Music Listening as Indicator of Depression Risk (Static and Dynamic)

What is Depression?

Depression is classified as a mood disorder. It may be described as feelings of sadness, loss, or anger that interfere with a person's everyday activities.

Objective: examine time-varying music consumption, in terms of acoustic content, and its association with users well-being.

Hypothesize: the following Spotify users who demonstrate high depression risk that is characterized by low well-being scores:

- greater overall consumption of music, especially music that is perceived as sad
- higher repetition in music tracks owing to ruminative and repetitive engagement.
- increased level of variability and/or inertia in terms of the acoustic and emotion information of music across time

Dataset:

The participants' listening histories were extracted and survey for K10 ,Age, healthy, unhealthy ,SWLS ,SSQ-Family , SSQ-Friends .

Data of individual consist of :endTime, artistName, trackName, msPlayed

Feature Extraction:

Spotify public API. Spotify package was employed to search for each track in Spotify database and retrieve the values for 10 features that Spotify provides. Eight of these were audio features which comprised danceability, loudness, speechiness, acousticness, instrumentalness, liveness, tempo, and mode.

Additional two emotion features representing the valence and energy/arousal were also retrieved. For each quadrant we calculated a quadrant prevalance score (QPS) which is

calculated as the proportion of tracks in the respective quadrants in each user's listening history.

Session : A session was defined as a period of continuous listening activity, with a subsequent session occurring after an inactivity of at least two hours.

The reason for using a smaller time interval/resolution based on sessions as opposed to larger intervals like days or weeks is due to the fact that emotions are more transient and short-lived than mood states which may span for days. This session based on 2 hours is called dynamic session, while for considering all history till now is static session. Formula for RI is as follows:

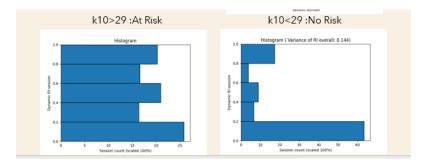
2)Dynamic RI =
$$\sum_{j \in N_u} \frac{\sum_{i \in T_{u,j}} (tr_{i,j} \times I(tr_{i,j} >= 2))}{\sum_{i \in T_{u,j}} tr_{i,j}} \qquad \text{(repetitiveness index)}$$
3)Static RI =
$$RI_u = \frac{1}{N_u} \sum_{j \in N_u} \frac{\sum_{i \in T_{u,j}} (tr_{i,j} \times I(tr_{i,j} >= 2))}{\sum_{i \in T_{u,j}} tr_{i,j}}$$
where,
$$N_u : \text{number of sessions for user } u$$

$$T_{u,j} : \text{all unique tracks in } jth \text{ session for user } u$$

$$tr_{i,j} : \text{frequency of track } i \text{ in } jth \text{ session}$$

$$I(condition) : \text{indicator function, 1 if } condition \text{ evaluates to true, else 0}$$

Found Pattern:



Here person at risk has 50% of Dynamic RI>=0.5, while Person not at risk has 60% of Dynamic RI <0.2

Which shows at risk person is tend to listen songs repeatedly!

Understanding survey parameters:

Age: Age of the individual.

K10: Kessler Psychological Distress Scale

K10 score	Categorisation
10 to 15	Low distress
16 to 21	Moderate distress
22 to 29	High distress
30 to 50	Very high distress

Healthy: reflect positive musical experiences that contribute to well-being. (ex music for relaxation, enjoyment, or social connection.)

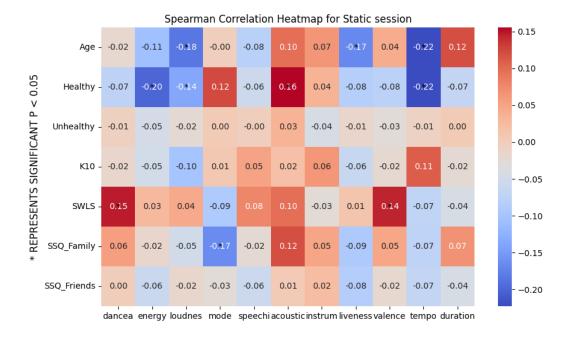
Unhealthy: highlight negative musical experiences that may intensify negative mood(ex. music to dwell on negative emotions or reinforce distressing thoughts)

SWLS: Satisfaction with Life Scale, a measure of life satisfaction.

SSQ-Family: Social Support Questionnaire - Family, a measure of perceived social support.

SSQ-Friends: Social Support Questionnaire - Friends, a measure of perceived social support.

Looking at static session



* represents p<0.05 : Significant spearman correlation

Significant –ve correlation between age and loudness, liveness, tempo

WE can see as age of person increases , he'll tend to listen songs having less loudness and tempo in real life.

Significant –ve correlation between healthy score and energy(arousal), loudness, tempo Again person listening to songs having less energy, loudness and tempo is expected to have positive of song on him(as per healthy score defined before).

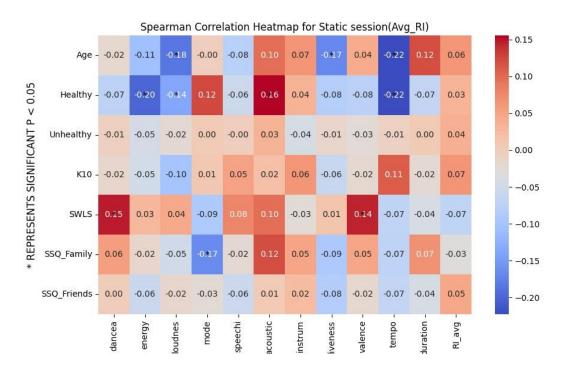
Significant +ve correlation between healthy score and acousticness

Significant +ve correlation SWLS and daceability, valence

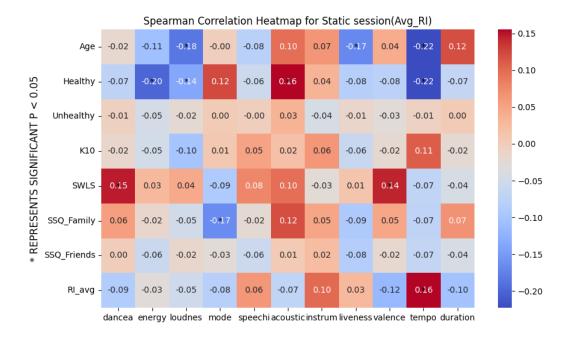
Person who is satisfied with his life would listen songs having more danceability feature and valence(positive songs), which can be seen in real life.

Significant –ve correlation SSQ_Family and mode

Plot 2:



Significant +ve correlation between Static RI and tempo(measured in Beats per minute)



+ve correlation between Static RI and K10 which was expected! (one of hyphothesis)

The positive association between Repetitiveness Index and K10 reflects the ruminative coping style which is characteristic of individuals at-risk for depression which may result in intensifying their negative moods

Valence-arousal:

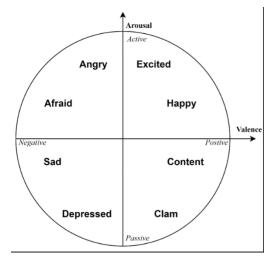
Spotify APT provided for track:

Energy: (taken as arousal in paper):

Energy represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. For example, death metal has high energy.

Valence:

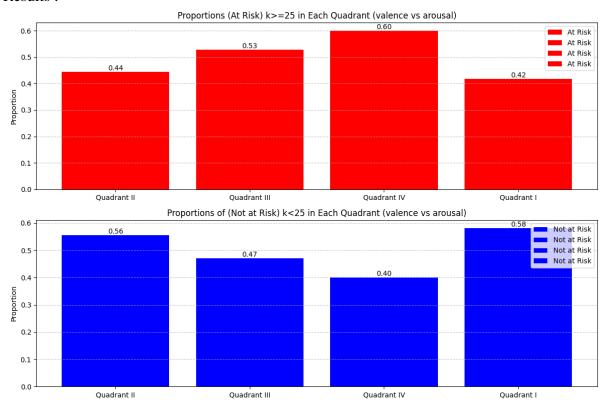
A describes the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry).



For each quadrant we calculated a quadrant prevalance score (QPS) which is calculated as the proportion of tracks in the respective quadrants

And mapped with k10 of users

Results:



Inference: Third and fourth quadrant has more users at risk of depression, signifying depressed people tend to listen songs of low arousal. (one of hyphothesis)

Individuals with high K10 scores are characterized by states that are high in anxiety and arousal. When using music as a coping mechanism, a natural choice may be to listen to music that is low on arousal owing to their already heightened physiologically aroused states.

Dynamic Measures Computation:

A person with **high instability** implies higher fluctuations in music consumption with respect to the features/emotions

Since, instability has been found to have mathematical dependency on the other two measures, that is, it is **directly proportional to variability** and **has inverse relation** with inertia.

Therefore, I restrict analyses to computing only variability and inertia. These two dynamic measures were calculated for all the session-based acoustic features.

Variability calculated as standard deviation of scores across sessions.

Inertia is calculated as the autocorrelation coefficient (with time lag of 1 session)

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                                                                                                                                       For each person variability and
   Session wise for Person
                                                                                                                                       inertia was calculated
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This is how I first found average acoustic features, then found its variability and interia respectively for individual person.

Understanding Inertia and Variability:

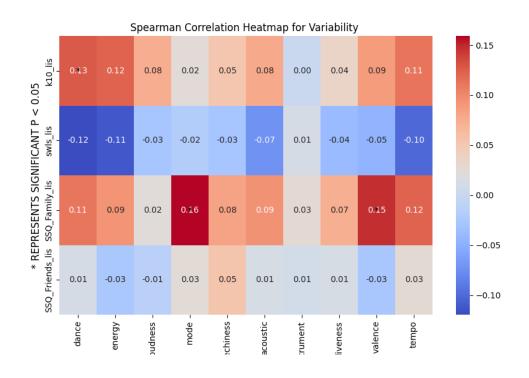
High Variability:

- 1. High variability indicates that the scores or values across different sessions are widely spread out or fluctuate significantly.
- 2. In the context of emotions, high variability might indicate that an individual's emotional state fluctuates frequently and is less stable across different sessions or time points.

High Inertia:

- 1. High inertia, indicated by high autocorrelation coefficient, suggests that there is strong predictability or stability in the feature or emotion from one time-point to the next
- 2. In the context of emotions, high inertia might indicate that an individual's emotional state at one time-point strongly predicts their emotional state at the next time-point.

Plot for variability:



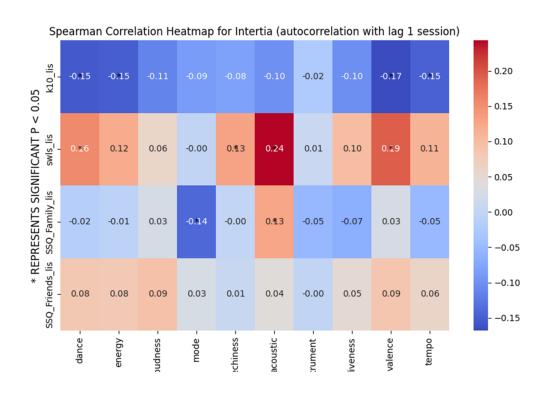
INFERENCE VARIABILITY:

Significant +ve correlation between K10 and danceability

Individuals experiencing higher levels of psychological distress or instability tend to have more varied preferences in the danceability of the music they listen to across different sessions

Significant +ve correlation between SSQ_Family and mode(melodic and harmonic behaviour),valence

Plot for Inertia:



Inference Inertia:

Significant -ve correlation between K10 and danceability, energy (arousal), valence ***, tempo

This means that person at risk of depression is not listening to songs of steady valence throughout, which is result of Mood and emotional changes going

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Significant +ve correlation between SWLS and danceability, speachiness, acousticness, valence

Significant -ve correlation between SSQ_Family and mode

Significant +ve correlation between SSQ_Family and acousticness