Tuning In: A Comprehensive Analysis of Music Recommender Systems, Playlists, and Algorithmic Fairness

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Executive summary

The global recorded music industry's growth in the past decade has been mostly generated by the streaming segment. The role of online platforms – in particular Music Streaming Services (MSS) – in the music industry has become pivotal, particularly concerning gatekeeping and the curation of music recommendations. Technology-based innovations, such as AI and big data, play a major role in transforming the current music industry business models. In particular, the use of algorithmic systems and packaging music into playlists have an increasing importance for music ecosystems. This is also the case from a research perspective.

Algorithmic curation has been a strong focus in the digitisation of music through MSS. This section recalls the 4 different types of recommender systems: collaborative filtering, content-based filtering, context–based systems and hybrid recommender systems. The music industry has entered a new paradigm of the attention economy, where there is a growing competition for the listeners' attention. MSS are radically changing the way people consume music as they provide access to almost an unlimited number of songs. Datafication, which refers to the process of monitoring and analysing users' consumption patterns, has become central to MSS and the features that they offer. They have, in this context, an increasing role in the discoverability of music.

MSS offer personalised recommendation features, mostly through the curation of playlists. These playlists can be categorised as proprietary playlists, which consist of algorithmic and editorial playlists and user-generated playlists. Proprietary playlists belong to either MSS providers themselves or to third parties. Regardless of the initial conception and distinction between algorithmic and editorial, proprietary playlists tend to employ an algo-torial logic. This logic follows an iterative progression that begins with a prompt, yet constant algorithmic evaluation of the curated songs after their initial inclusion on a designated playlist. In addition to proprietary playlists, MSS consumers also engage in the curation of user-generated playlists. For the curation of these playlists, the user interaction is driven by the motivation to control a context-sensitive arrangement.

The question of fairness is gaining visibility in economic, political and scientific circles alike as people experience the algorithms' effects in their daily lives. There is an important tension in the research between fairness and performance of the algorithm, and the subject also seems to be controversial in literature. Current distinctions include: group fairness vs. individual fairness; awareness-based fairness vs. rationality-based fairness. Researchers in computer science are mostly looking for biases in data, rather than taking a comprehensive perspective or by taking into consideration a human's point of view. This highly reductive approach did not succeed in achieving algorithmic fairness, as only part of this question is dealt with by those mitigating algorithms. Moreover, a consensus as to which criteria to use to evaluate the fairness of an algorithm remains elusive, making this a challenging endeavour.

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This Fair MusE (Promoting Fairness of the Music Ecosystem in a Platform-Dominated and Post-Pandemic Europe) report aims to build an interdisciplinary and comprehensive understanding on how platforms and their algorithmic systems work, as well as their impact on consumption, and to highlight potential risks in terms of fairness. In contrast to the literature, we believe that MRS and playlists require a multi-stakeholder approach so that their impact can be fully grasped. To contribute to a fairer music ecosystem, we need to understand biases and strategies in algorithms.

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List of acronyms

AI - Artificial intelligence
AVMSD - Audiovisual Media Services Directive
IFPI - Federation of the Phonographic Industry
MRS - Music Recommender System(s)
MSS - Music Streaming Service(s)
RS - Recommender System(s)
VSP - Video-Sharing Platforms

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1 Introduction

For the past decade, the global recorded music industry has been growing exponentially. According to the International Federation of the Phonographic Industry (IFPI, 2023), **most of the revenue growth was generated by the streaming segment in 2022** (67%), with 589 million people using a paid music streaming subscription by the end of that year. While the global streaming segment accounted for just 100 million USD back in 2005, this segment reached 17.5 billion USD and accounted for 67% of the total global market revenues in 2022. The situation in Europe is no different, with the same report naming Europe as the world's second-largest region for recorded music revenues, with the streaming segment accounting for 26% of the global streaming revenues. Undoubtedly, these shifts in the music industry are attributed to digitalisation and platformisation of the industry (Poell et al., 2019), which have created a favourable environment for the thriving growth of online Music Streaming Services (MSS).

The rise of digital technologies, including personalisation and other AI applications, virtual reality and blockchain, has reshaped the music industry's market structure (Darvish et al., 2022; Lu & Chang, 2019). Streaming platforms have utilised music data to create personalised recommendations, serving as both a valuable source of data and a powerful surveillance tool (Drott, 2018). They have positioned themselves as a means of reintegrating listeners into "digital enclosures" under greater rights holder control, yet challenges remain in converting freemium users to paying subscribers (Drott, 2018).

Numerous stakeholders in this sphere have transitioned from being mere product and service suppliers to becoming facilitators of innovation and collaboration in the digital economy (Rayna & Striukova, 2015). The market for MSS is a competitive one, dominated by Spotify (31%), Apple Music (15%), Amazon Music (13%), Tencent Music (13%) and YouTube Music (8%) (MIDiA, 2022). **MSS, however, do not compete against each other on music content, but on other elements. In particular, MSS compete in how they recommend music to consumers**. Further implications point out to how digitalisation has deeply modified the way people access recorded music, discover, and consume it, with Datta et al. (2017) underlining MSS' ability to increase consumer welfare by helping consumers discover new high-value content and by reducing search frictions. Similarly, customers are no longer passive participants; instead, they have evolved into active co-creators of value (Setzke, 2021). According to Arditi (2017), digital technologies have led to the hyper-commodification of the recorded music industry, in which the music industry expands the consumption of music and lays the 'digital music trap' to consumers who are caught in the endlessness of music consumption.

Certainly, MSS are not the only way through which music is consumed in an online environment, as music consumption goes (far) beyond these services. The use of music in **synchronisation** (songs

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are combined with moving images) and in video games are other mediums worthy of attention (Arevalo, 2023; Arkenberg & Patel, 2022; Tien-Dana, 2023). Arkenberg and Patel's (2022) research particularly concludes that "Gen Z gamers (born between 1996 and 2010) have a strong relationship with music—with music they hear in games, discover while watching game streamers, share with other players, and listen to while gaming. This opens up more opportunities for stronger partnerships and better integration between music and gaming companies". **Of another particular importance in music consumption is the role played by video-sharing platforms (VSP),** such as YouTube and TikTok, which stimulate music consumption. TikTok, whose growth has been sustained by the integral role of music, launched its own eponymous MSS entitled TikTok Music in the second half of 2023.[1] In the launch of TikTok Music, which TikTok called a 'social music streaming service', its developers announced that the service will "**harness the power of music discovery** on TikTok" and will include known features present in other services such as real-time lyrics, a Shazam-style music identification tool called Song Catch and a new feature to let consumers stream songs that are viral on TikTok (Tencer, 2023). In other words, the music industry is still there for the taking.

Research on digitalisation and platformisation has largely focused on the economics of platforms, their multi-sidedness, the driving forces behind platforms' growth, innovative business models, pricing strategies, anti-competitive effects generated by the platform condition, their sometimes-dominant positions, and their unfair business practices. Media and communication scholars have brought the platform debate into the cultural and public policy realm by investigating platforms' expansion into the media sector (Mansell, 2015). **More recently, (AI-based) recommender systems and curation practices have come to the forefront of scientific investigation**. In particular, platforms' algorithmic systems are accused of being unfair because they sustain or amplify biases and imbalances against some categories of creators, performers or works (Abdollahpouri et al., 2020). Based on a literature review on the impact of algorithmically driven recommendation systems on music consumption and production, research by Hesmondalgh et al. (2023) shows that there is a sustained interest in algorithmic recommendation in the realm of culture.

In comparison to the audiovisual streaming market, which has received the most attention by scholars and regulators alike, as well as tying into the 2018 Audiovisual Media Services Directive's (AVMSD) revision (Ranaivoson et al., 2023), social scientists' interest in the online MSS market has surfaced more recently. Most of the issues pertaining to this interest are related to high platform fees, licensing and copyright, and unfair revenue distribution to the artists (Hesmondalgh et al., 2021; Mazziotti, 2020). Nevertheless, similar to the platform discourses in the audiovisual sector, concerns are expressed regarding the platforms' role in, and impact on, the music sector, notably regarding fair remuneration, content and exposure diversity, artist visibility, business practices, and power struggles. Yet, **the impact of MSS and their algorithms over consumption and their**

[1] Available as of November 2023 in Indonesia, Brazil, Singapore, Mexico and Australia.

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influential power remain largely understudied. Additionally, the predominant focus of research on online music platforms has centered around MSS, notably at the expense of VSP.

Hesmondalgh et al. (2023) point out the limited research on the impact of MRS on music markets, as well as the effect on consumers' experience, and how consumers of online MSS understand systems of recommendation. Considering that online platforms have become "privately owned public spaces, largely governed by the commercial incentives of private actors, rather than the collective good of the broader society" (Owen, 2019), **the aim of this Fair MusE report is to build a comprehensive understanding on how platforms and their algorithmic systems work, as well as their impact on consumption, and to highlight potential risks in terms of fairness.**

Based on a comprehensive report consisting of a wide range of literature on the influence of algorithmic systems in the music industry, with a focus on the consumption side, this shortened report synthesises the main findings. Building on an interdisciplinary literature from computer science, information science, cultural economics, cultural policy and communication sciences, combined with industry insights, we first made a **synthesis of the various identified problematic matters.** Subsequently, we investigated the **practical effects of algorithms** (recommender systems in particular) **and playlists' design on consumption,** by paying special attention to **all the aspects that can impact the fairness** of the system.

The sustained interest in algorithmic recommendations in the media and entertainment industries is allocated by academic computer scientists, and critical social science and humanities researchers. However, as highlighted by Hesmondalgh et al. (2023) and experienced first-hand during our traditional (narrative) literature review, these academic bodies rarely collaborate and combine their knowledge. Thus, in line with Fair MusE's multi-disciplinary and multi-methodological approach (Mazziotti & Ranaivoson, 2023), this report addresses this specific collaborative research gap between various fields by representing the combined efforts of both academic computer scientists, who tend to be more solution-oriented and technical, and critical social science and humanities researchers who explore the complex potential social and cultural aspects of problems. Thus, by collaborating, we combine the strengths and weaknesses of our academic approaches to reach a common, holistic understanding of the problematic aspects of recommender systems and their impact on consumption. By joining our expertise, we also propose mitigating technical and policy-oriented solutions.

The structure of the report is as follows. Section 2 details Music Recommender Systems' role in the music industry and briefly explains how they work. This is followed by section 3 which takes a closer look at playlists, and how they are created and curated. Section 4 proposes a definition of algorithmic fairness for online music consumption, and discusses the impact of biases. The last section concludes the report.

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2 Music Recommender Systems as forms of algo-torial curation

2.1 Music Recommender Systems' key role in the music industry

Digital platforms, and in particular Music Streaming Services (MSS), have become pivotal in the music industry, particularly concerning gatekeeping and the curation of music recommendations. MSS currently have an important role in the capacity of people to discover and consume music. The MSS' purpose is to provide a broad access to music to satisfy their clients. In contrast, their consumers may encounter the occasional inability to find the song they are looking for, which can be an overwhelming experience. In doing so, MSS have changed the way people are discovering and consuming music (Mok et al., 2022).

When MSS were first introduced to the market, the overriding sales pitch relied on unlimited access to music (Maasø & Spilker, 2022). However, the overwhelming amount of music that is available on demand creates an issue of discovery. More specifically, Luck (2016) asserts that it would take approximately 200 years to listen to every track if consumers want to fulfil their desire for discovering new music on a single service. Reflecting upon this issue, the music industry responded with a consensus in 2012: MSS would henceforth compete by offering the best recommendation features (Eriksson et al., 2019) via their **music recommender systems** (MRS). Recommender Systems (RS) themselves can be defined as "systems that match users to items in order to maximise some metric (or a combination of metrics)" (Melchiorre et al., 2021, p. 3). They were developed in the 90s to help match the available content or product with the users' preferences (Mocholi et al., 2012). To fulfil that mission, RS need to be defined with metrics that are important for them and must be tuned accordingly. Based on various types of content filtering processes, MRS have the potential to shape users' music consumption patterns and preferences.

In the short history of music streaming, three phases can be identified: the Unlimited-Access Phase, the Social-Streaming Phase, and the Algorithmic-Streaming Phase (Maasø & Spilker, 2022). Throughout these phases, **algorithmic systems have evolved to play an increasingly prominent role in recommending music to consumers.** They have transitioned from relying on metadata tagging to gathering acoustic and contextual information to suggest song and artist associations (Maasø & Spilker, 2022). Such systems are designed to nudge user behaviour, gratifying platform owners and stakeholders by favouring specific content. Algorithmic systems, both visible and invisible to users, are used to present or hide music in interfaces, shaping the content users are exposed to (Beer, 2009; Bucher, 2012). Metrics and data gathered through datafication influence strategic planning

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and execution of music distribution for various stakeholders within the music industry (Hagen, 2015a).

Algorithmic curation has been a strong focus in music digitalisation. Initially, curation was associated with human involvement, utilising expertise and judgement to select content that is relevant, valuable, and coherent for a particular audience or context (Cunningham et al., 2006). Through their development, recommendation systems and the algorithms they operate with have branched into different types and levels of complexity. Originating from the field of Information Retrieval, early recommender systems were extensions of search and visualisation systems to make the content of a database more visible to consumers, e.g. the FilmFinder project (Ahlberg & Shneiderman, 1994). With the advent of E-commerce, recommender systems soon came to play a pivotal role not only in the user interface but also for the value generation. The business case for recommender systems propelled a large volume of computer science research, which was first occupied with solving computational scaling problems, e.g. Linden et al. (2003), and later with the user-oriented questions of the purposes of and use of recommendations, e.g. Herlocker et al. (2004).

An important aspect in the design and implementation of **(Music) Recommender Systems is that they involve several stakeholders**: consumers, online platforms, advertisers, music providers, etc. A multi-stakeholder approach is therefore necessary to properly analyse their impact (Ranaivoson et al., forthcoming) since these stakeholders come with partially conflicting or competing objectives. Thus, Bugliarello et al., (2022) include among them the short-term satisfaction of consumers, the exposure of emerging artists, and the platform's interests in facilitating discovery and boosting strategic content.

There is a variety of filtering techniques that can be utilised to predict or evaluate the utility of the recommended items. More recently, the techniques also use machine learning / reinforcement learning methods to select and/or rank recommendations are being applied, e.g. by Spotify (Tomasi et al., 2023) and by YouTube (Zhao et al., 2019). The technology used for selecting, organising, and filtering content has become so advanced that the concept of curation is often used when discussing algorithms. The most complex MRS are the embodiment of these advancements, utilising algorithmic filtering in collaboration with big data to create personalised suggestions that bring utility to customers in mass amid the unprecedented scale of readily available musical content (Schedl et al., 2021). The developments that MRS have gone through to achieve this degree of complexity have left a large impact on the music industry. Ren et al. (2019) classify these systems in four methods: content-based, collaboration-based, context-aware and hybrid methods.

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2.2 Different methods to recommend content

Collaborative Filtering is the most simple and widely used implementation that makes recommendations based on items that other users with similar tastes have liked in the past (Ricci et al., 2015). This technique is often referred to as "people-to-people correlation" due to the similarity of taste between users being calculated based on the similarity in the rating history of the users. The methods with which collaborative filtering is implemented can vary in complexity. For example, the neighbourhood-based method focuses on the relationship between items or users, and has achieved popularity based on its simplicity, efficiency, and ability to produce accurate and personalised recommendations (Nikolakopoulos et al., 2021). More advanced methods such as latent factor models, including matrix factorization like singular value decomposition, map both items and users to the same latent factor space. This space is used to explain ratings by characterising both products and users in terms of factors automatically inferred from user feedback (Koren et al., 2021). Deep learning has also begun to be used widely in recommender systems as they save time and are able to process unstructured raw data such as text and sound (Zhang et al., 2021). In the music industry in particular, all these variations in collaborative filtering implementations have their unique applications and have been considered for the music industry throughout the years.

Content-based filtering takes place when the system makes recommendations of items similar to those the user has liked in the past. The similarity between items is calculated based on features associated with the compared items (Ricci et al., 2015). Its basic methods aim to match the attributes of the user profile against the attributes of the items. Often, these attributes are materialised in the form of metadata of the items, such as keywords. In MRS, metadata can include the genre, artist, melody, beats per minute, and the like. Notably, collaborative filtering is limited by the richness in detail of the items recommended which can pose a problem as there are no global standards, thus, leaving room for biases and the responsibility to artists and their representatives. To combat this, the items can be indexed through external techniques. The semantic indexing techniques of data have been grouped as exogenous and endogenous, where the origin of the source used to create the indexing determines its affiliation (Musto et al., 2022). The exogenous sources can also include subjective data, such as what people say about the music in terms of quality and likability (Freeman et al., 2022). The ability to include various datasets, allows content-based filtering to increase its complexity and level of detail when providing recommendations.

Context–aware systems take into account additional information to the typical entities of users and items being recommended. The information used typically includes time, place, who is listening and with whom, amongst others, to provide recommendations based on the present context (Ricci et al., 2015). The growth of context-aware recommender systems can be broadly attributed to the widespread adoption of smartphones, which allow for the capture of real time spatio-temporal data (Lathia, 2015). By increasing the amount of relevant information, this specialised type of

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recommender system has been integrated in the music industry for several years. This is seen with Spotify utilising contexts such as day of the week, time of the day, user's region, type of user's device, and the platform on the device to provide relevant recommendations (Hansen et al., 2020). There are three popular different algorithmic paradigms incorporating this contextual information: reduction-based, contextual post filtering, and context modelling with each method applying the contextual information at various stages of the prediction model (Adomavicius et al., 2022). Context-aware systems are currently one of the most researched topics in the field and have a potential to greatly impact a variety of industries, including music.

Hybrid recommender systems are based on a combination of different techniques, where the advantages of one system are meant to compensate for the disadvantages of another (Ricci et al., 2015). Deep learning techniques have increased the usability of these hybrid systems, such as through neural network frameworks where content and collaborative features are able to compensate one another in providing accurate and personalised recommendations (Paradarami et al., 2017). Hybrid systems can also include the presence of human curation in tandem with various filtering techniques to capture any nuance that may be lost by the automated systems (Freeman et al., 2022). Further combinations of filters and systems are possible, as within each there are various algorithmic methods utilised that could be leveraged.

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3 The growing importance of playlists[2]

3.1 Playlists' functions for consumers and the music industry

A playlist is "a set of songs meant to be listened to as a group, usually with an explicit order" (Fields & Lamere, 2010, p. 7), which can be created by artists, intermediators, the platforms hosting the playlist themselves or consumers. Playlists are a specific way to order collections of music, e.g., to facilitate the finding of a song, according to a theme, a mood or a specific variable (year, genre, etc.). As such, playlists are specific forms – arguably the most important one – of MRS. They have become an increasingly vital tool for guiding listeners' unique music experiences, especially as the abundance of music choices can be overwhelming and time-consuming to navigate. They can allow listeners to easily discover music that resonates with them (McGuire, 2017). Whether it is indie rap or electronic jazz/rock fusion, there are playlists available for various genres and/or activities (to relax or to party or for workout, etc.), which makes it more convenient for listeners to find their preferred music in any context.

Scholars have explored playlists from various perspectives, including their role in fan 'labour', platform brand differentiation, user practices, the digital music commodity and gatekeeping (Drew, 2005; Hagen, 2015b; Morris, 2015; Morris & Powers, 2015). Eriksson (2020) emphasises playlists as 'container technologies' that assemble, preserve, and transport music objects in principles of modularisation and automation that enhance the playlists' control and remote oversight.

Playlists offer insights into the broader structural dynamics within the platform economy, particularly concerning the politics of 'selection' through which platforms seek to create platform dependence (van Dijck et al., 2018). The interplay between editorial and algorithmic logic, alongside market pressures and tensions, shapes playlists and their prominence on platforms (Packer, 2016). **Playlists are not only used for music curation and discovery, but also as a way to distinguish one's MSS from the competition**, by offering distinctive experiences to their own service (Hesmondhalgh, 2021). Across many music streaming services, playlists serve as a stand out feature that repackages music in a form that is native to the milieu of these services (Bonini & Gandini, 2019). They are recognized as a sociotechnical feature that reveals the politics of selection, which is a key mechanism that governs the attempt to create platform dependence (Prey, 2020; van Dijck et al., 2018). Research indicates that Spotify has been actively promoting the playlist format since 2012 and encouraging listeners to consume music through playlists rather than other formats (Eriksson et al., 2019; Prey et al., 2022). Additionally, Spotify uses its editorial capacity to promote its own

[2] In this section, most examples relate to Spotify. We used Spotify for the case study because of its domination of the global music streaming market. It results that Spotify plays a crucial role in music ecosystems, that it has been the most researched and it may be the most familiar for readers – even those without a Spotify account.

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playlists over those created by major labels and third parties, providing more opportunities for independent music on Spotify playlists compared to commercial radio playlists (Prey et al., 2022).

The impact of playlists on users' consumption and sense of belonging is another research topic. For example, collaborative consumption models like those offered by collaborative playlists (Park et al., 2019) where several consumers can curate the playlists, reinforce Belk's (2013, p. 486) claim that "sharing and other collaborative consumption practices in digital spaces enhance the sense of imagined community and aggregate extended self in a digital age". Additionally, according to Morris and Powers (2015), streaming services create an illusion of consumers' increased control through expanded access to a wide variety of music across different locations. However, empirical studies from recent years (Elberse, 2013; Lynskey, 2017; Snickars, 2017) suggest that consumers are experiencing a decrease in control over their music choices.

3.2 A typology of playlists

There are different types of playlists, with larger sociocultural implications. **A first distinction is made between algorithmic and editorial playlists**, with the algo-torial logic (Bonini & Gandini, 2019) representing a combination of both. **A second distinction is to be made depending on who initially creates and curates the list of songs: the platforms themselves, third parties or MSS' consumers.**

Algorithmic playlists revolve around the intricate assortments of songs that are exclusively derived from a suite of proprietary algorithms (Aguiar & Waldfogel, 2018; Bonini & Gandini, 2019). Gillespie (2014) describes the logic of any algorithmic form of content curation as being dependent on the proceduralised choices of a machine that is designed by human operators to automate some proxy of human judgement, as well as to unearth patterns across collected social traces. Algorithmic playlists can either manifest as a standardised form or a more personalised curation. Spotify's *Today's Top Hits*, for example, is a popular playlist that displays the same repertoire of songs in a consistent order across all user accounts (Aguiar & Waldfogel, 2018; Prey, 2020). The playlist itself is generated based on the most streamed songs in a given period of time, which makes it a standardised version of algorithmic playlists. Conversely, personalised ones rely on individual traces of unique listening patterns and affirm that the curations that one consumer receives persistently vary from what the other consumers see on their interface. This includes the order in which the songs are presented as well. Notable examples of playlists that fit this description include *Daily Mix*, *Fresh Finds*, *Release Radar*, *Discover Weekly*, and a revamped version of *Spotify Radio*. (Anderson et al., 2020; Bonini & Gandini, 2019; Kasap & Yalcintas, 2021; Prey, 2020).

Editorial playlists are defined by how they were initially created and curated by professional human editors and not algorithms (Morris et al., 2021). The editorial logic depends on the subjective choices

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that experts themselves make and authorise through institutional processes of training and certification, or through a validation process conducted by the public through the mechanisms of the market - which is the basis of editorial playlists on Spotify entails and how it was first conceived and perceived (Gillespie, 2014). Editorial playlists could either be owned and operated by the MSSs themselves, run by third-party brands, curated by playlist businesses, or compiled by platform consumers.

Part of the success of editorial playlists can be ascribed to their adept incorporation of the nostalgic, personal and eccentric elements from existing musical compilations. Concurrently, from a business perspective, editorial playlists serve as pivotal nodes for accruing advertisement revenues. These playlists represent a lucrative income stream, which significantly contributes to Spotify's quarterly income of roughly €120 million in 2019 (Eriksson, 2020). Once the advertisers are allowed to access the resulting commodification of emotional states, the playlists will function as logistical devices that bind together listeners with advertisers and capital. Editorial playlists can then be compared to what Hawkins (2018) classifies as a "commercial skin" or package that encloses goods, as well as connecting them to market transactions. They go beyond the conventional function of sourcing and supplying musical content since they also transform consumers into a valuable resource, whose attention can be bought, sold and supplied on the market.

When acknowledging these profound values that enshroud editorial playlists, Eriksson (2020) contends that they allow the service to procure a higher bargaining power with rights holders and optimise its relational strategies. Bonini and Gandini (2019) assert that editorial decisions still matter significantly for music professionals. When prompted to provide a ballpark assessment of the extent to which personal taste, editorial playlists and algorithmic suggestions influence personal music consumption, one key informant - who works in the European music industry - explained that his choices are roughly 10% rooted in personal taste, 40% guided by editorial playlists, and 50% directed by personalised selections. The weight of individual instinct in guiding the choices has not completely disappeared, but it has been greatly diluted in favour of editorial directives. Relatedly, Webster (2021) highlights the existence of consumers who persistently rely on the guidance of editorial playlists to identify the selection of music that fits a specific mood or moment. In the context of working, for example, consumers would scout for playlists that radiate a serene demeanour, such as "Monday Motivation." Alternatively, if the goal is to partake in a workout session, their preferences would tilt towards the more upbeat editorial curations.

Algo-torial playlists

With the growing acknowledgement of **an algo-torial logic, which combines human and algorithmic influences**, the distinction between editorial and algorithmic playlists becomes somewhat archaic. As posited by Bonini and Gandini (2019), the algo-torial logic that governs the current state of proprietary playlist curations follows an iterative progression that begins with a prompt, yet constant algorithmic evaluation of the curated songs after their initial inclusion on a

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designated playlist. The initial phase of evaluation relies on multiple parameters, such as the frequency of plays, the total number of skips, the tally of plays completed, the time period for listening, the headcount of users who added the song onto their list of favourites and the passive or intentional modality of listening. After this evaluation period, the platforms' editors come in and rearrange the position of each track based on the analysis of these parameters. It is something that Spotify's *Release Radar* and *Discover Weekly* partake in, as they are constantly monitored by in-house editors who manage and improve the selections by using a combination of collaborative filtering, music structure analysis and a system of natural language processing algorithms that crawl through hundreds of review sites (Bonini & Gandini, 2019; Eriksson et al., 2019) .

In any case, platforms' playlists are seen as an efficient means to put more power in the hands of the platforms (Eriksson et al., 2019). In Spotify's case, considering that the service does not own the rights to any of its musical catalogue, Eriksson (2020) argues that editorial playlists offer a strategically important influence over music consumption. As of 2018, Eriksson (2020) reports that Spotify's editorial playlists have accounted for roughly 30% of the service's total streams.

User-generated playlists[3] constitute most of the MSS' playlists, with over 2 billion personal playlists on Spotify in 2020 (Prey, 2020). Each of these playlists contains digital traces that reveal an implication of the identity of the creator, the rationale behind ordering songs and the degree of popularity that is reflected through the unwavering display of likes. Data such as these traces have been described as a valuable proprietary asset, as it forms a key component for the process of curating Spotify's *Discover Weekly* playlists (Hamilton, 2021).

From the perspective of consumers, Hagen (2015b) reveals that the curation of user-generated playlists demonstrates a nascent approach of collecting music that is rooted in the conventional practice of pre-digital collecting. The practice of personal curation is a multifaceted endeavour that encompasses the activity of hoarding, sharing and searching as a means to cultivate a self-reflective digital music collection (Burkart, 2008). According to Hagen (2015b), this allows users to exert greater control on what to listen to, as well as their preferred listening order, while enabling a more context-sensitive design for the curations. The management of these curations can be distinguished as static, which imply that users retain the original arrangement of songs for the entirety of the playlists' observed existence, and dynamic, which involve a perpetual iteration of existing playlists by removing and including new tracks over time.

Despite facilitating greater control for users, Maasø and Spilker (2022) highlight that user-generated playlists are still presented as a relatively hidden feature. Proprietary playlists are still prominently positioned on the front page of all the services' interfaces, including Spotify's. When users open the service on their chosen devices, they are greeted with several rows of featured content on the home

[3] This type of playlists is also known as 'user-created playlists' or 'user-curated playlists' in several publications, and is classified as 'listener playlists' by Spotify.

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page, with a set of playlists that suggests a more prominent display of proprietary curations due to the personalised nature of the content headlines[4] (Jürgensmeier & Skiera, 2023; Krogh, 2023). While it remains suggestive for the home page, Pachali and Datta (2023) find that the 'Search' page on the interface features almost 90% of Spotify's proprietary playlists.

Additionally, further discussions on the importance of playlists can be found through the data behind MSS. For musicians and labels, understanding how playlists work and strategising to get featured on them can be instrumental in reaching a broader audience and advancing their careers in the digital age. However, the process of determining a song's placement on a playlist remains somewhat opaque, as artists and labels are still struggling to understand the criteria for playlist inclusions (Prey, 2020). This has led researchers to question the level playing field between artists and the alleged unfairness of the whole system. Datafication, the process of monitoring and analysing users' consumption patterns, has become central to this discussion, and data itself has become a valuable commodity for MSS (Hagen, 2022). It has also created a digital divide, with data-literate partners gaining power and greater positioning within the industry. While digital technologies have brought positive trends, increased security, and revenue to the music industry, there is a need to address competencies and skills required for artists to leverage these positive effects (Psomadaki et al., 2022; Watson & Leyshon, 2022; Zanella et al., 2021).

[4] Some common examples include 'Your top genres' and 'Made For You,' while an infrequent group of instances includes 'Late Night Jazz' or 'Rock 1973,' which incorporates recent listening or time of day (Krogh, 2023).

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4 Algorithmic fairness in online music ecosystems

The question of algorithmic fairness is a controversial topic among academics, particularly in computer science. Yet, it is a subject of growing interest[5] as algorithms become increasingly important in people's lives (Carey & Wu, 2022). In spite of their growing importance, Music Recommender Systems are also accused of being unfair and therefore of potentially harming consumers, artists and even the whole music industry. This is related to more general accusations towards Artificial Intelligence (AI). Negative effects of algorithms have already been demonstrated (O'Neil, 2016). For example, according to the AI Index Report, there is an important increase of incidents directly linked to the misuse of AI (Maslej et al., 2023). This is the case for generative models (see Brewter et al., 2023, among others). Regarding RS, they are accused of lacking transparency, threatening the exposure of content diversity, thereby challenging democracies, as well as violating consumers' rights and citizens' freedom of expression (Mazziotti & Ranaivoson, 2023).

4.1 Definition of algorithmic fairness

Algorithmic fairness involves ensuring that people are treated similarly by algorithmic systems – in our case MRS. Acknowledging the existence of a multitude of definitions of (algorithmic) fairness, Ferraro et al. (2021, p. 564) distinguish between group and individual fairness: "**Individual fairness** reflects that similar individuals should be treated similarly. **Group fairness** ensures that people of a protected group should be treated in the same way as the rest of the population." Related to the latter, Molina and Loiseau (2022) identify specific attributes as 'protected attributes', i.e., attributes that can lead to discrimination (e.g., gender, race, political opinion, religion, not being signed in a major label).

Wang et al. (2022) distinguish between awareness-based fairness and rationality-based fairness, with the objective of algorithms leading to a fair prediction or decision. **Awareness-based fairness** is based on users' perception or consists in taking in consideration users' feelings. Hence, it is a more user-based approach. On the other side, **rationality-based fairness** is based on statistical or causality analysis. While the latter is not necessarily superior to the former, there can be a gap between both assessments of fairness. For example, Ferwerda et al. (2023) illustrate that statistically objective popularity biases in recommendation lists are barely observed by users, even when corresponding fairness metrics clearly indicate them. The users' perception on popularity bias

[5] As Maslej et al. (2023) noted in their report that: "the number of accepted submissions to FAccT, a leading AI ethics conference, has more than doubled since 2021 and increased by a factor of 10 since 2018. 2022 also saw more submissions than ever from industry actors."

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is informed rather by subjective factors including familiarity, perceived popularity, satisfaction and perceived fairness. The ways in which fairness is perceived is also individualistic in nature, as Htun et al. (2021) explore, the personality of users impacts their perception on fairness and willingness to act towards reporting biases. In a group environment, those open to experiences did not consider fairness as very important in group playlists, as discovery had a greater value. Meanwhile, those with a conscientious disposition were more willing to report when unfairness was perceived.

4.2 Algorithmic biases

Biases are key in the way algorithmic fairness is analysed. Biases are systematic deviations in the algorithm output, performance, or impact, relative to a norm or standard (Fazelpour & Danks, 2021). **Researchers in computer science are mostly looking for biases, particularly in training data**, rather than taking a comprehensive perspective or by taking into consideration a human's point of view (Wang et al., 2022).

Platforms' profit-seeking strategies can be at the source of some biases. There is a tendency for online platforms to bias the order of recommendations in favour of catering to the most profitable transactions (Belleflamme & Peitz, 2018). Bourreau and Gaudin's (2021) theoretical model also shows that the royalty rates established between MSS and content providers (e.g., right owners) can bias recommendations. Based on their model, this can take place when the platform would recommend the largest percentage of the cheaper content, rather than the optimal content mix which the consumer would ideally like to consume. They conclude that there must be a trade-off between revenue-maximisation (i.e., by providing optimal recommendations to consumers) and cost-minimization (i.e., by offering biased, personalised recommendations).

On the other hand, stakeholders who supply and/or distribute the music can try to "game the system" (Siles et al., 2022) and manipulate their streams. An extreme case includes promoting a song or an artist by creating fake streams, fake uploads or fake playlists to generate artificial popularity. Other cases include a paradigmatic occurrence that was brought to light in March 2023, where MSS removed tens of thousands songs written by AI[6], and a form of manipulation that can occur through services like Fiverr[7] or Mechanical Turk[8], where people are paid to promote or to listen to music. Finally, a less malevolent, but probably more common source of biases relies on the quality of the datasets used to train AI-based RS, thus reflecting the developers' biases.

[6] https://www.forbes.com/sites/ariannajohnson/2023/05/09/spotify-removes-tens-of-thousands-of-ai-generated-songs-heres-why/

[7] https://www.fiverr.com/search/gigs?query=spotify&search_in=everywhere&search-autocomplete-original-term=spotify

[8] https://www.mturk.com/

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Research has identified two types of biases in the music industry that might potentially limit audiences' exposure to more music diversity. The most commonly known is the **popularity bias** in which music recommendations are reinforcing the popularity of already popular artists and songs (Kowald et al., 2020). There are concerns about the potential aggregation of music consumption around popular and mainstream content (Maasø & Spilker, 2022), with the use of algorithms being opaque to most listeners, as they remain unaware of the precise factors that influence the recommendations received (Prey, 2018). The aggregate narrowness and uniformity of music consumption can be attributed to various mechanisms in the design of MSS. A wealth of literature analyses popularity bias and subsequent mitigation strategies in various application domains (Abdollahpouri et al., 2017; Figueiredo et al., 2014; Wei et al., 2021). On the mitigation side, Boratto et al. (2022) present a reproducibility study focusing on user age and gender, applying various mitigation strategies in the music and movie domains. Different from the movie domain, the size of the user group was not indicative of the recommender accuracy in the music domain. Given their inconclusive results, it is important to look beyond popularity bias and demographic group size to understand the drivers of demographic differences. Būdaitė and Raišienė (2023) show that the reinforcement of the superstar economy, the lack of song turnover, and the diminution of acoustic diversity and local repertoire are linked to the streaming's economic model. Addressing this issue would require redesigning algorithms, editorial curation and interface design to encourage a more diverse and inclusive music consumption experience (Maasø & Hagen, 2020).

The least known and researched biases are **biases based on demographic characteristics** (i.e., ethnicity, gender, class, age, disability, sexuality and nationality), characteristics which also play a role in the different music recommendations generated by the algorithm (Schedl et al., 2015). Re-ranking is a promising method to mitigate gender bias. Ferraro et al. (2021) demonstrate breaking bias amplification through gradually increasing exposure for minority genders. Because these demographic-based biases are identity categories, they raise important questions of justice and inequality, expanding beyond the concept of biases (Hesmondalgh et al. 2023).

Although fairer models seem to be a part of the solution to reduce biases and their impact, they also display major problems. For example, it is possible to perform better on certain fairness benchmarks while having worse biases on other attributes (Maslej et al. 2023). Depending on the overall objective of the algorithm – e.g., to perform better – an algorithm can disadvantage a minority (Wang et al., 2022). Unfortunately, algorithms tend to reproduce existing societal biases (Mitchell et al., 2021). Moreover, algorithms are often proprietary and complicated to understand, which becomes problematic as people are unable to challenge them. Furthermore, people tend to erroneously believe that algorithms are neutral and objective (So et al., 2022).

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5 Conclusion

The recorded music industry's exponential growth is based on the development of music streaming, as well as the importance of music curation, in the context of very large catalogues of music being presently available on streaming services. There is, however, as pointed out by Hesmondalgh et al. (2023), limited research on the impact of Music Recommender Systems (MRS), including playlists, on music markets and consumers. There is also a limited amount of research on how MRS fit in the current functioning of online music ecosystems, and the way they should be regulated.

To start filling these gaps, this Fair MusE report aims to build an interdisciplinary and comprehensive understanding on how platforms and their algorithmic systems work, as well as their impact on consumption, and to highlight potential risks in terms of fairness. Whichever approach is used to develop MRS, they involve several stakeholders: consumers, online platforms, advertisers, music providers, etc. These stakeholders can have conflicting interests, including among themselves (e.g., music providers are competing to have their track on the most popular playlists). Among MRS, playlists have arguably become the most influential. Playlists are not only used for music curation and discovery, but also as a way to distinguish each service's position from the competition. Nevertheless, MRS raise concerns regarding algorithmic fairness, particularly when they do not treat people similarly. The research on this domain, however, is still predominantly found in computer science, with a focus on biases.

In contrast to this literature, we believe that MRS and playlists require a multi-stakeholder approach so that their impact can be fully grasped. To contribute to a fairer music ecosystem, we need to understand biases and strategies in algorithms. Such an approach considers biases on all sides, and not only in training data. This report has not responded to all questions pending in the literature. It needs to be understood as the basis for other outcomes to be further delivered by Fair MusE, which include the Music Copyright Infrastructure, the Music Data Dashboard, the Fairness Score and a White Paper to promote fairness in Europe's music ecosystems.

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