\rho = 0.269$; and *valence std* $\rho = 0.172$) which, again, is in line with the stereotypical image of a person open to experiences. Although users scoring higher on openness listen to many diverse music tracks, correlations with mean and skewness indicate more custom acoustic preferences. Open people prefer acoustic and instrumental tracks (*acousticness mean* $\rho = 0.284$, *skew* $\rho = -0.281$; *instrumentalness mean* $\rho = 0.186$, *skew* $\rho = -0.179$) while they prefer quieter tracks (*loudness mean* $\rho = -0.313$, *skew* $\rho = 0.139$) and lower energy and tempo (*energy mean* $\rho = -0.283$, *skew* $\rho = 0.263$; *tempo mean* $\rho = -0.22$, *skew* $\rho = 0.086$). We also notice a mediocre preference for live tracks (*liveness mean* $\rho = -0.104$, *skew* $\rho = 0.147$), and speechful tracks (*speechiness mean* $\rho = -0.079$, *skew* $\rho = 0.121$). Lastly, we find a considerable inclination to listen to longer tracks since not only the centre of the *duration* distribution is pushed to higher values when openness increases (*duration mean* $\rho = 0.106$) but also the tail toward longer tracks becomes heavier (*duration skew* $\rho = 0.149$).

People scoring high on **consciousness**, overall, seem to listen to fewer tracks (*# listening events* $\rho = -0.092$; *# tracks* $\rho = -0.097$). They also seem to be more selective when it comes to speechiness (*speechiness std* $\rho = -0.072$), even though there is no correlation with the respective mean, giving no insight into custom music preference.

Extraversion is positively correlated with danceabiltiy and valence (*danceability mean* $\rho = 0.13$; *valence mean* $\rho = 0.111$, *skew* $\rho = -0.115$). Users with high extraversion also spend less time listening to music (*# listening events* $\rho = -0.102$; *# tracks* $\rho = -0.091$; *duration mean* $\rho = -0.074$, *std* $\rho = -0.072$). Other correlations for extravert people involve tendency for more vocal tracks (*instrumentalness mean* $\rho = -0.079$, *std* $\rho = -0.079$, *skew* $\rho = 0.081$), and more selectiveness for energy and loudness (*energy std* $\rho = -0.076$; *loudness std* $\rho = -0.09$).

Agreeableness is the only trait that is correlated with the *mode* attribute, showing that higher values for this trait negatively impact the share of minor tracks (*% minor* $\rho = -0.107$). Similarly to open people, high agreeable people also prefer various levels of

	# listening events	# tracks	popularity mean	popularity std	popularity skew	acousticness mean	acousticness std	acousticness skew	danceability mean	danceability std	danceability skew	duration ms mean	duration ms std	duration ms skew	energy mean	energy std	energy skew
ope	0.051	0.095***	-0.133***	-0.048	0.102***	0.284***	0.297***	-0.281***	0.007	0.215***	-0.014	0.106***	0.205***	0.149***	-0.283***	0.281***	0.263***
con	-0.092***	-0.097***	0.011	0.041	-0.022	0.003	-0.024	-0.001	0.03	-0.049	-0.06	0.013	-0.058	-0.045	-0.012	-0.038	0.011
ext	-0.102***	-0.091***	0.047	0.042	-0.056	0.014	-0.03	-0.019	0.13***	0.011	-0.021	-0.074**	-0.072**	-0.056	-0.016	-0.076**	0.038
agr	-0.071**	-0.074**	0.059	0.017	-0.053	0.082**	0.067*	-0.083**	0.051	-0.041	-0.081**	-0.07*	-0.07*	-0.023	-0.076**	0.037	0.073**
neu	0.079**	0.067*	0.015	-0.038	0.006	-0.057	-0.026	0.06	-0.073**	-0.029	0.069*	-0.027	0.005	0.017	0.051	-0.007	-0.066*

	instrumentalness mean	instrumentalness std	instrumentalness skew	liveness mean	liveness std	liveness skew	loudness mean	loudness std	loudness skew	speechiness mean	speechiness std	speechiness skew	tempo mean	tempo std	tempo skew	valence mean	valence std	valence skew	% minor
ope	0.186***	0.182***	-0.179***	-0.104***	-0.018	0.147***	-0.313***	0.269***	0.139***	-0.079**	0.023	0.121***	-0.22***	-0.051	0.086**	-0.065*	0.172***	0.058	0.0
con	-0.035	-0.035	0.038	-0.048	-0.036	0.057	-0.005	-0.023	0.029	-0.051	-0.072**	-0.009	-0.029	-0.024	0.004	0.008	-0.018	0.011	0.004
ext	-0.079**	-0.079**	0.081**	-0.014	-0.018	0.02	0.03	-0.09***	0.056	0.05	0.062	-0.088**	-0.027	-0.035	0.01	0.111***	-0.016	-0.115***	-0.022
agr	-0.078**	-0.063	0.081**	-0.096***	-0.085**	0.079**	-0.009	-0.008	0.063	-0.074**	-0.033	0.046	0.006	0.035	-0.052	0.031	-0.003	-0.012	-0.107***
neu	0.011	0.001	-0.013	0.025	0.007	-0.019	0.04	-0.016	-0.063	-0.017	-0.043	0.01	0.049	-0.009	-0.013	-0.045	0.007	0.035	0.018

Figure 1: Spearman's rank-order correlations ρ between personality traits and audio features. Significant correlations are highlighted and shown with their respective p-values (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). p-values have been adjusted according to False Discovery Rate with a q-value of 5%

acousticness with a tendency for higher values (*acousticness mean* $\rho = 0.082$, *std* $\rho = 0.067$, *skew* $\rho = -0.083$). Other correlated audio preferences include: less intense (*energy mean* $\rho = -0.076$, *skew* $\rho = 0.073$), shorter (*duration mean* $\rho = -0.07$), less instrumental (*instrumentalness mean* $\rho = -0.078$, *skew* $\rho = 0.081$), low on speech content (*speechiness mean* $\rho = -0.074$) tracks, which are not performed live (*liveness mean* $\rho = -0.096$, *skew* $\rho = 0.079$). Additionally, agreeable people are more selective in their music choices (*# listening events* $\rho = -0.071$; *# tracks* $\rho = -0.074$; *duration std* $\rho = -0.07$; *liveness std* $\rho = -0.085$)

Lastly, **neuroticism** is mostly associated with preference for low danceability (*danceability mean* $\rho = -0.073$, *skew* $\rho = 0.069$). Higher neuroticism values are correlated with higher music consumption (*# listening events* $\rho = 0.079$; *# tracks* $\rho = 0.067$).

6 CONCLUSION AND FUTURE WORK

In this work, we studied the relationship between personality traits and audio features of the music users listen to. In contrast to past work on the topic, we modelled music preferences in a finer-grained way, using a set of 12 content-based features instead of loosely-defined music genres and styles. Analysing nearly 35 million listening events generated by 1,346 users with different personalities, we found meaningful differences in terms of correlations of music preferences among the five personality traits.

Following these results, we can positively answer our research question. There exist significant correlations between listeners' personality traits and music preferences in terms of audio features of the music they listen to. The overall correlations are weak to medium, with strongest effects for the openness trait.

We believe that our work can positively contribute to the creation of personalised music recommender systems. Given the significant and different correlates of music preferences, a user model involving personalities can be used to generate more tailored and custom recommendations, similarly to [18]. As an example, highly acoustic tracks may be recommended to people scoring high on openness and agreeableness but not to highly neurotic users. Our findings are especially useful in a cold-start scenario, when little or nothing is known of the user. Assuming that personality information is available, e.g., through "single sign-on" functionalities and/or automatic personality recognition techniques [1, 31], we can provide more personalised recommendations as opposed to recommending the most popular tracks during cold-start.

Given these findings, in future work, we plan to quantify the effect of personality information on music recommendation systems both in cold-start (similar to [6, 11]) and warm-start scenarios. In preliminary experiments, for example, we incorporated personality traits along with the user's listening history into a variational autoencoder architecture [17] to better capture the latent listening preferences of the users and produce better recommendations. Another avenue for future work is to devise machine learning algorithms to infer personality traits from music listening preferences, similarly to what Krismayer et al. [15] did for demographics prediction.

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