# Literature Review

## Paper 1 - Effects of Personal Characteristics on Music Recommender User Interfaces

### Citation

Millecamp, M., Htun, N. N., Jin, Y., & Verbert, K. (2018, July). Controlling spotify recommendations: effects of personal characteristics on music recommender user interfaces. In *Proceedings of the 26th Conference on user modeling, adaptation and personalization* (pp. 101-109).

[Controlling Spotify Recommendations: Effects of Personal Characteristics on Music Recommender User Interfaces (acm.org)](https://dl.acm.org/doi/pdf/10.1145/3209219.3209223)

### Summary

This paper talked about creating an effective UI that made users feel like they discovered new music and that it matched the taste/style of the inputs they provided. Focusing more on the user interface rather than the recommender algorithm itself, I learned that the radar graph made people feel like they were given better songs than a slider, so I will use that technique in my user interface for the recommender system. I also found the inputs to be interesting, rather than songs the authors utilized Artists, which makes sense because you can only determine genre from artist, not from track. Ideally, the user interface for our design will utilize either the current listener’s artists, or it will allow them to manually enter them. As for what attributes they found most important, they focused on energy, acousticness, danceability, instrumentalness, tempo, and valence.

**Takeaway:** Use a radar chart for user selection of energy, acousticness, danceability, instrumentalness, tempo, and valence.

**Chart, radar chart

Description automatically generated**

## Paper 2 - Factors Affecting Music Recommender Success

### Citation

Uitdenbogerd, A., & Schyndel, R. (2002). A review of factors affecting music recommender success. In *ISMIR 2002, 3rd International Conference on Music Information Retrieval, Proceedings* (pp. 204-208). IRCAM-Centre Pompidou.

[A review of factors affecting music recommender success (exlibrisgroup.com)](https://ap-st01.ext.exlibrisgroup.com/61RMIT_INST/upload/1666274280638/n2002001461.pdf?Expires=1666274402&Signature=ju819oowokU31zCj3Q-H~u-tjr-A3OA64kER0UGUxGLRPJhfh5vrmSNfoNchXM5fMml3dt~iOVHQ69gNFYs1jo79tkxuMDMex26fled3kaXXNoQXgwRNPbbXZlXrR7pp6U0aaji1eF4wsXTMCe2n0YJk5cfmUEhkAZF-Q1pyHgIoRct-o6Kee3BcuUFfLcuGR0MgsEXtPRrYTQHeHhQnNwr6WQzEg4FGmW0ynQoaEiAjShH6FK34mWjIQtWwljKAX15FshYbYiWQczy4bVxV~QnWruV430JkVgQOpyl4Pl5Rncv4qneK7TDw4n6nlpaKpyU2ohNfanmq-jcA~Ia6nw__&Key-Pair-Id=APKAJ72OZCZ36VGVASIA)

### Summary

This paper discusses various factors that can influence a person’s musical taste. One of the first factors discussed is geolocation, which was also mentioned in the first paper. It seems that it may be useful for our recommender to access the user’s country to help find songs that match their preferences. The paper also discusses people of similar ages often share the same music taste because there is a higher chance they heard the same music at the same time during their development years prior to turning 24. If we are able to utilize other user’s music preferences, we could use age as a way to tie similar users together. Tempo also showed to be a large factor in determining if people like recommended songs. We should pay attention to tempo and potentially give it a greater weight in the recommender algorithm. One warning that this paper discusses is accurate genre classification, since there are so many. We will be using Spotify as a sole source of genre classification, so we should investigate how this is done and check for consistency.

**Takeaway:**  Use geolocation, give higher weight to tempo in recommender, investigate consistency of genre classification using Spotify.

## Paper 3 - An Efficient Hybrid Music Recommender System Using an Incrementally Trainable Probabilistic Generative Model

### Citation

Yoshii, K., Goto, M., Komatani, K., Ogata, T., & Okuno, H. G. (2008). An efficient hybrid music recommender system using an incrementally trainable probabilistic generative model. IEEE Transactions on Audio, Speech, and Language Processing, 16(2), 435-447.

[04432655.pdf (kyoto-u.ac.jp)](https://repository.kulib.kyoto-u.ac.jp/dspace/bitstream/2433/50284/1/04432655.pdf)

### Summary

The authors in this paper sought to solve a similar problem to the one we are trying to solve – providing recommendations of songs that are not just the most popular for each genre, but also match user preferences. They discuss how collaborative filtering tends to keep recommending the same popular artists for each genre, since they have the most listeners. By going beyond this, users can discover new artists and new music that may not be popular, but match their music tastes. Their model unifies collaborative and content-based data utilizing probability theory. Their data sets correlated signal processing theory to get track / artist features with the sales and popularity of the track / artist on e-commerce sites – truly an interesting approach basing popularity off of actual sales. All of this is done incrementally, so the model builds itself dynamically. The advantage of this approach, is that it took 10 minutes to train the base model, and only 5 seconds to update the model. So if we can train a model similar to this, and dynamically update latent variables, we could have a recommender system that requires very little computational cost, but maintain high accuracy and processing speed.

**Takeaway:**  Consider using probability theory to train a base model, so that incremental updates require little processing power and could be done on something as lightweight as a mobile device. Content based filtering may be the better approach to take if just using available Spotify data.

## Paper 4 - Build Your Own Music Recommender by Modeling Internet Radio Streams

### Citation

Yoshii, K., Goto, M., Komatani, K., Ogata, T., & Okuno, H. G. (2008). An efficient hybrid music recommender system using an incrementally trainable probabilistic generative model. IEEE Transactions on Audio, Speech, and Language Processing, 16(2), 435-447.

[04432655.pdf (kyoto-u.ac.jp)](https://repository.kulib.kyoto-u.ac.jp/dspace/bitstream/2433/50284/1/04432655.pdf)

### Summary

This paper seeks to solve the “rich get richer” problem with recommender systems that typically rely on the usage of the service to improve recommendations. For example, millions of people use YouTube and Spotify to listen to music, so how can a new streaming app compete with the billions of track plays and ratings that these services have access to? To answer that question, they used internet streaming playlists on radio stations to jump start their recommender system. An issue I see off this initially is that internet radio is heavily disproportionate in the variety of music it offers. For instance, there could be hundreds of stations that play popular genres of music like pop, but only a handful of less popular genres like metal and classical. Handling new users with no data, is done by utilizing popular music found on the internet – not a bad approach.

**Takeaway:**  For users new to Spotify, or users that have below a predetermined quantity of music listened to, we could default recommendations to some of the most popular playlists on Spotify at the time the user accesses our app.

## Paper 5 - Each to His Own: How Different Users Call For Different Interaction Methods in Recommender Systems

### Citation

Knijnenburg, B. P., Reijmer, N. J., & Willemsen, M. C. (2011, October). Each to his own: how different users call for different interaction methods in recommender systems. In *Proceedings of the fifth ACM conference on Recommender systems* (pp. 141-148).

[Each to his own: how different users call for different interaction methods in recommender systems (acm.org)](https://dl.acm.org/doi/pdf/10.1145/2043932.2043960)

### Summary

This paper focusses on the relationship between five interaction methods (how we can use the recommender system) and three user characteristics (the types of people using the system). They suggest that the best way to interact with a UI is based on the type of person using it, and their experience in the subject that is being recommended / how it is being recommended. What they found is that the five interaction methods really make no difference on how people feel about the recommendations. Rather, they find that certain types of people prefer certain interaction methods. The authors offer great recommendations, which I will copy and paste below because I find them THAT useful:

Designers seem to have to find a way to combine the simplest method (TopN) and the most complex method (Hybrid), while avoiding their respective downsides. Combining these methods in a single recommender system is a difficult design challenge. One option is to spatially separate the two interaction methods in different sections of the system. Another option is to temporally separate them: start with the TopN, carefully introduce implicit recommendations, and then introduce explicit controls as well. A final option is assign the correct method to each user: try to discover before (or during) the interaction what the user’s characteristics are, and then tailor the interface to [their] specific needs.

More generally, we show that designers and researchers alike should investigate the impact of their system on the user’s satisfaction in terms of both process and outcome. Being satisfied with the system itself and the outcomes of using it are two separate concerns, which may at times even be in conflict with one another.

**Takeaway:**  Allow flexibility in the user interface and recommendation system, so that the user can not only tailor their recommendations, but also their interaction.