Context

“naturalistic”

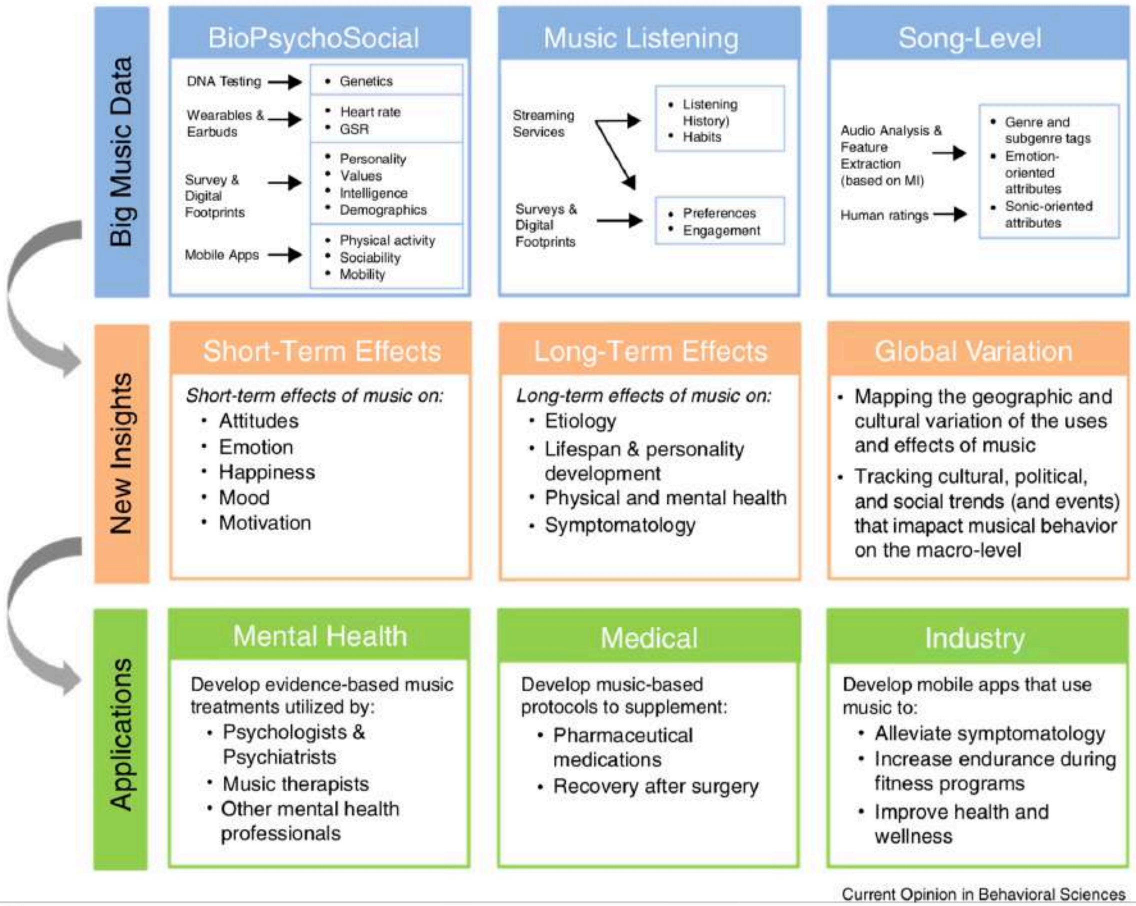
“ecologically valid”

Lab2Land
Big Music Data

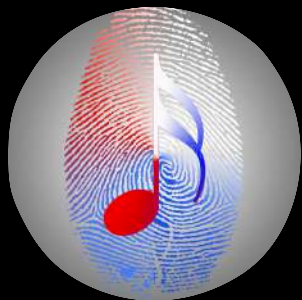
Current Opinion in Behavioral Sciences
Volume 18, December 2017, Pages 50-56

Music and big data: a new frontier

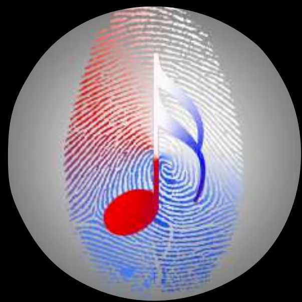
David M Greenberg [1,2], Peter J Rentfrow [3]

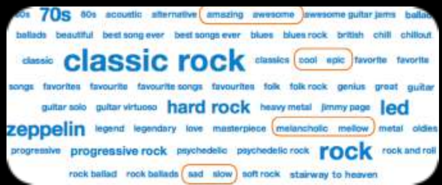


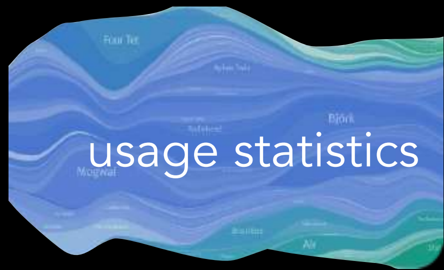
What can it reveal?
Big Music Data

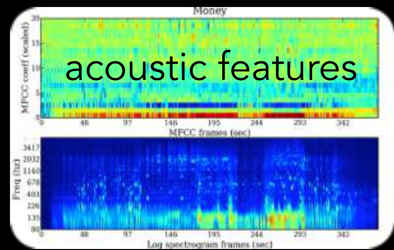


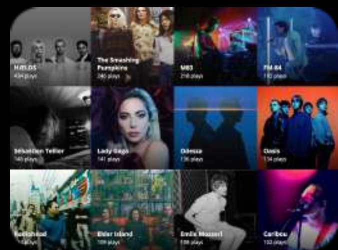
Multimodal representation of music consumption



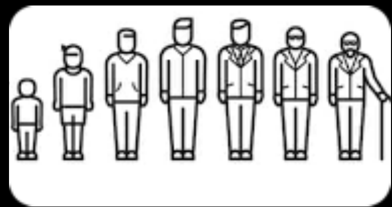


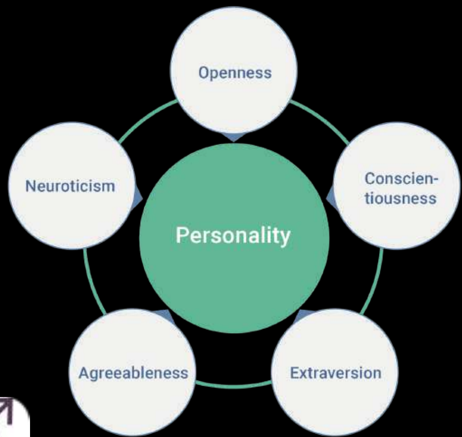


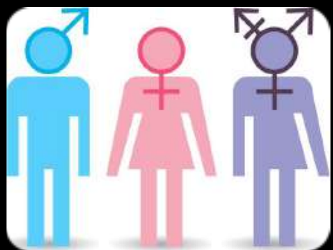




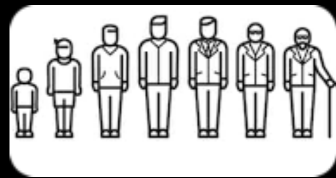
Lab2Land
Big Music Data

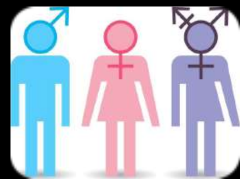






Age, Gender





Last.fm-1K users dataset

http://ocelma.net/MusicRecommendationDataset/index.html

each entry:user ID, song title, artist name, and timestamps

Liu, J.-Y., & Yang, Y.-H. (2012). Inferring personal traits from music listening history. Proceedings of the Second International ACM Workshop on Music Information Retrieval with User-Centered and Multimodal Strategies - MIRUM '12.

Age, Gender

Context

- **Hour-of-day histogram**: 24-D histogram that simply counts the number of songs a user listens to in each hour of a day. Normalize so that it sums to one.
- **Hour-of-day entropy**: Entropy of the hour-of-day histogram.
- **Working-hour ratio**: Percentage of songs that are listened to from 8 to 19 o'clock in a day.
- **Day-of-week histogram**: 7-D histogram that simply counts the number of songs a user listens to in each day of a week. Normalize so that it sums to one.
- **Day-of-week entropy**.
- **Working-day ratio**: Percentage of songs that are listened to from Monday to Friday in a week.
- **Month-of-year histogram**: 12-D histogram that simply counts the number of songs a user listens to in each month of a year. Normalize so that it sums to one.
- **Month-of-year entropy**.
- **Working-month ratio**: Percentage of songs that are listened to in the "working months" (excluding July and August) in a year.

Song Histogram

top 50/user w.r.t top10000 of all

Artist Histogram

Song Tag Histogram

top 100 tags/song or artist

Artist Tag Histogram

Content

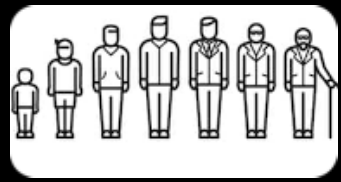
- **Danceability**: The ease with which a person could dance to a song, over the course of the whole song [22].
- **Loudness**: Perceived intensity of a sound.
- **Key**: The estimated overall key of a track (ranges from 0 to 11 and corresponds to one of the 12 keys: C, C#, D to B).
- **Mode**: The estimated mode; 0 (minor) or 1 (major).
- **Tempo**: The overall estimated tempo of a track in beats per minute (BPM).
- **Pitch**: Frame-by-frame chromavector, corresponding to the 12 pitch classes [24]. We take the mean and standard deviation (SD) for temporal integration [16].
- **Timbre**: Frame-by-frame MFCC-like feature vector, corresponding to the 12 basis functions that are loosely related to perceptual qualities such as brightness, flatness, and attack strength [7]. We also take the mean and SD for temporal integration.

top 15 songs/user

Liu, J.-Y., & Yang, Y.-H. (2012). Inferring personal traits from music listening history. Proceedings of the Second International ACM Workshop on Music Information Retrieval with User-Centered and Multimodal Strategies - MIRUM '12.

Age, Gender

n = 144,142



>< 24

Context

Content

SVM Classifier

71.1%

66.1%

F = 382

M = 502

which features gave better accuracy?

Liu, J.-Y., & Yang, Y.-H. (2012). Inferring personal traits from music listening history. Proceedings of the Second International ACM Workshop on Music Information Retrieval with User-Centered and Multimodal Strategies - MIRUM '12.

Age, Gender

Context

Feature	Age	Gender
Hour-of-day histogram	55.7%	**57.0%**
Hour-of-day entropy	45.7%	**57.1%**
Working-hour ratio	47.5%	48.4%
Day-of-week histogram	**58.9%**	47.2%
Day-of-week entropy	**61.4%**	48.9%
Working-day ratio	**61.1%**	47.0%
Month-of-year histogram	50.4%	47.5%
Month-of-year entropy	49.3%	50.4%
Working-month ratio	50.0%	50.4%

Content

Feature	Age	Gender
	71.1%	65.8%
	60.0%	62.2%
	64.6%	**66.1%**
	58.9%	63.6%
	46.4%	52.2%
	50.4%	49.7%
	50.4%	46.6%
	52.1%	52.8%
	46.4%	50%
	52.9%	54.3%
	59.3%	53.7%

What are the problems with this approach?

Liu, J.-Y., & Yang, Y.-H. (2012). Inferring personal traits from music listening history. Proceedings of the Second International ACM Workshop on Music Information Retrieval with User-Centered and Multimodal Strategies - MIRUM '12.

Age, Gender

Song title and artist name	Count
`Female`	
Wings of Words by Chemistry	3112
Heartbeats by the Knife	2632
Street Lights by Kanye West	2006
Staring at the Sun by TV on the Radio	1891
Such Great Heights by the Postal Service	1855
`Male`	
The Good, the Bad, the Queen	3149
Gimme More by Britney Spears	3111
Love Lockdown by Kanye West	2812
Heartless by Kanye West	2492
Welcome to Heartbreak by Kanye West	2357
`Adolescent`	
Wings of Words by Chemistry	3112
Love Lockdown by Kanye West	2265
Heartless by Kanye West	2211
Paranoid by Kanye West	2136
Amazing by Kanye West	2122
`Adult`	
Hung Up by Madonna	927
Bright Lights by Matchbox Twenty	894
Better Alone by Melanie C	835
Downfall by Matchbox Twenty	743
Enjoy the Silence by Depeche Mode	701

Table 3: Top listened songs for different groups

Project Idea: 2 last.fm datasets -> improve accuracy

Liu, J.-Y., & Yang, Y.-H. (2012). Inferring personal traits from music listening history. Proceedings of the Second International ACM Workshop on Music Information Retrieval with User-Centered and Multimodal Strategies - MIRUM '12.

Musical Preferences, Personality & Gender (Back2Lab)

n = 93
35 sad
25 non-sad

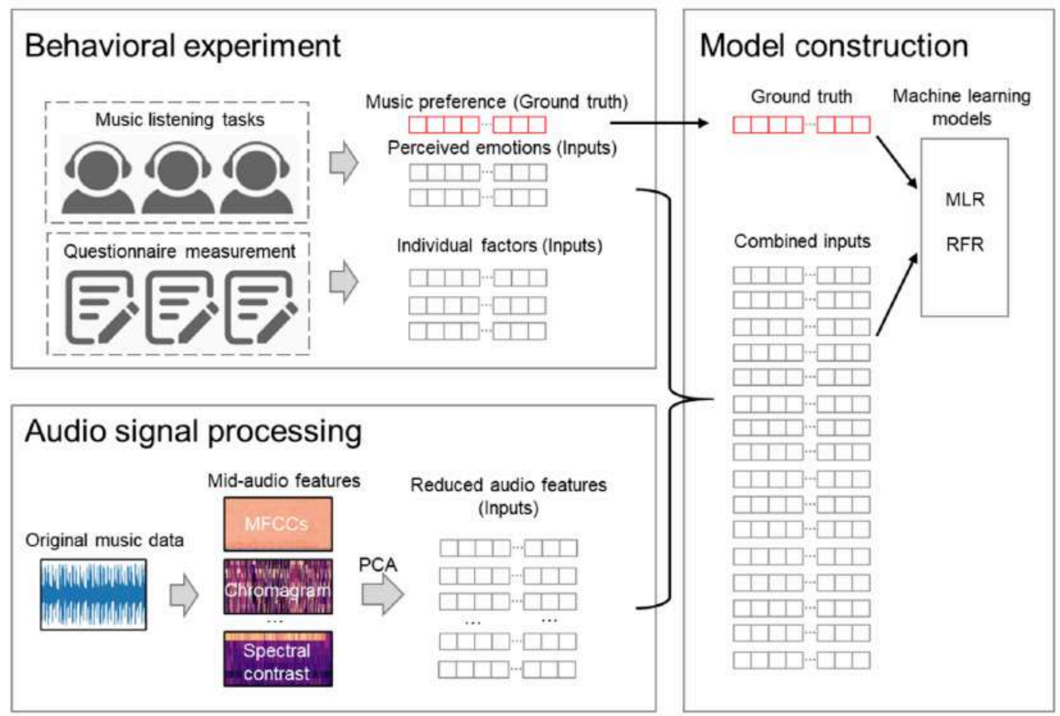


FIGURE 1. **The framework of this study.**

60 Chinese popular songs (25-30 secs)

L. Xu, Y. Zheng, D. Xu and L. Xu, (2021) "Predicting the Preference for Sad Music: The Role of Gender, Personality, and Audio Features," in IEEE Access, vol. 9, pp. 92952-92963, 2021, doi: 10.1109/ACCESS.2021.3090940.

Musical Preferences, Personality & Gender (Back2Lab)

–> gender and Big Five personality factors on the preference for sad music in the Chinese social environment

–> constructed sad music preference prediction models using audio features and individual features as inputs

L. Xu, Y. Zheng, D. Xu and L. Xu, (2021) "Predicting the Preference for Sad Music: The Role of Gender, Personality, and Audio Features," in IEEE Access, vol. 9, pp. 92952-92963, 2021, doi: 10.1109/ACCESS.2021.3090940.

Musical Preferences, Personality & Gender (Back2Lab)

- males prefer sad music more than females
- significant interaction effect between gender and the extraversion factor is observed
- perceived relaxation and happiness of music play an important role in the prediction of sad music preferences
- poor model accuracy

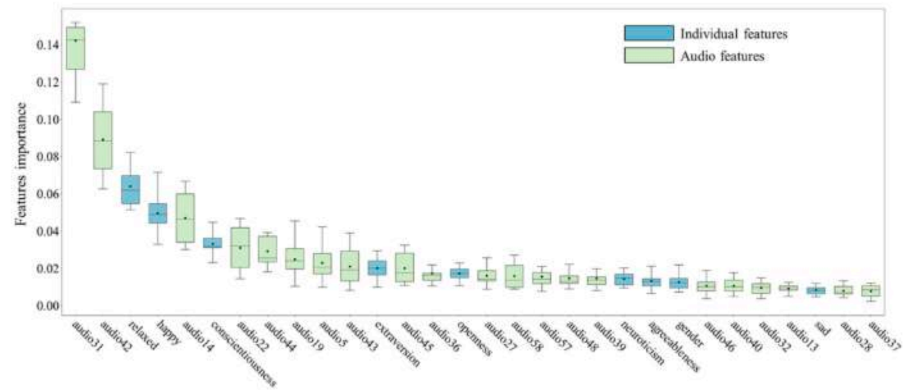


FIGURE 5. Distribution of importance of each feature for the best performing model. Boxplots are arranged in descending order of the mean value. The top 30 features are included for visibility, and the trend of the remaining features is approximately the same. The black dots indicate the mean values, and the black dotted lines indicate the median values. Audio31, audio42, audio 14, and audio 22 indicate the 31st,42nd, 14th, and 22nd PCA components, spectral centroid and spectral rolloff have the highest loadings in these components.

L. Xu, Y. Zheng, D. Xu and L. Xu, (2021) "Predicting the Preference for Sad Music: The Role of Gender, Personality, and Audio Features," in IEEE Access, vol. 9, pp. 92952-92963, 2021, doi: 10.1109/ACCESS.2021.3090940.

Musical Preferences, Personality & Gender (Back2Lab)

GitHub repo

data: https://github.com/xl2218066/PredictSadMusic

Project Idea: Redo in India - but also add empathy

L. Xu, Y. Zheng, D. Xu and L. Xu, (2021) "Predicting the Preference for Sad Music: The Role of Gender, Personality, and Audio Features," in IEEE Access, vol. 9, pp. 92952-92963, 2021, doi: 10.1109/ACCESS.2021.3090940.

Musical Preferences & Personality


UMAP 2017 Short Paper UMAP'17, July 9-12, 2017, Bratislava, Slovakia

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

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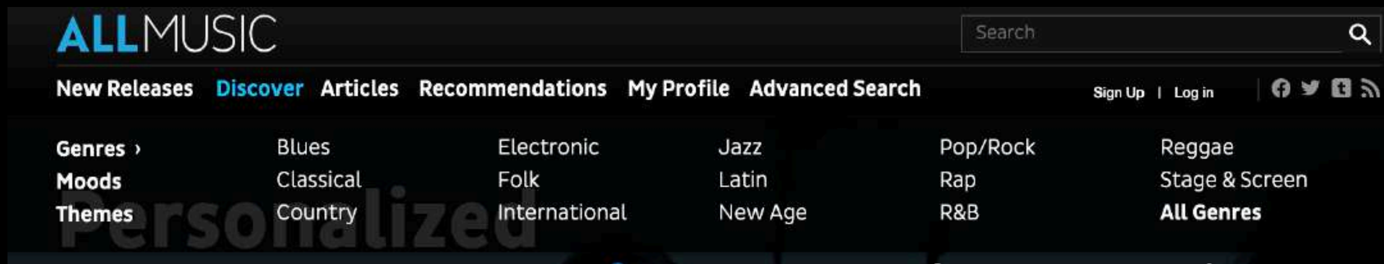
last.fm

n = 1415 ,
83 countries



Genre tags 18 genres

UMAP 2017 Short Paper — UMAP'17, July 9-12, 2017, Bratislava, Slovakia

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Musical Preferences & Personality

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

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

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

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

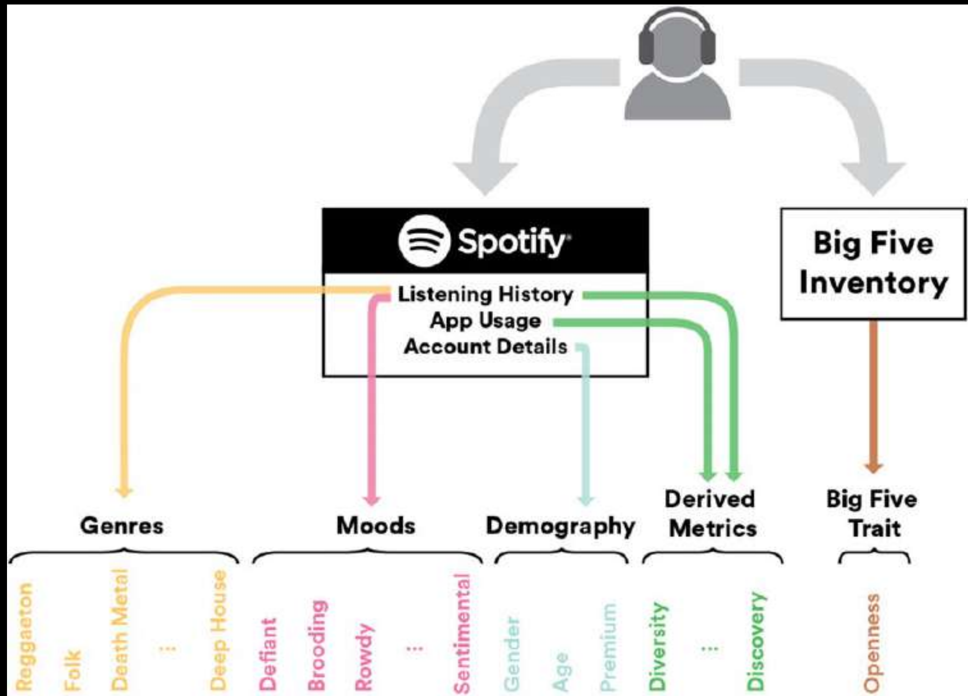
Table 3: Mapping of music attributes and genres of the work of Rentfrow & Gosling [20].

genre?!

what is the problem with this approach?

Musical Preferences & Personality

n = 5808
(3 months)



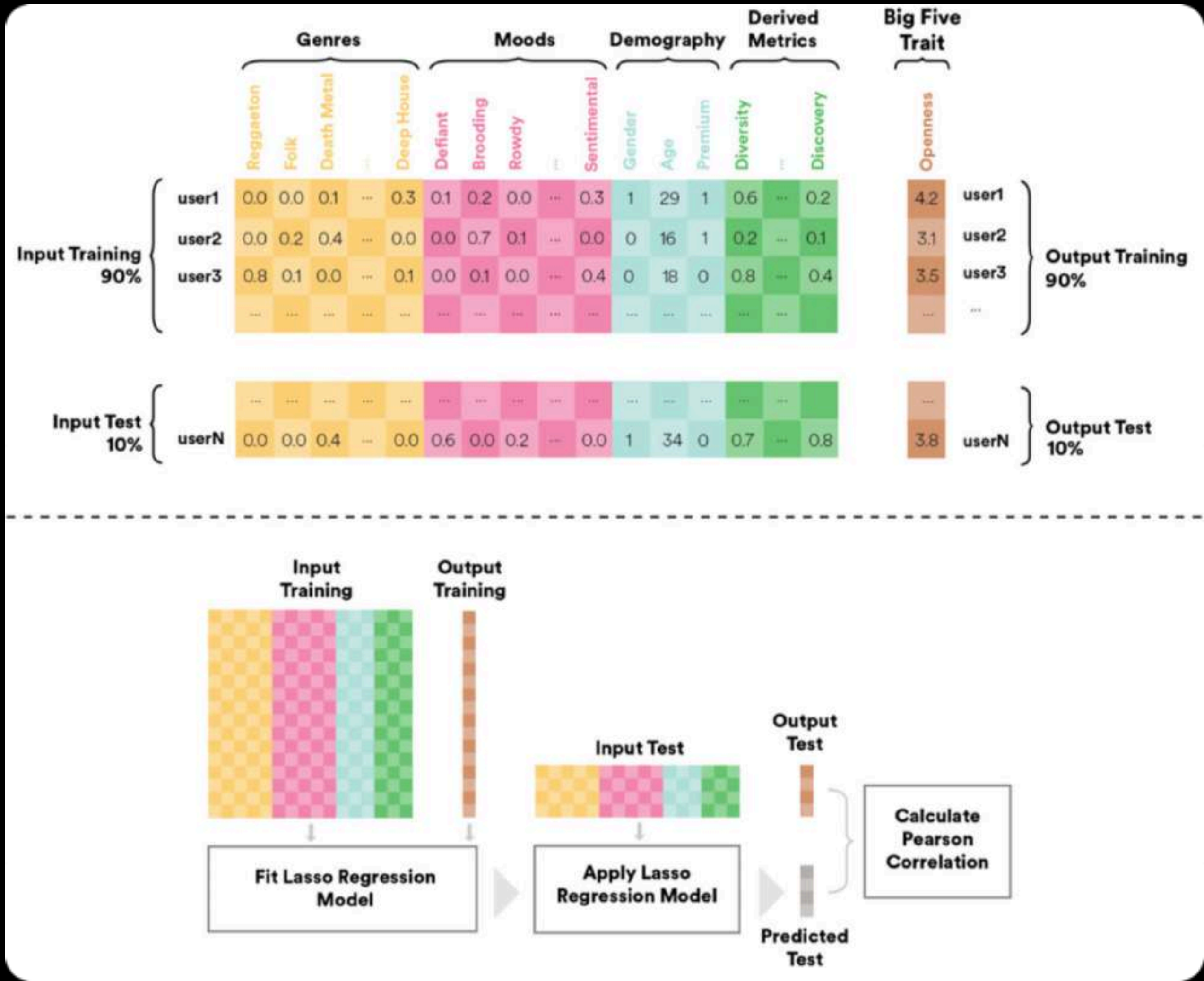
Spotify for Artists

gracenote
A NIELSEN COMPANY

acoustic features

Anderson et al.,(2020). "Just the Way You Are": Linking Music Listening on Spotify and Personality. Social Psychological and Personality Science.

Musical Preferences & Personality



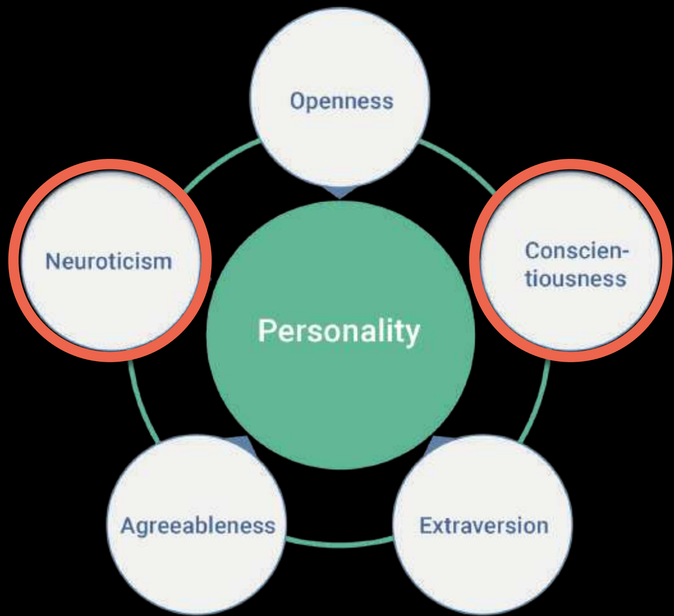
Anderson et al.,(2020). "Just the Way You Are": Linking Music Listening on Spotify and Personality. Social Psychological and Personality Science.

Musical Preferences & Personality

Table 1. Pearson Product–Moment Correlations (Averaged Across 10-Folds) Between Predicted Values From Regression and Actual Values for Each Trait and Product Pair.

Openness	Conscientiousness	Extraversion	Agreeableness	Emotional Stability
.309 95% CI [.285, .332]	.363 95% CI [.340, .385]	.294 95% CI [.270, .317]	.262 95% CI [.238, .286]	.374 95% CI [.351, .396]

Note. CI = confidence interval.



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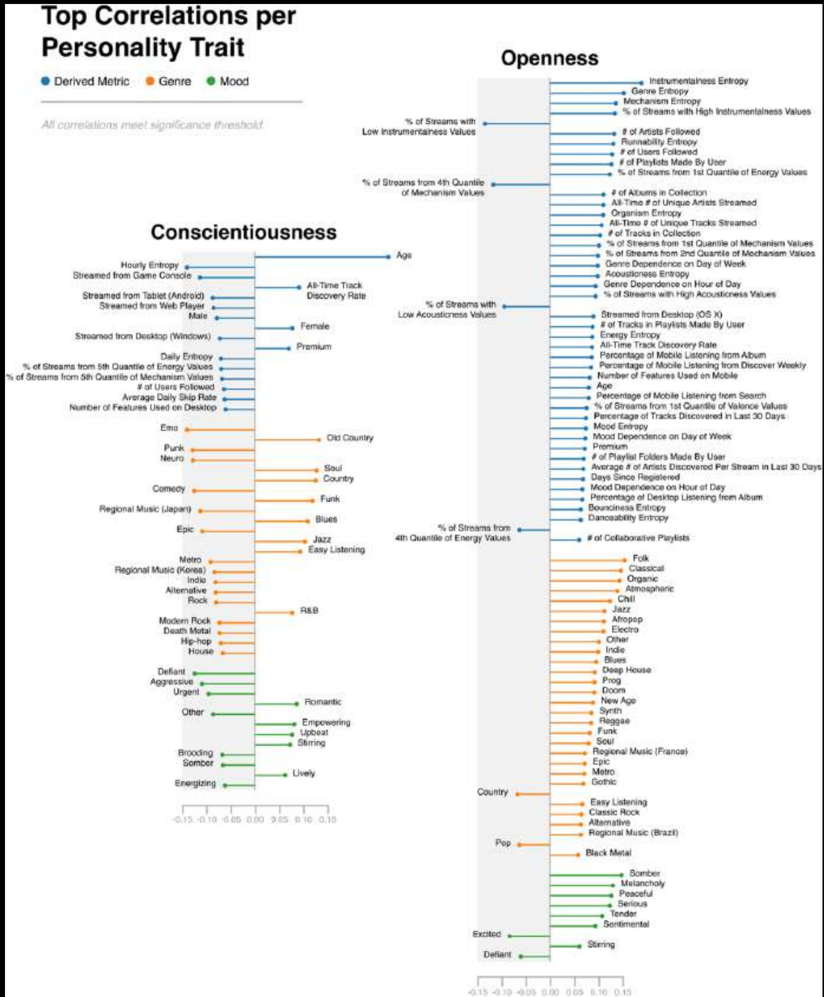
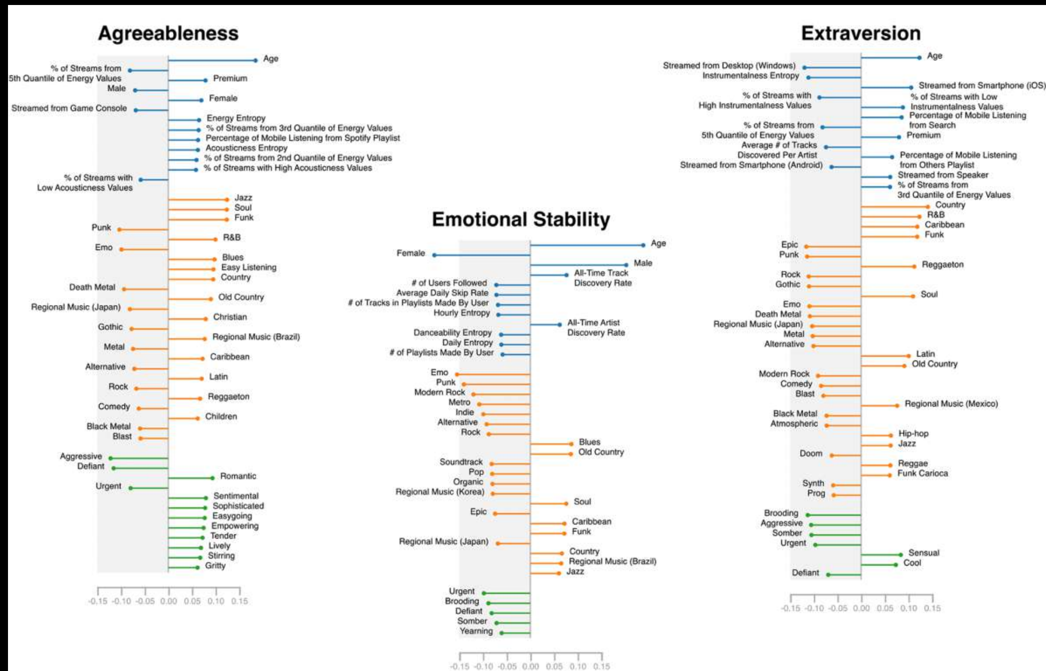
Musical Preferences & Personality





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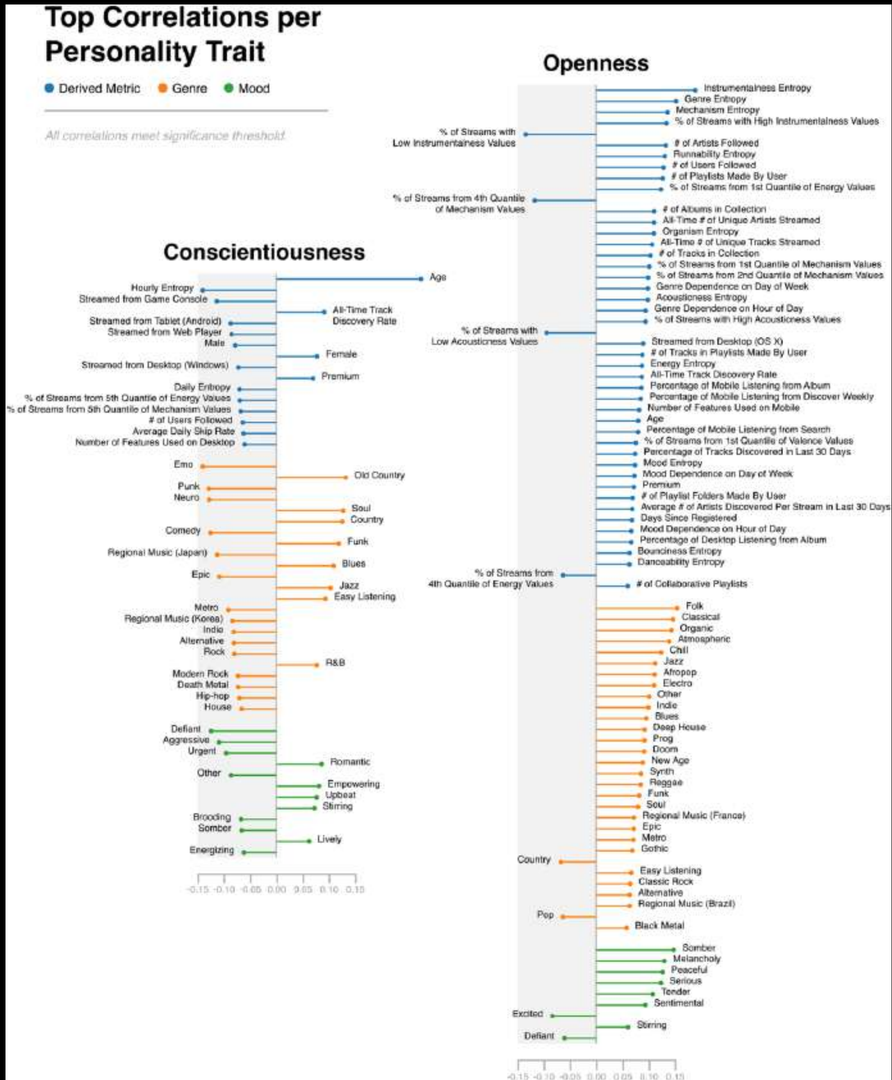
Musical Preferences & Personality



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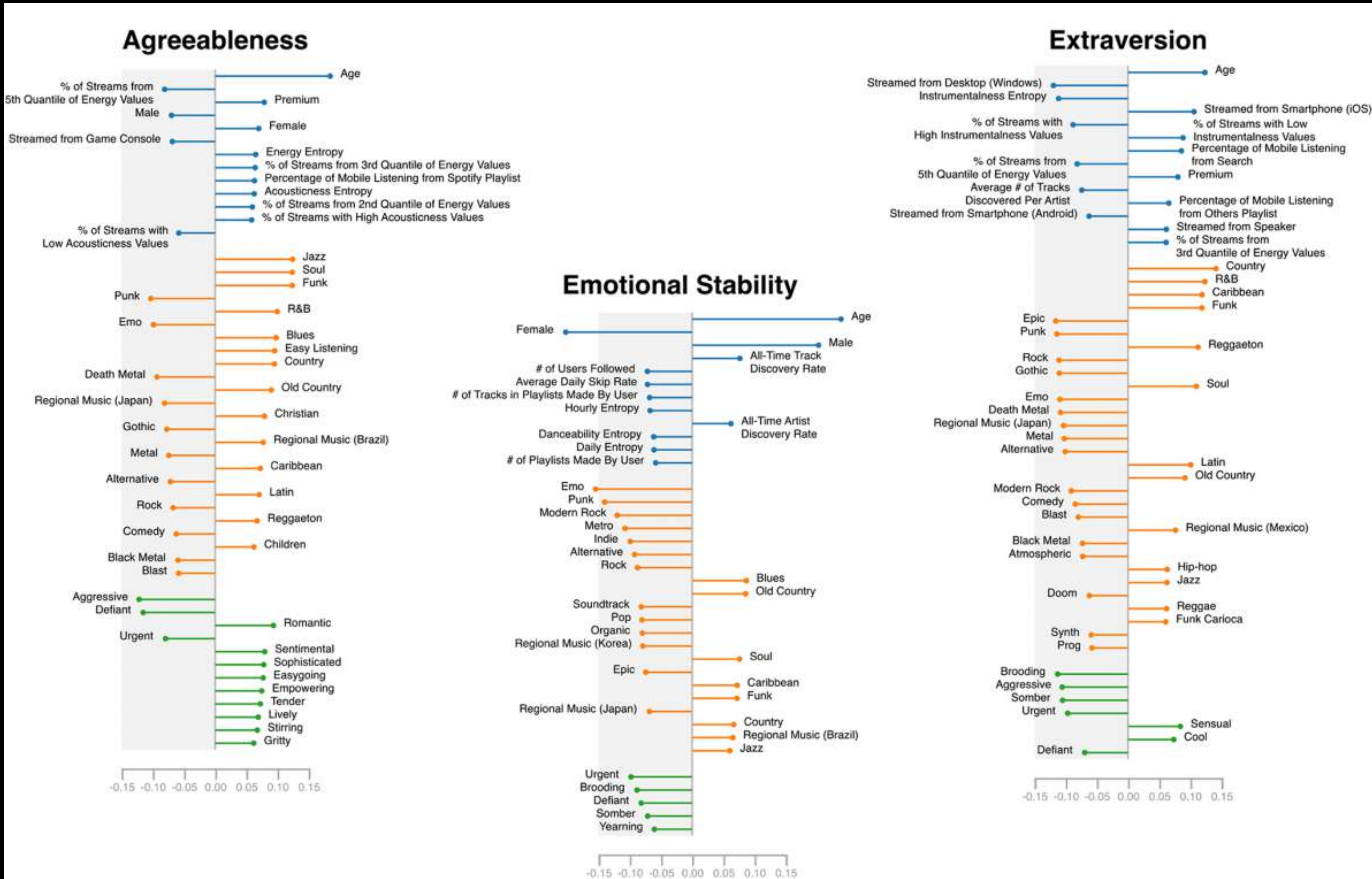
Musical Preferences & Personality



Anderson et al.,(2020). “Just the Way You Are”: Linking Music Listening on Spotify and Personality. Social Psychological and Personality Science.

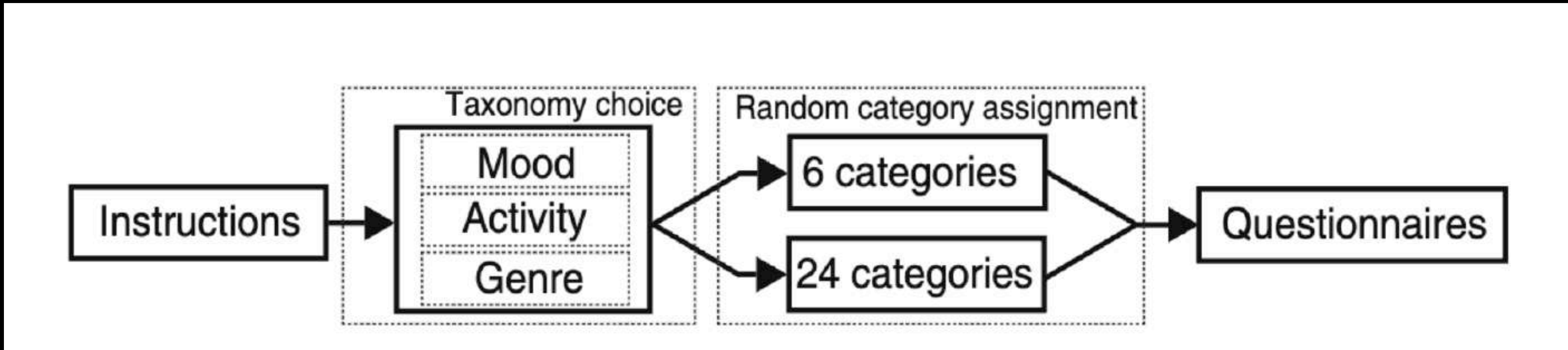
Musical Preferences & Personality

What are the problems with this approach?

- 3 months
- 66 genres
- 25 moods
- genre x mood?

Anderson et al.,(2020). "Just the Way You Are": Linking Music Listening on Spotify and Personality. Social Psychological and Personality Science.

Musical Preferences, Personality & Musical Expertise



n = 297

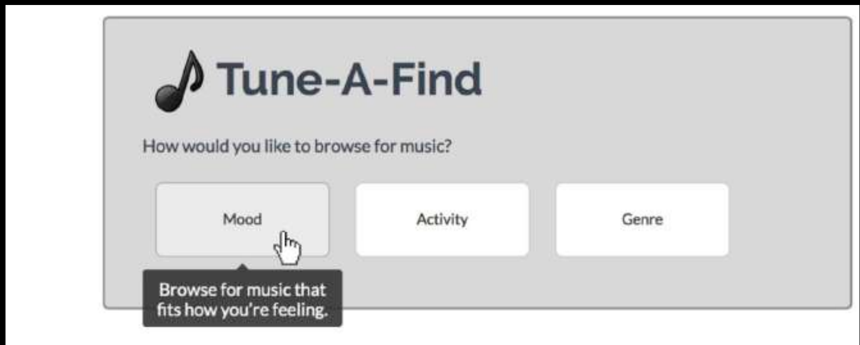


Fig. 2 Screen shot of Tune-A-Find with the "Mood" tooltip

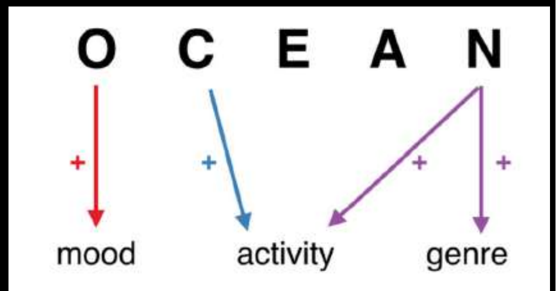
user experience, musical expertise, personality, and demographics

Ferwerda, B., Yang, E., Schedl, M., & Tkalcic, M. (2019). Personality and taxonomy preferences, and the influence of category choice on the user experience for music streaming services. Multimedia tools and applications, 78(14), 20157-20190.
Chicago

Musical Preferences, Personality & Musical Expertise

- choice of a taxonomy (mood, activity, or genre) to browse for music, is related to their personality
  - eg: O –> mood, C –> activity, N –> genre, activity

- over choice is moderated by music expertise
  - emotion experts (e.g., those who easily identify with emotions in music) had more difficulties making a decision with an increased choice set (i.e., a negative relationship with expertise).



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Chicago

Musical Preferences & Personality @IIIT

last.fm

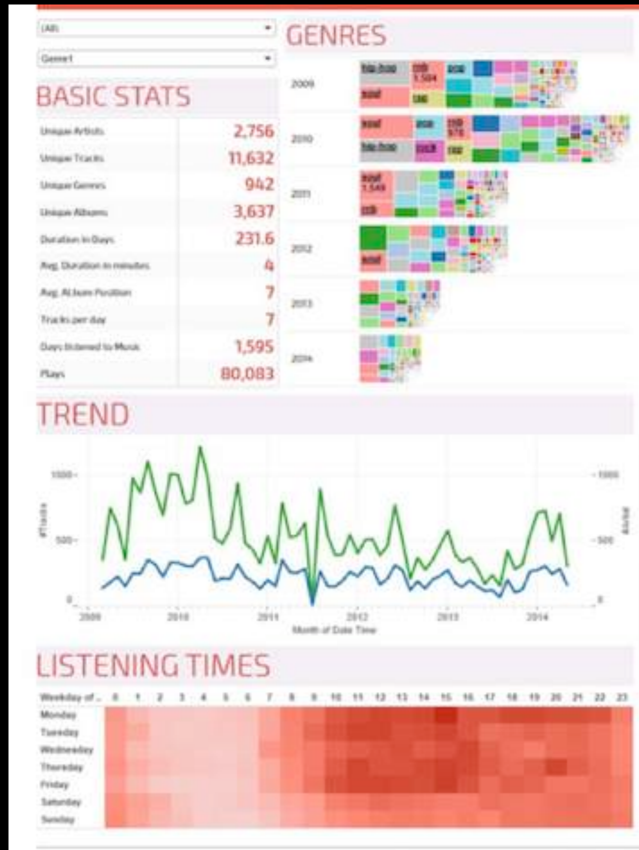
~600 users

Healthy-Unhealthy Music Scale

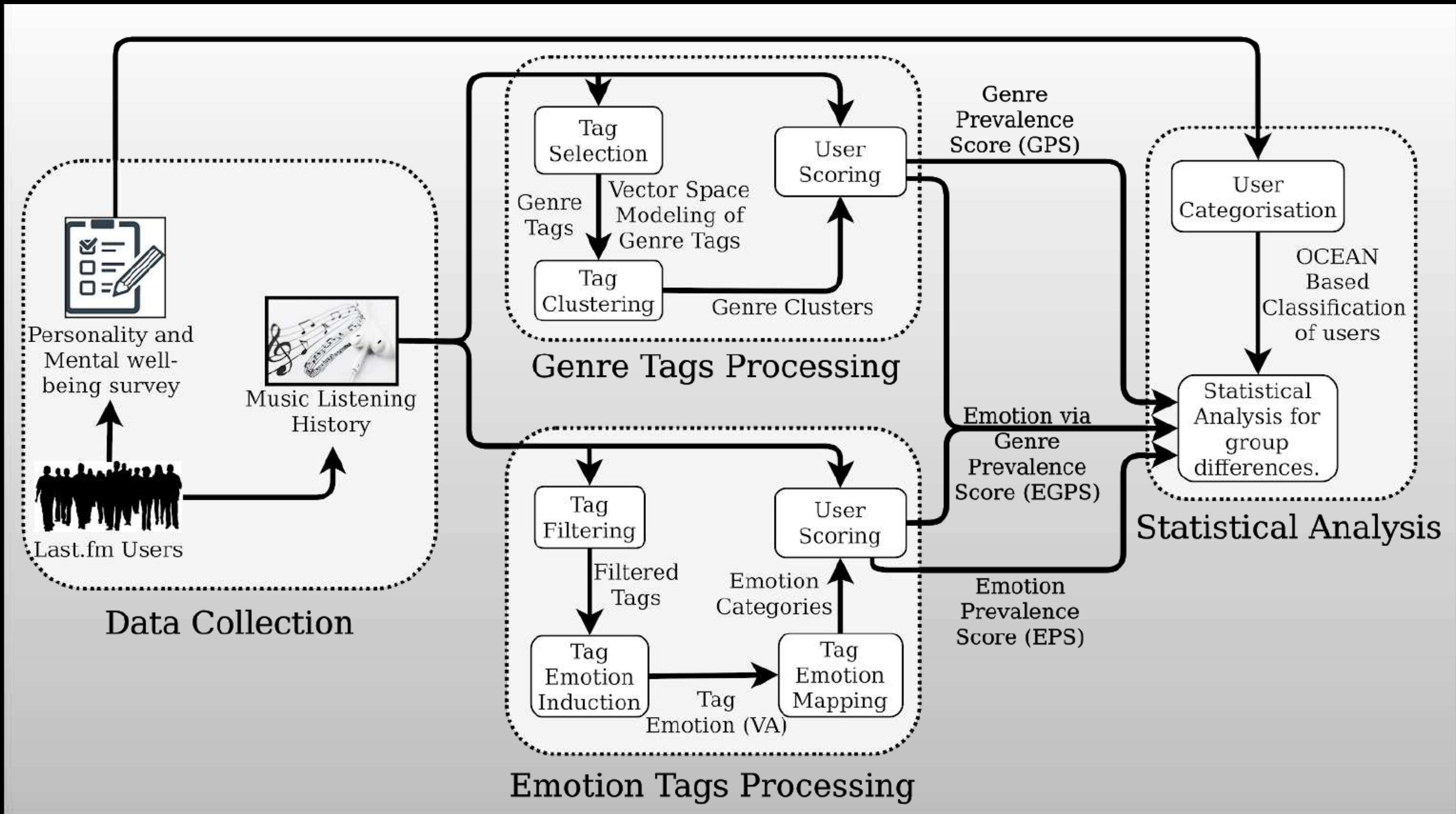
Psychological Distress Score

At-Risk

No-Risk



Musical Preferences & Personality @IIIT



Goyal et al.,(in prep). "I guess that's why they call it the blues": Personality and the interplay between emotion and genre

Musical Preferences & Personality @IIIT

genre tags

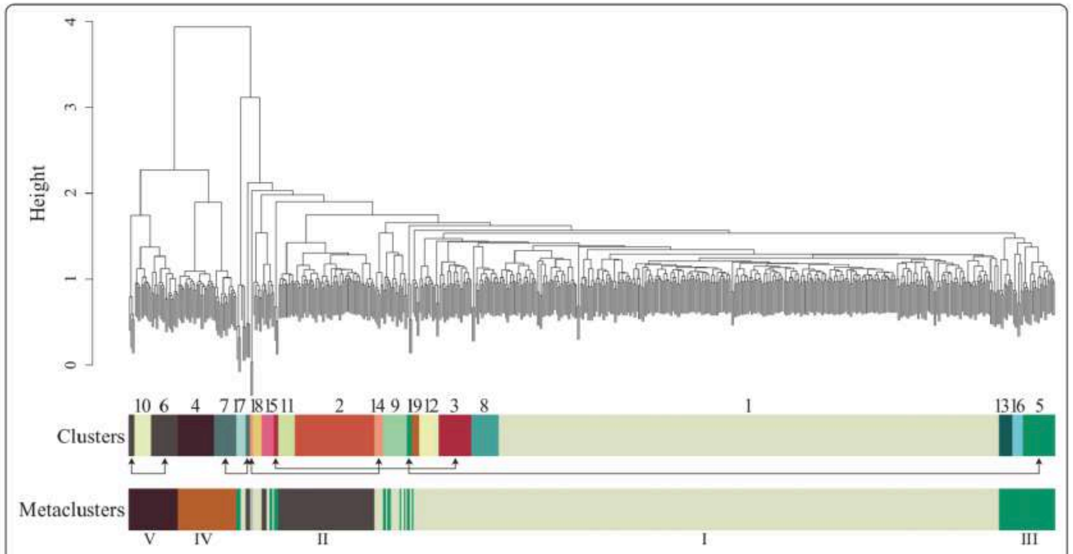


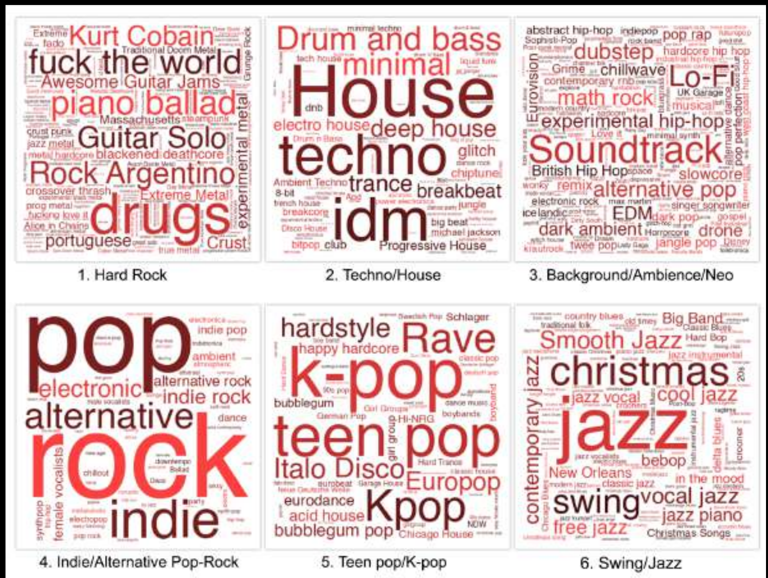
Figure 1 Hierarchical dendrogram and hybrid pruning showing 19 cluster solution (upper stripe) and 5 cluster solution (lower stripe).

17 data-driven genre clusters

Goyal et al.,(in prep). "I guess that's why they call it the blues": Personality and the interplay between emotion and genre

Musical Preferences & Personality @IIIT

resulting genre clusters



Goyal et al.,(in prep). "I guess that's why they call it the blues": Personality and the interplay between emotion and genre

Musical Preferences & Personality @IIIT

6. Swing/Jazz

Genre Clusters that exhibit Significant Correlations (p < 0.05) with Personality Traits

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

11. Neo-pop/Dream-pop/Shoegaze

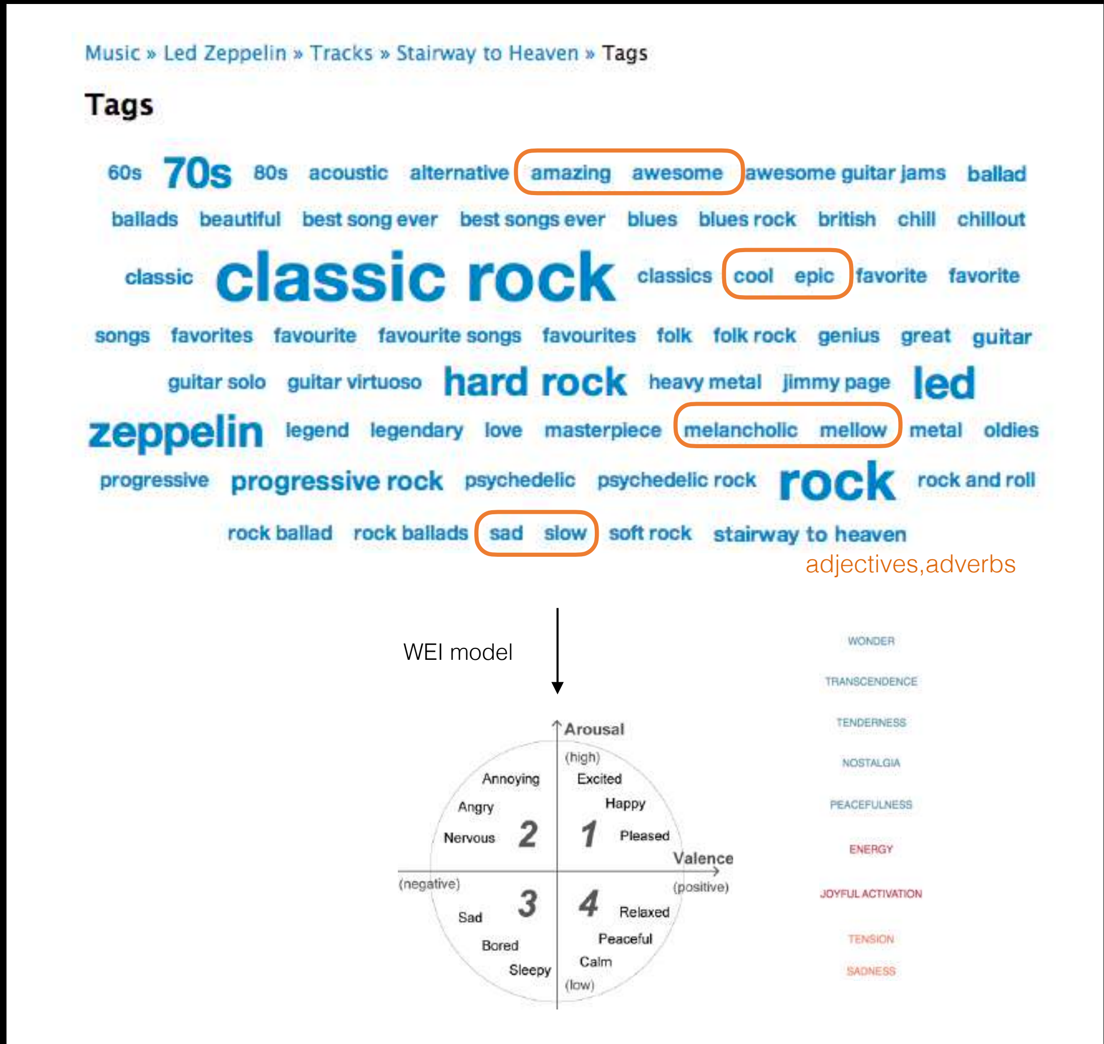
14. World Music

9. Hip-hop and rap

16. Trance

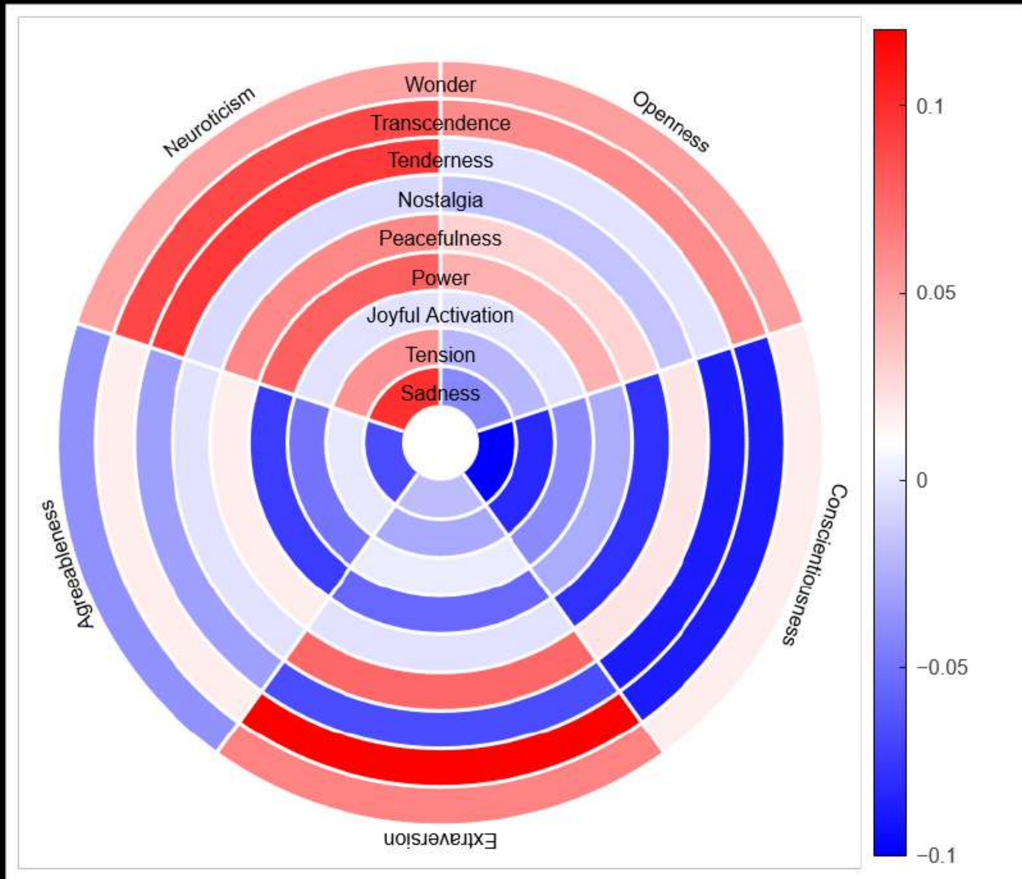
Musical Preferences & Personality @IIIT

emotion from tags



Goyal et al.,(in prep). “I guess that's why they call it the blues": Personality and the interplay between emotion and genre

Musical Preferences & Personality @IIIT



Goyal et al.,(in prep). “I guess that's why they call it the blues": Personality and the interplay between emotion and genre

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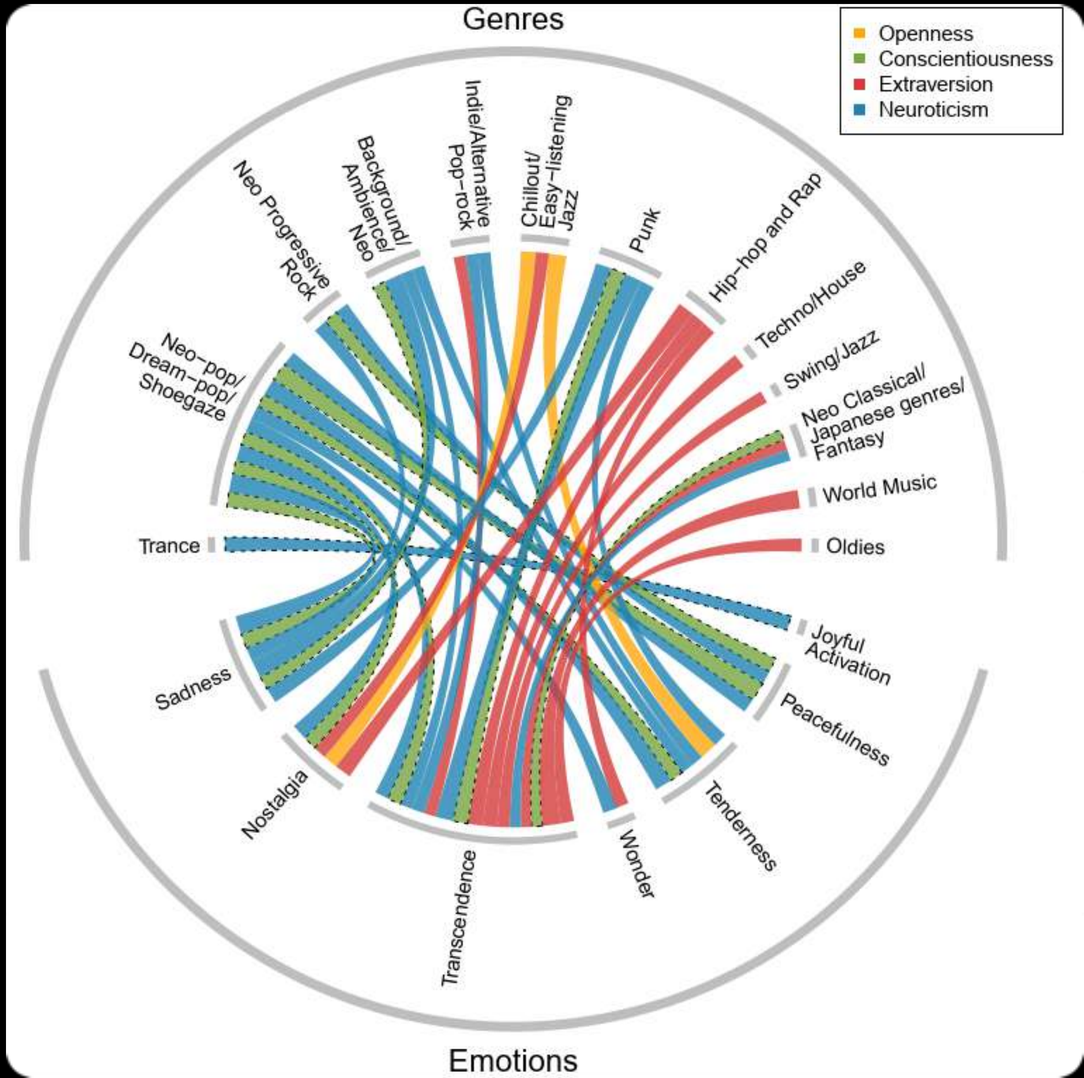

What are the problems with this approach?

Goyal et al.,(in prep). “I guess that's why they call it the blues": Personality and the interplay between emotion and genre

Musical Platforms