2023

Do Music Recommender Systems Impact Users' Musical Preferences?

TOPIC AREA: IMPLEMENTING MACHINE LEARNING TOOLS AND TECHNIQUES IN MUSIC RECOMMENDER SYSTEMS

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RESEARCH METHODS AND PROFESSIONAL PRACTICE NOVEMBER 2022
UNIT 7, LITERATURE REVIEW

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1. Introduction

Music Recommender Systems (MRS) have become a persistent part of life for millions of users worldwide, particularly those who use online music platforms such as Apple Music, Spotify, Last.fm, and many more (Hosanagar, 2014; Kowald et al., 2021; Schedl et al., 2018). Each of these platforms uses MRS to identify songs that users may like, based on information gathered about the user's music preferences (Hosanagar, 2014; Kaminskas & Ricci, 2012).

1.1. MRS Background

These platforms use machine learning techniques such as *collaborative filtering, content-based recommendations,* or a hybrid of both techniques, to develop recommendation algorithms (Adomavicius & Tuzhilin, 2005; Kaminskas & Ricci, 2012; Neal, 2012; Poulose, 2022; Ricci et al., 2010; Vall, 2019). Collaborative filtering leverages data from other users to provide recommendations (Ricci et al., 2010; Smith & Linden, 2017). A well-known example of collaborative filtering is Amazon's recommender that suggests products that similar users have purchased (Smith & Linden, 2017). Content-based techniques analyse user data, such as listening history, to recommend other items (Kaminskas & Ricci, 2012; Ricci et al., 2010). Hybrid systems combine these approaches and may also incorporate additional factors such as human behaviour (Ricci et al., 2010;

Smith & Linden, 2017). In effect, this allows users to off-load the cognitive burden of deliberate music selection whilst simultaneously determining what type of music users hear (Helberger et al., 2018; Kaminskas & Ricci, 2012; Shedl et al., 2018).

1.2. Research Question, Audience, and Purpose

Given the influence MRS have on musical exposure, this survey aims to assess whether or not MRS usage impacts users' musical preferences. Benefactors of this review are researchers capable of furthering progress in this emerging field, and MRS users who desire to understand the effects of outsourcing cognitive functions to algorithms.

This literature review surveys existing research about MRS impact on user references, describes the merits of current theories, and proposes research concepts to resolve gaps. The ultimate goal is to increase the understanding causational effects between machine learning and human behaviour beyond MRS.

2. Approach and Methodology

This survey is a mapping review designed to assess the status of literature, and research gaps, pertinent to the impact of MRS on music preferences (Booth et al., 2022). Activities were conducted using the Search, Appraisal, Synthesis, and Analysis – SALSA – framework, as applied to mapping reviews (Booth et al., 2022; Grant & Booth, 2009).

2.1. Search

Initial searches were conducted to scope relevant terminology and concepts and aligned to a research territory map shown in **Figure 1** (Booth et al., 2022; Dawson, 2015).

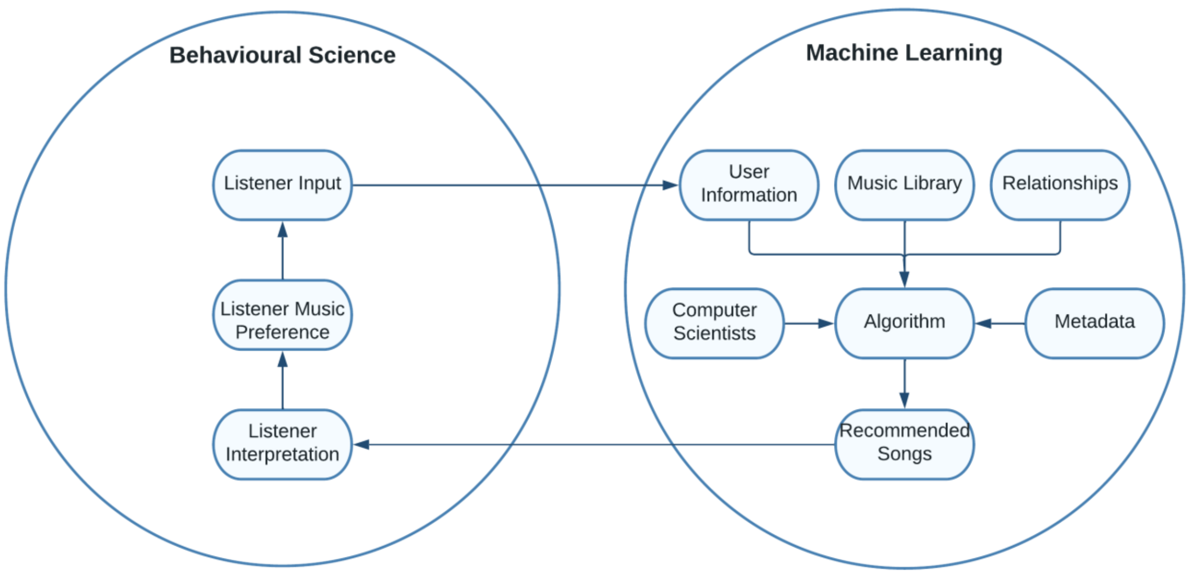

Figure 1: A research territory map of MRS impact on user preferences (Dawson, 2015)

Sources about the fundamental concepts in this research, such as recommender systems, machine learning, and behavioural science yielded important terms such as “music information retrieval” (Kaminskas & Ricci, 2012), “collaborative filtering” (Ricci et al., 2010), and “filter bubble” (Pariser, 2011).

Searches on Google Scholar and the University of Essex e-Library were designed to cast a wide net and return a maximum number of directly and indirectly relevant sources. Boolean techniques were used to combine criteria, as demonstrated below:

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(“music recommender” OR “music information retrieval")
AND (“user preference” OR “user rating”)
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Literature examining the relationship between MRS and music preferences was defined as relevant and included in this survey. Literature on related topics was incorporated to examine and explore novel concepts in this topic but was not assessed in the same manner as directly relevant literature.

2.2. Appraisal

This survey, and surveys conducted on related topics, concluded that research on the unintended consequences of MRS is sparse when compared to the widespread adoption of MRS (Porcaro et al., 2021; Schedl et al., 2018). Whilst the search methodology produced more than one thousand results, only fifty-four appeared to be relevant to the course of study, and only three were experiments that directly examined the effect of MRS on users' musical preferences (Adomavicius et al., 2018, 2021; Kowald et al., 2021).

Research on underlying topics, such as recommender service technology and audience preferences, was abundant and helped refine search parameters and contextualise relevant literature. There were scores of tangentially related studies of recommender systems in retail, social media, and political domains whose findings offer suggestions to this field, albeit inconclusively (Adomavicius et al. 2013, 2018, 2019, 2021; Smith & Linden, 2017).

2.3. Synthesis

Aggregative synthesis of the available literature revealed that the relevant studies correlate MRS impact on user musical preferences through user ratings or willingness to purchase songs (Adomavicius et al. 2018, 2019, 2021). Previous surveys focussed on determining MRS impact on music preference diversity (Hosanagar, 2014; Kowald et al., 2021; Porcaro et al., 2021; Shedl et al., 2018) and MRS variables affecting users' musical preferences (Braunhofer et al., 2013; Kaminskas & Ricci, 2012; Schedl et al., 2018).

2.4. Analysis and Key Findings

This survey has produced two notable findings from research, experiments, and other surveys.

2.4.1. Finding 1: MRS impact user preferences by limiting music exposure

Dozens of studies have examined the notion that recommender systems are predisposed to creating "filter bubbles," a concept popularised by Eli Pariser in which a user's recommended information becomes increasingly homogeneous with each iteration of a recommendation service (Adomavicius et al., 2021; Levy, 2021; Pariser, 2011; Porcaro et al., 2021). This theory suggests that preferences are reinforced through confirmation bias and a lack of exposure to divergent information (Adomavicius et al., 2013, 2021; Levy, 2021; Pariser, 2011; Porcaro et al., 2021). This phenomenon is exemplified with social media news article recommendations, which have been found to increase political polarisation in audience members (Levy, 2021). This process is cyclical in nature (Levy, 2021), and is diagrammed below in **Figure 2**.

Figure 2: A logic diagram of recommender system influence developed from Levy (2021)

Gediminas Adomavicius, a prevalent researcher of the human effects of recommender systems, found that similar patterns occur with users and MRS (Adomavicius et al., 2021). Furthermore, Adomavicius et al. found that ratings calculated by MRS influenced user ratings and inferred that MRS influence users' music preferences (2021). Thus, it may be inferred that MRS influence user music preferences in the same manner as social media recommender systems impact political views, depicted in **Figure 3**.

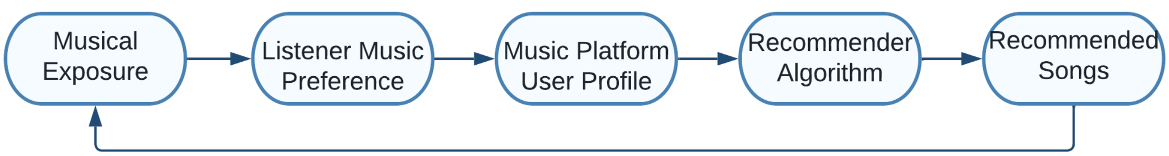

Figure 3: A logic diagram applied to Figure 2, adapted from Adomavicius et al. (2021)

2.4.2. Finding 1: Gaps and Weaknesses

Despite the sound logic and existing body of research, these theories present several weaknesses. Prior research by Adomavicius et al. revealed that consumer preferences can be manipulated by recommender system-generated ratings, in what is called an "anchoring effect" (Adomavicius, 2013, 2021; Cosley et al., 2003). However, this research assumes that a user's rating accurately represents their preference (Adomavicius, 2013). Findings from Aziz et al. indicate that user ratings may not accurately reflect user sentiment (2022). The 2022 study found that rating inflation is common on a multitude of online platforms, leading to less meaningfulness in ratings and a potential deviation between user ratings and user preferences (Aziz et al., 2022). Though existing literature presents logical arguments associating MRS impact on user preferences (Adomavicius 2018, 2019, 2021), this could be confirmed with an experiment that measures user preferences without relying on a rating system prone to bias (Aziz et al., 2022).

The impact and existence of “filter bubbles” is also a topic of contention, with several studies finding the phenomenon to be either insignificant or non-existent (Bruns, 2019; Haim et al., 2018; Jones-Jang & Chung, 2022). Bruns argues that pre-existing biases cause users to interpret information differently, and that personalised recommendations have little bearing (2019). Other studies conclude that despite the curation of information to target audiences, recommender services actually increase user exposure to heterogeneous information and incidental learning (Haim et al., 2018; Jones-Jang & Chung, 2022).

Furthermore, the majority of recommender system literature that serves as the basis of MRS research is based on commercial and retail data, not music (Adomavicius et al., 2013, 2019; Cosley et al., 2003). Literature suggests that users may interpret this data differently (Shedl et al., 2018); thus, performing foundational experiments about “anchoring effects” and recommendation-induced bias with music information would validate conclusions from Adomavicius et al. (2018, 2019, 2021).

2.4.3. Finding 2: MRS are not designed for diversity

A nascent body of literature examines the factors behind the lack of diversity in MRS results (Kowald et al., 2021; Porcaro et al., 2021; Shedl et al., 2018). Porcaro et al. state that homogeneity in MRS begins with the technology workforce, who fail to represent the diversity of its content or its audience (2021). This trend is perpetuated in underlying recommender system technology, which is specifically designed to identify and retrieve similar information (Adomavicius & Tuzhilin, 2005; Fleder & Hosanagar, 2009; Kowald et al., 2021; Neal, 2012; Porcaro et al., 2021; Poulose, 2022; Ricci et al., 2010; Shedl et al., 2018; Vall, 2019). Porcaro et al. posited that MRS diversity stems from the interaction of two domains of music information: *Poietic*, information about the origination of the music, and *Esthetic*, information about the interpretation (2021). After studying the factors in each domain, Porcaro et al. assessed that including historical, social, cultural, and psychological data would increase MRS recommendation diversity (2021).

Shedl et al. reached similar conclusions after evaluating current shortfalls within MRS and identified diversity as a desirable parameter for MRS users (2018). In addition to cultural and psychological factors, Shedl et al. recommend including situational variables such as time, location, activity, and weather to generate diverse, yet relevant, MRS recommendations (2018). In a 2021 study, Kowald et al. examined the preferences and behaviour of “beyond-mainstream” music listeners, a population underserved by MRS. Instead of focussing on user attributes, this research identified nuances between musical subgenres and developed a model to preserve subgenre distinction in MRS recommendations (Kowald et al., 2021).

2.4.4. Finding 2: Gaps and Weaknesses

A lack of diversity in MRS is the inverse condition of the previously discussed *filter bubble,* and instead of assessing the impact of surplus congruent information, attempts to explain how an absence of variety impacts user preferences (Helberger et al., 2018; Porcaro et al., 2021). This presents unique challenges, as a successful MRS needs to provide recommendations that are not only diverse, but also accepted by the user (Helberger et al., 2018; Shedl, 2018). Additionally, the field has yet to establish standard criteria and measurements for diversity in MRS, preventing comparison between studies and observations (Helberger et al., 2018; Kowald et al., 2021; Porcaro et al., 2021; Shedl et al., 2018). Lastly, at the time of this literature review, there has not been a study measuring the impact of MRS diversity against a control group; thus, research in this field remains theoretical in nature.

3. Conclusion

This literary review sought to assess the impact of MRS on user musical preferences. Findings suggest that 1) an excess of similar music may constrain musical preferences (Adomavicius et al., 2021; Levy, 2021; Pariser, 2011; Porcaro et al., 2021), and conversely, that 2) a lack of exposure to diverse music fails to broaden, and may also constrain, musical preferences (Kowald et al., 2021; Porcaro et al., 2021; Shedl et al., 2018). These findings are reinforced by the fact that MRS are specifically designed to present users with similar music information (Adomavicius & Tuzhilin, 2005; Fleder & Hosanagar, 2009; Porcaro et al., 2021; Poulose, 2022; Ricci et al., 2010). While the effect of abundantly homogeneous information on user preferences remains controversial

(Bruns, 2019; Haim et al., 2018; Jones-Jang & Chung, 2022), research supporting and opposing such findings are based on research that focusses on non-music data (Adomavicius et al. 2013, 2018, 2019, 2021).

This review suggests three follow-on efforts to validate existing assumptions, and to provide a basis for future research:

i. Conduct an experiment that measures user music preferences without relying on a rating system prone to bias.

ii. Study anchoring effects and recommendation-induced bias specifically with music information.

iii. Conduct an experiment that measures the impact of a diverse MRS against a traditional MRS control group.

Continued research is vital due to the proliferation of recommender systems for which MRS can serve as a proxy (Adomavicius et al., 2018, 2021; Shedl et al., 2018), and for both researchers and music listeners alike to grasp the unintended consequences of recommender services.

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