Personality Traits and Music Genres: What Do People Prefer to Listen To?

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ABSTRACT

Personality-based personalized systems are increasingly gaining interest as personality traits has been shown to be a stable construct within humans. In order to provide a personality-based experience to the user, users' behavior, preferences, and needs in relation to their personality need to be investigated. Although for a technological mediated environment the search for these relationships is often new territory, there are findings from personality research of the real world that can be used in personalized systems. However, for these findings to be implementable, we need to investigate whether they hold in a technologically mediated environment. In this study we assess prior work on personality-based music genre preferences from traditional personality research. We analyzed a dataset consisting of music listening histories and personality scores of 1415 Last.fm users. Our results show agreements with prior work, but also important differences that can help to inform personalized systems.

CCS CONCEPTS

•**Human-centered computing** → **User models; User studies;** •**Information systems** → *Recommender systems;*

KEYWORDS

Music, Personality, Recommender Systems, User Modeling

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1 INTRODUCTION

Personality traits are increasingly being incorporated in systems to provide a personalized experience to the user. Personality has shown to be a stable construct and is often used as a general user model to relate behavior, preferences, and needs to [16]. Relating behavior, preferences, and needs to such a general model allows for implementation across platforms [1]: it can be inferred from one platform and implemented into the other. The advantage of personality traits being applicable across platforms is that questionnaires can be omitted (by inferring personality from a different platform) and situations where data is scarce (e.g., cold-start problem [24]) can be overcome.

There is a growing body of research investigating and exploring the relationship between personality traits of users and technologically mediated behavior, preferences, and needs (e.g., health [15, 22], education [2, 18], movies [3], music [7–9, 23]). However, extensive personality research has been done already on real world (social) interactions that may apply to a technological setting as well. Since technologies are becoming increasingly ubiquitous and pervasive, the possibilities that users have reach much further than in real world situations. It is for these real world findings that we need to verify whether they still apply in a technological setting before able to implement them for personalization.

In this work we assess one of these personality related findings of real world interactions. We look at prior work of Rentfrow & Gosling [20] in which they investigated whether personality is related to preferences for specific music genres. To investigate the relationship between personality and music genre preferences, we used a subset of the myPersonality dataset. Next to users' personality scores, this subset consist of the listening history of Last.fm (an online music streaming service) [1] users. By analyzing the listening histories of 1415 users in relation to their personality, we found agreements with prior work of Rentfrow & Gosling, but also important differences. Our insights may help to inform personalized music systems. For example, music recommender systems can improve their cold-start recommendations by knowing which music genres to recommend to their users.

2 RELATED WORK

Currently, there are two different personality related research directions focusing on: 1) personality-based personalization, (e.g., health [22], education [2, 18], movies [3], music [7–9, 23]) and 2) implicit personality acquisition from user-generated content (e.g., Facebook [11, 14], Twitter [19], Instagram [10, 12], and fusing information [21]). Since traditional personality research is done in real world settings, both of the aforementioned research directions often explore new territory: personality relationships in a technological

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

context. For example, in the area of personality-based personalization Ferwerda et al. [13] looked at differences in how users browse for music (i.e., browsing music by genre, activity, or mood) in an online music streaming service. Others investigated personality-based diversity preferences in recommender systems (e.g., [3, 6]): Chen, Wu, & He [3] investigated diversity preferences in movie recommendations. In the area of implicit personality acquisition research mainly focuses on user-generated content of users' social media accounts. Quercia et al. [19] found that how users behave on Twitter consist of cues to predict their personality. Similarly, Golbeck, Robles, & Turner [14] were able to develop a personality predictor based on the characteristics of a user's Facebook account.

There are also results from traditional personality research that can inform design of personalized technologies. For example, research in education has shown that there are differences in learning that can be related to the personality of the individual (see [5] for an overview). Although the right personalized technology still needs to be investigated, the results from the real world can inform to which personality traits to pay attention to. Other findings are seemingly more directly transferable to a technological setting. Rentfrow & Gosling [20] found that personality traits are related to music genre preferences. By testing preferences within predefined sets of 20 music pieces, they asked their participants to rate the preference for each of the songs (0 - 20 scale: no preference - strong preference). Although their findings may look like they are directly implementable for personalization, current online music systems (e.g., online music streaming services) provide their users with an almost unlimited amount of content that is directly at their disposal. Not only provide this convenience for the user, it also allows them to easily explore content outside of their initial interest. Hence, users may be prone to try out different content more than they in real life would do and even their preference may change more often or becomes more versatile. Therefore, it is important to assess whether results from the real world still apply in a fast growing technological environment.

In this work we explore a dataset of an online music streaming service consisting of the total listening history of their users. We use this dataset to investigate whether music genre relationships exists with the personality of the listener, and whether the found relationships are in line with findings of Rentfrow & Gosling [20].

3 METHOD

In order to investigate the relationship between personality and music genre preferences in an online music streaming service, we made use of the myPersonality dataset. [2] The dataset originates from a popular Facebook application ("myPersonality") that is able to record psychological and Facebook profiles of users that used the application to take psychometric (e.g., personality, attitudes, skills) tests. The dataset contains over 6 million test results, with over 4 million Facebook profiles. Users' personality in the myPersonality application was assessed using the Big Five Inventory to measure the constructs of the five factor model: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism.

We only used the subset of the myPersonality dataset that contains the music listening history of Last.fm users (i.e., play-count of artists that a user listened to). The subset consists of users' complete listening histories (i.e., from the moment they started to use Last.fm) until April 27 (2012). We complemented the dataset by adding the listening events of each user until December 18 (2016) by using the Last.fm API. [3] A total of 2312 Last.fm users with ~40 million listening events from 101 countries are represented in the subset.

Through the Last.fm API, we crawled additional information about the artists by using the "Artist.getTopTags" endpoint. This endpoint provided us with all the tags that users assigned to an artist, such as instruments ("guitar"), epochs ("80s"), places ("Chicago"), languages ("Swedish"), and personal opinions ("seen live" or "my favorite"). Tags that encode genre or style information were filtered for each artist. The filtered tags were then indexed by a dictionary of 18 genre names retrieved from Allmusic. [4] For each user, the artists that were listened to were aggregated by the indexed genre with their play-count. The genre play-count for each user was then normalized to represent a range of $r \epsilon [0,1]$, this in order to be able to compare users with differences in the total amount of listening events.

4 ANALYSIS

For the analysis we filtered out users with zero play-counts (users who registered, but did not make use of Last.fm) and people listening to less than five different artists. This left us with a total of 1415 users (~20 million listening events) of 83 countries in our final dataset for analysis.

Spearman's correlation was computed between personality traits and the genre play-count to assess the relationship of personality and genre preferences. Alpha levels were adjusted using the Bonferroni correction to limit the chance on a Type I error. The reported significant results adhere to alpha levels of $p < .001$.

5 RESULTS

The results show significant correlations between personality traits and genre preferences (see Table 1). Below the results related to each personality trait. A positive correlation indicates that participants scoring high in the personality trait show a higher tendency to listen to such music genre, while a negative correlation indicates the opposite effect.

Openness to Experience

Those users scoring high on the openness to experience trait show most correlations with different music genres. They show correlations with new age (r =.101), classical (r =.136), blues (r =.120), country (r =.106), world (r =.134), folk (r =.214), jazz (r =.139), and alternative (r =.115) music. This indicates that open users tend to listen to a wide variety of music genres.

Conscientiousness

Conscientious users only show a correlation with folk (r =-.115) and alternative (r =-.104) music. However, the correlation coefficient indicates a negative correlation meaning that conscientious music listeners tend to listen less to folk and alternative music.

[2] http://mypersonality.org/

[3] http://www.last.fm/api

[4] http://www.allmusic.com

	O	C	E	A	N
R&B	-.002	.026	**.103**	.021	-.012
Rap	-.019	-.017	**.129**	.008	-.049
Electronic	.077	-.029	.034	-.033	-.002
Rock	-.055	-.016	-.072	-.017	.057
New Age	**.101**	.008	-.067	-.019	-.031
Classical	**.136**	-.037	-.064	-.032	.000
Reggae	.017	-.042	.061	.009	-.041
Blues	**.120**	-.011	.023	-.011	-.044
Country	**.106**	-.049	-.002	**.104**	-.012
World	**.134**	-.021	-.006	-.028	-.020
Folk	**.214**	**-.115**	-.044	**.104**	.002
Easy Listening	.041	.010	.018	-.027	-.012
Jazz	**.139**	-.007	.042	.031	-.061
Vocal (a cappella)	**.120**	-.020	.006	-.021	.006
Punk	.002	-.061	-.020	.001	.030
Alternative	**.115**	**-.104**	-.031	.060	**.101**
Pop	-.034	.035	.056	.056	-.030
Heavy Metal	-.031	-.023	-.076	-.069	-.001

Table 1: Spearman's correlation between music genres and personality traits: (O)penness to experience, (C)onscientiousness, (E)xtraversion, (A)greeableness, and (N)euroticism. Significant correlations after Bonferroni correction are shown in boldface (p <.001).

Extraversion
Extraverts are positively correlated with: r&b (r =.103) and rap (r =.129) music. The results show that extraverts seem to listen more to r&b and rap music compared to other genres.

Agreeableness
Agreeable users show to be positively correlated with country (r =.104) and folk (r =.104) music, meaning that they on average tend to listen more to these music genres.

Neuroticism
Neurotic users show a positive correlation with alternative (r =.101) music, meaning that they listening on average more to alternative music than to the other genres.

6 DISCUSSION

Our results show significant correlations between personality traits of users and the music genres that they prefer to listen to. The goal of this study was to see whether the results of prior work [20] in a real world context would also be valid when analyzing online listening behavior. In order to make a comparison, the results of the work of Rentfrow & Gosling are shown in Table 2. They analyzed the music pieces that they presented to their participants on its music attributes, and divided the music genres into four categories: reflective & complex, intense & rebellious, upbeat & conventional, and energetic & rhythmic (see Table 3 for a mapping with the music genres). Instead of preselecting music pieces for participants to rate, we analyzed historical behavior of online music listeners. Hence, our data consists of so many music pieces that we were not able to

	O	C	E	A	N
Reflective & Complex	**.41**	-.06	-.02	.03	.04
Intense & Rebellious	**.15**	-.03	**.08**	.01	-.01
Upbeat & Conventional	**-.08**	**.18**	**.15**	**.24**	-.04
Energetic & Rhythmic	.04	-.03	**.19**	**.09**	-.01

Table 2: Correlations between music attributes and personality traits of prior work of Rentfrow & Gosling [20]: (O)penness to experience, (C)onscientiousness, (E)xtraversion, (A)greeableness, and (N)euroticism. Significant correlations are shown in boldface.

Reflective & Complex	Classical	Jazz	Blues	Folk
Intense & Rebellious	Alternative	Rock	Heavy Metal	
Upbeat & Conventional	Country	Pop	Religious	Sound Tracks
Energetic & Rhythmic	Rap & Hip-Hop	Soul & Funk	Electronica & Dance	

Table 3: Mapping of music attributes and genres of the work of Rentfrow & Gosling [20].

make such genre mapping based on the music attributes. We refer to both Table 2 and Table 3 for comparisons with prior work on the correlations and the genre mapping respectively.

For the openness to experience personality trait, we found agreements with prior work of Rentfrow & Gosling [20]. For example, they found that open people prefer to listen to reflective & complex genres (e.g., classical, blues, jazz, and folk music) as well as to intense and rebellious music (e.g., rock, alternative). However, our results also show additional correlations with other music genres. Our results show that those who score high on the openness to experience trait have a more divers genre listening behavior than found by prior work. The preferences for such a diverse range of music genres may be explained by the traditional nature of this personality trait. Open people have been shown to have a preference for variety in general [4], which may also be applied to music genre preferences.

Rentfrow & Gosling [20] showed that conscientious people have a preference for upbeat & conventional music (e.g., country, pop, religious, and sound track music), whereas our results show a negative correlation for alternative and folk music. However, in line with our results, the replication of the Rentfrow & Gosling study by Langmeyer, Guglhör-Rudan, & Tarnai [17] found the conscientiousness personality trait to be negatively correlated with intense & rebellious music (e.g., alternative music).

In line with prior works [17, 20], our results show that extraverts have a preference for r&b and rap music, which can be mapped to the energetic & rhythmic music (e.g., rap, hip-hop, and soul music) attribute.

Also the agreeableness personality trait shows agreements with prior work. Our results show that agreeable users tend to listen more to country and folk music. Rentfrow & Gosling [20] showed that their results indicate that agreeable people especially have a preference for upbeat & conventional music, such as country, pop, and religious music.

Lastly, we found a correlation with those scoring high on neuroticsm and a preference for the alternative music genre. Although Rentfrow & Gosling [20] did not find any relationship with the neuroticism trait in their work, the replication study of Langmeyer, Guglhör-Rudan, & Tarnai [17] did. They found that neuroticism correlates with intense & rebellious (e.g., alternative, rock, and heavy metal music).

7 CONCLUSION & LIMITATIONS

In this work we investigated the relationship between music genres and personality traits by analyzing online music listening behavior of Last.fm users. Besides investigating this relationship, we foremost wanted to see whether there are agreements with the results of Rentfrow & Gosling [20] of music genre preferences in a real world context. By analyzing a large scale dataset of Last.fm music listening histories, we were able to find distinct relationships between personality traits and music genres, but also agreements with prior findings of Rentfrow & Gosling (and the replication study of Langmeyer, Guglhör-Rudan, & Tarnai [17]).

Although we found support for all our findings, it is difficult to make direct comparisons with the results of prior work [17, 20]. One problem that we were facing is that they clustered their results into categories of music attributes (see Table 2 and Table 3). Although a mapping to music genres is provided (Table 3), it is not possible for us to see to what extent correlations exist between personality traits and music genres. We could only identify whether the music genre correlations that we found exist in the music attributes mapping. Prior work was able to make music attributes inferences by preselecting music pieces for their participants. In contrast, We analyzed a dataset consisting of ∼20 million listening events, making it impossible to assess the pieces on their music attributes.

By not clustering the analyzed music genres on its music attributes, we are able to provide more fine-grained correlations between music genres preferences and personality traits. This may be especially useful for personality-based personalized systems. Although music genres may be the same on an attribute level, they may have a complete different impact on the user. Hence, music genre differentiation is important to have for personalized systems.

Our work contributes to the personality-based work for personalized systems. We provide with our work insights on whether and how music personality-based results from the real world transfers to a technological context. By analyzing a large scale dataset we are also able to provide insights based on a more realistic scenario.

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