Personality and the Interplay between Emotion and Genre in Music Preferences

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by

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CERTIFICATE

It is certified that the work contained in this thesis, titled “Personality and the Interplay between Emotion and Genre in Music Preferences“ by Yash Goyal, has been carried out under my supervision and is not submitted elsewhere for a degree.

Date

Advisor: Dr. Vinoo Alluri

To Dr. Vinoo, Family and Friends

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Abstract

Research over several decades has demonstrated modest and moderately consistent relationships between personality and music preference, but has primarily relied on self-reported data and lab-based listening experiments. Recently, music preference research has begun to take advantage of online listening data from platforms such as Spotify and Last.fm in order to more directly link listening behavior to individual differences. This study extends this new line of research by investigating the associations between naturally occurring music listening behaviors and personality traits, utilizing listening data acquired from Last.fm. We examined social-tagging data by extracting tags related to musical genre and emotion from frequently listened tracks of each participant and clustered them into broader categories to study their association with OCEAN traits. We further evaluated preferences in terms of co-occurring genre and emotion tags and analyzed listening patterns over time to better understand natural patterns of listening as they relate to personality. Our results corroborated previous research and revealed several novel associations that could be used to provide more accurate and highly customized music recommendations, tailored to the user's personality. Then, we comment on existing music preference frameworks and their relevance to naturally occurring music listening behavior. Finally, we compare and analyze the emotions derived from semantic tags and acoustic features, shedding light on the interplay between subjective and objective measures of emotions in music listening and how they relate to personality.

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Chapter 1

Introduction

1.1 Motivation

Music plays a significant role in our everyday lives and has been a key aspect of human existence throughout our evolutionary history. From the intensity of a live Rock or Metal concert, to the tranquility of a flute played during meditation, to having a good cry while listening to a favorite singer-songwriter, we turn to different types of music to experience a wide range of emotions [32, 60, 69]. We take for granted that the type of music we choose says something about us; not only is it common to discuss music preferences when getting acquainted with others [53], we make (somewhat accurate) judgements about others' personalities based on their music preferences [54]. The pervasive presence of music in society makes it an ideal avenue for studying human behavior and understanding the intricate connections between music, emotions, and individual differences. One intriguing aspect is how people utilize music in diverse ways, driven by various motives such as emotion regulation, seeking connection with a virtual other, and self-expression. Exploring these motives and the role of music in fulfilling psychological needs can provide valuable insights into the complexity of human experiences. Furthermore, music reflects both short-term mood-related states, such as humming along to a tune, as well as long-term personality traits, which influence individuals' music associations and preferences. Understanding how individual differences modulate music preferences and the corresponding psychological states can contribute to a deeper comprehension of the interplay between music and personality. The relationship between personality and music preferences is an important topic within music psychology from both theoretical and applied perspectives; it is highly relevant to understanding the role of music in everyday life, but also represents a pivotal aspect in the development of personalized music recommendation systems.

Certain music genres have been found to evoke specific emotional responses. For example, energetic and upbeat genres like Pop or Dance tend to elicit feelings of happiness and excitement, while melancholic and introspective genres such as Blues or Alternative Rock may evoke a sense of nostalgia or sadness. Individuals with higher levels of extraversion may gravitate towards genres that elicit excitement and stimulation, while those with higher levels of neuroticism may be more drawn to genres that match their introspective or melancholic tendencies. Furthermore, the interplay between personality and musical attributes like genres, emotions can be bidirectional. Music has the power to influence our emotions and can serve as a tool for emotion regulation. Individuals may intentionally choose certain music genres to modulate their emotional states or seek solace and comfort in genres that align with their emotional needs. This interplay between emotions, music genres, and personality highlights the complex and dynamic nature of the relationship between music and human psychology. By exploring the intricate interplay between emotions, music genres, and personality traits, we gain a deeper understanding of how music preferences are intertwined with our psychological characteristics. This knowledge not only enhances our understanding of the role of music in shaping human behavior but also has practical implications. It can inform the development of personalized music interventions tailored to individuals' emotional and personality needs, promoting well-being and enhancing the therapeutic potential of music experiences.

1.2 What is Personality?

Individual differences refer to the unique and distinct characteristics that differentiate one person from another. These differences encompass various aspects of human behavior, cognition, and personality, which contribute to the rich diversity observed among individuals. Personality, in particular, is a significant dimension of individual differences. It denotes an individual's stable patterns of behavior or affect in given situations, for example, whether one avoids or seeks out strangers at a party and can be understood from biological, cognitive, developmental, and psychodynamic perspectives [15]. The dominant paradigm for studying personality is the Five Factor Model or Big Five, which has been developed and validated over many years [34], and has largely achieved the status of a consensus model [42]. The Big Five consists of five bipolar dimensions (traits) [34] which are:

- Openness to experience encompasses intellectual curiosity, receptiveness to new ideas, sensitivity to beauty, and willingness to try new things. Individuals high in openness to experience are typically imaginative, creative, and open-minded.

- Conscientiousness refers to an individual's tendency to display self-discipline, act dutifully, and strive for achievement in line with personal goals or external expectations. Conscientious individuals are often organized, responsible, and diligent in their pursuits.

- Extraversion represents an individual's inclination towards engaging in a breadth of activities and deriving energy from interactions and engagement with the outside world. Extraverts tend to be sociable, outgoing, and seek stimulation from their environment.

- Agreeableness reflects an individual's concern for social harmony, cooperation, and their inclination to get along well with others. Agreeable individuals tend to be compassionate, empathetic, and value interpersonal relationships.

- Neuroticism reflects an individual's tendency to experience negative emotions, such as anger, anxiety, or depression. Individuals high in neuroticism may be more prone to mood swings and emotional instability.

1.3 What are music preferences?

Music preferences refer to an individual's subjective inclinations and choices when it comes to the types, genres, and specific songs they enjoy listening to. It is a highly personal aspect of musical engagement that can vary widely between individuals. Understanding music preferences is essential as it offers insights into an individual's unique taste, emotional responses, and the potential influence of music on their psychological well-being.

There are various approaches to characterize music preferences, each providing a different perspective on the subject. One approach involves using social tags, which are user-generated keywords or labels associated with songs or artists. Social tags can capture the subjective interpretations and meanings that listeners assign to music. By analyzing these tags, researchers can gain insights into the thematic and semantic dimensions of music preferences, allowing for a more nuanced understanding of why individuals are drawn to particular songs or genres [13, 65].

Another approach is to examine the acoustic features of music. Acoustic features are objective characteristics of sound, such as tempo, loudness, and instrumental complexity. These features can be extracted and quantified to provide measurable representations of music. By analyzing acoustic features, researchers can uncover patterns and associations between specific musical characteristics and individuals' preferences. This approach provides a more objective perspective on music preferences, focusing on the sound and structural elements that attract listeners [6].

Emotions play a crucial role in shaping music preferences. Certain genres or songs are often associated with specific emotional experiences, such as joy, sadness, or nostalgia. By exploring the emotional responses evoked by different types of music, researchers can gain insights into why individuals are drawn to particular genres or songs. Emotion-based characterization of music preferences allows for a deeper understanding of the affective impact that music has on listeners' subjective experiences [36].

Lyrics also contribute to the characterization of music preferences. The lyrical content of a song can resonate with individuals on a personal and emotional level, influencing their affinity for specific artists or genres. The themes, storytelling, and poetic elements in lyrics can connect with listeners' experiences, values, and beliefs, making lyrics a significant factor in shaping music preferences [7].

Additionally, genre itself serves as a prominent way to characterize music preferences. Different genres represent distinct styles, themes, and cultural associations that resonate with individuals. Genres offer a categorization framework that allows researchers to examine patterns and preferences within specific musical styles, further enhancing our understanding of music preferences [48, 19].

1.4 Previous Research

Modest correlations have been found between participants' music preferences and their personality traits using the Big Five, with varying degrees of consistency. Across several studies, Openness has been consistently correlated with liking for music with high levels of complexity, such as Jazz and Classical, and weakly correlated with genres characterized by intensity, such as Rock and Heavy Metal [17, 28, 52, 71]. Extraversion has been found to relate to liking for energetic genres such as Dance, Hip-Hop and Pop in several studies [17, 52, 71]. However, studies have also yielded inconsistent results [17, 28]. Furthermore, Schfer and Mehlhorn (2017) [63] performed a meta-analysis and found that the average correlation coefficient linking personality to music preferences is only 0.058, suggesting the relationship between individual differences and music preferences may be more trivial in reality than in popular imagination.

However, several aspects of music preference research merit further examination before accepting this conclusion. One potential weakness of previous research is the use of self-report to assess music preferences. Dunn et al. (2012) [19] explored the relationship between self-reported preference for genre and participants' actual music listening behavior using an experimental platform in which 70,000 audio tracks were tagged with 16 industry standard genre labels, and found only weak to moderate correlations with self-reported preference scores (r-value ranged from .11 to .43). This result may reflect differences in participants' perceptions of genre compared to industry-standard labeling, as genre boundaries are notoriously ambiguous [48]. One user's understanding of what is meant by ”Rock” may easily differ from another's, and genre taxonomies differ notably between large, commercial platforms [48]. The concept of genre is also challenging in its scalability to granular subgenres and new syntheses between existing genres (e.g., ”Unblack Metal” or ”Medieval Folk Rock”), making a comprehensive genre taxonomy all but impossible to create [5]. As the use of electronic and computationally-based sounds expands the number of timbres available to artists, and internet sharing allows for rapid exchanges of musical ideas and opportunities to combine new sounds innovatively, the problem of classifying music is likely to become continually more complex. Using a limited number of genre labels to explore the relationship between personality traits and preferences is therefore likely to be inadequate to capture the full range of listeners' preferences.

1.5 Music being consumed digitally: New opportunities

The advent of Big Data and social media platforms provides new opportunities to explore music listening behaviors in larger numbers of users with respect to a range of parameters, including emotion [30]. An ideal platform for research into personality and preference is Last.fm, due to the availability of a public API through which data on users' listening history and metadata describing users' listening behaviors is available. Last.fm makes use of social tagging, which refers to ”free text labels that are applied to items such as artists, albums and songs” [39]. Users on platforms such as Last.fm apply social tags to label music not only with perceived genre, but also with words describing mood, emotion and related activities.

Carlson, Saari, Burger, and Toiviainen (2017) [13] have used social-tagging data to identify musical excerpts characteristic of particular genres for use in a survey of music preferences. The use of this data achieved moderate to strong correlations between listener ratings of heard excerpts and self-reported liking for the represented genres (r-value ranged from .37 to .84). However, the sample size in this study was relatively small and participants' real-world listening behaviors were not measured. Ferwerda et al. (2017) [24] also used social tagging as a means to identify genre. Their results generally corroborated previous work in showing modest significant correlations between personality and music listening behavior (Spearman's rho ranged from -.1 to .21), the largest number of which were between Openness and genres including Folk, Jazz and Blues, but also included correlations between Extraversion and R&B and Rap, Agreeableness and Country, and Neuroticism and Alternative music. However, these findings are based on a limited number of genre labels derived from the AllMusic lexicon, and thus may not reflect a full or adequately nuanced range of musical styles as perceived by listeners, nor do they take into account the role of emotion as it relates to preference and personality.

1.6 Gaps in existing research

The development of a genre-free music classification system, such as the MUSIC (Mellow, Unpretentious, Sophisticated, Intense and Contemporary) model proposed by Rentfrow, Goldberg and Levitin (2011) [51] provides one solution for studying individual difference and music preference [29]. However, this solution does not necessarily align with how typical users describe their music preferences; that is, using genre-level terminology [52]. Schfer and Mehlhorn (2017) [63] have suggested that neither genre nor a limited number of musical attributes such as those used in the MUSIC model can adequately account for the variety of ways listeners describe and categorize music.

Although regulation of mood and emotion are common reasons for listening to music [58], research has largely failed to take emotion into account when considering the relationship between personality and music preference. Differences in the quality, intensity, and frequency of emotions experienced in everyday life are linked with differences in personality. Extraversion correlates with the experience of positive emotions, while Neuroticism correlates with that of negative emotions, both in general [50] and in the context of music listening [35, 68]. Extraversion and Neuroticism have both been shown to moderate neural responses to music listening [49]. It is not yet known, however, how this may influence music preference and listening behaviors. For example, it is plausible that personality relates to music preferences that are congruent with a typical emotional state (i.e., an extrovert may gravitate towards energetic and cheerful music), but the opposite may also be true (i.e., a listener with high neuroticism may choose music incongruent with negative emotions in order to self-regulate). Furthermore, Eerola (2011) [20] found that the expression of valence was more consistent within than between genres, suggesting different conventions for the expression of emotion within different musical styles. Biedermann et al.

(2019) [10] showed that different genres of music can induce different emotional responses independent of listeners' preferences. These findings all suggest the relationship between individual differences and music preference may be more complex and nuanced than has been accounted for by previous studies.

Recent work has begun exploring the relationship between musical emotion and music preferences. Mood was considered by Anderson et al. (2021) [4], who used streaming data from Spotify to investigate the link between Big Five personality traits and an extensive set of metrics and found that such naturally occurring behavioral listening data was more useful than self-reported music preference alone in predicting personality. Genre information was extracted by curators at Spotify, using the combined evaluation of acoustic information, cultural knowledge and machine-assisted approaches to label 66 genres. Mood was derived from audio signal features and using a supervised machine learning approach, but was not considered in relation to genre, nor were interactions between genre and mood explored in associating personality and preference. As with previous studies, Openness was linked with a liking for a broader variety of music while the other traits demonstrated mixed results. Results also showed a number of associations between mood and personality, with Openness positively correlated with moods including somber and melancholy, Conscientiousness with lively and empowering moods, and Agreeableness with moods including romantic and easygoing, Extraversion with sensual and cool moods, and Neuroticism positively correlated with brooding, defiant and somber moods. However, it is unclear how closely these moods resemble those actually perceived by listeners. It is furthermore not clear how these labels relate to the findings of previous work on mood and emotion in music, for example the widely-used Geneva Emotional Music Scale (GEMS) [70] or the two-dimensional Valence-Arousal model. Fricke et al. (2019) [25] used the Million Song Dataset (MSD) [9], a collection of audio features and meta-data for a million songs, to model music preferences in terms of emotion dimensions represented by Valence, Arousal, and Depth. By projecting acoustic features of music into the VAD space, they were able to reconfirm that musical preferences can indeed be represented based on emotional connotations. However, the MSD does not provide data which may be useful to understanding individual differences in listening behavior, such as user-specific sociodemographic information, playcounts and time of listening. Thus, while emerging evidence suggests a relationship between musical emotion and preference, how this relates to individual differences requires further exploration.

Analysis of social tagging data from Last.fm has previously been used to classify music according to mood and emotional content [41, 57]. However, the possible relevance of such data to music preference research has not yet been adequately explored. Melchiorre and Schedl (2020) [43] correlated a large number of acoustic features such as acousticness, speechiness, duration, loudness and danceability from Spotify with listener's personality data from Last.fm, and found relationships between, for example, Openness and acousticness, however significant correlation values were generally quite small and often difficult to meaningfully interpret (e.g., a Spearman's rho of -.08 between Agreeableness and acousticness skew). Moreover, acoustic features typically vary within a piece of music which then renders the average feature value not as perceptually meaningful as other attributes such as genre or mood/emotion. In addition, these acoustic features are not all perceptually relevant; for example, loudness is irrelevant as listeners may decide to adjust volume level according to their states. Speechiness of a track may also be related to the attention the listener pays to the lyrics, which may or may not be congruent with the music, may vary greatly in terms of emotional connotation, and may not be defined at all for purely instrumental music, such as much of classical music.

1.7 Research Objectives

- To go beyond previous work making use of naturalistic user listening data by taking advantage of perceptually valid social tagging data to better understand the role of musical mood and emotion in the relationship between music preferences and personality.
- To employ a data-driven approach to developing genre clusters to explore users' listening behaviors, rather than relying on previously existing models. This can reveal unsupervised underlying ontology for music organization which is perceptually relevant.
- To investigate the association between personality traits, genre, and the preference for emotions making use of the Geneva Emotional Music Scale (GEMS) [70] which provides more nuanced music-specific emotions via the Valence-Arousal space allowing for a greater degree of interpretability than, for example, those used by Anderson et al. (2021) [4].
- To explore a varied number of top tracks to gain a better understanding of how personality relates to user listening behavior over time.
- To examine the relationship between personality and music preferences in a novel, ecologically valid way.
- To compare and analyze the emotions derived from semantic tags and acoustic features when mapped onto a Valence and Arousal (VA) space and investigate their congruence and differences in relation to personality traits. This could shed light on the interplay between subjective and objective measures of emotions in music listening.

1.8 Thesis Roadmap

The remainder of this thesis is organized as follows:

- Chapter 2 introduces a novel dataset specifically created to address the limitations of relying solely on self-reported data and the scarcity of datasets that combine naturally occurring listening histories with measures of personality, mental well-being, and musical engagement strategies. Additionally, it presents the evaluations performed on the dataset to ensure criterion validity and internal consistency.

- Chapter 3 explores the association between personality traits and genres based on social tags.
- Chapter 4 investigates the relationship between personality traits and emotions based on social tags.
- Chapter 5 focuses on the interplay between emotions and genre and examines its relation with personality traits.
- Chapter 6 compares the association of emotions derived from social tags and acoustic features with personality traits.
- Finally, Chapter 7 summarizes and serves as the conclusion providing directions for future work in the domain.

Chapter 2

Dataset

We present a novel dataset designed to overcome the limitations associated with relying solely on self-reported data and the lack of available datasets that integrate naturally occurring listening histories with measures of personality, mental well-being, and musical engagement strategies. This unique dataset aims to fill this research gap by offering a comprehensive and extensive source of information, enabling a deeper exploration of the complex interplay between music consumption, psychological factors, and individual preferences. Additionally, we assess criterion validity and internal consistency of our dataset, ensuring its reliability and accuracy in measuring the intended constructs.

2.1 Details of the survey

An online survey was designed wherein participants were asked to fill their Last.fm usernames and demographics followed by standard scales for assessing their mental wellbeing, musical engagement strategies and personality. Participants were solicited on the Last.fm groups of social media platforms like Reddit and Facebook. The inclusion criterion required being an active listener on Last.fm for at least a year prior to filling the survey. The survey form required the users' consent to access their Last.fm music history. A total of 541 individuals (Mean Age = 25.4, SD = 7.3) were recorded to be eligible and willing to participate in the study consisting of 444 males, 82 females and 15 others. Most of them belonged to the United States and the United Kingdom accounting for about 30% and 10% of the participants respectively. Every other country contributed to less than 5% of the total participants.

2.1.1 Measure of mental well-being

The Kessler's Psychological Distress Scale (K10) questionnaire [37] was used to assess mental well-being. It is a measure of psychological distress, particularly assessing anxiety and depression symptoms. Individuals scoring 29 and above on K-10 are likely to be at severe risk for depression and hence, constitute the *"At-Risk"* group. Those scoring below 20 are labeled as the *"No-Risk"* group [62] as they are likely to be well. There were 193 participants in the *No-Risk* group and 142 in the *At-Risk* group.

2.1.2 Measure of musical engagement

The Healthy-Unhealthy Music Scale (HUMS) survey was administered to assess musical engagement strategies which resulted in two scores per participant, Healthy and Unhealthy. It is a 13-item questionnaire which was developed for assessing musical engagement strategies that identified maladaptive ways of using music.

2.1.3 Measure of personality traits

Personality information was obtained using the Mini-IPIP questionnaire [18] which results in scores for the Big Five traits of Personality namely Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism.

2.1.4 Music Listening History

Each participant's listening history for a duration of time t (t =$\pm$6 months, $\pm$3 months) was extracted centered around the time they filled in the survey. For each participant, the top 500 tracks based on track play-counts were considered. The percentage of overlap between participants' listening histories for $\pm$3-month and $\pm$6-month durations is shown using Raincloud plots [1] in Figure 2.1. A Raincloud plot is a visualization tool that combines a split-half violin plot, a scatter plot, and a boxplot in order to simultaneously depict individual data points, the overall distribution of the data, and key statistical summary measures. A sizable overlap (i.e., greater than 60 %) was found between participants' listening histories for the two durations as can be seen in Figure 2.1. The $\pm$3-month duration, which can be presumed to not be greatly affected by seasonal factors, such as holiday music.

For each track in participants' listening histories, we extracted the top 50 social tags based on tag-weight, that is, the frequency of the tag being assigned to the track. Subsequently, these tags were used to evaluate genres and emotions associated with user-specific listening histories, as described in the following section. We repeated this analysis considering participants' top 250 and top 100 tracks to identify trends in the data and add to the robustness of our results. To obtain acoustic features for tracks on Last.fm, we utilized the Spotify[1] public API. Spotipy[2] package was employed to search for each track in the Spotify database and retrieve values for 9 features provided by Spotipy. Among these features, seven were audio-related, including danceability, loudness, speechiness, acousticness, instrumentalness, liveness, and tempo. Additionally, two emotion features representing valence and energy/arousal were also obtained.

[1] www.spotify.com
[2] developer.spotify.com

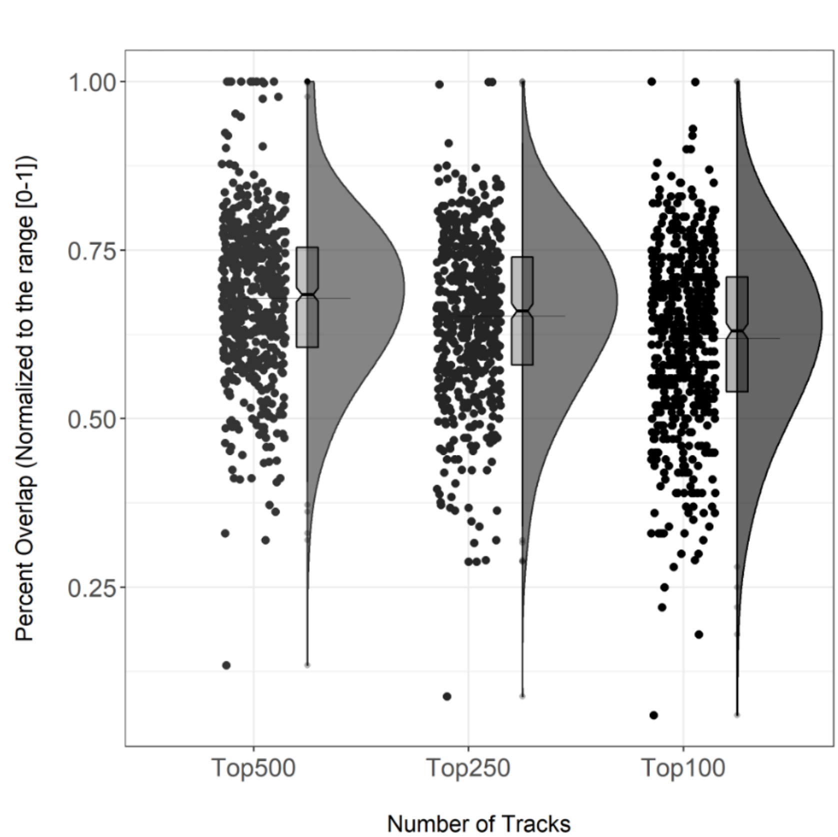

Figure 2.1: Raincloud Plots depicting the Distribution, Raw data, and Boxplots for Percent Overlap between ±3-month and ±6-month Listening Data for each Participant

2.2 Internal consistency

2.2.1 Mental Well-being

The Cronbach's alphas for Unhealthy scores obtained from HUMS and K10 scores were found to be relatively high at 0.80 and 0.91 respectively. A significant correlation (r=0.55, df=539, $p < 0.001$) between Unhealthy Score and K10 was found which is in concordance with past research studies in the field [59]. As can be seen in Figure 2.2, the At-Risk group displayed higher mean and median Unhealthy score compared to No-Risk while Healthy scores were comparable. Partial correlations between Unhealthy, Healthy, and K10 are presented in Table 2.1. K10 scores exhibit significant positive correlation only with Unhealthy for both the groups. The moderate correlation between Healthy and Unhealthy scores for the No-Risk population indicates that both of these subscales capture a shared element, most likely active music listening.

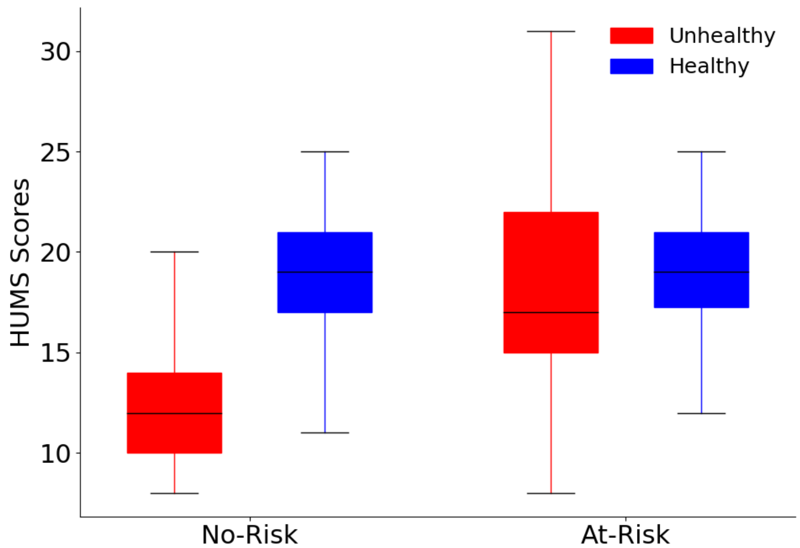

Figure 2.2: Boxplot of HUMS scores for No-Risk and At-Risk Groups.

	No-Risk		At-Risk	
Scales	Healthy	Unhealthy	Healthy	Unhealthy
Healthy	1.0	0.36**	1.0	-0.14
Unhealthy	0.36**	1.0	-0.14	1.0
K10	0.07	0.26**	-0.11	0.22*

Table 2.1: Partial Correlation Values between HUMS & K10. (*$p<0.01$ & **$p<0.001$)

2.2.2 Personality traits

The Cronbach's alphas for Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism were computed to be 0.64, 0.68, 0.83, 0.78, 0.71 respectively. As displayed in Table 2.2, significant Spearman correlations between personality traits Neuroticism and Extraversion ($r=-0.15$, $p<0.001$), Neuroticism and Conscientiousness ($r=-0.35$, $p<0.001$), Openness and Agreeableness ($r=0.14$, $p<0.01$), and Extraversion and Agreeableness ($r=0.30$, $p<0.001$) were found to be consistent with previous work [67], adding to the internal consistency of the dataset. Also, in line with previous research [38, 66], a significant positive correlation was observed between K10 score and Neuroticism ($r=0.68$, $p<0.0001$) adding to the internal consistency of the data and confirming construct validity.

Trait	O	C	E	A
C	-0.02	1		
E	0.10*	0.03	1	
A	0.14**	0.03	0.30***	1
N	-0.02	-0.35***	-0.15***	0.02

Table 2.2: Spearman Correlation Values of OCEAN Scores. (*$p<0.05$, **$p<0.01$, ***$p<0.001$)

2.3 Studies published using our dataset

- Goyal, Y.,Hanji, S.,Carlson, E.,Surana, A.,Kala, D., & Alluri, V. (2023). I guess that's why they call it the blues": Personality and the interplay between emotion and genre. European Journal of Personality. (Under review)

- Goyal, Y., Alluri, V. (2021) Artist2Risk: Predicting Depression Risk based on Artist Preferences. In the 16th International Conference on Music Perception and Cognition.

- Goyal, Y., Hanji, S.,Carlson, E., Alluri, V. (2021). Tag-based and acoustic-feature based emotions associated with online music consumption and personality. In the 16th International Conference on Music Perception and Cognition.

- Hanji, S., Goyal, Y.,Alluri, V. (2021). Exploring gender-specific music preferences associated with risk for depression on online music streaming platforms. In the 16th International Conference on Music Perception and Cognition.

- Surana, A, Goyal, Y, Alluri, V. (2020) Static and Dynamic Measures of Active Music Listening as Indicators of Depression Risk. In Speech, Music, and Mind with Audio Satellite Workshop, INTERSPEECH 2020.

- Surana, A., Goyal, Y., Srivastava, M., Saarikallio, S, and Alluri, V. (2020) TAG2RISK: Harnessing Social Music Tags for Characterizing Depression Risk. In Proc. of the 21st Int. Society for Music Information Retrieval Conf. (ISMIR), Montral, Canada, 2020.

Chapter 3

Personality and Genres

This study delves into the examination of the association between personality traits and genres, utilizing social tags as a basis for analysis. By analyzing the social tags associated with different genres, we aim to uncover patterns and relationships between individuals' personality traits and their preferences for specific music genres.

3.1 Methodology

Figure 3.1 depicts the procedure used in our study.

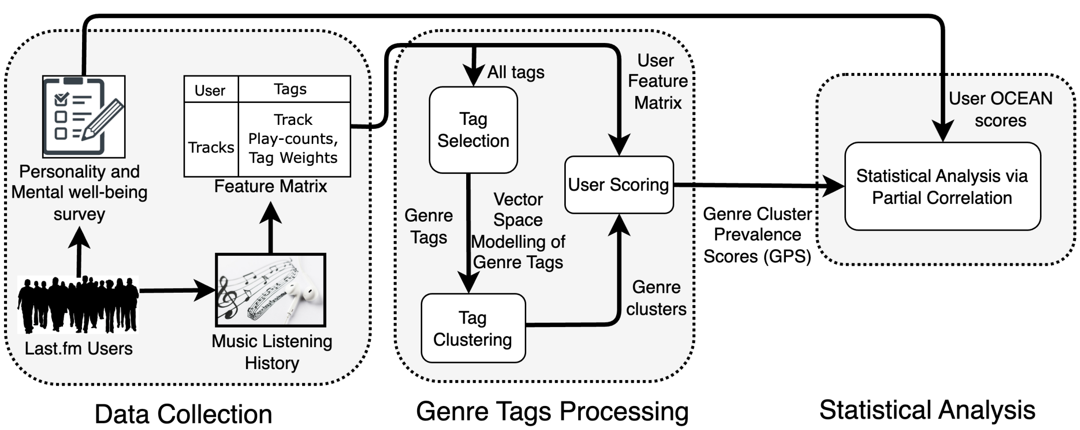

Figure 3.1: Methodology: Personality and Genres

3.1.1 Tag Selection

Last.fm tags contain a wide range of information including artist, genre, album, instrument, mood, amongst others. We focused only on tags representing genre-related information. A multi-stage model proposed by Ferrer and Eerola (2011b) [22] mapped the social tags on Last.fm onto different semantic layers such as Affect, Album, Artist, Genre, Instrument, Lyrics, etc. where each tag could have been mapped to more than one layer. The results of this model were made publicly available by the authors, which we used as a basis to filter out the genre-tags. In their study, the tags that had 'genre' as the most probable semantic layer led to the formation of a set of 5062 genre-tags. Subsequently, the tags in the participants' listening history that appeared in these 5062 genre-tags were subjected to clustering, described as follows.

3.1.2 Tag Clustering

The goal of clustering was to obtain genre clusters such that the tags within each cluster are closely related. This makes it possible to assign a meaningful label to each cluster, representing a higher level of organization, which allows for further analysis. The filtered set of genre-tags were organized in three stages following the procedure in Ferrer and Eerola (2011) [21]. The first stage involved creating a *Term-Document Matrix* $X = x_{ij}$, such that each track 'i' corresponds to a Document and each genre-tag 'j' corresponds to a Term. This results in a binary matrix *X(0,1)*, that is, $x_{ij} = 1$ if 'j' occurs in the top 50 social tags of track 'i', else $x_{ij} = 0$. The second stage involves computing a similarity matrix *D* of size $n \times n$ with elements d_{ij} where $d_{ii} = 0$, and when $i \neq j$,

$$D_{ij} = \frac{ad}{\sqrt{(a+b)(a+c)(b+d)(c+d)}} \tag{3.1}$$

where *a* is the number of (1,1) matches, *b* = (1,0) matches, *c* = (0,1) matches and *d* = (0,0) matches. D_{ij} is symmetric in the sense that it gives equal weightage to dual absence (0,0) and dual presence (1,1), and this property is known to work well for ecological applications. Subsequently, this similarity matrix was used for clustering in the next step.

A hierarchical clustering algorithm was applied to the similarity matrix, using Ward's minimum variance method as it yields compact spherical clusters when compared to other approaches [21] and has other advantages as described in Jain and Dubes (1988) [33]. Once a hierarchical structure was obtained in the form of a dendrogram, its branches were "pruned" using the dynamic hybrid tree cut algorithm [40] which gave rise to the final set of clusters. A word cloud was created for each genre cluster using its constituent tags. Each cluster was assigned a representative label based on its associated word cloud. The labels were also confirmed for appropriateness by consulting professional musicologists.

3.1.3 User-specific Genre Prevalence Score

After the tags were organized into meaningful genre clusters, we calculated a *Genre Prevalence score (GPS)* for each user-cluster pair. The GPS indicates the prevalence of genre-tags associated with the respective genre cluster in the user's listening history. This score was obtained by computing the products of the normalized genre-tag weights and the normalized play-count values, which were then summed up for each track in the user's listening history, as given in Equation 3.2

$$S_{u,c} = \frac{\sum_{j\epsilon V_{\text{tr}}} \left(N_{j,c} \times tr_{\text{u,j}}\right)}{\sum_{i\epsilon T_{\text{u}}} tr_{\text{u,i}}} \tag{3.2}$$

where

$$N_{j,c} = \sum_{k\epsilon Tags_{\text{c}}} \frac{tw_{\text{j,k}}}{\sum_{l\epsilon V_{\text{tg}}} tw_{\text{j,l}}} \tag{3.3}$$

$N_{j,c}$: the association of track j with genre cluster c
T_u : all tracks for user u
V_{tg} : all genre-tags obtained after tag selection
V_{tr} : all tracks having at least one genre-tag from V_{tg}
$tr_{u,i}$ (or $tr_{u,j}$) : playcount of track i (or j) for user u
$tw_{j,k}$: tag weight of tag k for track j
$Tags_c$: all tags in V_{tg} which belong to genre cluster c

3.1.4 Statistical Analysis: Partial correlation and Bootstrapping

In order to associate GPS with personality traits, Spearman partial correlation was performed. To adjust for individual-level covariates, age and gender were controlled while performing partial correlation. Since multiple correlations were performed, we used Benjamini-Hochberg (B-H) procedure to reduce Type I error. Further, for the correlations that were significant with B-H correction, bootstrapping with replacement was done to ensure that the correlations are not by chance and to evaluate the true significance of the observed correlation. Significance estimation was performed via bootstrapping with replacement for a total of 10000 iterations. In each iteration, the score for GPS was kept constant while personality traits, age and gender were randomly sampled (with replacement) and assigned to the prevalence scores. Next, the Spearman rho-value for their GPS was computed respectively for each iteration. As a result, we obtained a bootstrap distribution for the Spearman rho-value from which we estimated the significance of the observed statistic.

3.2 Results

A set of 4766 genre-tags were obtained after genre tag selection. The clustering stage yielded 17 clusters. The clusters were labeled on the basis of their corresponding word clouds which are displayed in Figure 3.2. The wordclouds were generated based on the prevalence of genre tags in the listening history data for all participants using their top 500 tracks over a duration of six months. The genre tags in each cluster are ranked based on how frequently they occur. The larger the size of a tag in a wordcloud, the higher its prevalence, and hence would have greater influence within that cluster.

Figure 3.2: Wordclouds for Genre Clusters

Table 3.1 displays the results of the statistical analysis that were observed to be significant for GPS.

Top Tracks	O	C	E	A	N
500	*Swing/Jazz**, *Chillout-, Easy Listening Jazz**	*Neo-pop/Dream-pop/Shoegaze* (-)*	Techno/House*, *Hip-hop and Rap***, *World Music****		*Neo-pop/Dream-pop/Shoegaze**, *World Music*(-)*, *Trance* (-)*
250	*Chillout-, Easy Listening Jazz**		*Hip-hop and Rap**, *World Music***		*Trance* (-)*
100			*Hip-hop and Rap***, *World Music**	*Hard Rock* (-)**	*Neo-pop/Dream-pop/Shoegaze**, *Punk**, *Trance* (-)*

Table 3.1: Genre Clusters that exhibit Signicant Correlations with Personality Traits.

(-) indicates that individuals with low scores on the corresponding personality trait are more likely to listen to the genre. (* $p<0.05$, ** $p<0.01$, *** $p<0.001$)

Extraversion and Neuroticism exhibit relatively stable genre-cluster profiles irrespective of the number of tracks chosen. Specifically, higher extraversion was consistently associated with a greater preference for energetic and rhythmic genres including *Hip-Hop/Rap* and *World Music* in addition to a positive correlation with *Techno/House*, albeit only when the top 500 tracks were considered. On the other hand, Neuroticism is associated with a predisposition for listening to less energetic and more mellow music, represented by *Neo-pop/Dream-pop/Shoegaze*. A negative association was also consistently observed between Neuroticism and high arousal music represented by *Trance*. Additionally, we observed a positive association with *Punk* for the top 100 tracks and a negative association with *World Music* for the top 500 tracks. A positive association was found between Openness and subgenres of Jazz including *Swing/Jazz* for the top 500 tracks, and *Chillout-, Easy Listening Jazz* for the top 500 and top 250 tracks. We fail to find consistent trends for traits Agreeableness and Conscientiousness. These inconsistent results include negative correlations between Conscientiousness and *Neo-pop/Dream-pop/Shoegaze* for the top 500 tracks and between Agreeableness and *Hard Rock* for the top 100 tracks.

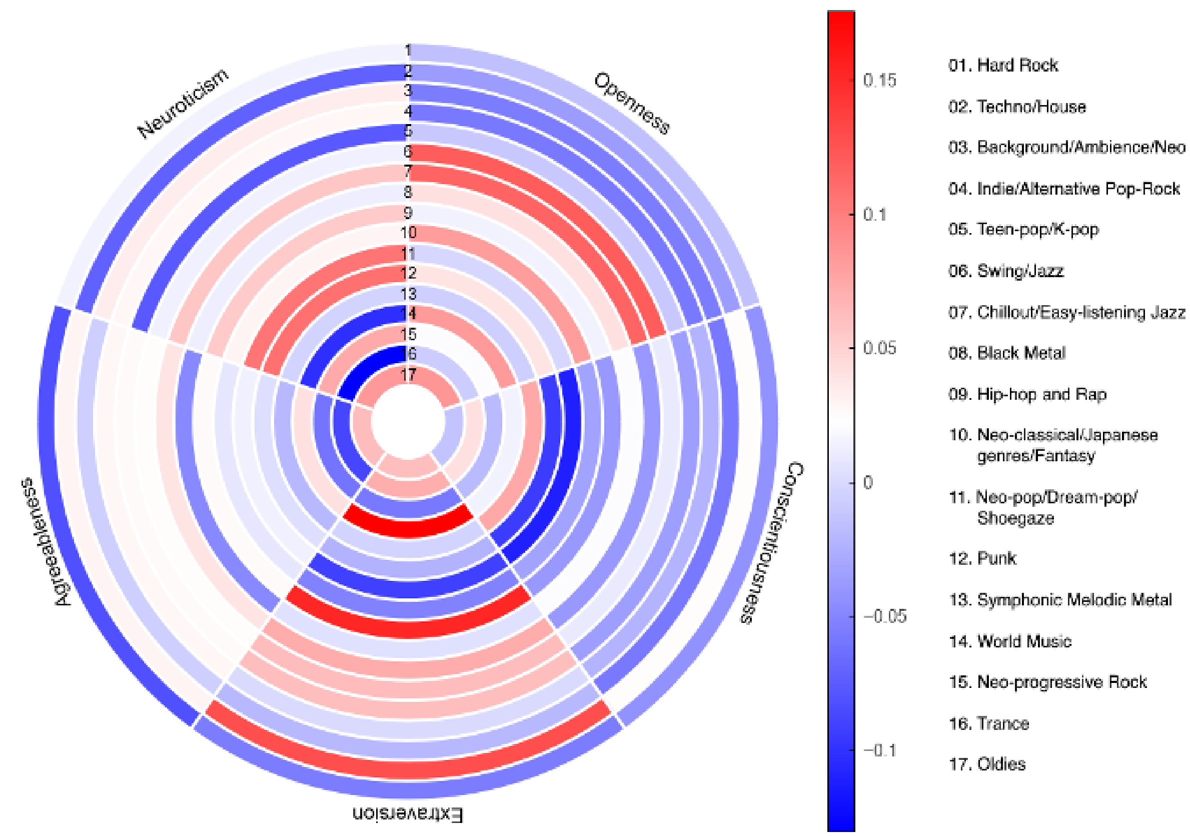

Figure 3.3: Radial Heatmap of Correlation Coefficients between OCEAN traits and the 17 Genre Clusters for the Top 500 Tracks

Figure 3.3 shows the strength of associations between all traits and genres, regardless of whether the association is significant, in the form of a radial heatmap for the top 500 tracks. It is possible that an association (i.e., partial correlation) was significant but was filtered out after applying B-H correction. Such associations are represented by darker shades in the heatmap, even though they are not present in the results in Table 3.1. For example, we observed negative correlations between Conscientiousness and *Punk*, Extraversion and *Neo-pop/Dream-pop/Shoegaze*, Agreeableness and *Trance*, and positive correlation between Neuroticism and *Punk*, which were significant prior to correction.

The heatmap also depicts some interesting trends, for instance, there is a clear contrast in the genre preferences of Neuroticism and Extraversion. Extraversion is positively associated with *Techno/House*, *World Music*, and *Hip-hop/Rap* (shown in red), while Neuroticism has a negative correlation with these genres (shown in blue). Similarly, *Neo-pop/Dream-pop/Shoegaze*, *Punk* and *Neo-progressive Rock* correlate positively with Neuroticism but negatively with Extraversion. Likewise, there is a contrast between the genre preferences of Neuroticism and Conscientiousness, wherein Neuroticism is positively associated with a preference for *Neo-pop/Dream-pop/Shoegaze* and *Punk*, while Conscientiousness is negatively associated with these genres. The above contrasts are in agreement with the negative correlation of Neuroticism with Extraversion and Conscientiousness, found in subsection 2.2.2.

3.3 Conclusion

Extraversion is associated with listening to *Hip-hop and Rap*, Techno/House, and *World Music* genre clusters, which are characterized by a high degree of danceability and include a diverse array of subgenres, including 'funk', 'neo-soul', 'dancehall', 'dub', 'idm', 'bossa nova', 'afrobeat', and 'flamenco'. This result appears to reflect extraverts' need for external stimulation to feel energized, corroborating previous research findings associating Extraversion with preference for energetic and rhythmic genres.

The music preferences of those with high levels of Neuroticism appear to reflect a lower need for arousal in order to reach an optimal state, as shown in the negative association with the genres *Trance* and *World Music*. *Trance* music, characterized by its repetitive beats and fast tempo, is often perceived as stimulating and energizing. However, it may be experienced as overwhelming or even anxiety-provoking for those with high Neuroticism. *World Music*, which often incorporates a wide range of unfamiliar instruments, rhythms, and cultural influences, may be perceived as unsettling and less comforting for individuals with high Neuroticism.

A novel finding is the relationship between Neuroticism and liking for *Neo-pop/Dream-pop/Shoegaze* music, which is characterized by heavy synthesizer-based electronic mixtures, often with indistinct vocals that are layered and heavily processed. These features create dreamy and atmospheric soundscapes that have an ethereal, otherworldly quality which may be perceived as soothing and calming. This may be indicative of the need to have an immersive experience that provides an escape from a reality perceived as stressful or threatening. Neuroticism's correlation with higher risk for depression [2, 65] may relate to the use of music for avoidant coping [45]; along with the possible link to music-based rumination, this finding further corroborates the link between Neuroticism and increased risk for potentially maladaptive uses of music.

Moreover, we find a positive correlation between high Neuroticism and *Punk*, but only for the top 100 tracks. *Punk* music is known for its fast, energetic, and often aggressive sound, as well as its lyrics that often express rebellion and dissatisfaction with society. While the aggressive nature of the genre may not seem to be an appealing choice for individuals with high Neuroticism, they may identify with the themes of alienation and dissatisfaction expressed in the lyrics of *Punk* music and find it to be an outlet for expressing their own feelings. Furthermore, some *Punk* subgenres like Punk-Rock, Punk-Pop and Punk-Folk tend to be more melodic and less aggressive which might be more appealing for individuals with high Neuroticism.

Our results do not show any link between Neuroticism and Classical music, which was observed both by Delsing et al. (2008) [17], and Dunn et al. (2012) [19]. The lack of Classical music as a genre cluster itself may reflect the music preferences of the sample at hand overall, possibly indicating that individuals preferring Classical music are less likely to use Last.fm.

Results revealed a positive correlation between Openness and the genre clusters *Swing/Jazz* and *Chillout-, Easy Listening Jazz*. These genres are known for their intricate melodies, complex harmonies, and improvisation, which may appeal to the emotional and creative nuances of those with high Openness. This is in line with previous results showing an association between Openness and a predilection for complex music belonging to genres such as Blues and Jazz [17, 28, 52, 71] and *World Music* [11]. Despite the skewed median score of 4.25 (on a scale of 1 to 5) for Openness, it is striking that the results of this relationship between personality and preference are so consistent across studies.

Additionally, we observe Openness to be linked with a greater preference for diverse genres such as *World Music*, Oldies, and *Neo-classical/Japanese genres/Fantasy* (Figure 3.3), suggesting that individuals scoring high on Openness have a wide range of preferred music.

Conscientiousness was found to be negatively associated with *Neo-pop/Dream-pop/Shoegaze* music, albeit only for the top 500 tracks. Conscientiousness is a trait characterized by organization, responsibility, and attention to detail, and this may indicate a lower preference for *Neo-pop/Dream-pop/Shoegaze* music as these genres often have a more experimental, free-form, and chaotic sound. Conscientious individuals may prefer music that is more structured, traditional, and predictable. They may prefer music that is more grounded in reality as compared to the surreal themes found in these genres. We also observe a lower preference among individuals with high Conscientiousness for *Punk* (Figure 3.3), which is aligned with them being less inclined to fast-paced, raw and often chaotic sound. They may also be less drawn to the often rebellious and non-conformist themes found in *Punk* music, which is in line with previous self-reported studies [28]. Anderson et al., 2021 [4] also found a similar negative association between Conscientious Spotify users and the genre *Punk*. It is noteworthy that this relationship is consistent across studies and music listening platforms.

In line with previous studies, Agreeableness was found to be negatively associated with preference for intense and rebellious genres such as *Hard Rock*, *Trance* and Black metal [4, 28]. However, it should be noted that the results for *Trance* and Black metal were insignificant after applying B-H correction, and the result for *Hard Rock* was only found to be significant for the top 100 tracks. *Hard Rock* and metal music often feature loud and distorted instruments, fast-paced rhythms, and lyrics that deal with darker themes such as violence and anger. On the other hand, individuals scoring high on Agreeableness may prefer music that is more melodic and harmonious, and they may be less drawn to the often dark and aggressive themes found in these genres.

3.4 Key Findings

- Extraversion is associated with energetic and rhythmic genres such as *Hip-hop, Rap, Techno/House,* and *World Music*.

- Neuroticism is linked to lower preferences for stimulating genres like *Trance* and *World Music*, while showing a positive association with dreamy *Neo-pop/Dream-pop/Shoegaze* music.

- Individuals high in Neuroticism also exhibit a preference for *Punk* music, possibly due to identification with themes of rebellion and dissatisfaction expressed in the lyrics.
- Openness is positively correlated with genres like *Swing/Jazz* and *Chillout/Easy Listening Jazz*, reflecting a preference for intricate melodies and complex harmonies.
- Conscientiousness is negatively associated with chaotic *Neo-pop/Dream-pop/Shoegaze* music, indicating a preference for more structured and traditional music.
- Agreeableness is linked to a lower preference for intense and rebellious genres such as *Hard Rock, Trance*, and *Black Metal*.

Chapter 4

Personality and Emotions

This study focuses on exploring the association between personality traits and emotions, utilizing social tags as a basis for analysis. By examining the social tags associated with different emotions, we aim to uncover patterns and relationships between individuals' personality traits and their preferences for specific music-evoked emotions.

4.1 Methodology

Figure 4.1 depicts the procedure used in our study.

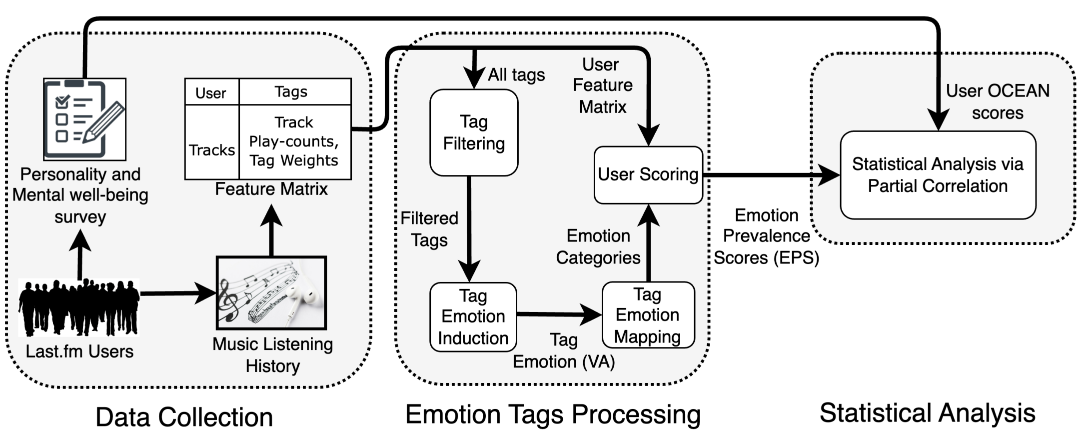

Figure 4.1: Methodology: Personality and Emotions

4.1.1 Tag Selection

To associate each personality trait with the emotional content from participants' music listening histories, we followed the approach described by Surana, Goyal, et al. (2020) [65]. Social music tags were initially subjected to removal of punctuation, stopwords, and spell-checks. Subsequently, they were filtered by selecting only the adverbs and adjectives by means of Parts of Speech (POS) tagging

[16] followed by manual selection in order to remove words which were not emotionally-laden (eg: very, quite). As a result, tags that remained after filtering had a mood/emotion associated with them. Then, a word-emotion-induction (WEI) model, which is a 3-layer neural network, was used to get valence (V), arousal (A) values for each of the tags [12]. In order to obtain more nuanced, music-specific emotions, we projected the 9 first-order factors of the GEMS model, that is, *Wonder*, *Transcendence*, *Nostalgia*, *Tenderness*, *Peacefulness*, *Power*, *Joyful Activation*, *Tension* and *Sadness* onto the VA space using the WEI model. The tags were further assigned to emotion categories based on the proximity of the tags in the VA space to these 9 GEMS emotions.

4.1.2 User-specific Emotion Prevalence Score

We calculated an Emotion Prevalence score (EPS) for each of the 9 emotion categories, for each user in the same manner as done for genre in Equation 3.2 with the difference that tags are associated only with emotions.

$$S_{u,c} = \frac{\sum_{j \epsilon V_{\text{tr}}} \left(N_{j,c} \times tr_{\text{u,j}} \right)}{\sum_{i \epsilon T_{\text{u}}} tr_{\text{u,i}}} \tag{4.1}$$

where

$$N_{j,c} = \sum_{k \epsilon Tags_{\text{c}}} \frac{tw_{\text{j,k}}}{\sum_{l \epsilon V_{\text{tg}}} tw_{\text{j,l}}} \tag{4.2}$$

$N_{j,c}$: the association of track j with emotion category c
T_u : all tracks for user u
V_{tg} : all emotion-tags obtained after tag selection
V_{tr} : all tracks having at least one emotion-tag from V_{tg}
$tr_{u,i}$ (or $tr_{u,j}$) : playcount of track i (or j) for user u
$tw_{j,k}$: tag weight of tag k for track j
$Tags_c$: all tags in V_{tg} which belong to emotion category c

Statistical tests, as described in subsection 3.1.4, were then done on EPS to identify their association with personality traits.

4.2 Results

Figure 4.2 presents wordclouds for GEMS emotion categories, which were generated using the same technique that was used for Genre wordclouds.

Figure 4.2: Word Clouds for GEMS Emotion Categories.

Note: The term ”funk” emerged as the most prominent tag within the wordcloud for *Sadness*. However, this does not refer to the music genre Funk, but possibly to the idiomatic phrase to be in a funk, which means to be in a sad and melancholic state.

Table 4.1 displays the results of the statistical analysis that were observed to be significant trait-wise for EPS.

Top Tracks	O	C	E	A	N
500			*Transcendence**		
250			*Transcendence**		
100					*Tenderness**

Table 4.1: GEMS Emotion Clusters with Signicant Correlations for the Personality Traits. (*p<0.05)

Extraversion was found to be linked with a preference for music tagged with positively valenced and moderately high arousal emotion tags falling under *Transcendence*, for the top 500 and top 250 tracks. Neuroticism on the other hand was linked with a preference for music associated with tags representative of positive valence and low arousal emotion, *Tenderness*, but only for the top 100 tracks.

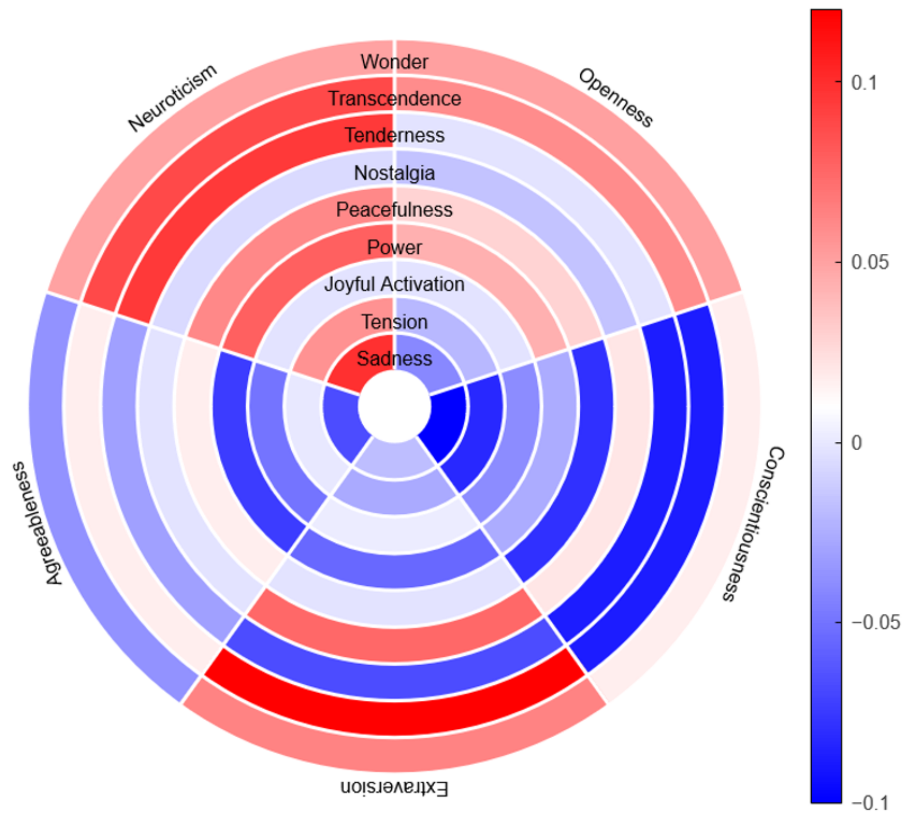

Figure 4.3: Radial Heatmap of Correlation Coefficients between OCEAN Traits and GEMS Emotions for the Top 500 Tracks

Figure 4.3 shows the strength of associations between all traits and emotions, regardless of whether the association is significant, in the form of a radial heatmap for the top 500 tracks. The heatmap portrays that Neuroticism, which is characterized by emotional instability, anxiety, and moodiness, has a positive correlation with the majority of emotions. The implications of this finding are discussed in further detail in section 4.3.

Prior to B-H correction, we found Neuroticism to be positively associated with the emotions *Sadness* and *Transcendence*, while Conscientiousness was found to be negatively associated with the same emotions. This contrast in emotion preferences is further highlighted in the heatmap and aligns with the contrast in their genre preferences observed in section 3.2.

4.3 Conclusion

Extraversion was linked with the positively valenced emotion *Transcendence* for the top 500 and top 250 tracks. Extraverted individuals tend to seek out novel, stimulating experiences that evoke strong emotions. Music that is transcendental in nature is often associated with feelings of awe, wonder, and elevation, which may provide them this type of experience.

The tags associated with individuals belonging to high trait Neuroticism were consistently associated with low arousal and positively valenced emotion *Tenderness*, albeit only for the top 100 tracks. This reflects the lower need for arousal for listeners with high Neuroticism, (compared, for example, to extraverts), and may indicate the use of music to try to lower arousal as a means of managing heightened, anxious states. Thus, although we did not collect information about listeners' own emotional states before or during listening, it is plausible that Neuroticism is more likely to lead to state-incongruent music choices when compared to other personality traits. However, state-congruent music choices may be represented by the association between Neuroticism and listening to music representing *Sadness*, which was found to be significant prior to B-H correction. These results corroborate those obtained by Surana, Goyal, et al. (2020) [65] wherein *Sadness* and *Tenderness* were the predominant tag-based emotions for individuals with high psychological distress scores and at-risk for depression, who also score high on Neuroticism. It is possible that listening to sad music may reflect either adaptive or maladaptive coping, depending on context and cognitive strategy; for example, sad music listening may be an example of the use of music as Solace, as defined by Saarikallio's (2008) [61] Music in Mood Regulation scale. However, it is also possible that listening to sad music may indicate the use of music in rumination.

Furthermore, the radial heatmap in Figure 4.3 shows Neuroticism to be positively associated with most emotions, which could be indicative of neurotic participants' usage of music to regulate emotions. This finding is consistent with a meta-analysis of 13 studies done by Miranda and Blais-Rochette (2020) [44], who found that people higher in Neuroticism are more prone to use music listening as an accessible resource to regulate their negative emotions or manage whatever affects their mood in everyday life.

The lack of any significant results for trait Openness is in line with the very nature of Openness, that is, being open to experiencing various emotions. Openness is related to a developed cognitive ability to appreciate and evaluate various art forms and feelings allowing them to explore complex music with varying emotions [47]. Agreeableness and Conscientiousness also do not display any significant results, which combined with the inconsistency of genre results suggests a lack of an identifiable pattern or trend among listening habits related to these traits.

4.4 Key Findings

- Extraversion is associated with the positively valenced emotion of *Transcendence*, indicating a preference for music that evokes feelings of awe, wonder, and elevation.

- High Neuroticism is consistently associated with low arousal and the positively valenced emotion of *Tenderness*, suggesting a lower need for arousal and the use of music to manage heightened anxious states.

- Neuroticism is positively linked with a wide range of emotions, potentially indicating the use of music as a means of emotion regulation for individuals high in Neuroticism.
- The lack of significant results for trait Openness suggests that individuals high in Openness are open to experiencing a variety of emotions and may appreciate complex music with varying emotional qualities.
- Agreeableness and Conscientiousness do not display any significant results, suggesting a lack of identifiable patterns or trends in music listening habits associated with these traits.

Chapter 5

Personality and the Interplay between Genres and Emotions

This study investigates the interplay between emotions and genre, specifically exploring its relationship with personality traits. The chapter delves into the examination of how different music genres evoke specific emotional responses and how these emotional experiences may vary based on individuals' personality traits.

5.1 Methodology

Figure 5.1 depicts the procedure used in our study.

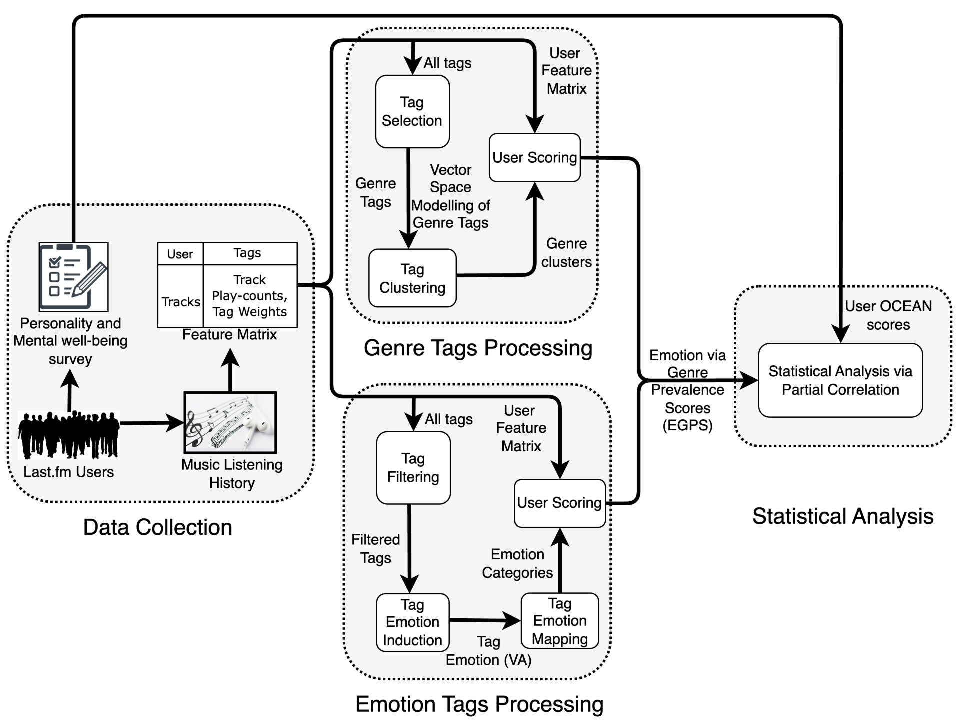

Figure 5.1: Methodology: Personality and the interplay between Genres and Emotions

5.1.1 User-specific Emotion via Genre Prevalence Score

We calculated an Emotion via Genre Prevalence score (EGPS) for each of the 9 emotion categories and 17 genre cluster combinations to check for variations in the emotion prevalence associated with each of the genre clusters. This score represents the distribution of emotions associated with a genre cluster. Here, we only take the emotion tags co-occurring with the tags comprising the genre-cluster, which were normalized by their respective tag weights and play-count values and then summed for all the tracks in the listening history. The computation is similar to Equation 3.2 and Equation 4.1 with the difference that only the tracks which have both genre and emotion tags are considered in the numerator.

$$S_{u,c,g} = \frac{\sum_{j \epsilon V_{\text{tr,g}}} \left(N_{j,c} \times tr_{\text{u,j}} \right)}{\sum_{i \epsilon T_{\text{u}}} tr_{\text{u,i}}} \tag{5.1}$$

where

$$N_{j,c} = \sum_{k \epsilon Tags_{\text{c}}} \frac{tw_{\text{j,k}}}{\sum_{l \epsilon V_{\text{tg}}} tw_{\text{j,l}}} \tag{5.2}$$

$N_{j,c}$: the association of track j with emotion category c
T_u : all tracks for user u
V_{tg} : all emotion-tags obtained after tag selection
$V_{tr,g}$: all tracks having at least one emotion-tag from V_{tg} and one genre-tag from genre cluster g
$tr_{u,i}$ (or $tr_{u,j}$) : playcount of track i (or j) for user u
$tw_{j,k}$: tag weight of tag k for track j
$Tags_c$: all tags in V_{tg} which belong to emotion category c

Statistical tests, as described in subsection 3.1.4, were then done on EGPS to identify their association with personality traits.

5.2 Results

Since a listener's top 100 tracks may be prone to seasonal variations and influenced by short term preferences, we report the results for emotion-via-genre analysis which are consistent across the top 500 and top 250 tracks. Figure 5.2 displays the EPGS results, that is, the emotions associated with different traits within the genres they listen to. The associations shown in these figures only include those which were found to be significant trait-wise for EPGS for both top 500 and top 250 tracks.

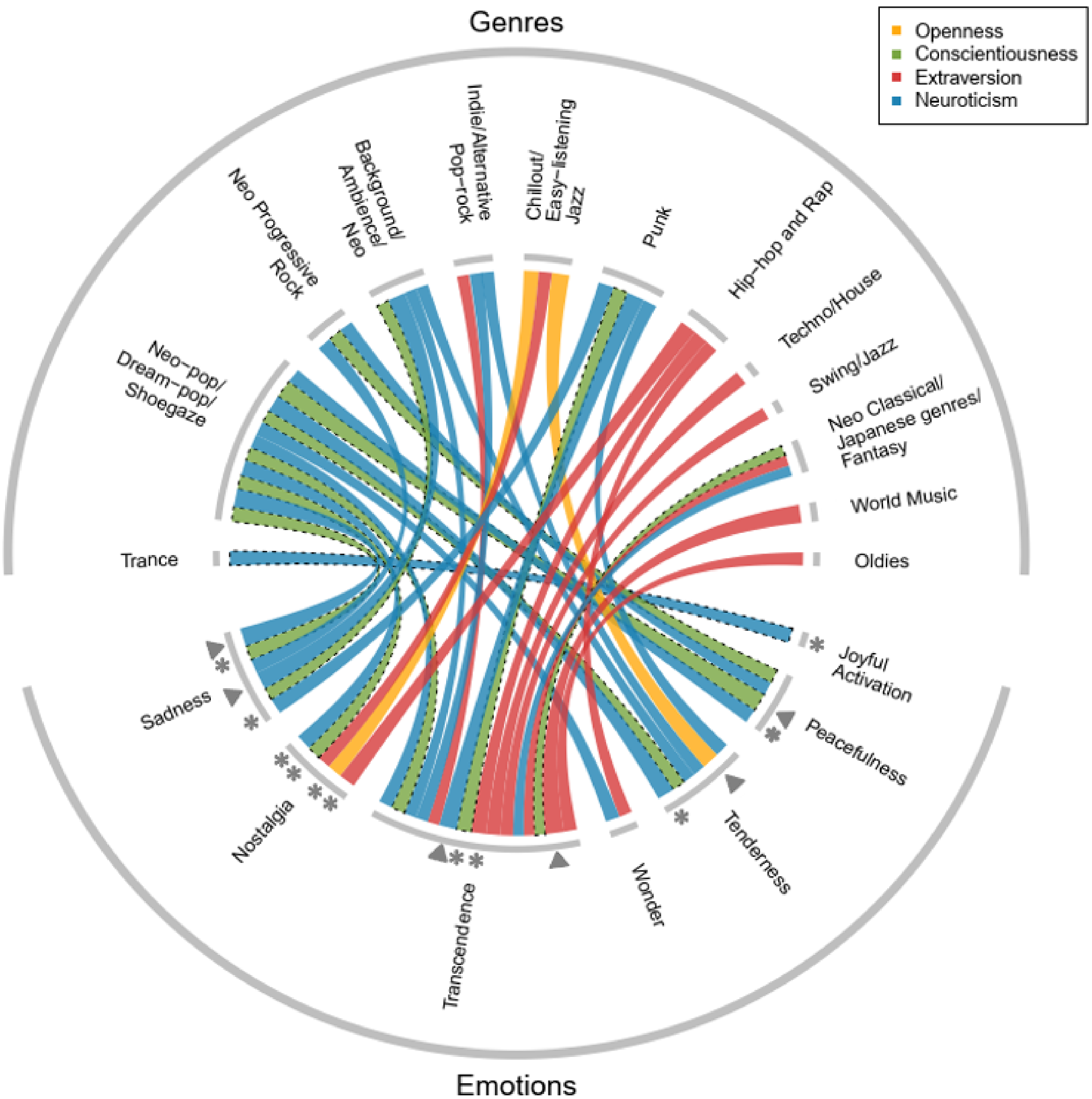

Figure 5.2: GEMS Emotions Prevalent within the Genres Preferred by OCEAN Traits (Consistent across the Top 500 and Top 250 Tracks)

Note. The thickness of the links is directly proportional to the absolute value of the correlation coefficient. The links with dashed borders denote negative correlations. ✱ denotes p <0.01, ▲ denotes p <0.001.

Figure 5.3: Emotion-via-Genre Wordclouds for Extraversion

Note. The ranking of the emotion tags is based on the correlation coefficients computed between the emotion-genre combinations and Extraversion which were statistically significant. This is different from the wordclouds shown in Figure 4.2 which do not consider nuanced information about emotion-genre interplay. The size of the tag depicts its importance in the specific cluster.

As can be seen in Figure 5.2, Extraversion is related to liking a wide range of genres, most of which are associated with high energy and a fast tempo. These include *Techno/House*, *Indie/Alternative Pop-rock*, *Swing/Jazz*, *Hip-hop and Rap*, *Neo-classical/Japanese genres/Fantasy*, *World Music* and Oldies co-occurring with emotion tags for *Transcendence*. As shown in the wordclouds in Figure 5.3, the most prevalent tags for *Transcendence* include 'psychedelic', 'emotional', 'groovy', 'hot', and 'uptempo'. The cluster *Hip-hop and Rap* is additionally associated with *Nostalgia*, which includes tags like 'catchy', 'best', and 'chill', and with *Wonder*, which comprises tags like 'soul', 'funky', and 'masterpiece'. Extraversion is also linked with a preference for *Chillout/Easy-listening Jazz* co-occurring with *Nostalgia*, consisting of tags like 'chill', 'best', and 'progressive'. Overall, high Extraversion appears to be linked with music which is positively valenced in terms of emotions and highly energetic in terms of genres.

Figure 5.4: Emotion-via-Genre Wordclouds for Conscientiousness (All Negative Associations)

Note. The size of the tag depicts its importance in the specific cluster.

As shown in Figure 5.2, Conscientiousness is associated with a lower preference for the genre cluster *Neo-pop/Dream-pop/Shoegaze* co-occurring with emotion tags representing *Transcendence*, *Sadness*, *Peacefulness*, *Nostalgia*, and *Tenderness*. Conscientiousness was also associated with a lower preference for *Background/Ambience/Neo* co-occurring with *Sadness*, *Neo-progressive Rock* co-occurring with *Peacefulness*, and *Punk* along with *Neo-classical/Japanese genres/Fantasy* co-occurring with *Transcendence*. As displayed in Figure 5.4, word clouds for *Sadness* co-occurring with *Neo-pop/Dream-pop/Shoegaze* and *Sadness* co-occurring with *Background/Ambience/Neo* include ”sad”, ”melancholy”, ”funk” and ”depressive”. *Peacefulness* co-occurring with *Neo-pop/Dream-pop/Shoegaze* and with *Neo-progressive Rock* includes tags such as ”mellow”, ”relax”, ”nice”, and ”calm”. In addition, *Transcendence* co-occurring with *Punk*, *Neo-pop/Dream-pop/Shoegaze*, and *Neo-classical/Japanese genres/Fantasy* includes ”psychedelic”, ”groovy”, and ”emotional”. Apart from this, *Tenderness* via *Neo-pop/Dream-pop/Shoegaze* consists of tags like ”beautiful”, ”epic”, and ”dreamy”, while the tags ”best”, ”chill”, ”progressive”, and ”catchy” are observed for *Nostalgia* via *Neo-pop/Dream-pop/Shoegaze*.

Figure 5.5: Emotion-via-Genre Wordclouds for Neuroticism

Note. The size of the tag depicts its importance in the specific cluster.

Figure 5.2 exhibits that Neuroticism is associated with a higher preference for the genre cluster *Neo-pop/Dream-pop/Shoegaze* co-occurring with emotion tags representing *Sadness*, *Transcendence*, *Tenderness*, *Peacefulness*, *Wonder*, and *Nostalgia*. Additionally, high Neuroticism is associated with a greater preference for *Neo-progressive Rock* co-occurring with *Peacefulness* and *Sadness*; *Background/Ambience/Neo* co-occurring with *Sadness*, *Transcendence*, and *Tenderness*; *Punk* co-occurring with *Sadness*, *Transcendence*, and *Tenderness*; *Indie/Alternative Pop-rock* co-occurring with *Tenderness* and *Transcendence*, and *Neo-classical/Japanese genres/Fantasy* co-occurring with *Transcendence*. Furthermore, High Neuroticism is associated with a low preference for Trance co-occurring with *Joyful Activation*.

Figure 5.5 depicts the wordcloud for *Sadness* co-occurring with the aforementioned genres, which contains tags such as ”sad”, ”funk”, ”melancholy”, and ”depressive”. Likewise, the wordcloud for *Transcendence* comprises ”emotional”, ”psychedelic”, ”groovy”, and ”legend”, the wordcloud for *Tenderness* includes ”beautiful”, ”lovely”, ”dreamy” and ”good”, the wordcloud for *Peacefulness* contains ”mellow”, ”relax”, ”calm” and ”quiet”, the wordcloud for *Wonder* contains ”melodic”, ”soul”, ”masterpiece”, and ”funky”, and the wordcloud for *Nostalgia* contains ”chill”, ”best”, ”progressive”, and ”catchy”. Finally, the wordcloud for the negative association with *Joyful Activation* consists of tags such as ”love”, ”sexy”, ”happy”, and ”awesome”.

Neuroticism is associated with a preference for a wide variety of genres co-occurring with *Transcendence*, *Sadness*, and *Tenderness*, indicating their affinity for such emotions independent of the genre of music. Additionally, those with high Neuroticism appear to exhibit an inclination towards low-arousal emotions, such as *Sadness*, *Peacefulness*, *Tenderness*, and *Nostalgia*, which are spread across the valence spectrum.

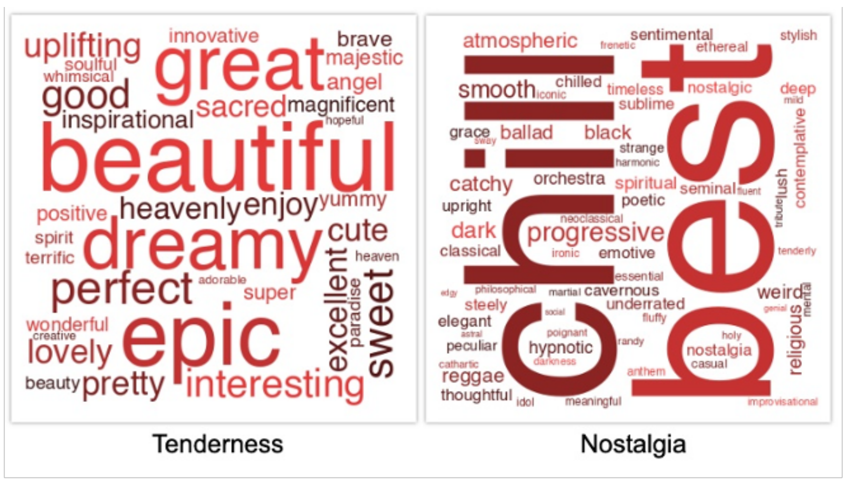

Figure 5.6: Emotion-via-Genre Wordclouds for Openness

Note. The size of the tag depicts its importance in the specific cluster.

Figure 5.2 reveals that Openness was found to be associated with a higher preference for *Chillout/Easy-listening Jazz* music co-occurring with the emotions *Tenderness* and *Nostalgia*. Figure 5.6 supplements these findings by displaying emotion word clouds for the same co-occurrences. The most predominant tags for *Tenderness* include ”beautiful”, ”dreamy”, ”epic”, and ”great”, and for *Nostalgia*, they include ”chill”, ”best”, ”progressive”, and ”smooth”. Openness was not found to be linked with a large number of specific genres and/or emotions, perhaps because they tend to seek a diverse range of experiences and prefer to explore rather than adhering to specific genres or emotions.

5.3 Conclusion

Personality traits are important in moderating the experiences we seek. The combination of an individual's personality traits and their emotional response to different genres of music can influence the types of music they seek out and enjoy, as they may be drawn to specific emotions that certain genres elicit. The emotional associations of different music genres were investigated in a study conducted by Zentner, Grandjean, and Scherer (2008) [70], wherein participants who were found to have high preference and high familiarity for certain music genres were asked to rate the frequency of various "feeling" labels they experienced while listening to the genre. Their results showed that Jazz and Classical music were linked to emotions such as longing, amazement, spirituality, and *peacefulness*; Techno and Latin American music elicited disinhibited, excited, active, agitated, energetic, and fiery emotions, while Pop/Rock music was found to evoke emotions such as aggression, anger, rage, irritation, and revolt. The above findings suggest that a more comprehensive understanding of individuals' musical preferences can be attained by taking into account both genre and emotion simultaneously. While musical preferences represented by genres and emotions have been investigated separately, this is the first time we demonstrate the interplay between them and how they relate with personality traits. The variation of emotion clouds within a genre for each personality (Figure 5.3, Figure 5.4, Figure 5.5, Figure 5.6) clearly indicates that genre or emotion alone as a feature is indeed insufficient at capturing musical preferences.

Overall, Extraversion demonstrates consistent results when combining genre and emotions, revealing the trait's relationship to preference for joyful, happy-sounding, arousing music of the same energetic genres as described in section 3.3, which include *Hip-hop and Rap*, *Techno/House*, and *World Music*. This is in line with previous studies that demonstrate that Extraverts indeed rely highly on external positive arousing experiences for regulating their states [55, 68]. Besides, in Figure 5.3, most genres co-occur with *Transcendence*, which indicates Extraverts' seeking of intense experiences [3]. *Hip-hop and Rap* additionally co-occurs with *Wonder* and *Nostalgia*, which are again associated with positive affect. Nostalgic *Hip-hop and Rap* music may provide a way for these individuals to connect with others who share a similar appreciation for the genre, and the emotional themes of the music (such as memories of the past and a sense of wonder) may appeal to their desire for intense emotional experiences. The co-occurrence of *Chillout/Easy-listening Jazz* with *Nostalgia* can be analyzed in a similar manner.

Conscientiousness was found to be negatively associated with experimental and unorthodox genres like *Neo-progressive Rock*, *Neo-pop/Dream-pop/Shoegaze*, and *Background/Ambience/Neo* co-occurring with low arousal emotions such as *Sadness*, *Tenderness*, and *Peacefulness*. Further, there is a negative correlation with *Neo-pop/Dream-pop/Shoegaze* co-occurring with all emotions in Figure 5.4, indicating a lower preference for this genre cluster regardless of the emotion associated with it. Individuals with high Conscientiousness tend to be organized, dependable, and have a strong sense of duty. These traits may lead them to prefer music that is more structured and predictable. It is also possible that these genre clusters are more associated with a laid-back and relaxed mood, which might not align with an individual with high Conscientiousness who might be more goal-oriented and have a stronger focus on getting things done. This is in line with a finding by Rentfrow and Gosling (2003) [52], where Conscientiousness was associated with Upbeat and Conventional music, which is described in their study as music that expresses predominantly positive emotions, is simple in structure, and is moderately energetic. This result also agrees with Anderson et al (2021) [4], where Conscientiousness was negatively correlated with *Punk*, *Rock*, Alternative and Indie music, and positively correlated with music described as "Romantic", "Upbeat" and "Empowering". This finding is a testament to the strength of this approach of investigating emotions via genre in capturing nuanced information of individual preferences.

The results for Neuroticism contrast with those for Conscientiousness, as high Neuroticism was found to be associated with a preference for unconventional genres like *Neo-pop/Dream-pop/Shoegaze*, *Neo-progressive Rock*, *Indie/Alternative Pop-rock*, and *Background/Ambience/Neo*, co-occurring primarily with low arousal emotions such as *Sadness*, *Tenderness*, *Peacefulness*, and *Nostalgia*. section 3.3 describes how these genres might resonate with individuals with high Neuroticism, and the current findings can be explained along similar lines. The co-occurrence with low arousal emotions reinforces the results presented in section 4.3, as low arousal music may serve as a means of managing feelings of heightened anxiety and potential overstimulation. We also observe associations where the aforementioned genres co-occur with *Transcendence*, which suggests that these individuals may seek escape from daily stressors by embracing otherworldly experiences as discussed earlier, especially in combination with genres like *Neo-pop/Dream-pop/Shoegaze*.

On the other hand, there is a negative correlation between Neuroticism and Trance co-occurring with *Joyful Activation*, which implies that low Neuroticism is associated with high arousal and overall positive emotions, akin to those demonstrated by high extraversion. This is expected since Neuroticism and Extraversion are known to correlate in an inverse fashion. For Openness, *Chillout/Easy-listening Jazz* co-occurs with low arousal emotions like *Tenderness* and *Nostalgia*. As the name suggests, *Chillout/Easy-listening Jazz* typically comprises mellow, smooth and soothing musical arrangements which can be linked with the emotion *Tenderness*, and the Jazz subgenres in its wordcloud have a nostalgic connotation, since Jazz was more prevalent in the past century. The tender and nostalgic emotions elicited by this type of music may also resonate with the individual's own emotions, leading to an increased appreciation for the genre. We did not find many genre-emotion combinations to be associated with individuals with high Openness, which possibly implies relatively less specificity in their choices. Highly open listeners are more likely to be open to experiencing emotions that are not typically associated with a particular genre and are often comfortable embracing unconventional forms of musical expression. Overall, the results revealed the granularity in musical preferences associated with personality traits via a combination of type of music and emotions.

5.4 Key Findings

- Extraversion is associated with a preference for joyful and energetic music genres, such as *Hip-hop, Rap, Techno/House*, and *World Music*. *Transcendental* music genres were also linked to Extraversion, suggesting a desire for intense experiences.
- High Neuroticism is associated with unconventional genres like *Neo-pop/Dream-pop/Shoegaze, Indie/Alternative Pop-rock*, and *Neo-progressive Rock*. These genres co-occur with low arousal emotions, reflecting a preference for music that helps manage anxiety and provides an escape from stressors.
- Conscientiousness is negatively associated with experimental and unorthodox genres like *Neo-progressive Rock* and *Neo-pop/Dream-pop/Shoegaze*. Individuals with high Conscientiousness prefer more structured and predictable music and may be less drawn to laid-back and relaxed genres.
- Neuroticism is positively associated with a preference for unconventional genres and co-occurs with low arousal emotions. These genre-emotion combinations reflect the use of music as a coping mechanism for managing heightened anxiety and seeking otherworldly experiences.
- Openness is associated with a preference for *Chillout/Easy-listening Jazz*, which co-occurs with emotions like *Tenderness* and *Nostalgia*. Highly open individuals appreciate mellow and soothing music arrangements and are open to experiencing a wide range of emotions across genres.
- The results highlight the importance of considering both genre and emotion simultaneously to gain a comprehensive understanding of individual musical preferences based on personality traits.

Chapter 6

Personality and Emotions: Tags vs. Acoustic

This study aimed to identify differences in emotions associated with music consumption related to listeners' personalities in a naturalistic context. We compare how emotions derived from tags match (or differ from) those derived from content-based acoustic features when mapped onto a Valence and Arousal (VA) space.

6.1 Methodology

Figure 6.1 depicts the procedure used in our study.

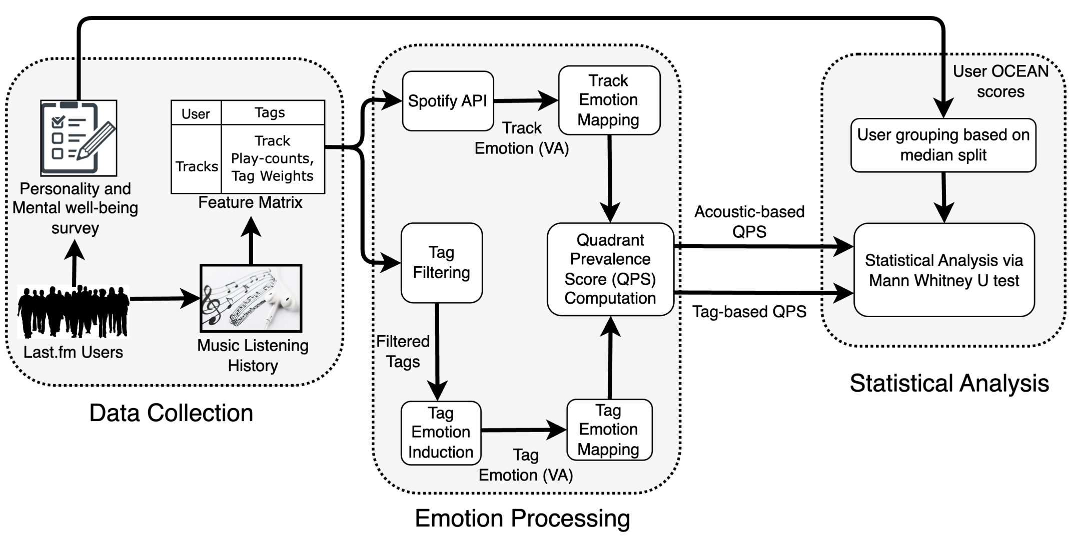

Figure 6.1: Methodology: Personality and the interplay between Genres and Emotions

6.1.1 Emotion processing

For tag-based emotions, the same procedure was followed as done in subsection 4.1.1 with the only difference being that the tag was assigned to a quadrant in the VA space (Figure 6.2) based on its VA values instead of being categorised into one of the 9 GEMS emotions. To extract acoustic features from each track, we utilized the Spotify public API, specifically using the Spotipy package. This allowed us to search for each track in the Spotify database and retrieve two emotion features that represented ”valence” and ”energy/arousal”, derived from the acoustic information of the track. The acoustic-based VA values were then used to map each track to a quadrant in the VA space. The proportion of tracks in each of four quadrants in the VA space was computed representing a Quadrant Prevalence Score (QPS) for tags and acoustic features separately.

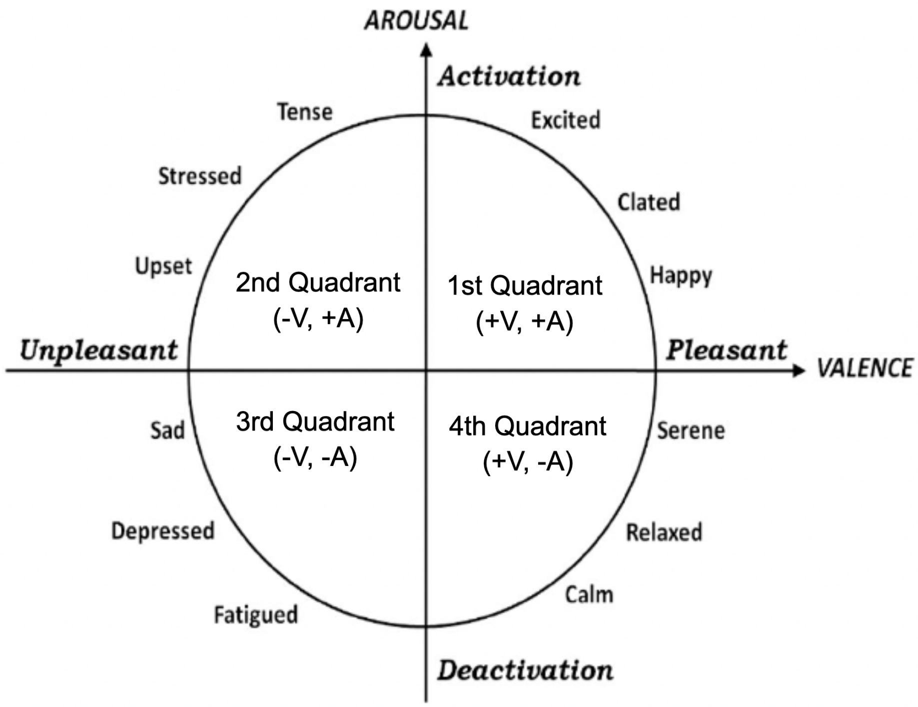

Figure 6.2: Four quadrants of Valence-Arousal space.

6.1.2 Statistical Analysis

Participants were grouped per trait using a median-split following which Mann-Whitney-U Test was used to evaluate QPS differences with permutation tests for significance estimation. For each of the 4 VA quadrants, we performed a two-tailed Mann-Whitney U (MWU) Test on the *QPS* between the High and Low groups obtained for each personality trait (Table 6.1). We further performed bootstrapping (random sampling) with replacement to account for Type I error and ensure that the observed differences are not due to chance. This was done for both tag-based and acoustic-based QPS separately.

Trait	Median Score (M)	Number of participants in Low group (Score <M)	Number of participants in High group (Score >M)
Opennesss	4.25	265	216
Conscientiousness	3.0	235	257
Extraversion	2.25	233	266
Agreeableness	4.0	259	201
Neuroticism	3.0	225	265

Table 6.1: Distribution of participants based on median split

6.2 Results

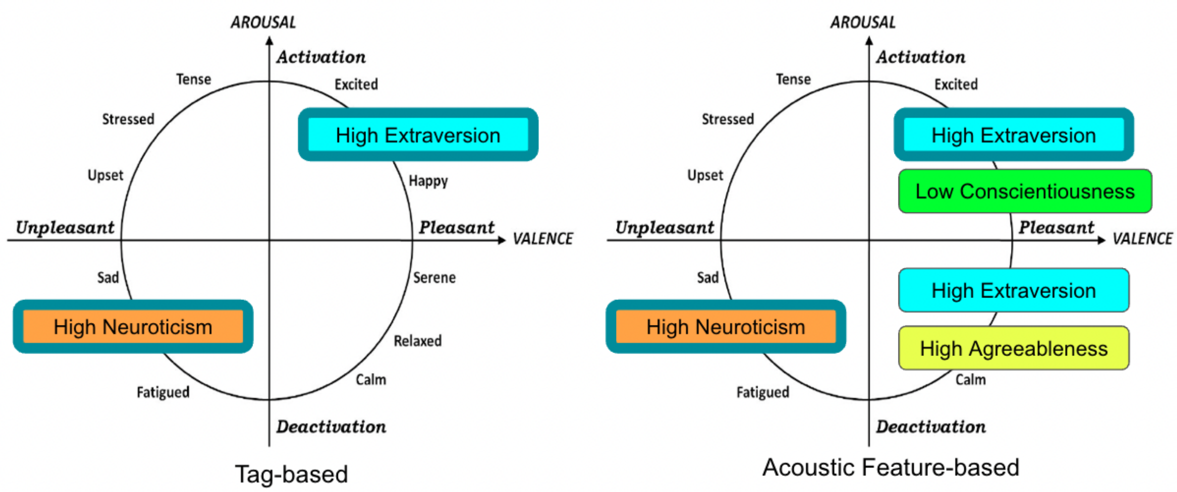

Figure 6.3: Personality traits which showed significant group differences ($p < 0.05$)

As shown in Figure 6.3, the results congruent for tag-based and acoustic-feature-based approaches include higher preference for music belonging to the 1st quadrant (+V,+A) for High Extraversion individuals (tag-based U=27124.5, $p < 0.05$, acoustic-based U=27203, $p < 0.05$) and 3rd quadrant (-V,-A) for High Neuroticism individuals (tag-based U=25182, $p < 0.01$, acoustic-based U=26727, $p < 0.05$). High Extraversion and High Agreeableness also exhibited a higher preference for the 4th quadrant (+V,-A) while low Conscientiousness for 1st quadrant, albeit only based on acoustic-features.

6.3 Conclusion and Key Findings

- Emotions derived from semantic-based and acoustic-based models show agreement for Extraversion and Neuroticism, aligning with previous research on their associations with positive and negative emotional experiences [56].
- Acoustic features provide more significant differences compared to semantic tags, indicating that acoustic information may be more useful for music recommendation systems [8].
- Individual differences in emotional processing may influence the preference for acoustic-based emotional analysis, suggesting variations in how individuals perceive and interpret emotions in music.

These findings emphasize the potential of acoustic features in capturing emotional nuances and their practical implications in developing personalized music recommendation systems.

Chapter 7

Conclusions and Future Work

This study provides a rich example of new research into identifying associations between music preferences and personality traits in an ecologically valid, naturalistic context. Notably, the co-occurrence of genre and emotions is investigated for the first time, making this an important step forward which has implications in designing recommendation systems and understanding musical engagement in everyday life. While our results are generally consistent with previous self-reported and experiment-based studies done on music preferences and personality, we additionally report some novel findings for specific personality traits and music preferences.

Regarding the consistency of listening behaviors, we found a high overlap between 6-month- and 1-year-listening histories, suggesting that six months is enough to capture long-term music preferences irrespective of individual differences. Results showed that listeners with high Neuroticism tend to engage in repeated music listening, which has been previously identified as a form of rumination [26]. This is in line with previous research linking high Neuroticism to greater risk for internalizing disorders such as depression and anxiety [31, 46], as well as repetitive music listening [27, 59, 64, 65]. However, the association between trait Neuroticism and repetitive listening does not hold when age and gender are taken into account, suggesting that this relationship may be specific to a particular age-range or moderated by gender. This is in line with Carlson et al. (2015) [14], who found that Neuroticism related differently to neural correlates of music listening and uses of music in mood regulation, depending on gender.

Our analysis also provides new insights derived from observing trends that emerge based on the number of top tracks chosen (n = 100, 250, 500). Specifically, preferences related to traits Extraversion and Neuroticism demonstrate stable genre-cluster profiles irrespective of the number of tracks chosen, which suggests that these choices may not be prone to transient factors such as current hits and/or seasonal variations (although the listening history did not include Christmas season). Similarly, a stable emotion profile was exhibited for trait Extraversion for top 500 and 250 tracks. The interplay between personality, emotions, and genres reveals several novel insights and the results and implications are discussed in subsequent sections.

The complexity of the obtained results raises one of the overarching questions not adequately addressed by previous work: do musical preferences reflect personality or compensate for it? Do some personalities use it to compensate while others to mirror their own traits/states? Overall, these results suggest that musical preferences reflect personality in both trait-congruent and trait-incongruent ways, with Neuroticism representing a particularly complex example of this. Research has shown that listeners may choose music in order to enhance a current mood state, whether positive or negative, or to attempt to change it [61]. Given that Neuroticism is characterized by a tendency to experience negative emotion, it is reasonable to expect neurotic listeners to sometimes use music to try to compensate for this tendency by choosing happy-sounding music, but also understandable that listeners who more often experience negative emotion may appreciate or feel connected with sad music. Results for Extraversion indicate a more straightforward, congruent connection between personality and preferred music, as do results for Openness, as choices seem to support listeners' desires for a wide range of intense experiences and a variety of aesthetic stimuli respectively. For Conscientiousness, trait congruity or incongruity is more difficult to interpret in the context of emotion, as Conscientiousness is not characterized as a tendency towards a particular affective state per se. One possibility is that conscientious listeners may use music to help them focus and work, or to distract from thoughts of work, but further research is needed to clarify what musical features or emotions may be chosen for these purposes.

7.1 Key Contributions

To conclude,

- The uniqueness of our dataset lies in its inclusion of naturally occurring listening activities, accompanied by assessments of users' personality traits, mental well-being, and levels of musical engagement strategies. This comprehensive approach provides a valuable opportunity to explore the interconnectedness between various facets of human behavior, offering insights that contribute to our understanding of the intricacies of human psychology and the richness of human experiences.

- This work investigates the co-occurrence of genre and emotions for the first time in relation to personality traits. Identifying emotional connotations of music within preferred genres via tags helps us in pinpointing unique listener experiences which capture not only the acoustic attributes but also semantic associations thereby resulting in the identification of timbral environments, which have been considered as anthropomorphic projections of the self [23]. This is an important step forward which has implications in designing recommendation systems and understanding musical engagement in everyday life.

- Our approach of genre-clustering to create an ontology of music preferences in an ecologically valid music listening context circumvents the genre-related ambiguity that occurs in self-reported studies. This approach can lead to a deeper understanding of how individuals perceive and categorize music genres. As a result, music recommendation algorithms can be enhanced to consider not only surface-level genre labels but also the underlying emotional and perceptual qualities that influence individual preferences.

- Acoustic features provide more significant differences compared to semantic tags, suggesting that acoustic information may be more valuable for music recommendation systems [8]. However, considering both emotion information from tags and acoustic features could lead to a better understanding of how music relates to personality and emotional experiences.

7.2 Limitations and Future Work

A limitation of our work is that the current dataset sample was predominately male. To address this limitation, we employed gender as a covariate in the partial correlations conducted during our statistical analysis. The above limitation was also true of the sample used by Dunn et al. (2012) [19]. This may indicate some general bias in the gender profile of users of Last.fm, which is supported by Rentfrow and Gosling's (2003) [52] report that 60 percent of users of one online platform were male. The disparity may also reflect a bias in recruitment if males are more likely to agree to participate than females, or a combination of both factors. However, a trade-off between ecological validity and sample representativeness is not uncommon. Furthermore, additional research is necessary to determine whether gender differences exist in the relationship between personality and music listening behavior.

Further research can also take into account additional details such as liked- and disliked-artists since research by Ferrer and Eerola (2011a) [21] has shown that there are often mismatches between participants' stated genre preferences and artist preferences, suggesting musical artists may be a better measure of preferences than genre overall. To add to this, incorporating features extracted from the music signal itself, lyrical content (eg: themes, emotions), and the user's physiological signals that depict emotional state/mood via wearable sensors such as Fitbits or smart watches could contribute towards creating an enhanced, positive user experience by providing music recommendations that are tailor-made for the user.

Related Publications

- Goyal, Y.,Hanji, S.,Carlson, E.,Surana, A.,Kala, D., & Alluri, V. (2023). I guess that's why they call it the blues": Personality and the interplay between emotion and genre. European Journal of Personality (Under review) *

- Goyal, Y., Alluri, V. (2021) Artist2Risk: Predicting Depression Risk based on Artist Preferences. In the 16th International Conference on Music Perception and Cognition.

- Goyal, Y., Hanji, S.,Carlson, E., Alluri, V. (2021). Tag-based and acoustic-feature based emotions associated with online music consumption and personality. In the 16th International Conference on Music Perception and Cognition.

- Hanji, S., Goyal, Y.,Alluri, V. (2021). Exploring gender-specific music preferences associated with risk for depression on online music streaming platforms. In the 16th International Conference on Music Perception and Cognition.

- Surana, A, Goyal, Y, Alluri, V. (2020) Static and Dynamic Measures of Active Music Listening as Indicators of Depression Risk. In Speech, Music, and Mind with Audio Satellite Workshop, INTERSPEECH 2020.**

- Surana, A., Goyal, Y., Srivastava, M., Saarikallio, S, and Alluri, V. (2020) TAG2RISK: Harnessing Social Music Tags for Characterizing Depression Risk. In Proc. of the 21st Int. Society for Music Information Retrieval Conf. (ISMIR), Montral, Canada, 2020**

Author Contributions

- * : Yash Goyal and Shivani Hanji are joint first authors with equal contributions.

- ** : Yash Goyal and Aayush Surana are joint first authors with equal contributions.

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