Interactive Music Genre Exploration with Visualization and Mood Control

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INTRODUCTION

- Recommender Systems:
  - Purpose
  - Types (Personalized, Non-personalized, and Mixed)
  - Filter bubble issue
  - Limitations of existing systems

- Visualizations:
  - Bar chart
  - Complex Contour plot

- Mood Control:
  - Why is mood important?
  - Importance of mood control

PROBLEMS ADDRESSED

RQ1: How do different types of visualization (bar charts or contour plots) influence the perceived helpfulness for new music genre exploration?

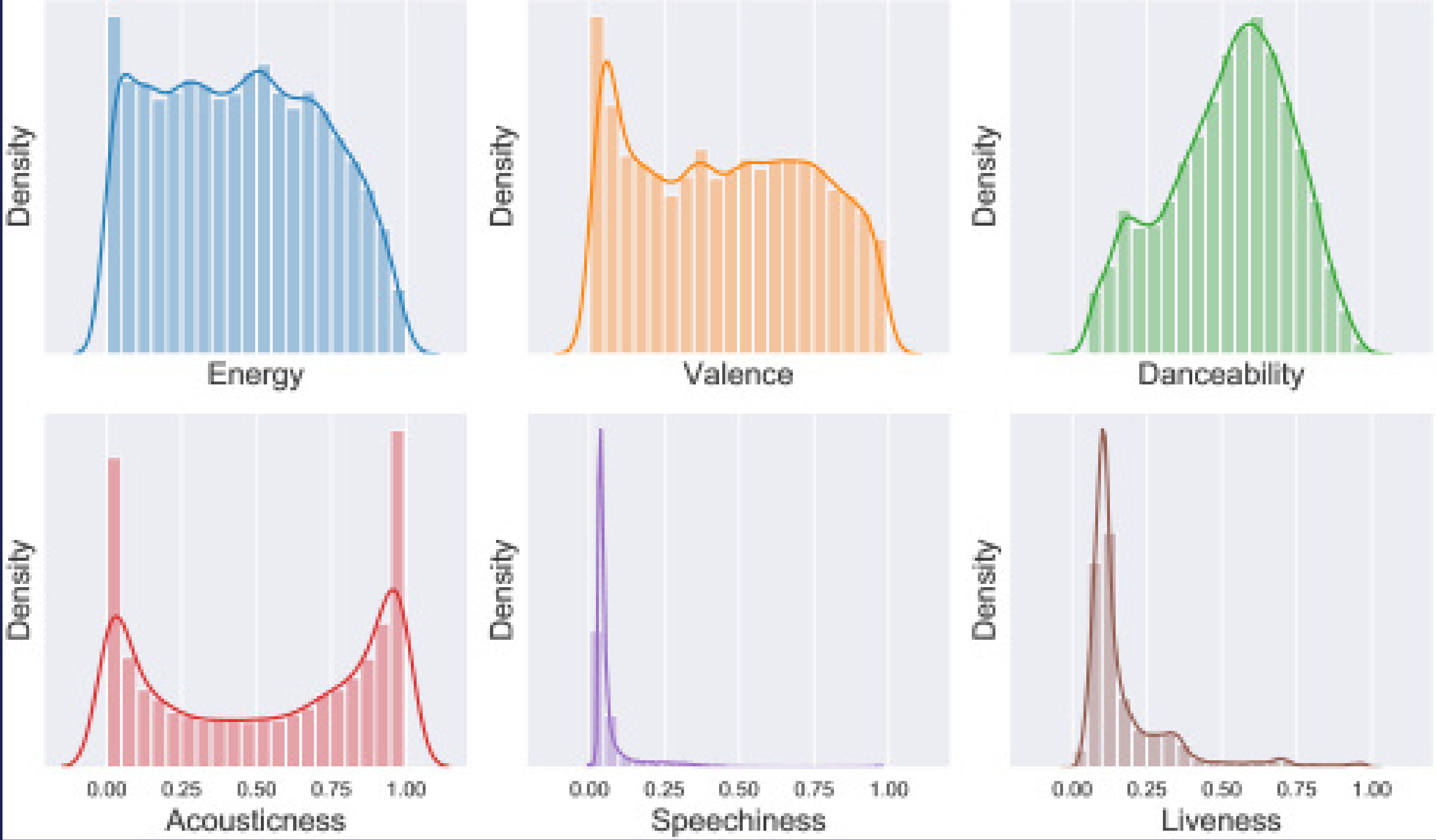
RQ2: How does mood control improve the perceived helpfulness for new music genre exploration?

RELEVANCE

	Research Paper	Our Project
Focus	Recommendations	Recommendations & Analysis
Dataset	Spotify Music Dataset	
Solution	Understand how visualization affects helpfulness for new music genre exploration	Interactive music-feature, genre exploration, and User matching.
Mood Control	Understand its influence on perceived helpfulness for new music genre exploration	To provide highest degree of interactivity to the user

DATASET

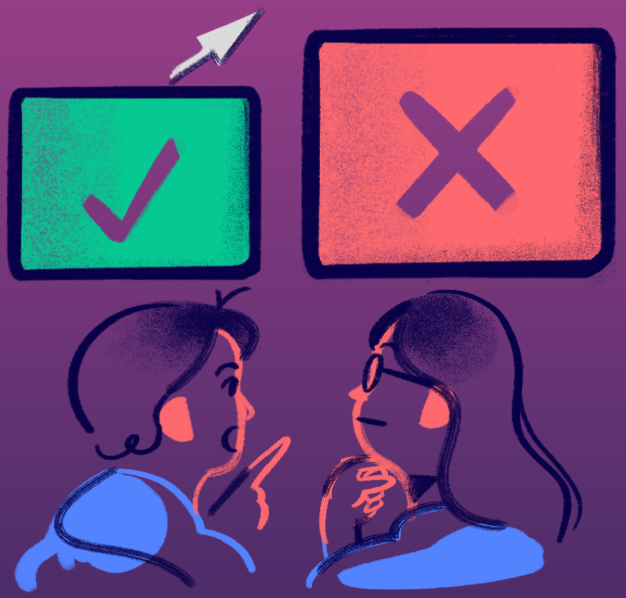
- Test Data : Data fetched from participants of the user study.
- Train Data : Recommendation data has 10 music genres with 3300 tracks in each genre.
- Spotify API.
- Best Features:
  - Energy
  - Valence



- Valence: positiveness of a track.
- Energy: measures the intensity of tracks

SOLUTIONS

Dashboard

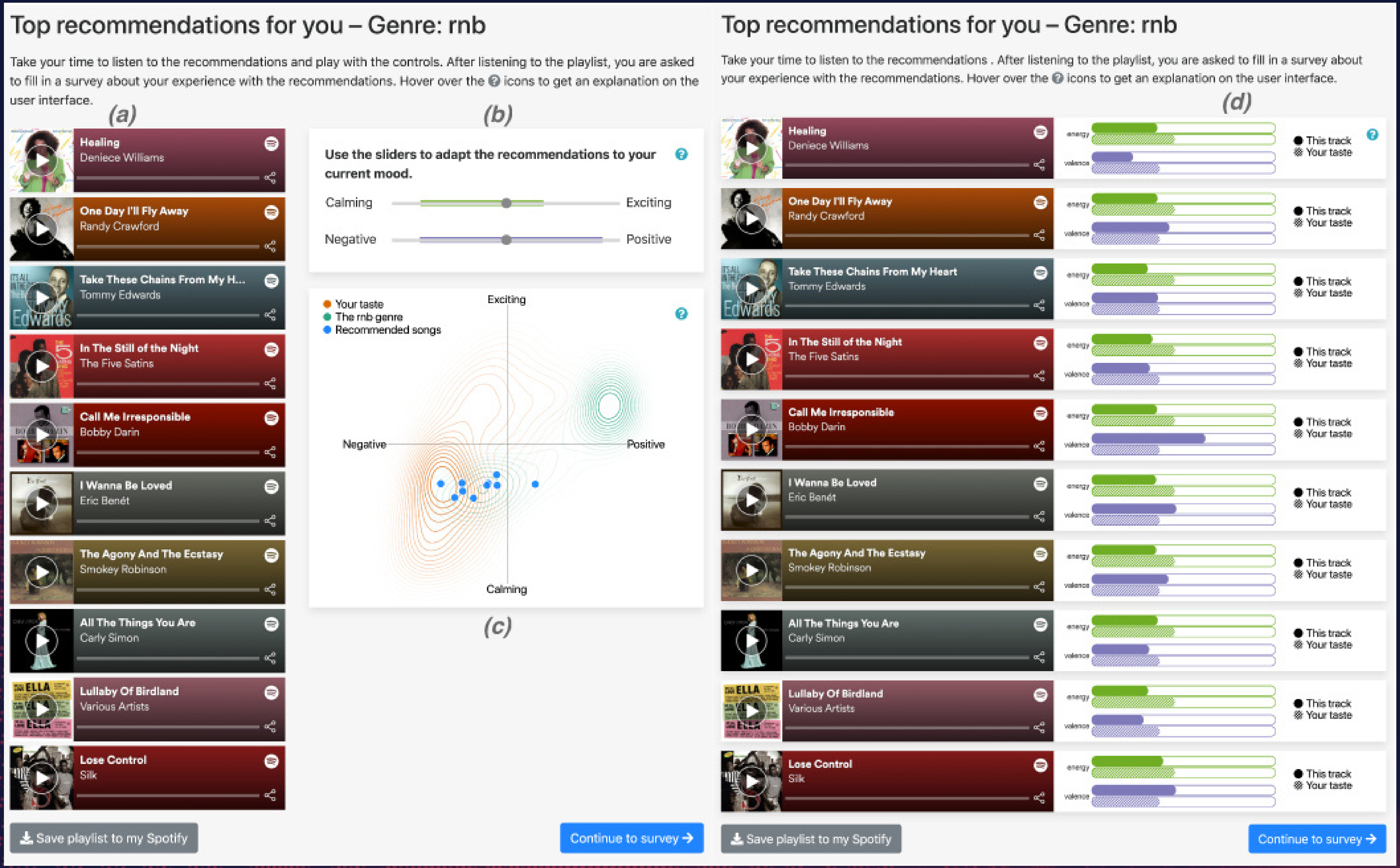


User Study

Evaluation of study results

DASHBOARD

(a) Top 10 recommended songs presented in playlist style
(b) Two mood sliders for adjusting valence and energy
(c) Contour plot
(d) Bar charts



USER STUDY

- Study Design:
  - 2x2 Mixed-Factorial design.
  - Variables/ Factors:
    - Mood Control (between-subjects factor)
    - Visualizations (within-subject factor)

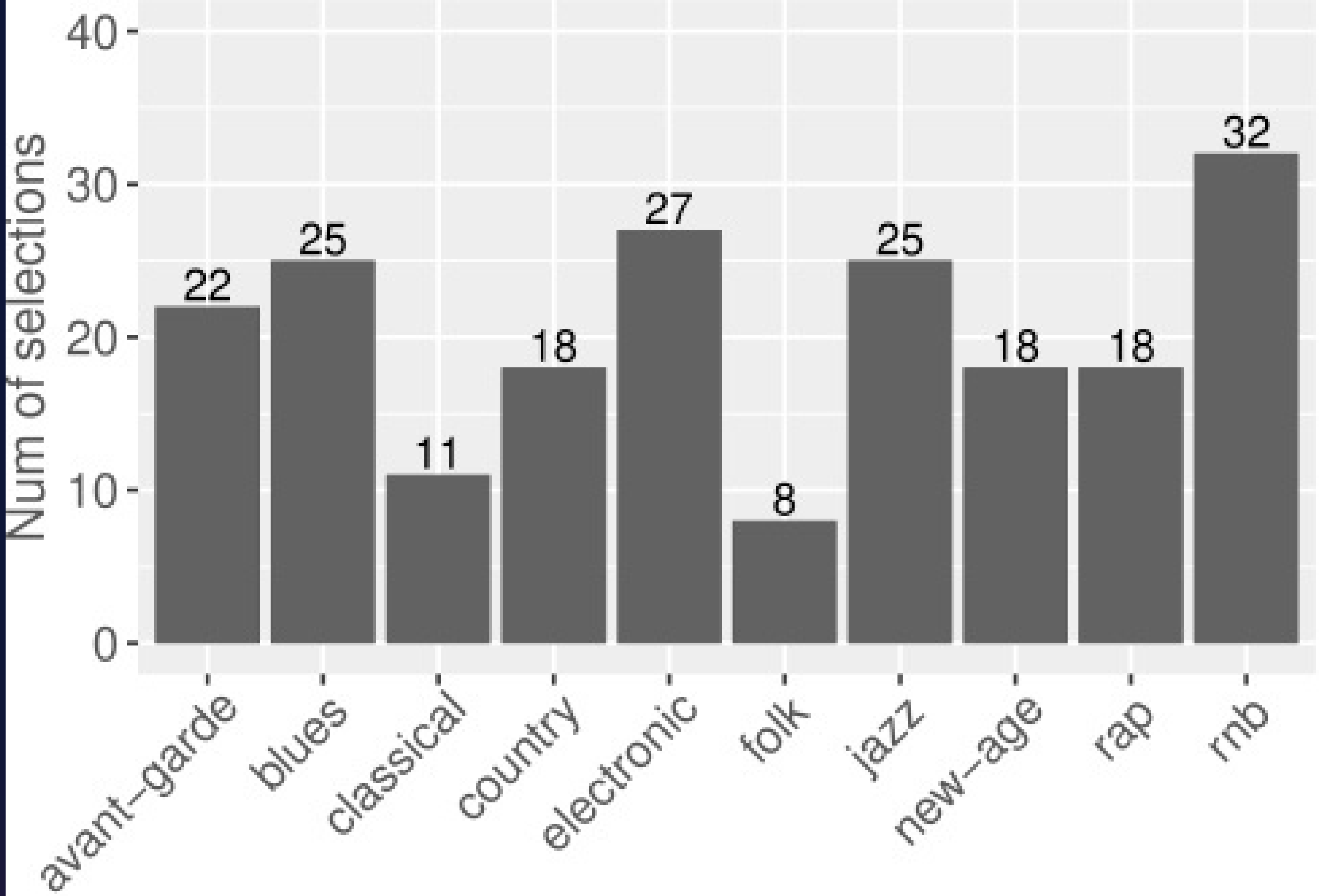
- Participants:
  - 102 participants
  - Most from JF Schouten participant database of Eindhoven University of Technology and remaining from convenience sampling.
  - Mandatory Spotify account and no visual or hearing impairments.
  - Had to participate in Musical Sophistication Index Survey (MSIS).

- Study Procedure:
  - Participants randomly assigned to conditions with or without mood control for genre exploration.
  - Two phases, each featuring a different visualization, and a questionnaire at the end.

- System and Objective Measures:
  - System Subjective Aspects (SSA) from questionnaires.
  - User Interactive Behaviors (INT) from interactivity.
  - Musical Sophistication on Active Engagement (MSAE) and Musical Sophistication on Emotional Engagement (MSE) from MSIS.

USER STUDY - DESCRIPTIVE STATISTICS

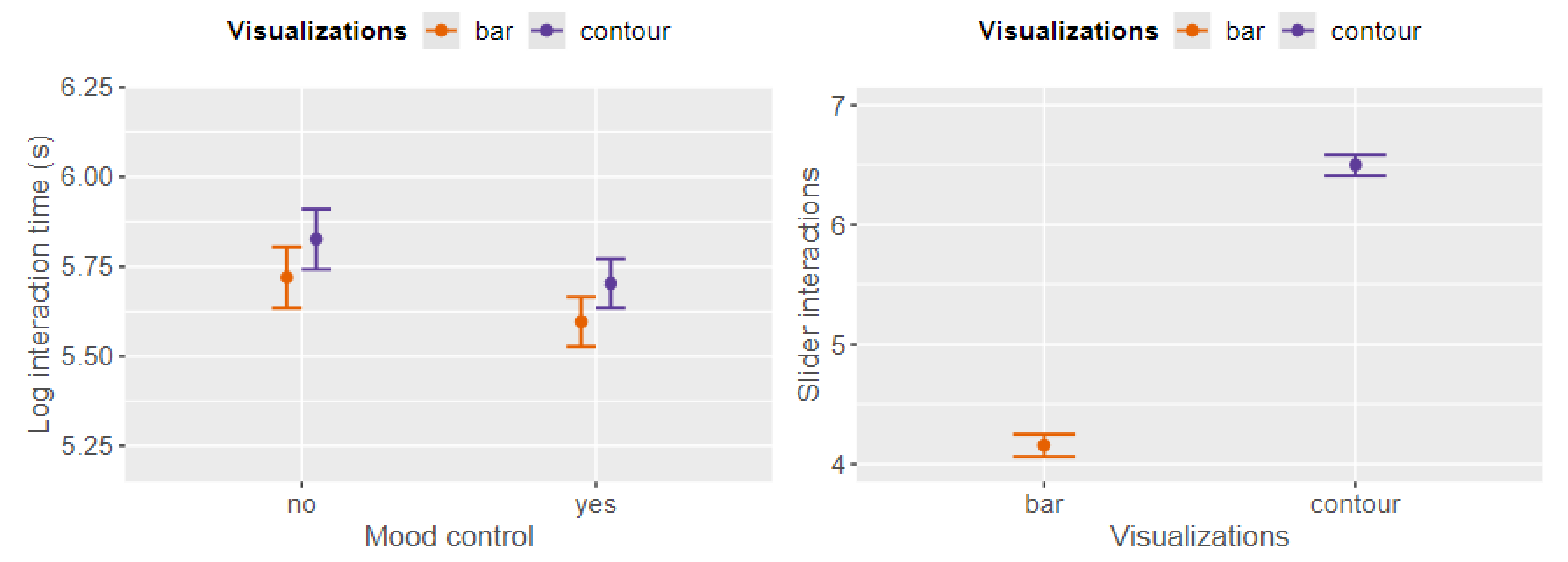
Subjective constructs	Question item	SEM coef.
Perceived control	I feel in control of modifying the recommendations.	0.894
AVE=0.617	The recommender allows only limited control to modify the recommendations.	-0.368
Alpha=0.78	I found it easy to modify the recommendations in the recommender.	0.672
Informativeness	The {contour chart is, bar charts are} informative.	0.895
AVE=0.729	The {contour chart has, bar charts have} no real benefit to me.	-0.861
Alpha=0.88	I can find better recommendations using the {contour chart, bar charts}	0.753
Helpfulness	The playlist supports me in getting to know the new genre.	0.705
AVE=0.644	The playlist motivates me to more delve into the new genre.	0.493
Alpha=0.83	The playlist is useful in exploring a new genre.	0.672
Understandability	I understand how the recommended songs relate to my musical taste.	0.763
AVE=0.701	It is easy to grasp why I received these recommended songs.	0.771
Alpha=0.85	The recommendation process is clear to me.	0.593
	The recommended songs fitted my preference.	
Accuracy(dropped)	I would give the recommended songs a high rating.	
	I liked each of the recommended songs provided by the system.	



EVALUATION OF USER STUDY - INTERACTION DATA

Different Conditions:

- Log Interaction Time
- Track Interactions
- Slider Interactions in the mood control conditions
- Playlist saved or not



(a) Interaction time in different conditions (log transformed)

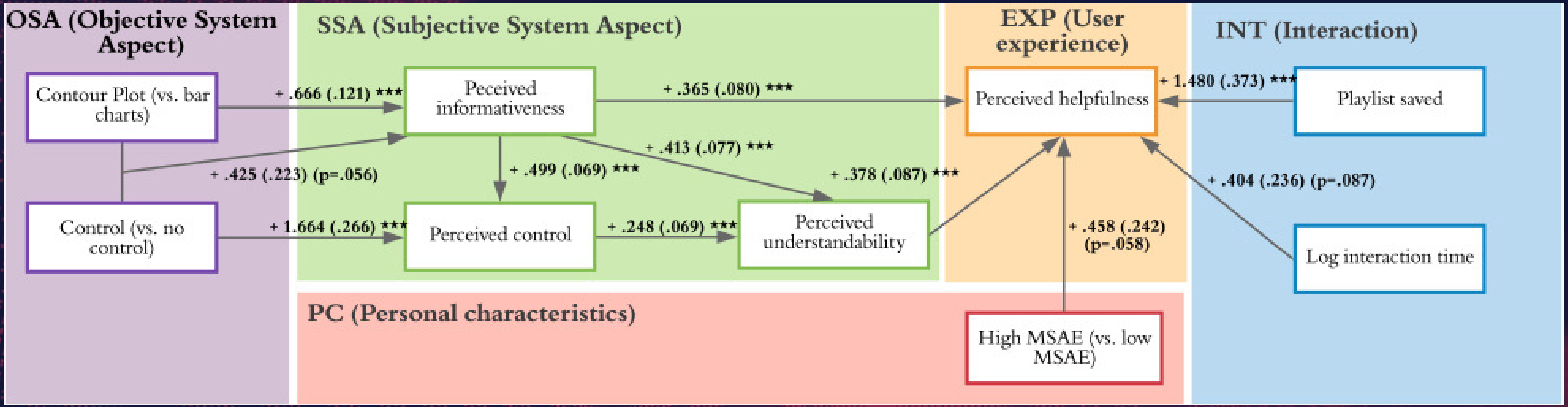
(b) Mood slider interactions in different visualizations

INSIGHTS:

- Users interacted with the system shorter in the second phase.
- Users interacted with the system longer with the contour plot than the bar chart.
- Users interacted with the recommended tracks slightly less in the second phase than in the first phase.
- Users used the slider much more with the contour plot than with the bar charts.
- Users saved the playlist 14.2% of the time regardless of the conditions or the experimental phase.

EVALUATION OF USER STUDY - SEM

- SEM - Structure Equation Model
- Important Components:
    - Perceived Informativeness
    - Perceived Control
    - Perceived Understandability
    - Perceived Helpfulness
    - MSAE - Musical Sophistication on Active Engagement

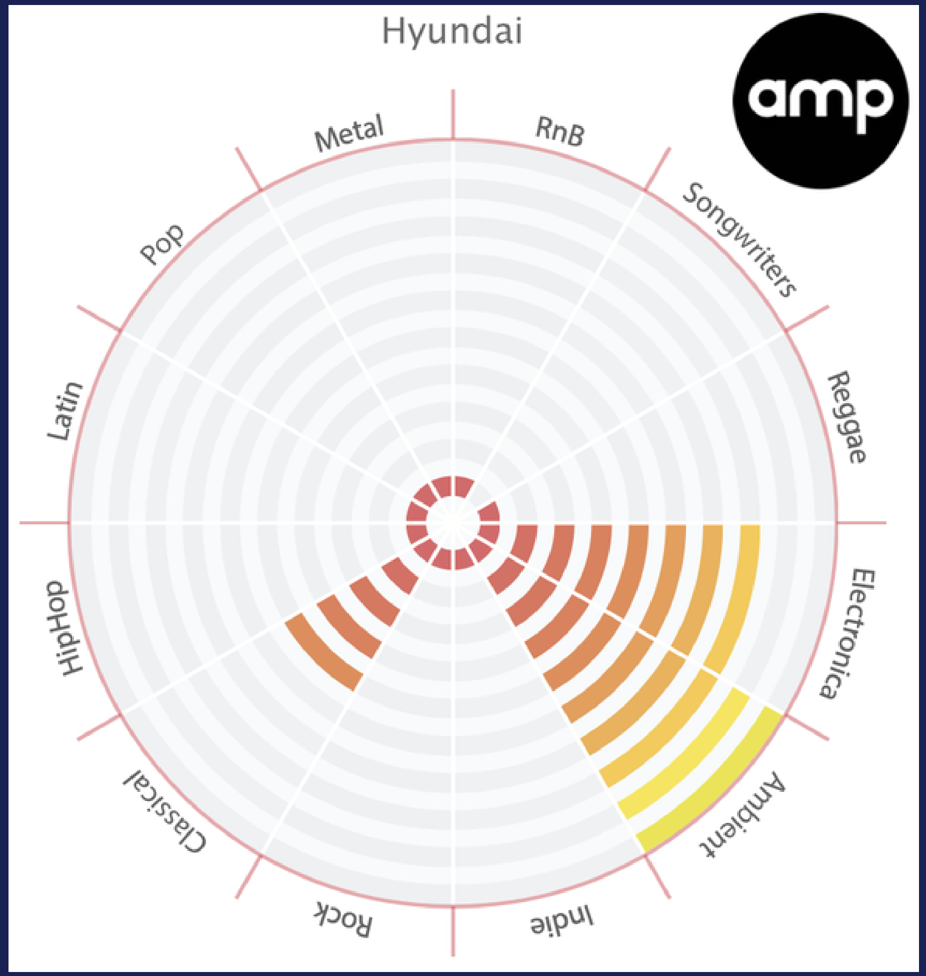


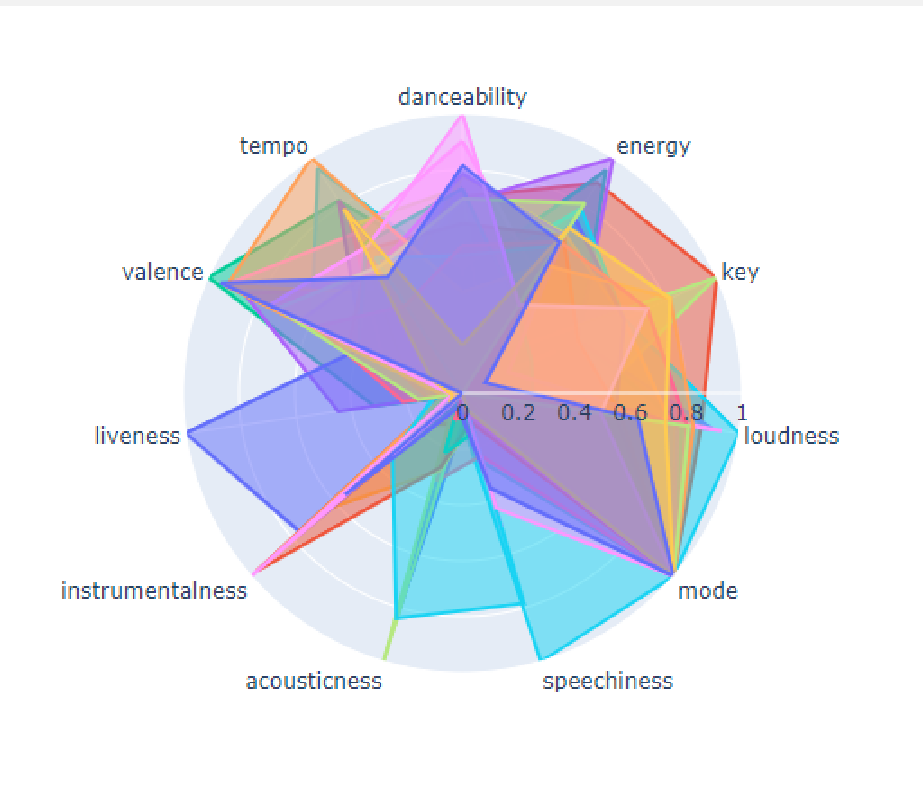
LIMITATIONS

- Non-generalizable results
- Complexity of contour plots
- Information loss in song features
- Limited visualization techniques
- Limited set of genres to recommend
- Study only measured the short-term effects of the interactions and experiences of the users.

FUTURE WORKS

- Diverse participants.
- Diverse visualization techniques:
  - Radar charts,
  - Polar area charts
  - etc.
- Extending the mood control to other dimensions or categories.
- Integrating user feedback and adaptation mechanisms.





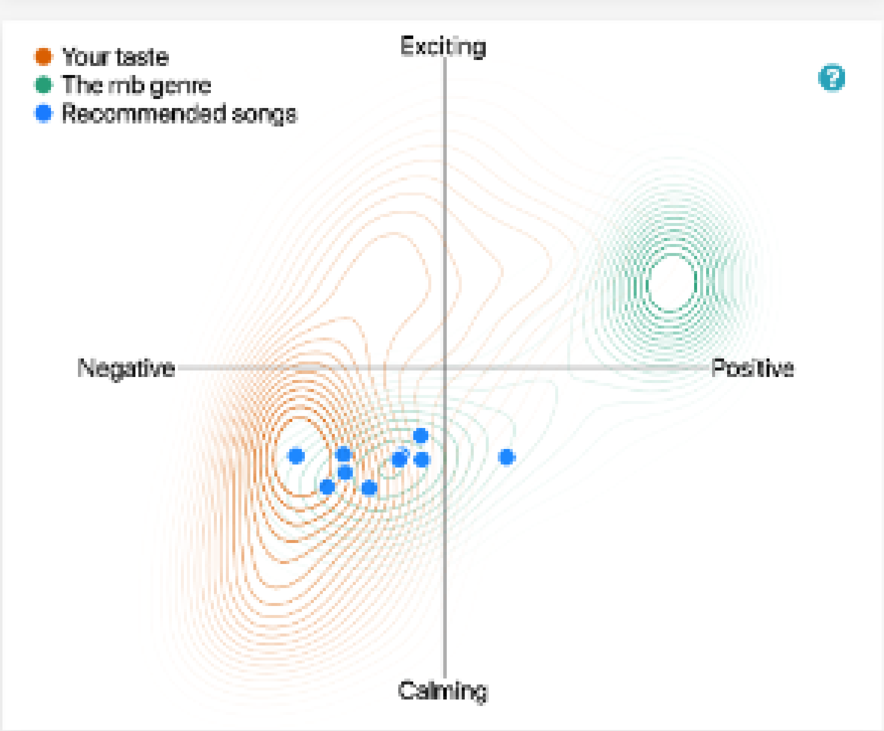
Thank you

APPENDIX

- Recommendation Methods:
  - Personalized:
    - This method calculates a track’s recommendation score in each feature dimension using a Gaussian mixture model. The tracks with the highest scores, averaged over all feature dimensions, are returned as the recommendations.
  - Non-Personalized:
    - This method calculates recommendation scores based on the prototypical tastes of the genre.
  - Mixed:
    - This method provides recommendation by combining scores of the two above algorithms.
- Filter Bubble Issue:
  - The "filter bubble" refers to the isolation of individuals within personalized information ecosystems, limiting exposure to diverse content and viewpoints based on their preferences, potentially reinforcing biases and restricting the discovery of new information.

APPENDIX

- Audio Features:
  - Energy: measures the intensity of tracks
  - Valence: positiveness of a track.
  - Danceability: How suitable a track is for dancing based on tempo, rhythm, and beat strength.
  - Acousticness: The likelihood of music being acoustic (without electric amplification).
  - Speechiness: The presence of spoken words or vocal content in the music.
  - Liveness: The perception of whether the music was recorded live or in a studio setting
- Graph Types:
  - Complex Contour Plot : is a combination of one scatter plot with two contour plots
  - Bar Chart



APPENDIX

- Expectations:
  - Investigate the influence of two visualizations and mood control on perceived helpfulness for new music genre exploration.
  - Measure user's perceived informativeness, control over the system, and understandability of recommendations.
  - Expect the contour plot to be more helpful than the bar chart due to its ability to visualize relations between the new genre, recommended songs, and current preferences.
  - Anticipate increased informativeness to improve user understanding of recommendations and perceived helpfulness for exploring new genres.
  - Acknowledge that contour plots might be complex for some users, potentially affecting their perceived informativeness.
  - Anticipate the addition of mood control to increase helpfulness for new genre exploration by enhancing controllability and understanding of recommendations.
  - Examine the effectiveness of mood control in both visualizations, expecting it to be more beneficial when combined with the contour plot.
  - Expect a positive interaction effect between contour plot and mood control on user perceptions, indicating greater effectiveness when combined.
  - Anticipate users to interact differently with the system based on the visualization type, potentially utilizing sliders more with the contour plot.

APPENDIX

CONSTRUCTS:

- Perceived control: This construct measures how much users feel in control of modifying the recommendations. It was derived from Pu et al. [1], who used three items to assess the perceived control of a recommender system.
- Perceived informativeness: This construct measures how informative users find the visualization of the recommendations. It was constructed by the authors of this paper, who used three items to assess the perceived informativeness of the contour plot or the bar charts.
- Perceived accuracy: This construct measures how accurate users find the recommendations. It was derived from Knijnenburg et al. [2], who used three items to assess the perceived accuracy of a recommender system.
- Perceived understandability: This construct measures how easy users find it to understand the recommendations and the recommendation process. It was constructed by the authors of this paper, who used three items to assess the perceived understandability of the recommendations.
- Perceived helpfulness: This construct measures how helpful users find the recommendations for exploring a new music genre. It was derived from Liang et al. [3], who used three items to assess the perceived helpfulness of a music genre exploration tool.
- User interaction time: This is an objective measure of how long users interacted with the system in each phase. It was measured by logging the time users spent on the recommendation page.
- Track interactions: This is an objective measure of how many tracks users listened to or hovered over in each phase. It was measured by logging the user actions on the recommended tracks.
- Slider interactions: This is an objective measure of how many times users used the mood control sliders in each phase. It was measured by logging the user actions on the sliders.
- Playlist saving behavior: This is an objective measure of whether users saved the playlist to their Spotify profile in each phase. It was measured by logging the user actions on the save button.
- Musical sophistication: This is a personal characteristic of users that measures their musical expertise in active engagement and emotional engagement. It was measured by using the Goldsmith Musical Sophistication Index [4], which is a survey of 18 items.

APPENDIX

- SEM Evaluation:
  - The contour plot is more informative than the bar chart, as it shows the relation between the new genre, the recommendations, and the user's preferences.
  - Mood control increases perceived control by allowing users to adjust the recommendations based on their mood.
  - The contour plot also indirectly increases perceived control via informativeness.
  - Understandability is positively affected by both informativeness and perceived control.
  - Users understand the recommendations better when the visualization is more informative, and the recommendations are more controllable.
  - There is no direct effect of visualization or mood control on understandability, only indirect effects via informativeness and control.
  - The contour plot is more helpful than the bar chart for new genre exploration, as it is more informative and understandable.
  - Mood control improves helpfulness by increasing perceived control and understandability.
  - The combination of contour plot and mood control has the highest impact on helpfulness.
  - Users with higher musical sophistication on active engagement perceive the recommendations to be more helpful than users with lower musical sophistication.
  - Users who save the playlist or interact longer with the system also perceive the recommendations to be more helpful.

APPENDIX

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