Empathy and Music Preferences: Exploring Music Listening Behaviours in Naturalistic Settings

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Abstract

Empathy has been linked to music preferences in controlled laboratory settings, but naturalistic settings like music streaming platforms remain unexplored. This study investigates how trait empathy influences music preferences and sequential listening behaviors in real-world settings. To this end, we collected and analyzed one-year Spotify listening histories of 290 Indian university students alongside their trait empathy scores, measured using the IRI scale. Our results reveal that individuals who score high on the IRI subscales of Empathic Concern, Fantasy, and Perspective Taking prefer sad music. Moreover, those scoring high on Empathic Concern or Perspective Taking were found to be more likely to transition from happy to sad music. These findings partially align with previous lab-based research, specifically for the subscales of Empathic Concern and Fantasy, while providing novel insights into the relations between the Perspective Taking subscale and music consumption. The study also provides novel insights into sequential listening behaviours, thus, strengthening the evidence that empathy shapes musical preferences and listening behaviors across diverse contexts.

Keywords: empathy; music preferences; listening history; sequential listening; valence-arousal; spotify; naturalistic data

Introduction

Music is commonly used in everyday life for various purposes such as mood regulation, stress reduction, social bonding, and cognitive enhancement (Saarikallio, 2011; Schäfer, Sedlmeier, Städtler, & Huron, 2013). Research suggests that individuals actively engage with music to manage emotions, cope with stress, and enhance overall well-being (Goethem & Sloboda, 2011). Additionally, music plays a crucial role in identity formation and social interactions, facilitating communication and emotional expression (Hargreaves & North, 1999).

Individual differences in music preferences have been extensively explored, highlighting how personality traits and cognitive styles shape musical engagement (Rentfrow & Gosling, 2003; Greenberg, Baron-Cohen, Stillwell, Kosinski, & Rentfrow, 2015). Research suggests that these preferences are not only linked to short-term emotional and motivational states such as mood and concentration (Huang & Shih, 2011; McCraty, Barrios-Choplin, Atkinson, & Tomasino, 1998), but also reflect stable aspects of personality (Lamont & Webb, 2010; Kent, 2006). For instance, certain traits have been associated with a preference for specific musical styles, suggesting that the way individuals interact with music may provide insight into their broader psychological characteristics (Rentfrow, Goldberg, & Levitin, 2011).

One relevant trait is empathy, which can be defined as the ability to understand and respond affectively to another person's experience (Tomasello, Carpenter, Call, Behne, & Moll, 2005). Previous studies have found that more empathic people tend to enjoy certain genres (Clark & Giacomantonio, 2013), prefer mellow music (with low arousal and negative valence) (Greenberg et al., 2015), and experience more intense emotions in response to music (Ladinig & Schellenberg, 2011; Vuoskoski & Eerola, 2012).

The Interpersonal Reactivity Index (IRI) (Davis, 1980) is a validated and widely used scale for measuring trait empathy. It is a multi-dimensional scale consisting of four components, that is, Fantasy (FS), Perspective Taking (PT), Empathic Concern (EC), and Personal Distress (PDS). FS refers to the tendency or the ability to identify oneself with situations faced by fictional characters. PT is the tendency to shift one's own perspective to that of another person. EC captures the capacity to experience feelings of compassion or concern towards others. PDS taps into the self-oriented feelings of fear or apprehension in response to negative experiences of others (Davis, 1980).

Huron & Vuoskoski (2020) theorise that individuals scoring high on EC and FS prefer sad music (characterised by negative valence and low arousal) as it elicits feelings of sympathy and increases listener's absorption. Along similar lines, Kawakami and Katahira (2015) found that FS and PT were associated with a preference for, and more intense emotional responses to, sad music among children. However, studies so far have been limited to a lab setting, where participants are exposed to experimenter-selected music in controlled settings. Furthermore, they do not capture the temporal or dynamic nature of music listening.

People spend hours listening to music, and continually make judgements about whether they like what they hear or not (DeNora, 2000). The emergence of online music streaming platforms like Spotify[1] and Last.fm[2] have enabled users

[1] www.spotify.com
[2] www.last.fm

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to stream music of their choice at any time and place, with greater control over the music they listen to. Thus, it has become increasingly important to delve deeper into the temporal aspects of music consumption. While there have been works studying music preferences associated with personality traits using listening histories from streaming platforms (Hongpanarak & Mongkolnavin, 2021; Ferwerda, Tkalcic, & Schedl, 2017; Melchiorre & Schedl, 2020; Anderson et al., 2021), no studies have been carried out to explore the link between empathy and music consumption in a naturalisic setting.

This study aims to bridge the gap between laboratory-based research and real-world listening behaviors by exploring the relationship between trait empathy and music preferences in a naturalistic setting, where participants have greater control over the music they listen to. Specifically, we investigate how individuals with high IRI empathy scores differ from their low-empathy counterparts in terms of their actual music listening preferences. Additionally, we examine sequential listening behaviors and dynamic transitions between music with varying emotional connotations. To this end, we collected data from Spotify users including their one year listening histories and IRI scores.

We hypothesize that, in line with previous lab-based studies, high FS and high EC individuals will demonstrate greater preference for sad music. Given their proclivity to sad music, we also hypothesize that they are more likely to transition to listening to sad music while streaming music online.

Methodology

Data Collection

680 University students (500 males) participated in an online survey wherein they were asked to fill in their demographics followed by standard questionnaires like IRI for assessing their empathy, Kessler's Psychological Distress scale (Kessler et al., 2012) for measuring mental well being, and Healthy-Unhealthy Music scale (Saarikallio, Gold, & Mcferran, 2015), amongst others. Participation was completely voluntary and informed consent was taken from each participant. Out of these, 350 students provided one year Spotify listening history in exchange for monetary compensation. Each participant was assigned a numerical code to maintain anonymity. Furthermore, the Spotify history provided had no identifiable information.

For the purpose of this study, we limit our analyses to their listening histories and trait empathy scores. The IRI statistics in Table 1 demonstrates a well-balanced distribution of IRI scores. Thus, median splitting was done to split particpants into low and high IRI groups for analysing group differences.

Music Listening History Participants were asked to obtain and upload their listening history data for the past one year from their Spotify accounts. Listening histories consist of several listening events. A listening event consists of the name of the track, artist, and duration for which the track was played along with the corresponding timestamp.

The data was preprocessed to remove participants with insufficient listening histories. This involved filtering out songs that were played less than 15 seconds, assuming that they were skipped, and then removing users with less than 500 listening events remaining. The final dataset used for the study comprised of listening histories of 290 users (211 males; age mean=20.35, SD=2.08), and contained 86239.13 hours of listening, spanning 136127 unique tracks and 1708490 listening events.

Table 1: *IRI statistics of the users in the dataset*

Subscale	Mean	SD
IRI-EC	25.17	4.57
IRI-FS	24.38	5.66
IRI-PT	24.24	4.60
IRI-PDS	19.88	4.64

Feature Extraction

In order to extract audio features for the tracks, we use the Spotify Web API[3]. These features comprised of *valence, energy/arousal, danceability, loudness, speechiness, acousticness, instrumentalness, liveness, tempo* and *mode*. Out of these, only valence and arousal were used for this study. We utilize the Russell's Circumplex Model of Affect (Russell, 1980), where an emotion is a point in a two-dimensional continuous space representing Valence and Arousal (VA). Valence here refers to the emotion conveyed by the track - positive or negative, while arousal refers to the energy or intensity of emotion. Tracks with high valence are usually happy and cheerful, while tracks with low valence are sad, angry and depressing. Tracks with high arousal are energetic in nature, while tracks with low arousal are calming.

Mean valence and arousal scores for each participant were calculated by taking the average of Spotify-derived valence and energy values of the tracks in their listening histories, weighted by the number of times they are played. Mathematically,

$$\text{mean valence} = \frac{\sum_{i=1}^{n}(\text{valence}_i \times \text{plays}_i)}{\sum_{i=1}^{n}\text{plays}_i}$$

where:

valence_i	valence value of the i-th track
plays_i	number of times the i-th track was played
n	total number of unique tracks

Mean arousal was calculated similarly.

Statistical Analysis

We performed two broad kinds of analyses, i.e., static and dynamic. Static analysis involved aggregating individual listening patterns, whereas dynamic analysis encapsulates the temporal or sequential aspects of music listening.

[3]https://developer.spotify.com/documentation/web-api

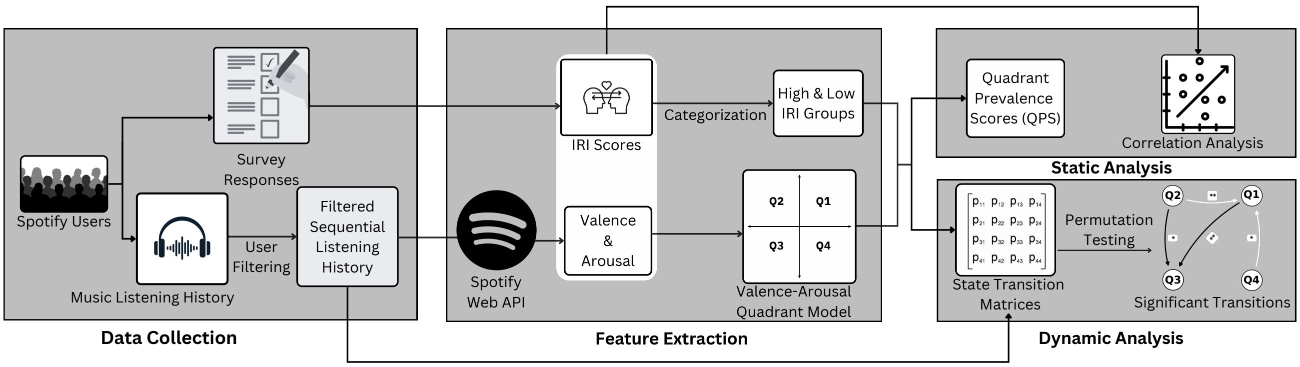


Figure 1: *Methodology pipeline*

Static Analysis We first calculated the Spearman correlations between the four IRI subscales, and then between the mean VA values and FS and EC scores. Then, we computed the Quadrant Prevalence Scores (QPS), which represents the overall preference of an individual or group towards each of the four VA quadrants.

Quadrant Prevalence Scores: Tracks were categorized into four quadrants as shown in Figure 2: positive valence-high arousal (Q1), negative valence-high arousal (Q2), negative valence-low arousal (Q3), positive valence-low arousal (Q4). For each participant, QPS is calculated as the percentages of songs from each quadrant in the listening history. Participants were divided into two groups—high and low—based on median splits of IRI subscales for analyzing group differences. The QPS for high and low groups in each of the four IRI subscales was calculated by taking the mean of the QPS for each participant in the group. Mathematically,

$$\text{Individual QPS}(Q_i) = \frac{n_{Q_i}}{\sum_{k=1}^{4} n_{Q_k}} \times 100$$

$$\text{Group QPS}(Q_i) = \frac{1}{N} \sum_{j=1}^{N} \text{Individual QPS}_{(j)}(Q_i)$$

where:

n_{Q_i}	Number of songs from quadrant Q_i in a participant's listening history
$\sum_{k=1}^{4} n_{Q_k}$	Total songs in participant's listening history
$i \in \{1,2,3,4\}$	Quadrant number
N	Number of participants in the group
$j \in \{1,2,\ldots,N\}$	Participant index

The group differences in QPS were tested for significance using permutation tests - participants were randomly sampled (with replacement) to create new groups of the same size as the original. This was repeated 10,000 times to create a null distribution of the group differences, using which the significance (p-value) of the QPS group differences was calculated.

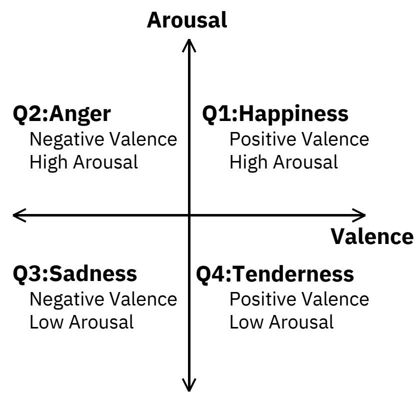


Figure 2: *Two-dimensional Valence-Arousal space, representing the four VA quadrants*

Dynamic Analysis of Transition Probabilities To analyze the transitions between the four VA quadrants, we constructed transition probability matrices based on the session-wise sequence of tracks played in users' listening histories.

Definition of a Transition Event: Let T_i represent a track played by a user, and let $q(T_i)$ denote the VA quadrant of track T_i. A transition event occurs when a track T_j follows track T_i, such that T_j starts within 10 minutes after T_i ends, and T_j is played for at least 15 seconds. If these conditions are met, we define a transition from $q(T_i)$ to $q(T_j)$.

Transition Probability Matrix Construction: To analyze the transitions at a group level, we need to aggregate the transition events of the individuals in the group. We define,

$C_{i,j}^{(k)}$ as the total count of transition events from Q_i to Q_j for participant k

Before summing $C_{i,j}^{(k)}$ for all participants in the group, we normalize the values using the total count of transition events for each participant k. This gives us the normalised sum of transition events from Q_i to Q_j as:

$$n_{i,j} = \sum_{k=1}^{N} \frac{C_{i,j}^{(k)}}{\sum_{i,j=1}^{4} C_{i,j}^{(k)}}$$

where:

N	Number of participants in the group
$C_{i,j}^{(k)}$	Total count of transition events from Q_i to Q_j for participant k
$\sum_{i,j=1}^{4} C_{i,j}^{(k)}$	Total count of transition events for participant k
$k \in \{1,2,\ldots,N\}$	Participant index

For a given group (e.g., high FS), we take the normalized sum of all transition events for the individuals in the group to construct the transition probability matrix P. P is a 4×4 matrix, where each element p_{ij} represents the probability of transitioning from quadrant Q_i to quadrant Q_j:

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \\ p_{41} & p_{42} & p_{43} & p_{44} \end{bmatrix}$$

where each element is computed as:

$$p_{ij} = \frac{n_{ij}}{\sum_{j=1}^{4} n_{ij}}$$

The denominator ensures normalization so that each row sums to 1. Thus, P represents the empirical probability distribution of transitioning between VA quadrants for a given group.

Permutation Testing for Significance: To assess whether the transition probabilities significantly differ between groups, we performed permutation testing. Specifically, we tested differences in transition probabilities for individuals scoring high vs those scoring low for each of the four IRI subscales.

Permutation Test Procedure: Let $P^{(A)}$ and $P^{(B)}$ be the transition probability matrices for two groups (e.g., high FS and low FS). The difference in transition probabilities between groups is quantified as:

$$D_{ij} = p_{ij}^{(A)} - p_{ij}^{(B)}$$

where $p_{ij}^{(A)}$ and $p_{ij}^{(B)}$ represent the probability of transitioning from quadrant Q_i to quadrant Q_j for groups A and B, respectively.

To test the null hypothesis (that the transition probabilities do not differ between groups), we performed permutation testing as follows:

- pool all individuals from both groups.
- randomly sample individuals (with replacement) to two new groups of the same sizes as the original groups.
- construct new transition probability matrices for the permuted groups and compute the difference:

$$D_{ij}^{*} = p_{ij}^{*(A)} - p_{ij}^{*(B)}$$

- repeat this process N times ($N = 10,000$) to generate a null distribution of D_{ij}^{*}.
- Compute the empirical p-value for each transition as:

$$p_{\text{perm}} = \frac{\sum_{k=1}^{N} \mathbf{1}(|D_{ij}^{*}| \geq |D_{ij}|)}{N}$$

where $\mathbf{1}(\cdot)$ is the indicator function (1 if condition is true, 0 otherwise).

Table 2: *Spearman Correlation Matrix with Significant Correlations for IRI subscales*

	IRI-EC	IRI-FS	IRI-PT	IRI-PDS
IRI-EC	–			
IRI-FS	0.249*	–		
IRI-PT	0.411*	0.225*	–	
IRI-PDS	0.0351	0.215*	-0.001	–

* : $p < 0.0001$

Table 3: *Spearman correlations between IRI subscales and Valence and Arousal scores (the average valence and energy values of the tracks in each participant's listening history, weighted by the number of playbacks)*

Subscale	Metric	Correlation	P-value
FS	Valence	-0.064	0.275
	Arousal	-0.085	0.150
EC	Valence	-0.150	**0.010***
	Arousal	-0.171	**0.003****
PDS	Valence	0.103	0.081
	Arousal	0.087	0.139
PT	Valence	-0.150	**0.011***
	Arousal	-0.173	**0.003****

* : $p < 0.05$ ** : $p < 0.01$

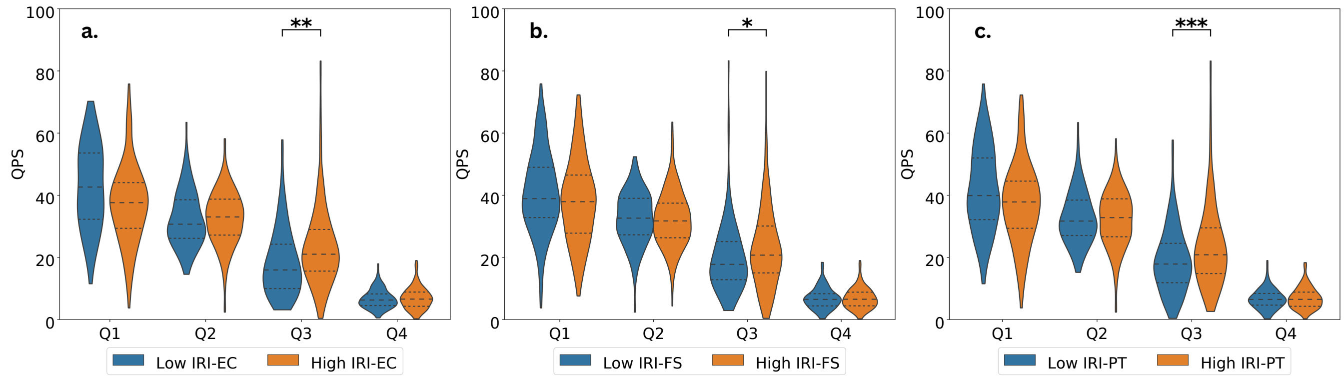
Results

Correlation Analysis

The correlation between the four IRI subscales is presented in Table 2. The results for the correlation analysis are summarized in Table 3. Significant negative correlations were observed between EC and both the average valence ($p = 0.010$) and arousal ($p < 0.005$) values of the tracks played by the user. Similar results were obtained for PT with average valence ($p < 0.05$) and arousal ($p < 0.005$). No significant correlations were found for FS or PDS with VA.

Quadrant Prevalence Scores

The Quadrant Prevalence Scores (QPS) for the entire dataset, as shown in Figure 4, indicate a strong skew towards songs with high arousal, namely Quadrants Q_1 and Q_2, which together comprise approximately 70% of the dataset. Conversely, Q_4 has the lowest QPS. The QPS analysis for group



$* : p < 0.05$ $** : p < 0.01$ $*** : p < 0.001$

Figure 3: *Comparison of QPS for High and Low empathy groups, split by median score- a.EC b. FS c. PT. Q1, Q2, Q3, and Q4 represent the 4 Quadrants in the Valence-Arousal space as shown in Figure 2.*

differences within the subscales of IRI have been elaborated upon in the following subsections. No significant results were found between the QPS of high and low PDS groups.

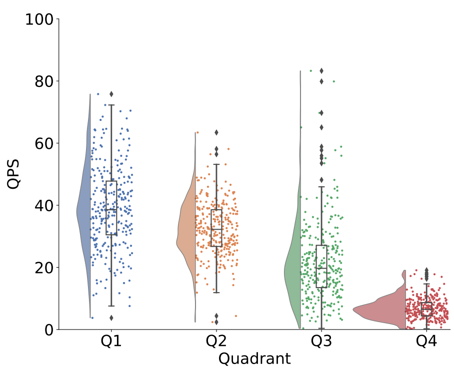


Figure 4: *Distribution of QPS across all participants.The dominance of Q1 and Q2 across all participants points towards their generally popularity.*

EC Group Differences QPS for individuals with high and low EC are illustrated in Figure 3a. While both groups follow the general trend of highest prevalence in Q_1 followed by Q_2, significant differences between the groups were observed only in Q_3. Specifically, high EC individuals had a significantly greater QPS in Q_3 ($p = 0.0012$) compared to their low EC counterparts.

FS Group Differences QPS for individuals with high and low FS are shown in Figure 3b. Similar to the EC group, the general trend remains consistent, with Q_1 being the most prevalent. However, significant differences between groups were observed only in Q_3. Specifically, high FS individuals had a significantly greater QPS in Q_3 ($p = 0.0240$) compared to their low FS counterparts.

PT Group Differences QPS for individuals with high and low PT are shown in Figure 3c. Significant differences between groups were observed only in Q_3. Specifically, high PT individuals had a significantly greater QPS in Q_3 ($p = 0.0009$) compared to their low PT counterparts.

Dynamic Analysis of Transition Probabilities

Permutation test results for cell-wise group differences are shown in Figure 5a, which illustrates the significant differences in transition probabilities for high vs low EC. The figures for FS, PT and PDS have been omitted due to no or insufficient significant differences.

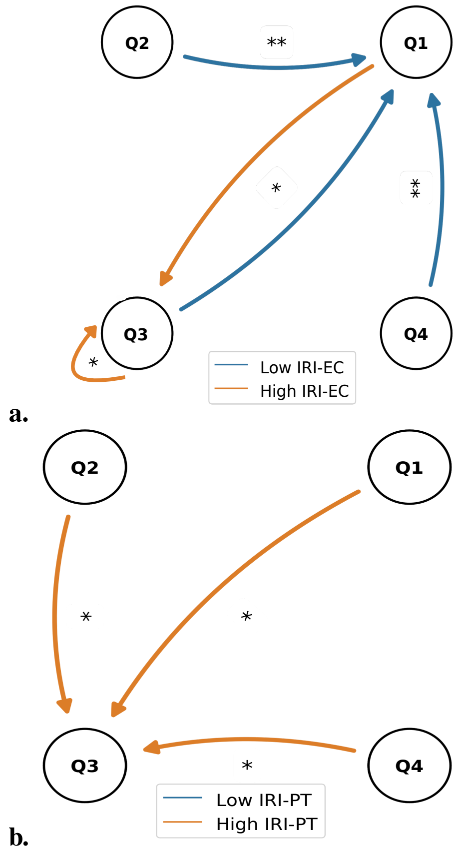
EC Group Differences For EC, significant differences were observed in 5 out of the 16 possible transitions. High EC individuals exhibited a greater probability of transitioning from Q_1 to Q_3 ($p < 0.05$), and staying in Q_3 ($p < 0.05$). On the other hand, low EC individuals exhibited a greater probability of transitioning from Q_2 to Q_1 ($p < 0.01$), Q_3 to Q_1 ($p < 0.05$) and from Q_4 to Q_1 ($p < 0.01$).

These findings indicate that high EC individuals tend to move towards Q_3, while low EC individuals are more likely to transition into Q_1.

FS Group Differences No significant differences in transition probabilities were found between high and low FS groups after the permutation test.

PT Group Differences Significant difference were observed in the transition probabilities from Q_1, Q_2 and Q_4 to Q_3 ($p < 0.05$), with no significant transition probabilities for low PT individuals.

PDS Group Differences For PDS, the only significant difference was observed in the transition probability from Q_1 to Q_2 ($p < 0.05$), with low PT individuals exhibiting a greater probability for the transition.



$*: p < 0.05$ $\quad$ $**: p < 0.01$

Figure 5: *a. High EC shows increased transitions to Q3, while low EC favors transitions to Q1*
b. High PT showing increased transitions to Q3 from all other quadrants, as compared to low PT

Discussion

This study is the first of its kind to examine the associations between trait empathy and music listening in a naturalistic Indian setting. The findings of this study partially corroborate previous works, while providing some novel insights.

Static Analysis

As hypothesized, we find that high FS and high EC individuals do demonstrate greater preference for sad music. However, we also identify signficant associations of high PT with sad music.

Results from correlation analysis indicate that individuals with high EC and PT scores exhibit a preference for music with lower valence and arousal levels, supporting previous laboratory and survey-based studies on Asian populations (Kawakami & Katahira, 2015). However, no significant correlations were found for PDS, which suggests that it may not play a strong role in shaping musical preferences in the Indian population.

The QPS analysis further supports these findings, revealing that high EC and PT individuals listen to a greater proportion of songs in Quadrant 3 (i.e., negative valence, low arousal) compared to their low-empathy counterparts. This aligns with previous findings that high EC individuals gravitate toward sad or melancholic music due to the heightened pleasure they draw from compassionately engaging with such music (Huron & Vuoskoski, 2020). QPS analysis also revealed the preference of high FS individuals for music with negative valence and low arousal (i.e., Quadrant 3), which is also in agreement with the theory that fantasy empathy may amplify the enjoyment of sad music by increasing absorption (Huron & Vuoskoski, 2020). The results for high vs low PT provide novel results, showing a preference for sad music (Q3) for high PT. The dominance of Quadrants 1 and 2 across all participants suggests that, while sad music is preferred more among certain groups, high-arousal music remains generally popular.

Dynamic Analysis

Dynamic analysis through transition probability matrices provided novel insights into sequential listening behaviors. Overall, we found that high EC and high PT transition to listening sad music (Q3), with low EC transitioning to happy music (Q1), but no significant results are found for FS. High EC individuals were significantly more likely to transition from positive valence and high-arousal to negative valence and low-arousal music (Q3). On the contrary, low EC individuals were significantly more likely to transition to Q1. This not only agrees with the static analysis, but furthers our understanding by revealing potential dynamic mood regulation patterns. Also, high PT individuals were significantly more likely to transition to Quadrant 3. This novel finding may be due to differences in the Indian demographic or the non-laboratory based setting of our study which could influence the patterns of music engagement and requires further controlled studies.

Conclusion

The use of real-world listening data from Spotify, rather than controlled laboratory settings, is a notable strength of this study. By analyzing music preferences in a naturalistic environment, we captured more ecologically valid insights into how individuals engage with music in their daily lives. However, some limitations should be acknowledged. First, Spotify's audio feature may not fully encapsulate the nuanced emotional content of a song. Second, while the dataset captures real-world music listening behavior, contextual factors such as social settings, time of day, and concurrent activities were not explicitly controlled. However, analyzing these trends in the long-term might minimize these transient effects and capture more stable listening patterns. Future research could also explore these factors in greater depth by incorporating methodologies such as experience sampling (Larson & Csikszentmihalyi, 2014) in addition to capturing momentary emotional responses to music through wearable sensors.

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