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Managing the Filter Bubble in Digital Journalism

Abstract

Filter bubbles have attracted much attention in recent years in terms of their impact on society, the need for regulation, and approaches to managing or avoiding them. We want to turn away from metaphors that aim at making “the bubble burst” and argue that filter bubbles are dynamic, rather slowly changing constructs that underlie temporal dynamics and need to be managed, and the user should be in control of them. Anchored in a research setting with a major public broadcaster, we follow a design science approach on how to design the temporal dynamics in filter bubbles and how to design users' influence over time. We qualitatively evaluate our approach embedded in a smartphone app prototype for personalized radio and found that the adjustability of filter bubbles leads to a better co-creation of information flows between information broadcaster and listener.

1. Introduction

The internet becomes more and more personalized. A considerable portion of news, search engine results, and advertisements are already tailored to the interests of the users, and music and video streaming services use recommender systems to personalize their offerings. While recommender systems help users to overcome information overload [1], critics say that they tend to create filter bubbles [2] and lead to an unbalanced consumption and biased perspectives, often without users being aware of it, and have damaging potential to society [3–5].

Personalization and filter bubbles drew a lot of attention in the last years in social science (e.g., [6–9]), computer science (e.g., [10, 11]), information systems (e.g., [12]), and law (e.g., [13, 14]) from technical, regulatory and societal viewpoints. Much work has been done that emphasizes the importance of filter bubbles for opinion formation and social processes, and diverse approaches have been proposed how to make users aware of unbalanced consumption of content (e.g., [4, 5, 15]) or how to avoid filter bubbles (e.g., [16]). However, the number of approaches proposed to manage filter bubbles is relatively small in comparison to the attention that filter bubbles receive in terms of impact.

In order to effectively manage filter bubbles, it seems helpful to reconsider the nature of filter bubbles. Pariser, who coined the term filter bubble, described it as a state where non-transparent algorithms create a “unique universe of information” [2, p. 10] and isolate users from a diversity of viewpoints and content. Filter bubbles are immaterial constructs and are based on algorithms that define the preselection of content. While it is commonly agreed that filter bubbles have a pure algorithmic background, they can be separated from echo chambers, which lead to a similar phenomenon of bias, but, in contrast, can be seen as the social counterparts of filter bubbles and refer to the peers of a recipient that have similar opinions and therefore lead to a reinforcement of the recipient’s opinion [17, 18].

As filter bubbles generally have a rather negative connotation, the idea to make them burst is obvious. But filter bubbles do not pop like soap bubbles or speculative bubbles. For example, in digital journalism, it is hard to find an event like the upcoming of a new article with a different opinion, a new topic or a new insight that could serve as the needle to make the bubble burst. Approaches that deal with “bursting the filter bubble” usually rather weaken the effect of the filter bubble and increase diverse exposure. The image of “bursting” the bubble might, therefore, be misleading. Regardless of whether the image of the bursting bubble is correct, we need approaches on how to get along with filter bubbles. Filter bubbles emerge from the application of a filter, lead to a preselection of content, and though the filter rules might be static, the filter is continually fed with new data from user feedback, so filter bubbles change over time. So, we argue that filter bubbles should be regarded as dynamic constructs that underlie *temporal dynamics*. In this view, filter bubbles may slowly inflate or deflate over time, according to the data the filter uses.

There are different ways of dealing with filter bubbles. One approach is preventive – to try not to let filter bubbles arise (to avoid them) by algorithms that run in the background and assure balance and diversity (e.g., [16]). The other approach is permissive – to allow filter bubbles but to give the user control over them, so the user can play the corrective factor (e.g., [4, 5, 15, 19, 20]). We want to focus on the latter – the manageability of filter bubbles.

As we regard filter bubbles as dynamic constructs caused by technology, the question of how to manage filter bubbles is synonymous with the question of how to design the *dynamic change*, also known as *temporal dynamics* [21–23] of filter bubbles. In recommender systems applications, users can often readjust and change the likes and ratings they gave for every item ex-post – but given dozens of likes every day, readjusting likes on an item-by-item basis can be quite time-consuming. Rather, adjustments (temporal changes) to the user's interests (likes) that make up the filter and subsequently the filter bubble, need to be made differently.

Hence, we ask the question: *How to design the change of filter bubbles over time and give users control over their dynamics?*

The remainder of this paper is structured as follows. In the next section, we draw upon related work. In Section 3, we depict our design science approach, the research setting, design requirements, and design principles. We follow with an evaluation and conclude with a discussion and limitations.

2. Related work

Research on filter bubbles is closely related to the research field of recommender systems [1]. Recommender systems can be roughly divided into collaborative filter approaches (which give recommendations on similar user behavior [24]), content-based filter approaches (which give recommendations on the similarity of items [25]), or hybrid approaches [26]. All approaches have in common that they tend to produce filter bubbles. In the following, we present related work from two different fields. First, we refer to approaches that directly aim at avoiding and controlling filter bubbles, and second, we refer to value co-creation, as giving users control over filter bubbles is a matter of co-creation of value between information provider (e.g., broadcaster) and information recipient (e.g., listener).

2.1. Approaches to avoid and control filter bubbles

Several approaches exist to avoid or reduce the risk of filter bubbles. Ekstrand et al. [27] propose a way to prevent filter bubbles by giving the user control over the algorithmic settings. This can be the selection of algorithms, or the possibility to combine one algorithm with another. They also propose to give the user control over the degree of diversity of the information from the user profile using adjustable variables [27]. Interactive Recommender Systems have been proposed that aim to give the user more control over the recommendation process and to improve transparency, e.g., [28].

Li et al. propose a system called "SCalable two-stage pErsonalized News rEcommendation system" (SCENE) to avoid filter bubbles. SCENE is a two-level algorithm whose first level divides articles into topic categories relevant to the user and whose second level recommends individual articles from these categories [29].

Iaquinta et al. [30] present a concept of a hybrid recommender system that combines a content-based approach with serendipitous heuristics in order to avoid filter bubbles with surprising suggestions. Required for their serendipity method is a content-based recommender system, that implements their anomalies and exceptions approach. They follow the idea that content should not be recommended if it is too similar to items the user has already consumed.

Webster & Vassileva [31] proposed an interactive visualization approach to explain and modify a collaborative filtering recommender system. The system shows the user which other users are most similar in terms of their preferences. Additionally, the user can change the degree of influence that the other users have on the recommendations individually for each user.

Bozdag and van den Hoven [5], Munson and Resnick [15], and Resnick et al. [4] present several approaches on how to "burst the filter bubble" by making the user aware of unbalanced consumption.

Nagulendra and Vassileva [19, 20] introduced an interactive visualization approach to illustrate and increase the awareness of the filter bubble in Online Social Networks. They designed their visualization based on a bubble metaphor to improve the comprehensibility of the filtering process in a way that is intuitive for the user. Category bubbles within the filter bubble show which categories are relevant from the recommender's perspective. The larger the bubble the greater the relevance of the category. Their system also offers the possibility to show which friends are most similar in terms of their interests. Additionally, users can modify the filter bubble by adding or deleting categories using a drag and drop function.

2.2. Value co-creation

In traditional journalism, value is mainly created by the information provider (broadcasters, media houses, publishers) and consumed by the information recipient. The recipient has a rather passive role with hardly any interaction possibility. In digital journalism, however, feedback channels exist that allow a value co-creation between information provider and recipient.

Value co-creation is one of the key axioms of service-dominant logic (SDL). As proposed by Vargo and Lusch [32], service rather than goods is the basis of economic exchange. Service is defined as "the application of specialized competences (knowledge and skills) through deeds, processes, and performances for the benefit of another entity or the entity itself" [32, p. 22]. SDL argues that value is (a) not created by a manufacturer or provider, (b) not embedded into products upon production, and (c) not exchanged in economic transactions (i.e., value in exchange). Rather, it argues that value is co-created when providers and customers interact—that is, when customers integrate their competencies with providers' service offerings (i.e., value in use or value in context), thereby making customers co-producers [32].

Traditional journalism focuses on producing and storing a tangible output (i.e., articles) that has embedded value that is exchanged. From the perspective of a media house, the goal is to create a product that is appealing for a target audience. Even though one might refer to traditional journalism as a "service," it offers little possibilities for customers to co-create value. Hence, we argue that journalism has traditionally been managed according to a goods-centered logic. However, the technical possibility to personalize journalistic content suggests that the notion of value co-creation is appropriate to describe, understand, and shape digital journalism. In digital journalism, the offer usually corresponds more to an individual service offer than to a mass offer.

3. Methodology and Research Setting

In order to achieve our research goal, we follow a design-oriented approach in the methodology of Design Science Research (DSR) [33–36]. Design science is a well-known research approach in IS and has been reemphasized in the last years. At the core of design science is the iterative design with continuous reflection and incremental refinement. So far, we conducted one design cycle, and aim at contributing a level 1 design science contribution in the terminology of Gregor and Hevner [37].

Our research took place in cooperation with a major public radio broadcaster in Germany. Public broadcasters have a public-service remit to fulfill, so the management of filter bubbles is of special interest to them. The research on the management of filter bubbles was embedded in a 2.5-year design-oriented research project on recommender systems in public broadcasting. In this research project, we built a smartphone app that contains an interactive radio player with a radio recommender system in the backend and a connection to the media library of the broadcaster. Next to the interactive radio player, the management of the user's filter bubble[1] was also a feature of the smartphone app. It is important to note that the paper at hand focuses on the user's control over filter bubbles, not on the automatic prevention of filter bubbles.

Another focus of the research setting is the view on filter bubbles from a content perspective. The term filter bubble usually describes a mixture of both unbalanced topics and unbalanced opinions. Both are considered critical in literature: Information flows which, for example, almost completely omit political information but mainly report on sports are just as critical as information flows which contain media bias in the form of right- or left-oriented opinions. In our research setting, we focus on **content filter bubbles**, i.e., we look at filter bubbles from the perspective of content. Thus, we do not address opinions inside the filter bubble.

From a technical point of view, we design the mechanisms for temporal dynamics of filter bubbles and the corresponding recommender system.

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[1] Actually, we do not manage the filter bubble itself, but the user-item-rating in the user profile that leads to the filter bubble. However, for illustration purposes, we stick to the idea of managing the filter bubble.

4. Design Approach

In our design approach, we distinguish the terms *items* from *topics*. *Items* are articles recommended by the recommender system (e.g., with the title “Methane emissions reach new record level”), whereas *topics* represent more aggregated areas of interest (e.g., “climate change”). Both may represent the *interests* of the user. Recommender systems always work on an *item* level (with user-item-ratings), whereas humans also tend to think in *topics*.

4.1. Design Requirements

During several workshops and discussions with experts from the broadcaster, we elicited four design requirements for the design of content filter bubbles. Most requirements we elicited refer to typical information quality dimensions as referred to in, e.g., [38] (such as “accuracy”, “timeliness”, “appropriate amount of data”, and “ease of understanding”). Next to informational quality, the controllability was a central requirement. More control over a recommender system has shown a better user experience [39] and interactive recommender systems increase transparency and trust [28]. The requirements we elicited can be described as follows:

DR1. Consumable. Filter bubble visualizations should represent the data used for filtering in an understandable and consumable way.

DR2. Accurate. Filter bubbles should reflect the data used for filtering in an accurate way.

DR3. Controllable. Users should be able to correct the bubble by removing and adding topics.

DR4. Expirable. Filter Bubbles should reflect the interests of the user in a timely way, i.e., filter bubbles have a “drain”. Old topics should automatically lose in importance over time (if they are not renewed by newer likes), so new topics can gain weight.

4.2. Design Principles

In the following, we present the design principles we developed to match the design requirements.

DP1. Visualization by word clouds. Recommender Systems (content-based, collaborative filtering, and hybrid) operate on user-item-ratings. For feedback during consumption, likes and ratings are a well-suited form of interaction. However, too many ratings result in data that is not easily consumable for users and the level of interaction would be too detailed. So, rather, aggregated information is needed for human interaction. For visualization of the filter bubble, we chose word clouds. Word clouds have proven to be a suitable form for explaining recommendations [40–42]. When making adjustments to a filter bubble, machines would operate on a different level (on user-item-rating level) than humans (on topic level, or both). The visualization by word clouds is a trade-off in favor of humans so that both machine and human can work on the same data. DP1 is intended to match DR1.

DP2. Item-Topic-Mapping. To bring data from user-item-ratings in a human-consumable form, metadata is needed for the recommended items to generate an item-topic-mapping. Different methods exist to generate metadata (a) manually by archivists, editors, or users, or (b) automatically by natural language processing (NLP) techniques such as named entity recognition [43], part-of-speech-tagging (PoS) [44], term frequencies, supervised and unsupervised machine learning (e.g., [45, 46]), or transfer learning approaches (e.g., [47, 48]).

In practice, manual tagging of keywords is often not feasible, or not to the required extent, as often only part of the media content is tagged by human agents. We chose a simple approach of automatic keyword generation by using the term frequency – inverse document frequency method (tf-idf) [45, 49] on the teaser texts and selecting the nouns only. More sophisticated approaches in NLP are imaginable. The topics are associated with items in a 1:n way, i.e., several topics can be tagged to one item. DP2 serves to fulfill DR1, DR2, and DR3.

DP3. Removing function. According to DR3, users should be able to manually remove topics from their word cloud (filter bubble), e.g., by dragging and dropping from the bubble to the outside. When a topic is removed by the user, we identify all items related to that topic using the item-topic-mapping described in DP2 and reset all likes of the identified items. The problem is, as we have a 1:n relationship of items to topics, we unintentionally also decrease other topics in their importance. For example, an item that the user liked is associated with the topics “Corona” and “health”. The user profile consists of various topics with different weights (number of likes shown in brackets), among them “Corona” (1), “health” (9), and “robots” (6). If the user manually removes the topic “Corona” from the filter bubble, also the topic “health” would lose importance, resulting in a user profile of “Corona” (0), “health” (8), and “robots” (6). The more data the user profile contains, the more detailed the user profile is and the less likely co-occurrence and dependencies on topics are.

DP4. Adding function. According to DR3, users should also be able to add topics. Using the item-topic-mapping described in DP2, we can identify the items related to the new manually added topics. However, we do not have a symmetric situation to removing topics (as described in DP3). When deleting topics, the user is aware that his former likes are likely to be reset. When adding topics, in contrast, the user will most likely not expect that some likes are set automatically, and further, there is no indication to which extent. So, when a user adds topics to his filter bubble, we decided that items concerning that topic should not be liked automatically but queued by the recommender system for upcoming recommendations. This way, the user will influence the recommendations by adding topics but set the likes on his/her own.

DP5. Aging function. According to DR4, older user-item-ratings should decrease in importance. The tricky part is here, that the aging function should be congruent with both a) the database for the recommender system and b) the visualization for the user. Regarding b), topics that lose in importance can also be displayed less important (e.g., by smaller fonts) and regarding a) the same aging function has to be applied in the recommendation engine, otherwise, the word cloud would fail to provide an accurate visualization (as required by DR1). The simplest way of an aging function is to give an expiry date to user-item-ratings, so no “smooth fade-out” function has to be implemented. DP5 serves DR4 in conjunction with DR1.

Figure 1 provides an overview of how design principles refer to design requirements.

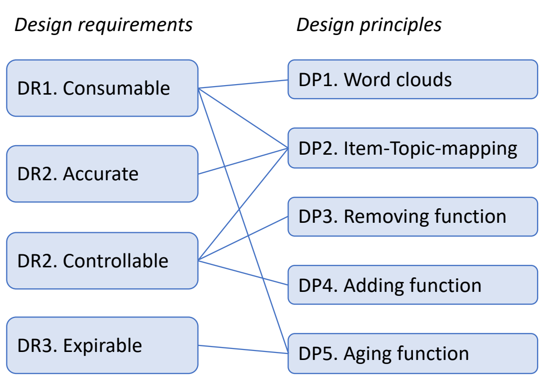

Figure 1. Overview of design requirements and design principles

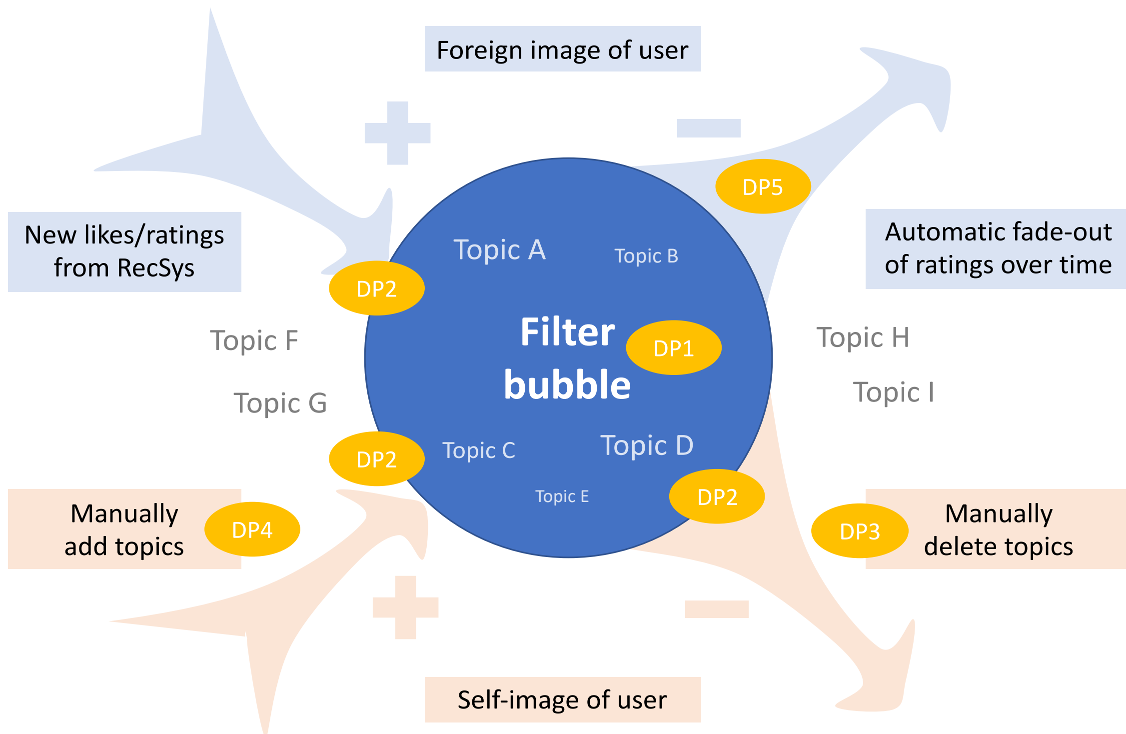

Figure 2. Temporal dynamics of a filter bubble

4.3. Temporal dynamics of filter bubbles

Figure 2 provides a view on the temporal dynamics of filter bubbles as designed in our approach. The filter bubble is visualized by a word cloud with different topics as depicted in DP1. For better understanding, the design principles are also allocated in Figure 2.

Sources for the filter bubble. The filter bubble has two sources. The first source is the likes and ratings from the user that are collected by the recommender system (upper left corner in Figure 2). In order to visualize the topics associated with these rated items, the item-topic-mapping is required (DP2). The second source is the manual adding of topics (lower-left corner in Figure 2) as described in DP4.

Drains for the filter bubble. The filter bubble has two drains. The first drain is an automatic aging of user-item-ratings (upper right corner in Figure 2) as described in DP5. The second drain is the manual removing of topics (lower right corner in Figure 2) as described in DP 3.

Value co-creation of the bubble. Over time, recommender systems collect feedback data from the user and build up a user profile in the form of user-item-ratings. Depending on the implementation, explicit and/or implicit feedback is collected. As a result, the recommender system builds up a *foreign image* of the user, which is not necessarily in line with the *self-image* of the user.

Research has shown that users might hesitate to feed recommender systems with feedback when they know that the feedback is stored in their user profile and influences subsequent recommendations. Algorithms have a hard time to distinguish if a user's interests are short-term or long-term, and which characteristic of the item is interesting for a user in particular. In other words, feedback possibilities of recommender systems are well-suited for data collection, but less suited for adjusting and managing, and users have almost no control over the data once it is inside the system.

The regular explicit or implicit feedback that users give to recommended items can already be seen as a form of value co-creation. The user actively or passively discloses information that is of use to render information more individually towards him/her. Value is not created by the information provider alone, but in co-creation with the recipient, resulting in personalized information streams.

With our approach, we enhance the concept of value co-creation. We allow users to correct the *foreign image* that the filter algorithm has of them with their *self-image*. The filter bubble as designed in our approach can be used to continuously adjust *foreign image* and *self-image*. Also, users can undo likes or views (as an implicit expression of interest) that were only of temporary interest for the user. In comparison, the possibility to give likes and dislikes provides only limited control over the data stored in the user profile and the resulting filter bubble.

Deflating and inflating bubbles. As a matter of continuous adjustment, the temporal dynamics between two sources and two drains of the bubble lead to temporary deflations and inflations of the bubble.

The smaller the filter bubble get (few topics inside), the stronger it personalizes. The bigger the bubble gets (many topics inside), the more diverse personalization becomes. When a user manually removes a topic from inside the filter bubble (or drags them out of the bubble), diversity decreases (all else being equal). When a user manually adds topics (or drags them from outside the bubble into the bubble) diversity increases (ceteris paribus). Speaking in metaphors again, filter bubbles do not burst from getting too big like balloons do. They can expand infinitely, and their effect disappears the greater they become.

5. Evaluation

5.1. Evaluation plan

For evaluation purposes, we developed a web app for smartphones that included three screens (Figure 3), (a) a simple player (play, pause, skip, rewind 15 seconds) with recommender feedback interactions, (b) a screen with a history of all consumed items and the user's rating in list form, and (c) visualization of the users' filter bubble in which users could also manage their filter bubbles. The prototype was connected to the media library of a public broadcaster. In the history screen, a list of all consumed items was shown and the corresponding rating. Users were able to change the ratings in the list ex-post and to reset all ratings. In the filter bubble screen, users could explore topics in their filter bubble, remove topics from their filter bubble or reset the whole bubble. The color coding and orientation of words were random. In this prototype, users were however not yet able to add topics.

Considering the early stage of developing filter bubble management for digital journalism, we chose a qualitative evaluation design with personal interviews. We developed an interview guideline for descriptive face-to-face interviews to get a rich description of the perception and acceptance of filter bubble management.

During the prototype development, we pre-tested our prototype with ten test listeners to see if there are major flaws we need to adjust in the prototype or our interview guideline. After that, for the subsequent evaluation, we conducted 34 interviews of 10 to 15 minutes between November 2019 and January 2020. As we decided to gather feedback from both regular radio listeners and non-listeners, we interviewed 50% listeners and 50% non-listeners. The age of our test persons ranged from 21 to 72 years.

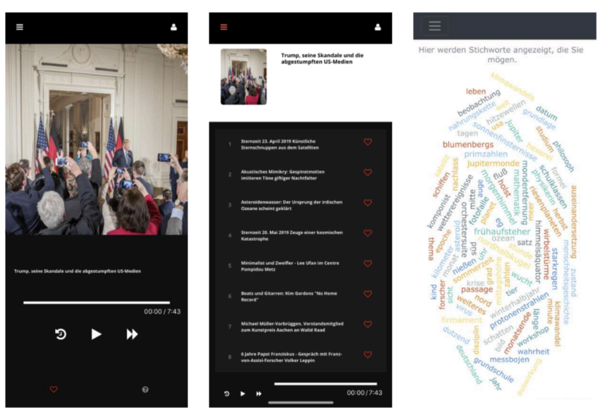

Figure 3. Prototype with player (left), history (middle) and filter bubble visualization (right)

After a brief introduction to our research project, we presented the prototype to the participants and asked them to express any experience and thought following the think-aloud method [50]. We did not explain the features of the prototype but wanted to see how users get along themselves, how intuitive the approach is, and hear what participants think while exploring the prototype. We helped when participants missed features or had problems using the prototype. We asked participants to screen at least 15 content items and like a couple of them to populate the filter bubble. After participants had used all features and produced enough data, we asked them in which regard they prefer to use the history (list of items) and in which regard they prefer to use the filter bubble to adjust their likes and interests.

5.2. Evaluation results

Perception of the word cloud in general. Some participants intuitively perceived value in seeing and being able to adjust the filter bubble. "This is a great feature. I would use this word cloud to train the recommender system. In the first weeks, I would probably check regularly, and afterward only occasionally." Next to the idea of training the recommender system after startup, other participants connected to issues they had with recommender systems before, such as, „on other platforms like Spotify or Youtube I sometimes wonder how my feed comes about. Especially on Youtube, I am annoyed by this. I would even tend not to click on certain things because I know that it will flush videos from certain areas into the feed that I don't want to see."

Most of the participants appreciated further interaction possibilities with the recommender system, and regarding the adjustability and the visualization of the filter bubble using the word cloud, users largely agreed that the ability to inspect the filter bubble, to adjust specific keywords and to reset the entire profile is very meaningful and valuable, from which we conclude a positive evaluation of DP1. Our findings are in line with [40], who found word clouds to be a suitable form for visualization of recommendation results.

Perception of topics inside the word cloud. The topics displayed by the filter bubble caused much attention. Some topics were as expected by participants, other topics were not expected and made participants curious. So, the evaluation of DP2 (the item-topic-mapping), on the one hand, resulted in acceptance (expected topics), and on the other hand resulted in surprise (unexpected topics), which led to a greater interest in scrutinizing and adjusting the filter bubble.

Often, it was not intuitive to participants that the words are editable (probably also because word clouds, as known from the internet, are usually static images), so we had to explicitly mention that words can be removed. However, after removing words from the bubble, all participants spoke positively about the removing function (DP3).

However, while most participants generally agreed with a word cloud visualization, participants also criticized the way we implemented the visualization. Some participants were irritated by the orientation of words, the color code, and complained about the chaotical order, such as, "I always have to turn the phone to read the words", and "some words are blue, some are yellow, and I don't know why". Those participants perceived the visualization of the history (list of items) as more pleasant and less confusing in direct comparison. Also, participants said they were used to working with lists, whereas the handling of interactive word clouds was rather unfamiliar to them. As a consequence of the chosen evaluation design, we could not separate functionality from the design of features, and we had not optimized usability. Other visualizations of the word cloud, such as different color codes, fonts, font sizes, text orientation and local arrangements such as clusters of words might result in a better acceptance of the word cloud and better intuitiveness.

We were not able to evaluate DP4 and DP5 as the adding function was not yet implemented in this design cycle (but we expect the user feedback not so much different from the topic removing function) and the aging function needs a different long-term evaluation setup.

6. Discussion, limitations and future research

In this research, we proposed an approach to manage filter bubbles for digital journalism by conceptualizing and designing the temporal dynamics of filter bubbles. We allowed users to interact with the filter bubble for a continuous value co-creation to align foreign image and self-image of the user. While this research provides a conceptual basis for the management of filter bubbles at an early stage, it can already inform providers of digital journalism how to design filter bubbles from a dynamic perspective and allow users to better co-create value by enhanced interaction possibilities. The results from this research might not only be of valuable insight for public broadcasters but also private media houses: Manageable filter bubbles might also be of value to private media offers in journalism, as some participants expressed their displeasure with not being able to adjust their media stream on existing platforms.

Limitations. Surely, our approach is not without limitations. With the word cloud and the item-topic-mapping, we only assumingly identify what exactly the user liked about the item (i.e., article). We cannot be sure if the user liked the content, the author, the format, the writing style, or something else. It is also possible that the user only liked part of the item. We do not know exactly – but recommender systems do neither. Still, we have an additional bias in the item-topic-mapping, and, in the worst case, we might present an image to the user that does not truly reflect his/her user-item-ratings, and therefore not truly fulfill DR2 (accuracy).

Also, there is a possible contradiction in the design requirements. Consumability (DR1) and accuracy (DR2) do not always go hand in hand, as consumability might require a reduction of information and a loss of accuracy. A loss of accuracy is therefore not only a limitation of our approach but also a limitation in the requirements. Still, the topic-item-mapping seems to be an enabler and motivator for interaction with the filter bubble.

Future Research. Future research should analyze how to improve the usability of interactive filter bubbles concerning color coding, font, font size, orientation, and local arrangements. Also, the level of granularity of topics may be important for research (e.g., what to display when a user is interested in football, but not in tennis) with a taxonomy in the background.

In this research, we focused on content filter bubbles. As a next step, also an opinion perspective (political orientation) could be integrated into the filter bubble, raising the question of how to categorize opinions, how to integrate them into the bubble visualization, and how to adjust political orientation. Furthermore, the bubble we designed represents the positive interests of the user, whereas topics outside the bubble can still be part of the recommendation, as the user is still open to those topics, but not intensely interested. However, there might be topics that users want to avoid. While this seems critical for public service journalism, it might also be of interest to private media houses to express and adjust negative interests. Further research has to investigate the solution corridor of manageable filter bubbles for digital journalism and their temporal dynamics.

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