The Public Service Approach to Recommender Systems: Filtering to Cultivate

Jockum Hildén

Abstract
Online media consumption has been radically transformed by how media companies algorithmically recommend content to their users. Public service media (PSM) have also realized the potential of recommender systems and are increasingly using these technologies to personalize their online offering. PSM are on the other hand required to disseminate diverse content, which can be incompatible with the logics of commercial recommender systems that primarily seek to drive up media consumption. Drawing on previous research on selective exposure and media diversity, this study presents the results from interviews with ten PSM informants across Europe, revealing that data scientists within these organizations are highly aware of the effects recommendations have on media consumption, and design the PSM online services accordingly. This study contributes with in-depth knowledge of how diversity has been interpreted at operational levels in PSM and how recommender systems are being adapted to a non-commercial setting.

Keywords
exposure diversity, personalization, recommender systems, public service media, selective exposure, nudging, public television, new media, law, regulation, policy

Online media consumption has been radically transformed by how streaming services present and recommend content to media users. An important part of this puzzle is the use of recommender systems, essentially a set of different algorithms that recommend content based on previous use, similar viewers, or other factors. These recommender systems actively personalize the feeds of their users, using the back catalogues of the media services to generate unique interfaces for their visitors.

1University of Helsinki, Finland

Corresponding Author:
Jockum Hildén, Faculty of Social Sciences, University of Helsinki, Unioninkatu 37, 00014 Helsinki, Finland.
Email: jockum.hilden@helsinki.fi
In Europe, public service media (PSM) companies are also realizing the potential of recommender systems and the merits of distributing content in a personalized way. Although PSM companies have not been as eager to employ recommender systems as the ecommerce industry and online publishers, the tide is clearly turning and PSM are looking to using viewer data to tailor content distribution.

The personalization of media content has nevertheless been seen as a worrying trend. Concerns have been raised that personalization leads to people’s exposure to media content becoming narrower due to the rise of “filter bubbles” (Pariser 2011), creating “echo chambers” (Sunstein 2007) in the process. The High Level Group on Media Freedom and Pluralism nominated by the European Commission also expressed that the personalization of news may impact democratic societies negatively, if citizens receive only news that support their own presuppositions (Vīķe-Freiberga et al. 2013, 27). The question of filter bubbles first surfaced with reference to personalized search results and then evolved to address how the Facebook News Feed recommends content (Bozdag 2013; Sunstein 2017), but the concept has also been used with reference to online news media (Beam 2014) and other online content (Knijnenburg et al. 2016).

While the merits of this critique have been questioned (Fletcher et al. 2020; Möller et al. 2018; Zuiderveen Borgesius et al. 2016), it is unquestionable that these public debates on content personalization and recommender systems have had an impact on how especially PSM develop their online services. For present purposes and in accordance with European Union (EU) law, PSM is defined as a universally available media service that bases its operations on a remit conferred by the respective Member States.1 The goals of public broadcasters—stated in the above-mentioned remits—include fostering democratic debate, promoting diverse content, and enabling social cohesion. For PSM, claims that personalization of content creates echo chambers and produces filter bubbles must be taken seriously.

The purpose of this contribution is to examine how PSM employees across Europe envision their recommender systems and how values associated with public service broadcasting have guided their design choices. Ten informants from eight PSM companies have been interviewed for this study. The present contribution focuses on media personalization within the public service mediasphere: the websites, smartphone apps, and smart television applications. The study addresses how European PSM approach the question of filter bubbles and take diversity into account in the design of their systems. The PSM employees’ responses are analyzed with the help of theories of selective exposure and media diversity. This study is one of the most comprehensive accounts of how PSM design their online offering and raises how normative goals of media diversity are implemented in practice.

The contribution proceeds as follows. I will first provide an overview of recommender systems and how they impact content personalization. I will then look at how recommender systems could be used to promote diverse content. Taken together, I will connect empirical studies on recommender systems to media policy debates on the normative merits of media diversity. I will proceed by linking these notions to the concept of selective exposure. After providing an overview of the materials and
methods used in this study, I will then present the results in relation to theories of selective exposure and media diversity. Lastly, I will address to what extent the interviews raise novel ways of conceiving diversity.

Algorithmically Curated Diversity

The question of how recommender systems impact PSM content consumption needs to be addressed from two related, but not identical, perspectives: whether recommender systems narrow their audience’s media habits, or worse, whether these systems lead to selective exposure to media content, which contributes to societal polarization. Given that personalization can be implemented in many ways, I will first provide an overview of the technologies used to recommend content to audiences.

Recommender Systems and Content Personalization

In this contribution I refer to personalization as an umbrella term that covers all online services that are algorithmically adapted to their users’ preferences either explicitly or implicitly (Beam 2014, 1022; Thurman and Schifferes 2012, 776). Recommender systems are the underlying technologies that enable personalization of content interfaces. In practice, recommender systems filter the existing content database according to a predefined set of rules and organizes the content in a specific order.

The most commonly used filtering technologies are the following: recommendations based on demographics that factor in the audience’s age, sex, location, or education, for example Montaner et al (2003, 308–313), recommendations based on previous media use and the similarity of consumed content (behavioral and content-based filtering) (ibid.), recommendations based on users with a similar consumption profile (collaborative filtering) (ibid.), recommendations based on active user feedback (knowledge-based filtering) (Burke 2001), and recommendations based on social networks, where users’ media consumption are also recommended to their social networking site connections (social-based recommender systems) (Sun et al. 2015).

These recommender systems are complemented with more general recommendations that are not personalized, such as editor-curated recommendations, most viewed, recent, or shared content. The recommender systems are further tweaked by rules that either narrow down or widen the scope of possible recommendations. Many companies combine recommender systems and adapt them for their own purposes. News sites tend to value breaking news over more personalized content, whereas streaming services tend to focus on usage patterns to a larger extent. Contextual data is also important. Recommending full-length films in the morning on mobile devices is probably not what people want, and weather reports for the U.S. should probably not be displayed to French users.

There are acknowledged weaknesses in all recommender systems (see Burke et al. 2011). Demographic recommendations are rarely accurate enough, behavioral and content-based filtering might result in very similar recommendations, collaborative filtering requires a lot of users and a lot of content to work properly, and
knowledge-based filtering requires the active participation of users. Some degree of variation in the recommended content is usually preferable. This does not necessarily mean that recommendations should be diverse, but that recommender systems should offer some degree of (positive) surprise. This is usually referred to as “serendipity” (Andersson Schwarz 2016; Kotkov et al. 2016).

On the other hand, the most valued commercial metric is the click through rate (CTR), that is, the relationship between exposed content and selected content. The diversity of recommendations might be a nice addition, but only if it leads to more daily usage. If, however, one departs from the CTR metric in favor of other metrics such as self-actualization and user satisfaction (see Willemsen et al. 2016), it might be worthwhile recommending lists of content the recommender system gives a low rating, items that are polarizing, or items that have not been previously consumed by others (Knijnenburg et al. 2016). While these lists might not generate as many clicks, they can lead to overall user satisfaction.

**From Exposure to Engagement Diversity**

Most European media legislation lists access to diverse and high-quality programing as one of the key public service goals (Council of Europe 2007; Council of the European Union 1999; Gibbons 2015; Karppinen 2013). However, diversity as such is rarely defined. Napoli (1999) provides a useful taxonomy of diversity, dividing it into three categories: source, content, and exposure diversity. Source diversity refers to both the plurality of media sources, their ownership as well as the diversity of the workforce at the media organizations. Content diversity refers to the diversity of programing, the diversity of represented demographic groups and diversity of opinion. Lastly, exposure diversity refers to the extent citizens consume diverse programing.

Due to how media consumption has evolved, the focus of policymakers and academics has partly shifted from spheres of production to those of distribution, which means that exposure diversity will have to be taken into account to a higher degree (Napoli 2011). Since recommender systems play such a prominent role in how content is consumed (Cobbe and Singh 2019), I propose that exposure diversity should be limited to what is shown to people either programmatically or linearly, whereas engagement diversity signifies what media content people choose to access, immerse themselves in, and share with their peers. My reason for including this fourth aspect of diversity is simple: this is how media companies operate, which Napoli (2010, 96) has also recognized in his other work on online advertising. To clarify, this distinction also means a departure from Napoli’s definition of exposure diversity that includes consumption of content. Rather than seeing the components of diversity as causally connected, content diversity is a precondition for exposure, and engagement diversity.

Ideally, all PSM employees should aim for fulfilling the public service remit in their work. On the one hand, this means that human resources should try to employ people from different backgrounds, that the script writers should include a diverse set of characters in drama productions, and that the casting directors should pay attention to who they are hiring for what role. It means that scheduling strategists should make
sure that there is diverse programing also during prime time. But since all that is produced no longer gets shown to all viewers the public service mission extends also to the technical employees designing recommender systems.

Mere access to the full programing portfolio says very little about what content is ultimately consumed (see also Cobbe and Singh 2019). Diversity can therefore no longer be measured in terms of program output, because the presentation of the output will be tailor-made and defined by people’s previous media use. On the other hand, it is of course true that media organizations cannot take full responsibility for what people end up actually consuming, but given that PSM have a legal obligation to provide diverse content, this should extend to an obligation to at least expose citizens to different viewpoints and types of programing. Furthermore, Bozdag and van den Hoven (2015, 250) would argue that minorities also have a right to be heard in the media, which adds another requirement that public service recommender systems should take into account.

The discussions on what content recommender systems should put forth partly resembles old debates on the purposes of public service broadcasting—to what extent is it in the public interest to show light entertainment? Is the paternalistic approach to public service broadcasting being revived in the digital age? Helberger (2015) acknowledges that while there are paternalistic tendencies in recommending diverse content to users, the situation is fundamentally different as PSM are no longer the gatekeepers that they use to be in the era of public service broadcasting monopolies.

Some researchers propose that citizens’ “media diets” may be purposely diversified with the help of recommender systems (Bozdag and van den Hoven 2015; Helberger et al. 2016). Helberger et al. (2016) suggest that PSM should employ recommender systems that expose their users to diverse content. They refer to trials where researchers increased the diversity of recommendations using long-tail dynamics, where less popular content was recommended even though more popular options were available (Lathia et al. 2010; Ozturk and Han 2014; Vargas and Castells 2011). Adomavicius and Kwon (2012) point out, however, that while it is possible to pick out recommendations from the long tail, the accuracy of recommendations will suffer. Other scholars have reached similar conclusions while trying to diversify recommendations (Smyth and McClave 2001). It is nevertheless possible to recommend slightly more diverse content without needlessly sacrificing the accuracy of the recommendations. It would therefore seem that it is up to the service provider to determine an appropriate engagement trade-off to be able to provide more diverse content. In practice this means an increased risk of losing the user’s interest.

It is worth highlighting that media policy scholars and recommender system engineers tend to define diversity quite differently (Möller et al. 2018). For engineers, diversity is often measured in terms of item-item similarity, typically based on item content (Shani and Gunawardana 2011, 288). For example, Nguyen et al. (2014, 681) define the diversity of movies by looking at the tags used to describe them on the Movielens service. While content tags might sometimes suggest some aspect of diversity, aggregated distances based on content tags might be seen as quite large despite the content being fairly similar from a media diversity perspective. On the other hand, theoretically
advanced conceptions of diversity are of little help if they cannot be operationalized (cf. Möller et al. 2018). It is equally important to be able to create rules and weights for algorithms so that the diversity goals are achieved (see Sørensen and Schmidt 2016).

The public service remits contain very general depictions of diversity, yet from the outset it is clear that they differ from the engineering perspective. For example, 7 § of the Finnish public service broadcasting law states that the PSM should offer “diverse information, viewpoints, and discussions” and support “equality, tolerance, cultural diversity.” Similarly, 14.1 of the BBC Charter states that “The BBC must ensure it reflects the diverse communities of the whole of the United Kingdom in the content of its output, the means by which its output and services are delivered (including where its activities are carried out and by whom) and in the organization and management of the BBC” (Secretary of State for Culture, Media and Sport 2016). Exactly how these goals of diversity should be incorporated in practice are not included in the remits, and they remain disputed (see Karppinen 2013). It is nevertheless clear that the duty to provide diverse content applies both to television programming and online news.

Some diversity aspects are also easier to incorporate into a recommender system than others. For example, genres and themes are easy to determine at least on a general level, but questions of demographic representation and the diversity of ideas and viewpoints are far more difficult as they require quite detailed content tags in order to work. Tagging content and attributing these tags to users might also be politically sensitive especially within the context of news recommenders. Willemsen et al. (2016) provide an alternative solution, where collaborative filtering is used to recommend items that are regarded as diverse based on the latent features an algorithm has identified. The items’ diversity is therefore decided based on what the algorithm perceives are the users’ preferences and not the diversity of the content as such, although the two are expected to correlate.

Another potentially sensitive issue is the question of whether dictating user choice toward more diverse content is an intervention with the users’ autonomy (Helberger et al. 2016, 11). So-called nudges, popularized by Thaler and Sunstein (2009), can be perceived as manipulative (cf. Hansen and Jespersen 2013). In Hansen and Jespersen’s (2013) view design that encourages certain choices should not be viewed as manipulative if it is transparent to users, but non-transparent nudging raises ethical concerns in most cases.

The calls for increasing the diversity of recommended content can be traced to the concerns that content personalization causes “filter bubbles” that shield audiences from contrarian viewpoints and lead to automated selective exposure. It must be stressed that narrowed media habits cannot be directly equated with selective exposure, but the two are not unrelated. As such, it is necessary to review the findings from studies on selective exposure to evaluate whether also public service recommender systems may contribute to societal polarization.

Filter Bubbles or Mere Organic Selective Exposure?

The question of whether personalized online services narrow people’s access to information and contribute to the polarization of society draws heavily on psychological
theories of cognitive dissonance. According to Festinger’s (1957) original theory, people tend to avoid situations where cognitions and beliefs are in conflict. Instead, people strive for cognitive consistency, either changing attitudes upon receiving new information, or actively ignoring or even questioning new information that conflicts with held beliefs. Traditionally, this has meant that people tend to subscribe to newspapers or watch television channels that promote similar attitudes as they hold themselves (Klapper 1960).

Whether the Internet increases or decreases selective exposure has not been conclusively proven in empirical studies (Dylko 2016; Fletcher et al. 2020). A vast number of studies on selective exposure have shown that people tend to consume media content that supports their worldview (Frey 1986; Garrett 2009a, 2009b; Hart et al. 2009; Iyengar and Hahn 2009; Knobloch-Westerwick and Meng 2009; Munson and Resnick 2010; Sears and Friedman 1967; Stroud 2010; Sweeney and Gruber 1984). It may be noted that most of this research has been focused on the consumption of news (see also Newman et al. 2019). This does not necessarily mean that people actively seek to avoid news that challenge their views, as Webster (2014, 34) points out.

However, when the presentation of content is automatically personalized, the question of whether one chooses to avoid certain types of content becomes increasingly irrelevant, as the choice is never actively presented. The consumption of content is not so much decided by the availability of content but by what is recommended by the media platforms (Cobbe and Singh 2019). According to Webster (2014, 143), the question of whether personalization is problematic depends on “the filter’s ability to cultivate, rather than simply cater to, our preferences.” In other words, personalization can be problematic even if people are not perfectly confined to filter bubbles—which is in itself unlikely, as there is a plethora of content being circulated on all kinds of platforms.

Although the concept of filter bubbles is based on the notion of technology steering consumption (Pariser 2011), the novelty does not lie in the underlying principle of selective exposure, but that people are less aware of the automatic sorting and filtering of information that happens before social media, search engines and now media companies present them with content. The big question that remains a matter of debate is whether technology intensifies this fundamentally human characteristic (Dylko 2016).

Empirical research on automated selective exposure both support and challenge the notion of filter bubbles. Importantly, the research tends to focus on social media and not on the personalization of media websites or apps. Most of the research comes from the U.S., where there is a clear dividing line between liberals and conservatives in terms of party affiliation (cf. Pew Research Center 2014). According to Benkler et al. (2017) the explanation cannot be technocentric, since the same insulation should be witnessed on the left as well as the right of the political spectrum. Instead, their research on hyperlinking practices suggests that the selective consumption of political content is not caused by algorithms but by human agency. Other studies have supported the claim that the composition of the users’ social network is the most decisive factor when looking at how diverse people’s news consumption is (Bakshy et al. 2015; Barbera et al. 2015; Bright 2016; Flaxman et al. 2016; Nikolov et al. 2015; Pentina and Tarafdar 2014).
In nations where political power is divided among several parties, political polarization is more difficult to measure, and it is unclear whether it would even be possible. It is also worth noting that the U.S. media environment is highly fragmented compared to Europe’s. The biggest television news reports reach only 10 to 15 percent of the population (Prior 2013). In that environment, it is natural that the focus is on social media that acts as gatekeeper to media content. In Europe, public service broadcasters are not equally dependent on social media and regularly reach over half of the population (see Newman et al. 2019), which means that recommender systems on the media websites themselves could potentially have a much bigger impact on what news and other content people eventually end up consuming.

Research on online news consumption has found that people actually read more diverse content online on generic news sites (Brundidge 2010; Kim 2011). There is still no convincing research on how the personalization of online news affects people’s reading habits, as the systems have not been in place long enough (Zuiderveen Borgesius et al. 2016). Beam (2014) conducted an experiment with different types of recommender systems that exposed fictional news articles to a sample of Ohio residents, but as the results can only be said to apply to the recommender systems applied in the experiment, it is difficult to draw wide-reaching conclusions from the results, apart from the obvious: design choices matter.

In another study on news recommenders by Möller et al. (2018) it was also demonstrated that recommender systems generally produce more diverse recommendations than human editors: personalized recommendations “showed no reduction in diversity over the non-personalized recommendations; on the contrary, personalized collaborative filtering produced the highest amount of topic diversity” (Möller et al. 2018, 971). There were nonetheless differences between recommender algorithms. It is also probable that studies on news recommenders lead to different results than studies on streaming services.

While the evidence appears to be somewhat inconclusive regarding the effects of personalized content and algorithmically curated content on the diversity of media consumption, it is possible to draw some conclusions. First, it appears that personalization based on social networks may partly narrow the diversity of media content both in terms of presentation and consumption. While recommender systems play a part in this, the most decisive factor is still people’s own social networks. The effect this has on PSM is tangential and depends on the extent viewers get their PSM content via social media. Second, there is very limited evidence of what impact the personalization of news services has on news consumption, and the empirical studies that have been conducted highlight that the type of recommender system matters greatly. Third, differences in media consumption between services are likely to reflect the partisanship of the consumers of certain media outlets rather than the differences in their recommender systems. Fourth, a lot of research focuses on political polarization, which is more pronounced in the U.S. than in Europe (Fletcher et al. 2020). PSM recommender systems are therefore unlikely to strengthen political polarization even if they might decrease the diversity of people’s media consumption.
Nevertheless, it is evident that recommender systems have an impact on what content people ultimately consume. Design choices can impact the level of diversity viewers are exposed to, and there is great variation between recommender systems. Importantly, the level of user involvement differs between services and can greatly affect the output of the recommender systems (see also Thurman and Schifferes 2012).

If exposure to diverse content is a stated goal of a media organization, it will thus have an impact on how recommender systems are created. In a study of PSM companies Norwegian NRK and Belgian VRT, Van den Bulck and Moe (2018) concluded that the personalization strategies these companies employ are largely dependent on views related to whether personalization strengthens or threatens universality. In other words, the perceived effects of personalization are one of the most deciding factors behind the technological choices involved. Andersson Schwarz (2016) has also demonstrated that similar considerations have hindered the otherwise technologically advanced Swedish public broadcaster SVT from implementing recommender systems. Even if one reaches the conclusion that filter bubbles do not contribute to political polarization, the literature on recommender systems still acknowledges risks with producing similar recommendations to users. This is contrary to the goal of diversity acknowledged in PSM remits.

From the discussion above it is obvious that there is a wide variety of normative questions that need to be solved in order to implement technologies that advance the diversity of recommended and consumed content. More often than not there can nevertheless be a disconnect between the strategic vision of media companies and the decisions taken on the ground. I will now present what methods and materials were used in order to gather insights on how recommender systems have been designed and implemented in the context of PSM.

**Materials and Methods**

This contribution presents results from interviews with ten PSM representatives from the following companies: the BBC and Channel 4 (UK), RTÉ (Ireland), DR (Denmark), YLE (Finland), RTS (Switzerland), VRT (Belgium), and ZDF (Germany). The level of sophistication of their recommender systems varies, as do their approaches to using third party services. Many PSM organizations are in the early stages of adopting personalization services, and there are vast differences between the different companies. It may be noted that commercially funded Channel 4 started working with personalization already in 2011 and has been regarded as a pioneer among PSM. All of the informants in this study work for companies that have introduced personalization to their streaming services, and some have also introduced personalized news recommenders.

The thematic, semi-structured interviews were conducted in the spring of 2017, either in person or via video conferencing software. The interviewees were selected partly based on referrals from other interviewees. Some interviews were conducted with two or three employees present at the same time. The interviews were recorded and transcribed.
At the time few PSM in Europe had advanced recommender systems in place, and the ones that did had some degree of knowledge of what their colleagues were planning. The interviewees were either in charge of the provision of digital services or worked directly with the personalization of the online services in data scientist or engineering roles. The interviews were focused on two themes: what recommender systems these companies employed, and how these informants addressed the question of diversity. The first theme included questions on the types of technologies they had considered, whether they had programmed the recommenders themselves or bought them from other providers. The second theme related to selective exposure and how the informants looked at the PSM goal to provide diverse content to their viewers. This order was chosen in order to first gather insight on the technical choices in order to continue asking questions on the normative nature of those choices. As noted in the literature, the choice of recommender system will have implications for the diversity of the content recommended. The questions related to two connected but separate themes: to what extent the informants believed that selective exposure was a problem, and how this problem was addressed when designing the recommender systems.

The informants were either senior technical management or data scientists employed at the PSM. While some informants were happy to be on record, others preferred to speak on the condition of anonymity. For this reason, the names of the informants have been redacted and are simply referred to with numbers. Not all informants have been quoted below. It must be stressed that the views expressed by the informants are not the official views of their employers. When a comment is specifically about a company policy, I have not redacted the company name, but in most cases I have left out the name of the company because it would be easy to identify the informants if it were included.

**Results**

Before turning to the question of designing recommender systems that promote diversity, I will provide some contextual information on the recommender systems PSM use. The PSM recommender systems are largely based on automatic personalization, which can be compared to a similar trend witnessed in Thurman and Schifferes’ (2012) research on personalization in news organizations. This is mostly a practical choice: people are used to personalized offerings on other platforms and do not bother with fine-tuning their services. At the BBC, 97 percent of the users are uninterested in customizing their personalization. The BBC informant did, however, regard the BBC as “morally obliged” to provide their users with the possibility of tweaking their recommendations—which can be related to the question of autonomy raised by Helberger et al. (2016). On streaming services, this tweaking is often limited to liking and disliking content, which is the case in the BBC + app (BBC 2020). The news apps provide more options such as Finnish YLE:s news app Uutisvahti, where users can search for themes and assign their own weights to those themes on a five-point scale.
The recommender systems are very similar across Europe. They are based on either behavioral or content-based filtering or collaborative filtering, and the personalization is partly dependent on the device being used. RTS, Bayerische Rundfunk (BR) and RTP are currently collaborating on a recommender system for public service broadcasters under the Personalization for EACH project (PEACH). RTS uses collaborative filtering to provide personalized content, whereas BR uses content filtering. The decision to use a certain recommender system is not ideological but constrained by the data sources available. The companies acknowledge the same weaknesses in different solutions as Burke (2001), highlighting the need for enough users for collaborative filtering and enough metadata on programing for content filtering.

The PSM cannot readily rely on recommender systems off-the-shelf, due to the fact that such commercial recommenders generally promote consumption over other values. In order to fulfil their public service goals, they either must build systems of their own or tweak existing systems in order to make sure that PSM goals are met. While some actors have opted for building their own recommender systems, attracting top talent to build these systems is difficult. Moreover, the data scientists and engineers are usually expected to work on a number of other different projects at the same time. In general, it is becoming more common that recommender systems are provided by external contractors and tweaked to the PSM environment instead of building the systems from the ground up—such is the case for the BBC, Danish DR and Irish RTÉ. The Finnish and Norwegian PSM have nevertheless opted for developing their own recommender systems. The PEACH project has also developed their own “diversified algorithm” (EBU Technology and Innovation 2019) based on Willemsen et al. (2016) latent feature diversification recommender model. It is also worth mentioning that the employees that work on streaming recommendations also work on other recommender systems within the organization.

The PSM employees are very skeptical of the whole concept of filter bubbles, and do not believe that recommender systems would cause people to only read news or watch programs that support their views and preconceptions, contrary to the scenarios Pariser (2011) and Sunstein (2007) envision. Instead, they often maintain that the generic pages are often more of a concern from the perspective of diversity.

“We are serving a very specific audience, which is news and sports junkies, and we’re doing that very well. But we are losing this other female audience, we’re losing a younger audience, we’re losing a rural audience. We have the content, it is there, but when they come to the site, all they’re seeing is news and sports, because that’s what we’ve been serving up.

. . .

What I’m finding is that the . . . organization is the filter bubble. In our case News, Current Affairs and Sports are what the organization seems to absolutely thrive on and pushes to the fore. And culture and all of those are seen as our public service stuff that we have to do, which, I suppose, I’m kind of challenging now.” (Interviewee 01)
The increased drive to look at analytics has in other words created a situation where segments are not treated equally online, as most of the users are thirty five years old men and the generic front page is prioritized according to their interests. The end result is a feedback loop where the most popular content gets the most coverage to the detriment of more marginal types of programing that interest smaller viewer groups. Recommender systems can mitigate this dynamic, bringing diverse content to viewers’ personalized front pages.

Two informants were of the opinion that the discussion on filter bubbles is fairly one-dimensional. They would like a more granular approach to the concept by looking at different types of filter bubbles. If someone is only interested in one particular type of sports it is probably not an issue that drives societal fragmentation and needs to be corrected by recommending diverse sports programing. Here it may be noted that the need to provide diverse content according to the public service goals might sometimes be conflated with the idea of countering filter bubbles. It is therefore a broader perspective than what is traditionally raised in the selective exposure literature. They do believe, however, that it is important that people do not receive a one-sided view of political news, for instance.

“We would love to see nudging on thematic basis not just genres. First we would probably like to prioritize political nudging. But in what case would you ever want to nudge for hobbies?” (Interviewee 02)

The points raised are in line with Helberger, Karppinen and D’Acunto’s (2016) and Möller et al.’s (2018) positions that stress the important of determining what function diversity serves in a specific context. Arguably it might not be worth the risk to question someone’s homogenous viewing if the topic in question has little relevance for democratic societies. Overall, PSM representatives are well-versed with the question of viewer autonomy and conservatively recommend content that is quite different from what users have consumed in the past.

“Maybe we can’t move you from X-Factor to political debates but we can move you from X-Factor to a hunting show. . . . It’s like being a DJ, how do you move people from pop to rock? You need to have a segue song so you don’t lose everybody on the dance floor.” (Interviewee 03)

One informant points out that it is possible to identify users who consume narrow and one-sided media content and recommend them more diverse content. The goal is, using Webster’s (2014) terminology, to cultivate, which is directly connected to the normative ideals associated with PSM. This way of looking at recommender systems is present in some form in all interviews.

There are also risks associated with the nudging toward diverse content. On the one hand people’s freedom to choose content might be limited (see Napoli 2011), and on the other hand the nudges might upset the users so that they will refrain from using the service in the future. Although PSM employees make no reference to Festinger’s
theory of cognitive dissonance, many informants are aware of the risks involved in recommending content outside users’ established fields of interest.

“There is a danger as your end user might not be interested in looking at the content you recommend, and we need to respect that. It is difficult to draw the line between respecting a viewer’s behavior and widening his view. In some areas people are willing to accept change. In others they don’t. . . . The filter bubble is a spectrum. The things in the center are unlikely to change, but the things around the edges are interesting. Those you can have an effect on.” (Interviewee 04)

As can be deduced from the quote, the data scientists working at the PSM companies are far from paternalistic in their views, signaling partly that they take the autonomy of their users into consideration, and partly that they are afraid to alienate viewers by enabling radically departing recommendations. Moving along the edges is an apparent strategy in several companies.

“Viewers don’t always navigate content through genres. They often watch content across multiple genres. We created microgenres and we’ve used that to understand how viewers navigate through content. We have a content cluster map that looks like a constellation. You see very quickly that there are small pockets of content that move together, and it is very hard to move viewers from the bottom left to the top right [of the constellation], it is just too big a distance. But there are lots of connecting shows that help you nudge a viewer through the different concentrations of programs to get them on a journey of wider discoverability, and I think that’s the longer-term objective.” (Interviewee 05)

There is a great deal of uncertainty in how these longer-term objectives will be fulfilled, and PSM companies are experimenting with different solutions. Another informant provides an alternative vision: what if instead of looking at the diversity of content, PSM instead focused on showing content that is popular in one demographic to a demographic that normally would not watch those types of programs?

“There’s a really high level of normativeness in saying that you want to move people between genres. And maybe that’s not the goal? Maybe that’s just a product of a lack of creativity? Maybe what you want to do is much more granular? Some people live in the provinces and watch antique shows and some people are living in [a city] and drinking fair trade latte and watch other kinds of shows. Those could be the filters. And maybe the goal is not to move you from documentary to entertainment to news; maybe the goal is to move you outside of your [city] bubble into the provinces bubble?” (Interviewee 03)

While such an elaborate recommender system is yet to be put in place, the idea demonstrates the difference between engineering perspectives on diversity and more normative definitions of media diversity. The PEACH diversified algorithm that relies on collaborative filtering to recommend diverse content could potentially achieve the normative goals of media diversity, but given that the algorithm does not address the
diversity of content but only diversity relative to user preferences, it is unclear whether it succeeds in recommending also diverse viewpoints, for example.

Trial runs at Danish DR, Finnish YLE and Irish RTÉ confirm Adomavicius and Kwon’s (2012) research results that long-tail recommendations will result in engagement loss. Nevertheless, RTÉ and YLE have demonstrated that personalization contributes to a higher CTR than a generic page even when diversity requirements are in place. Because the CTR can be up to 600 percent higher for personalized content compared to generic content, even a 30 percent decrease in engagement for diverse recommendations can be deemed acceptable. While recommendations that aim for more diversity defy commercial logic, this might be perceived worthwhile for PSM that aim to fulfill their public service remit and are not directly dependent on CTR. This view is also echoed by the developer of the PEACH project’s diversified algorithm (Eickhoff 2017).

People get worried that we’re building a tabloid. So, we’ve been demonstrating recommendations within our X-Factor universe. We’ve been showing people [in the organization] what the engagement cost is of giving people what they don’t actively want like domestic and international news instead of X-Factor. We can demonstrate what the engagement cost is at least in terms of click through rate, and then we can go to the media strategy management here and ask if they want to spend 60 per cent engagement loss in recommending broad content to people who are interested in X-Factor. And maybe the answer is yes? (Interviewee 03)

Although personalization may be used to introduce some aspect of diversity into monotone viewing habits, all of the informants raised the importance of manually curated recommendations in addition to automatic recommender systems (see also Van den Bulck and Moe 2018). Part of the problem is the lack of metadata as mentioned above, and limits of artificial intelligence (AI). A lot of companies have tried using machine learning for automatic metadata recognition, but a fully automatized process may result in faulty categorizations and bad recommendations. While it might not be feasible for smaller companies to curate content at a detailed level, editors can use slightly broader strokes to recommend content. This hybrid approach to recommender systems where manual curation precedes the personalized recommendations is becoming an important aspect of achieving exposure diversity.

**Discussion**

The interviews reveal that questions on diversity are of great importance for the teams working on personalization within PSM. The negative debate on filter bubbles and echo chambers has created political suspicion toward personalization and recommender systems that leave especially PSM vulnerable for critique. The PSM informants were highly aware of the concept of filter bubbles, yet most were dismissive of the phenomenon, and did not see it as problem in their own organizations. A much stronger concern is how the outstated goal of providing diverse content is interpreted.
in practice. It can of course be argued that the informants wish to demonstrate that their organizations take diversity seriously and amplify this message in the interviews, but given that their technical expertise is highly sought after, they could work for other employers that do not require this normative dimension. In other words, it appears that not only do they keep the public service institution in high regard, they are also interested in the challenge of developing diverse recommender systems.

The question of how diversity may be translated into concrete principles is nevertheless largely unresolved, and most trials at the PSM companies have focused on thematic or genre diversity. The difficulty in defining diversity on the level of ideas and viewpoints means that it is often easier to take genre diversity into account in the recommender system. Moreover, it is often easier to curate diverse recommendations with the help of editors. While human curation is resource intensive, for PSM it might be a smaller challenge to devote resources to curating content, as this expertise already exists within the organization, whereas data scientists and engineers often need to be recruited from other sectors. A hybrid approach to personalized recommenders where curators provide content lists is therefore becoming more common—as is the possibility to click on favorites. Given that PSM in Europe do not have access to datasets as large as some of the global streaming providers these strategies offset the pitfalls associated with bad recommendations due to lack of data.

Some PSM are experimenting with different concepts of diversity that are more focused on differences in viewers rather than a plurality of genres. The advantage of this approach is that it circumvents the difficult task in identifying different viewpoints and ideas in the content in order to expose viewers to a diverse set of opinions. These experiments rely on exposing content popular in one user cluster to a cluster that is diametrically different, essentially using collaborative filtering in a counter-intuitive way. While the accuracy of such recommendations is probably a lot lower than recommendations based on traditional methods and lead to lower engagement, the exposure diversity undoubtedly increases. A topic which therefore merits further study is to what extent PSM that have implemented recommender systems are willing to forego commercial metrics in order to promote diversity. As many PSM companies also rely on advertising income for their funding, it is possible that approaches diverge on this point.

It appears that using recommender systems for online streaming is becoming the new normal also for PSM. The next frontier is unquestionably news personalization, where some PSM, such as BBC and YLE, have taken more steps than others, like SVT in Sweden. News personalization is clearly closer to the alleged problem of filter bubbles, which explains why the question of personal choice becomes much more important. Future research could explore how especially news apps are designed, and how the PSM try to balance news personalization with goals of universality and diversity.

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ORCID iD
Jockum Hildén https://orcid.org/0000-0002-2091-0330

Notes
1. See European Commission 2009. It may be noted that public service media companies can be completely commercially funded, but most are predominantly publicly funded.
2. The basic idea behind collaborative filtering is that users with similar consumption patterns tend to like similar content. The recommender system recommends the content that one similarly profiled user has consumed to other similar users that have previously not consumed that film or song. This is how Spotify’s “Discover Weekly” service works (Pasick 2015).
3. Direct quotes have been lightly edited.

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**Author Biography**

**Jockum Hildén** is a postdoctoral researcher in the Communication Rights in the Age of Digital Disruption research consortium funded by the Academy of Finland. His research focus is on internet and media policy in the European Union.