Personality Traits and Music Genre Preferences: How Music Taste Varies Over Age Groups

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ABSTRACT

Personality traits are increasingly being incorporated in systems to provide a personalized experience to the user. Current work focusing on identifying the relationship between personality and behavior, preferences, and needs often do not take into account differences between age groups. With music playing an important role in our lives, differences between age groups may be especially prevalent. In this work we investigate whether differences exist in music listening behavior between age groups. We analyzed a dataset with the music listening histories and personality information of 1415 users. Our results show agreements with prior work that identified personality-based music listening preferences. However, our results show that the agreements we found are in some cases divided over different age groups, whereas in other cases additional correlations were found within age groups. With our results personality-based systems can provide better music recommendations that is in line with the user's age.

CCS CONCEPTS

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

KEYWORDS

Music, Personality, Recommender Systems, User Modeling, Age Differences

1 INTRODUCTION

Personality has shown to be a stable construct over time, and reflects the coherent patterning of one's affect, cognition, and desires (goals) as it leads to behavior [24]. This stability and coherency of personality has shown to be useful for systems to infer users' preferences and to provide personalized experiences to users (e.g., [8]). Hu & Pu [19] showed that personality-based personalized systems have an advantage over personalized systems not incorporating personality information in terms of increased users' loyalty towards the system and decreased cognitive effort.

The relationships between personality traits and users' behavior preferences and needs are increasingly being investigated (e.g., health [17, 26], education [2, 21], movies [3], music [8–10, 14, 27]). These studies normally analyze their sample as a whole and do not consider differences based on age groups. Arnett [1] showed that especially those in their adolescence and emerging adulthood phases experience a heightened chance of "storm and stress" [1] in which they try to find their place in society. Hence, differences may occur in behavior, preferences, and needs throughout different phases in life.

To investigate the relationship between personality and music genre preferences over different age groups, 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) [2] users. By analyzing the listening histories of 1068 users in relation to their personality and age, we found important differences across age groups. Our insights may help to inform personalized music systems. For example, personality-based music recommender systems can improve their cold-start recommendations (e.g., [5, 28]) by better knowing which music genres to recommend to their users of different age groups.

2 RELATED WORK

Currently, there are two different personality related research directions focusing on: 1) personality-based personalization (e.g., health [17, 26], education [2, 21], movies [3], music [8–10, 14, 27]) and 2) implicit personality acquisition from user-generated content (e.g., Facebook [12, 16], Twitter [22], Instagram [11, 13], and fusing information [25]). For example, in the area of personality-based personalization Ferwerda et al. [15] looked at differences in how users browse for music (i.e., browsing music by genre, activity, or mood) in an online music streaming service. 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. [22] found that how users behave on Twitter consist of cues to predict their personality. Similarly, Golbeck, Robles, & Turner [16] were able to develop a personality predictor based on the characteristics of a user's Facebook account.

Current personality-based research does not take into account differences between age groups. However, Arnett [1] notes that especially those in their adolescence and emerging adulthood phases

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[1] Storm-and-stress is a term first coined by Hall [18] to refer to a period in life in which people experience turmoil and difficulties.
[2] http://www.last.fm/

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may show deviant behavior. With music been shown to play an important role in our lives by providing support for a whole range of daily activities we engage in (e.g., sports, studying, sleeping) [23], differences (e.g., listening behavior, preferences, and needs) across age groups may especially be prevalent.

In this work we analyze a dataset of an online music streaming service consisting of the total listening history of their users. With this dataset we investigate whether differences in music listening behavior exist.

3 METHOD

In order to investigate the relationship between personality and music genre preferences across age groups in an online music streaming service, we made use of the myPersonality dataset. [3] 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, 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) and the day of birth in order to calculate their age. 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. [4] A total of 1066 Last.fm users with ~40 million listening events from 101 countries are represented in the subset.

The 1066 Last.fm users were split into three different age groups according to the primary life stages [4]: adolescence (age: 12-19), young adulthood (age: 20-39), and middle adulthood (age: 40-65). Having the day of birth of the 1066 Last.fm users as well as their complete listening history (with listening date), we could traceback users' age when listened to a certain song. Hence, users could fall into *multiple* age groups, which resulted in a sample size bigger than the original sample. The final dataset consists of 1479 Last.fm users divided over three age groups (adolescence: n =581, young adulthood: n =850, middle adulthood: n =48).

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. [5] For each user in an age group, 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

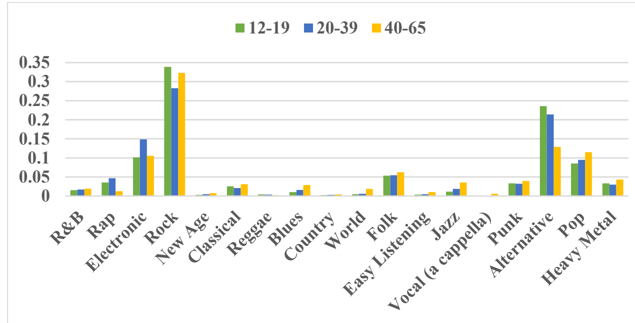

Figure 1: Normalized genre play-counts by age group.

in order to be able to compare users with differences in the total amount of listening events.

4 RESULTS

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 1068 users (adolescence: n =472, young adulthood: n =563, middle adulthood: n =33). The normalized genre play-counts by the different age groups are shown in Figure 1.

To investigate music listening differences between personality traits, 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 (see Table 1). The results of music genre preferences per personality trait per age groups are discussed in the following sections.

4.1 Openness

Adolescence (age: 12-19). For the adolescence group, several positive correlations were found with music genres: New Age (r =.142), Blues (r =.130), Country (r =.117), World (r =.114), Folk (r =.230), Jazz (r =.139), Vocal (r =.132), and Alternative (r =.131). Those scoring high on the openness scale show in general higher listening behavior to these music genres.

Young adulthood (age: 20-39). For the young adulthood group, we found the same kind of positive correlations with music genres: New Age (r =.105), Blues (r =.167), Country (r =.126), World (r =.217), Folk (r =.231), Jazz (r =.106), Vocal (r =.170), and Alternative (r =.116). An additional positive correlation was found with Electronic (r =.106), and a negative correlation with Rock (r =-.104) indicating that those scoring high on openness tend to listen less to Rock music in this age group. Next to Folk music, a stronger correlation was found for World music as well.

Middle adulthood (age: 40-65). When those scoring high on openness reach middle adulthood, their variation of listening to music genres shrinks significantly, but the strength of the correlations increases. We found positive correlations with Blues (r =.358) as

[3] http://mypersonality.org/
[4] http://www.last.fm/api
[5] http://www.allmusic.com

	Openness			**Conscientiousness**			**Extraversion**			**Agreeableness**			**Neuroticism**		
	12-19	20-39	40-65	12-19	20-39	40-65	12-19	20-39	40-65	12-19	20-39	40-65	12-19	20-39	40-65
R&B	-.019	-.004	-.053	-.026	-.009	.150	**.106**	.065	**.326**	-.049	.047	.326	.027	-.001	-.175
Rap	-.019	-.011	-.205	-.085	-.065	.059	.030	**.108**	.052	-.070	.062	.052	.003	-.072	-.158
Electronic	.046	**.106**	-.138	-.043	-.031	.152	.015	.038	-.246	-.090	-.050	-.246	.036	-.023	.133
Rock	-.075	**-.104**	.095	-.058	.016	-.124	-.085	**-.102**	-.182	.070	-.031	-.182	.014	.053	.182
New Age	**.142**	**.105**	.133	.037	-.053	.006	-.022	**-.184**	-.209	.008	.011	-.209	-.062	-.064	-.143
Classical	.080	.038	.266	.028	-.060	.261	**-.136**	**-.146**	-.136	-.070	-.010	-.136	-.015	-.005	-.080
Reggae	-.015	.046	.185	**-.102**	-.059	-.059	.039	.025	.046	-.032	.051	.046	.028	-.042	-.138
Blues	**.130**	**.167**	**.358**	-.048	-.046	.321	.060	.032	.252	-.006	.018	.252	-.054	-.005	**-.552**
Country	**.117**	**.126**	.325	-.067	-.073	.154	.005	.005	.128	.062	**.184**	.128	.049	-.027	-.109
World	**.114**	**.217**	.201	-.016	-.009	.217	**-.102**	-.054	.028	-.056	-.025	.028	.061	-.014	-.236
Folk	**.230**	**.231**	**.368**	-.014	**-.114**	-.268	.066	-.040	.181	**.101**	**.110**	.181	-.064	.004	-.217
Easy Listening	.084	.060	-.161	.020	.024	.256	.041	-.019	.212	-.073	.041	.212	.035	-.012	.006
Jazz	**.139**	**.106**	-.124	-.047	-.025	**.510**	.005	-.010	.062	-.053	-.068	.062	-.039	.004	-.106
Vocal (a cappella)	**.132**	**.170**	.282	.059	-.007	.125	.038	-.013	.136	-.074	-.001	.136	-.014	.002	-.091
Punk	-.032	-.008	.089	**-.130**	**-.103**	.081	**-.111**	-.029	-.074	.005	.006	-.074	**.101**	.049	.220
Alternative	**.131**	**.116**	.154	**-.108**	**-.165**	**.507**	-.010	-.052	-.027	.018	.029	-.027	**.129**	**.137**	.070
Pop	.021	.000	-.157	.045	.005	.052	.064	.017	.287	-.017	**.194**	.287	.040	-.010	-.275
Heavy Metal	-.033	-.044	-.117	-.005	-.012	.038	**-.148**	**-.126**	**-.339**	-.058	**-.105**	**-.339**	-.030	-.030	**.372**

Table 1: Spearman's correlation between music genres and personality traits over age groups. Significant correlations after Bonferroni correction are shown in boldface (p <.001).

well as with Folk (r =.368) music. Indicating that although the variation gets less, the music genre preferences for middle adulthood becomes more prominent.

4.2 Conscientiousness

Adolescence (age: 12-19). Those scoring high on conscientiousness in the adolescence group show mainly negative correlations with the listened music genres: Reggae (r =-.102), Punk (r =-.130), and Alternative (r =-.108). The results indicates that for this age group, conscientious users listen less to these music genres.

Young adulthood (age: 20-39). Negative correlations were also found between music genres and conscientiousness for the young adulthood group. Although the Punk (r =-.103) and Alternative (r =-.108) music genre is in line with the adolescence group, instead of Reggae, this group listens less to Folk (r =-.114) music.

Middle adulthood (age: 40-65). We found two correlations for the middle adulthood group: Jazz (r =.510) and Alternative (r =.507). Both correlation coefficients show high effects between conscientiousness and the music genres.

4.3 Extraversion

Adolescence (age: 12-19). The adolescence group show negative correlations with Classical (r =-.136), World (r =-.102), Punk (r =-.111), and Metal (r =-.148). A positive correlation was found with R&B (r =.106). The results indicate that extraverts in their adolescence phase listen less to Classical, World, Punk, and Heavy Metal music. However, the in general listen to more R&B.

Young adulthood (age: 20-39). For those scoring high on extraversion and fall in the young adulthood group show negative correlations with Rock (r =-.102), New Age (r =-.184), Classical (r =-.146), and Heavy Metal (r =-.126). A positive correlation was found with Rap (r =.108) music.

Middle adulthood (age: 40-65). The middle adulthood group of the extraverts show a positive correlation with R&B (r =.326) and a negative correlation with Heavy Metal (r =-.339).

4.4 Agreeableness

Adolescence (age: 12-19). The adolescence group show only a positive correlation with agreeableness for Folk (r =.101) music. This indicates that agreeable users show in this age group show a preference for Folk music.

Young adulthood (age: 20-39). A more varied music preference is shown for the young adulthood group. Positive correlations were found for Country (r =.184), Folk (r =.110), and Pop (r =.194) music. A negative correlation was found for Heavy Metal (r =-.105) music. Agreeable users in their young adulthood phase seem to prefer to listen to Country, Folk, and Pop, but less to Heavy Metal music.

Middle adulthood (age: 40-65). The middle adulthood group show a negative correlation with Heavy Metal (r =-.339) music, which indicates that their preference to listen to Heavy Metal goes down when reaching the age of middle adulthood.

4.5 Neuroticism

Adolescence (age: 12-19). Neurotics in their adolescence phase show positive correlations with Punk (r =.101) as well as with Alternative (r =.129) music, indicating an increase preference for these music genres.

Young adulthood (age: 20-39). Only a positive correlation with Alternative (r =.137) was found in the young adulthood group.

Middle adulthood (age: 40-65). For the middle adulthood group, music preferences seem to switch. A positive correlation was found with Heavy Metal (r =.372) and a negative correlation was found with Blues (r =-.552).

5 DISCUSSION

Our results show that there are differences in music listening behavior between personality traits, and that these difference can be further broken down by age groups. Overall, our results show that users in their adolescence and young adulthood phases show most variation in their music listening behavior. Not only does the variation become much less when reaching middle adulthood, the correlation strength increase significantly. This indicates that music preferences of the middle adulthood group becomes more established, which is in line with the storm-and-stress argument [1].

The openness trait shows most variation in listening to different music genres amongst the personality traits. This is in line with one of the few works that investigated the relationship between personality traits and music listening behavior [23]. However, what their findings do not show is that there are differences when considering age groups. For example, the addition of a preference for Electronic music in the young adulthood group.

Also the conscientiousness trait shows agreement with prior work [20]. However, additional unique correlations were able to be identified when taking different age groups into account. Our results show that the adolescence group shows an additional negative correlation with Reggae, the young adulthood group shows an additional correlation with Folk music, and the middle adulthood group shows an additional positive correlation with Jazz music.

Our results on extraversion show agreements with prior works [20, 23] as well. However, what the results of prior works do not show is that there is a division based on age. For example, our results show that the positive correlation of R&B and Rap, differ across age groups. The adolescence and middle adulthood group show positive correlations only with R&B, whereas only a positive correlation with Rap was found with the young adulthood group.

For the agreeableness trait, we found agreements with prior work [23] especially for the young adulthood group show: positive correlations with Country, Folk, and Pop music. These full agreements seem to only hold for the young adulthood group. We found less agreements with the adolescence and the middle adulthood group: only Folk music showed to be positively correlated.

The agreements we found with prior work [20] on neuroticism are divided across age groups. Whereas prior works showed grouped correlations with Punk, Alternative, and Heavy Metal music on neuroticism, our results show that these correlations do not hold for all age groups. We show that Punk and Alternative music is positively correlated with neuroticism for adolescence, but only Alternative music is positively correlated with neuroticism in the young adulthood group. Moreover, we show only a positive correlation with Heavy Metal in the middle adolescence group.

6 CONCLUSION & IMPLICATIONS

In this work we investigated whether there are differences across age groups in the relationship between personality traits and music genre preferences. When not considering differences across age groups, we show that we found agreements with prior works [20, 23] on the relationship between personality and music genre preferences. Whereas prior works analyzed their sample as a whole, we show with our results that differences exist in music genre preferences depending on age groups. With our results we validate the results of prior works, but show that there are cases where the previously found correlations with music preferences are divided over different age groups, whereas in other cases other (previously unrevealed) correlations show up within age groups.

Our work contributes to the personality-based work for personalized systems. The differences between age groups that we identified in this work may have important implications for the creation of personalized systems. The focus of the recommendations may differ depending on the age groups a user falls in. For example, the recommendations for adolescent extraverts could be focused on R&B music, whereas recommendations for extraverts in their young adulthood could be more focused on Rap music.

For our future work, we will extend our findings by actually trying to provide music recommendations to users and perform a user-centric evaluation on the recommendations. For example, including diversity in recommendations have shown to be an important feature on satisfaction [29]. In addition, Ferwerda et al. [6, 7] identified the prerequisites for diversification and found differences in diversity needs among personality traits. Our findings could help to inform the diversification in recommendations by incorporating different needs across age groups. For example, those scoring high on openness in their adolescence or young adulthood phases may be given more diverse genres (correlations were found with eight and ten different genres respectively), whereas the recommendations for those in their middle adulthood can be narrowed down to Blues and Folk.

In this work, we also did not take into account possible cultural differences. Although having the music listening histories of users from different countries, we disregarded country information in order to keep a big enough sample. In future work we will address possible cultural differences.

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