NewsViz: Depicting and Controlling Preference Profiles Using Interactive Treemaps in News Recommender Systems

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ABSTRACT

News articles are increasingly consumed digitally and recommender systems (RS) are widely used to personalize news feeds for their users. Thereby, particular concerns about possible biases arise. When RS filter news articles opaquely, they might "trap" their users in *filter bubbles*. Additionally, user preferences change frequently in the domain of news, which is challenging for automated RS. We argue that both issues can be mitigated by depicting an interactive version of the user's preference profile inside an overview of the entire domain of news articles. To this end, we introduce *NewsViz*, a RS that visualizes the domain space of online news as treemap, which can interactively be manipulated to personalize a feed of suggested news articles. In a user study ($N = 63$), we compared *NewsViz* to an interface based on sliders. While both prototypes yielded high results in terms of transparency, recommendation quality and user satisfaction, *NewsViz* outperformed its counterpart in the perceived degree of control. Structural equation modeling allows us to further uncover hitherto underestimated influences between quality aspects of RS. For instance, we found that the degree of overview of the item domain influenced the perceived quality of recommendations.

CCS CONCEPTS

• **Information systems → Recommender systems**; • **Human-centered computing → Human computer interaction (HCI)**; **Treemaps**.

KEYWORDS

News Recommender Systems; Interactive Recommending; Information Visualization; Treemaps; Structural Equation Modeling

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1 INTRODUCTION

The domain of news is currently subject to a substantial change as many roles that were formerly undoubtedly associated with humans are now increasingly performed by machines. A prominent example for such roles is the curation of online news in which recommender systems (RS) progressively act as *gatekeepers* and decide which articles will be included in a personalized news feed and which will not [43, 44]. While RS in general have become quite accurate in computing personalized recommendations, it has been argued that accuracy is only one of many quality aspects of a RS [4, 35, 40].

When content is pro-actively personalized, users might overestimate how representative recommendations for the entire item domain are and become trapped in *filter bubbles* [45] or *echo chambers* [14]. Possible results include ideological segregation [14], burgeoning populism [10] and distribution of conspiracy theories [8]. While it remains under discussion whether algorithmic filtering is the main reason for filter bubbles [18, 41], incidents like the scandal around Cambridge Analytica have resulted in a broad public interest of algorithmic transparency and filter bubble effects [19]. One way to tackle such concerns is making users aware of not only the recommendations but also of items the algorithm omits [42].

Consequently, one task of RS can be defined as letting users *explore or understand the item space* [27]. Providing such a broad *overview* was observed to make users aware of blind-spots in their profile [55], help them to develop new preferences [39], and increase control over the recommendations [37]. A prominent way of conveying an overview of the item space is to present it as a scatterplot or geographical map [16, 37, 50].

While map-based visualizations have proven to be able to foster overview in RS, they are prone to visual clutter and seldom make efficient use of the entire available screen space [29]. More space-efficient in this regard are *treemaps* [51]. Treemaps are used to visualize tree structures as map in which tree nodes are represented as cells. Besides other domains, visualizations based on treemaps have also been applied to RS [31, 48]. Richthammer and Pernul, for instance, utilize an interactive treemap to cluster recommendations regarding their content, thus aiding users in comprehending their own situational needs [48]. However, the potential of treemaps could even be exploited more extensively, when not only recommendations are visualized but also their relation to the user's preferences in context of the entire item space. Aligning this with interactive methods for treemaps [1] could also raise the users' control over their recommendations.

In this paper, we combine the above: We introduce *NewsViz*, a novel news RS that utilizes a treemap with interactive cells to provide an overview of the item domain, visualize the user's preference profile, and let this profile interactively be adjusted. In this way we aim at making the RS more transparent, reducing the risk of filter bubble effects, and enable control over recommendations. Summarized, we seek to answer the following research questions:

RQ1 How can a treemap visualization be leveraged to create an interactive control panel for RS?

RQ2 How are the aspects *overview*, *transparency*, and *control* influenced by the form of visualizing user preferences? How do they influence each other?

RQ3 What are possible benefits of treemap visualizations in terms of preventing filter bubble effects?

To answer these questions, we implemented *NewsViz* and conducted a user study that reveals high potential of treemaps to convey overview, transparency, and control in news RS. To investigate the effect of the treemap isolated from other aspects such as the recommendation algorithm, we compared *NewsViz* to a baseline system that replaces the treemap with an equally powerful interaction concept based on slider widgets. While both applications scored relatively high on the perceived degree of overview and transparency, we found that *NewsViz* outscored the slider-based prototype in terms of the degree of perceived control. Using structural equation modeling enables us to study the interdependencies of these constructs further, disclosing the particularly influential role of overview; not only on perceived transparency but also on less obvious aspects such as the system's effectiveness and the perceived quality of recommendations.

To summarize, we make the following contributions: (1) We demonstrate that treemaps can be used to control news RS more effectively compared to common slider widgets. (2) We underline the so far neglected importance of overview for RS and reveal implicit influences on aspects such as transparency and the perceived recommendation quality.

2 RELATED WORK

News articles are consumed increasingly digitally, thus lowering entry barriers for news distributors and costs of news dissemination. As the number of available news articles is growing, RS increasingly act as *gatekeepers* that automatically curate personalized news feeds [43, 44]. As a result, RS in the domain of news have a special responsibility since they can "exercise power over individuals" [9] in form of influencing the direction of their readers' awareness [9, 56]. But also from an algorithmic perspective, recommending news is particularly challenging: new items emerge constantly on arrival of recent news stories and user's preferences change frequently, sometimes even during the course of a day [30].

While providing control over recommendations is obviously particularly helpful in situations where user preferences vary often, surprisingly little research pursues to increase control in news RS. One exception is the qualitative study conducted by Harambam et al. [19], in which the authors observed that users of news RS strongly desire to have advanced means of interaction with the system. Harambam et al. mostly utilized sliders, which participants perceived as easy to use and "quite straightforward" but also as prone to overcrowd interfaces.

Outside the news domain, control of RS has been discussed in greater depth [21, 22]. Exerting control has been, beside others, related to supporting users to explore the item space [57, 58], influencing user satisfaction [12, 21, 28], and increasing trust into the RS [11]. Control in RS seems to be firmly tied to transparency of recommendations [22, 58], as users need to be educated of how to effectively influence recommendations.

Most often RS appear as *black boxes* to their users, as it remains opaque what data is used for personalization, why certain items are suggested, and how they relate to the user's preferences. Users who encounter such black box algorithms may react with distrust and may be reluctant to accept recommendations [25]. When transparency of a RS is low, it might also happen that users loose awareness of item space areas that are not recommended to them. Such users are effectively trapped in *filter bubbles* [45], which have been related to several negative societal consequences [8, 10, 14] and to a general threat for human creativity [33, 38]. However, others come to the conclusion that such concerns about filter bubbles are mostly exaggerated [18] or that filter bubbles are not primarily the result of RS but deliberately created by users themselves [2]. Nonetheless, algorithmic transparency and issues like filter bubbles have reached high visibility in the public and thus raised the demand for more transparent algorithms [19].

Opacity in RS can be tackled in various ways, for instance, by generating textual explanations for recommendations [25, 54] or by utilizing information visualization methods such as two-dimensional maps [16, 37] or Venn diagrams [46]. Accordingly designed transparent interfaces have shown potential to increase user satisfaction [17, 58] and may also help to educate users about their preferences thus facilitating self-reflection [33]. Following the same argumentative line, it was shown that when users feel educated about algorithmic workings of a RS, they can be more motivated to explore items beyond their usual interests [5], which helps them to receive more diverse recommendations [24] and have less blind-spots regarding the item space [20, 55]. In this sense, a broad, diverse, and unbiased viewpoint is a crucial necessity for democracy [23]. Not surprisingly, Jannach and Adomavicius list "help users to explore or understand the item space" as one of the purposes of a RS [27].

Such a comprehension of the item space can, for instance, be conveyed to users by utilizing visualizations based on maps or scatterplots [e.g. 16, 37, 50]. Corresponding visualizations have shown potential to increase transparency and user engagement [13, 15]. By leveraging the inherent comprehensibility of spatial relations, maps can help putting the user's preference model into context and thus letting recommendations become intuitively understandable [32]. A more abstract form of maps are *treemaps* [51], which are more space efficient as maps based on scatterplots [29]. Treemaps have also been applied to the domain of RS [31, 48].

Katarya et al. [31] and Richthammer and Pernul [48] utilize treemaps to depict the predicted fit of recommended movies in accordance to the active user's preferences. In particular, each treemap cell contains a recommendation and the size of those cells indicates how high the predicted rating of the corresponding item is. The prototype of Richthammer and Pernul adds a second hierarchical level, which groups recommendations regarding their movie genre. This visualization is accompanied with checkboxes that let users filter movies. Chang et al. [6] introduce a treemap-like interface for scrutinizing textual restaurant reviews. For different search queries, users can create separate treemaps. Each cell of

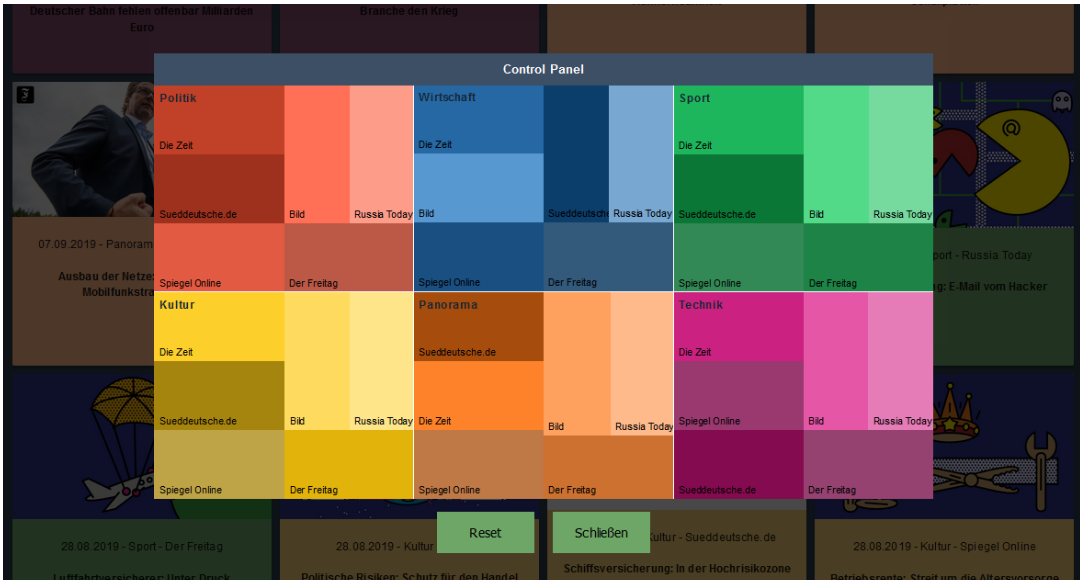

Figure 1: Screenshot of the *NewsViz* system. The user can hover any category or source inside the treemap visualization and scroll the mouse wheel up and down to enlarge or, respectively, shrink the corresponding cell. After finishing interaction, the user can click on a designated button or anywhere outside the panel to minimize it. In the background, the personalized news feed is updated with every interaction, thus providing immediate visual feedback to the user.

these treemaps corresponds to a keyword of the query. Relevance of keywords can be determined by users in changing the size of the corresponding treemap cell. Results of a user study show increased interaction quantity and general user satisfaction compared to a baseline system. Finally, treemaps have been used to display news in the commercial application *Newsmap*[1]. *Newsmap* demonstrates impressively how a large number of news can be displayed using a treemap.

3 *NEWSVIZ*: A TREEMAP TO CONTROL RECOMMENDATIONS OF ONLINE NEWS

As answer to our first research question ("*How can a treemap visualization be leveraged to create an interactive control panel for RS?*"), we propose *NewsViz* (see Figure 1). The following sections are organized according to the three central functions of *NewsViz*: 1) provide an overview of the item domain, 2) visualize the user's preference profile, and 3) let this profile interactively be customized.

3.1 Visualize the Domain Space of a News RS

In alignment with common news aggregation websites (e.g. *Google News*[2] and *SmartNews*[3]), the treemap in *NewsViz* is organized as hierarchy of news categories as uppermost hierarchical level and news sources as second hierarchical level. To support users in distinguishing category cells in the treemap easily, each is assigned a specific color. Sources are assigned a background color of their corresponding category but with a different saturation. In this way, cells become distinguishable without cluttering the visualization. To link news articles in the news feed and treemap cells, each article is colored according to its corresponding category-source combination (see Figure 1, in the background).

3.2 Represent the User's Preference Profile

The size (i.e. area) of each treemap cell reflects the number of articles in the news feed that pertain to the corresponding category or source. In the initial setup, all cells on one level have the same size, as the news feed consists of the same number of articles for each category-source combination. This state is also depicted in Figure 1. When preferences of the current user are known beforehand (e.g. elicited using click-through rates), they can be visualized as accordingly adjusted cell sizes in the treemap.

Since assessing the proportional influence of each treemap cell is a central requirement in our approach, the computation of cell alignment follows the algorithm for *squarified treemaps* [3]. Squarified treemaps are an alternative to treemaps that are created by using the *slice-and-dice* strategy. Thereby, squarified treemaps take the aspect ratio of the resulting cells into account thus favoring cells with balanced aspect ratio, i.e. squares. Opposed to slice-and-dice treemaps, squarified treemaps are cognitively easier to interpret, especially in terms of comparing cell sizes.

3.3 Let Users Interactively Adjust Their Preference Profile

While the treemap visualization could already be used to display preference profiles, we also target at supporting users in controlling their personalized news feed. Since preferences in our approach are displayed as cell sizes of the treemap, the most natural interaction concept is to let users directly adjust them. To this end, we follow the interaction concept of *pumping* [1], which is illustrated in Figure 2. In its initial state, cell sizes of the uppermost level in the hierarchy of

[1] http://www.newsmap.jp/
[2] https://news.google.com
[3] https://www.smartnews.com

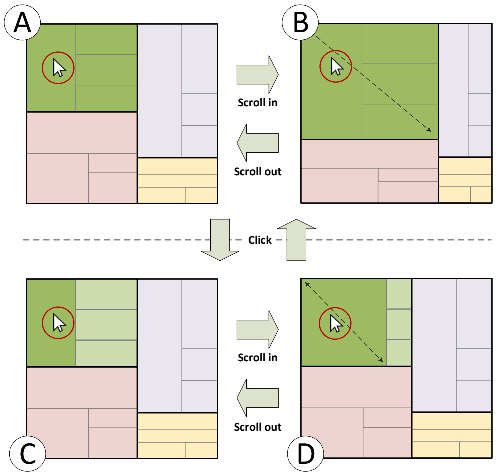

Figure 2: The interaction concept of *NewsViz*. When hovering a treemap cell and scrolling in or out, the size of the corresponding cell increases or decreases, respectively ($A \leftrightarrow B$). When clicking somewhere in the treemap ($A \leftrightarrow C$ and $B \leftrightarrow D$), the proportions of cells on the second level can be manipulated in the exact same way ($C \leftrightarrow D$).

NewsViz can be adjusted. This is done by hovering the mouse cursor over a category cell and moving the mouse wheel. According to the direction in which the wheel is moved, the currently hovered cell enlarges or shrinks, thus mocking a zoom behavior. In this sense, "zooming in" corresponds to enlarging the cell and, as a result, increasing the influence of the corresponding category. Template for this behavior is the concept *zoom and filter* of the *Information Seeking Mantra* [52]. When users click anywhere in the treemap, they can also adjust the size of cells for sources. Adjusting sizes of source cells is done in the very same manner as adjusting category cells. In order to prevent users to lose awareness of sources that are shrunk to a very small size, an according message is shown for each source cell that currently has no influence on the news feed.

Independent of which cells are currently manipulated, each single interaction step triggers an immediate update of the personalized news feed in the background (see Figure 1).

3.4 Implementation Details

We developed *NewsViz* as a web application using the Java framework *Spring Boot* for the backend in tandem with *Vue.js* for the frontend. The treemap visualization is based on the *javascript* library *d3.js* and extends an existing project for web-based treemap visualizations[4]. Background data for news were crawled as preparation for our user study. For this, we used the *NewsAPI*[5] and collected 779 articles from six different news sources, organized in six categories. Sources and categories were selected in order to represent a diverse data sample for the user study. We took special care to choose news sources with different political orientations.

Depending on the proportions of categories and sources in the treemap, the news feed is set up. The entire news feed consists of 100 articles. We chose this number of articles since it contains a reasonable amount of variety and on the other hand is not too large. The influence of each category, divided into sources, determines how many articles are passed to the news feed. Afterwards, articles are sorted according to their recency. This procedure follows one of the typical approaches of how to guarantee recency in news recommendations and is often referred to as *post-filtering strategy* [30]. We decided for a comparable simple recommendation algorithm, since our focus lies entirely on the visualization, the interaction concept, and the user's perception thereof.

4 STUDY SETUP

In order to evaluate *NewsViz* against a baseline system, we conducted an empirical user study. The study was designed as controlled lab study with two conditions: *NewsViz* and a second prototype based on slider widgets.

4.1 Slider-based Prototype

Since we wanted to test the treemap visualization of *NewsViz* isolated from other factors (e.g. the algorithm of news feed composition), the second prototype varies only in replacing the treemap with sliders to indicate preference weights. All other aspects (e.g. hierarchy of sources pertaining to categories and linking articles to categories by color) were maintained identically to the *NewsViz* condition. The result is depicted in Figure 3.

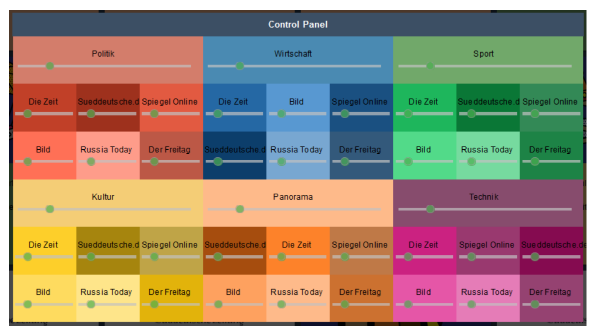

Figure 3: Screenshot of the control panel in the slider-based prototype. Current configuration of categories and sources is the same as in Figure 1.

Consequently, also the behavior on interaction of this baseline prototype mirrors *NewsViz* as closely as possible. Hence, sliders were not independent from each other but instead always displayed their relative value proportionally to the entire distribution of news. As a consequence, when interacting with one slider, the other sliders on the same level (i.e. categories or sources inside one category) reacted in form of adjusting themselves proportionally to yield at any given moment a total of 100% when all sliders are summed up.

4.2 Study Procedure

At the beginning of each user session, the current participant was randomly assigned to one of the two conditions. Then, independent of the condition, participants were asked to fill in a first questionnaire composed of questions regarding their background knowledge and demographical data. The study took place under controlled conditions: participants were alone in a room with a supervisor,

[4]https://github.com/albertopereira/vuejs-treemap
[5]https://newsapi.org/

who was not able to see their computer monitor. Questionnaires were shown using an online tool, which was presented in the same browser window as the prototype (24" screen with a 1920×1200px resolution). After finishing the first questionnaire, participants were given a brief introduction to the system (i.e. *NewsViz* or the slider-based variant). It was made clear to them, how to interact with the control panel, that each interaction will trigger an immediate re-calculation of recommendations, and that they could ask questions to their supervisor at any point of the experiment. All participants also received a sheet of paper with a brief paragraph about each news source, in case they were unfamiliar with it. Paragraphs were composed with information from Wikipedia in order to reflect the political orientation of that respective source.

Task 1: After the brief introduction, participants were given the task to use the control panel in order to configure the system regarding their personal preferences of online news. During the task they were allowed to switch between news feed and control panel as often as they wished. Participants were instructed to assess the quality of their recommendations by reading headlines and content teaser of recommended articles. As soon as they think their personalized news feed represents their preferences, participants were requested to fill another questionnaire with questions about their experience during this task.

Task 2: The second task took place as part of the questionnaire. Dependent on their condition, participants were presented with screenshots of four differently pre-configured control panels. Apart from the first profile being shown—which acted for introductory purposes and was neutrally configured—all configurations favored one source over the others. We asked participants to name this most influential source. This task addressed to measure how well participants can spot potential biases.

4.3 Instruments Used

The questionnaire, that was shown first to participants, was composed of questions about their news consumption (e.g. "*How often do you read online news each week?*") and general demographics, e.g. about their age. If not stated otherwise, all items were assessed on 5-point Likert scales.

After participants finished task 1, they were presented with questions about their experience with the system. To measure *transparency* and *overall satisfaction*, we used constructs from the *ResQue* questionnaire [47]. For assessing the individual perceived degree of control, users are able to exert over calculation of the personalized news feed, we used the construct of *interaction adequacy*, which we also took from *ResQue*. For measuring *recommendation quality* and *system effectiveness*, we utilized items that were introduced by Knijnenburg et al. [34]. These instruments were supplemented by three questions, we formulated ourselves for assessing the perceived *overview* of the item space: 1) "*The system helped me to get an overview of the entire spectrum of online news.*", 2) "*The system helped me to get an overview of the entire spectrum of categories.*", and 3) "*The system helped me to get an overview of the entire spectrum of sources.*"

At the end of the questionnaire, participants were given the choice to provide a qualitative comment.

Table 1: Mean values and standard deviations for variables assessed with *NewsViz* and the slider-based version. All variables use 5-point Likert scales. We only found a significant difference (marked with *) in the perceived degree of control (see Section 5.1).

	Treemap Condition		Slider Condition	
Variable	*M*	*SD*	*M*	*SD*
Overview	3.69	0.71	3.60	0.72
Transparency	4.03	1.03	4.29	0.69
Control	4.08*	0.67	3.45*	0.98
Recommendation Quality	4.01	0.59	3.97	0.46
System Effectiveness	3.71	0.65	3.71	0.58
Overall Satisfaction	3.94	0.91	3.97	0.84

4.4 Sample

We recruited 63 (31 female) participants for our user study, which were randomly assigned to conditions, resulting in sample sizes of $N = 32$ for the treemap condition and $N = 31$ for the condition based on sliders. The age of our participants ranged from 18 to 52 ($M = 27.02$, $SD = 6.74$) and most of them had a university (49.2 %) or high school degree (36.5 %). As profession, 55.6 % stated being students followed by 41.15 % who were currently working as employees. When asked for habits regarding their news consumption, participants answered that they are somewhat interested in online news ($M = 2.33$, $SD = 1.03$) and mainly did not pay for them during the last year (92.1 %). Participants received no incentive for taking part in our study other than a certificate of participation, which 14 of them needed as requirement for their study program.

5 RESULTS

The conducted experiment was designed to answer our research questions 2 and 3 introduced in Section 1. To answer *RQ2*, questionnaire results are compared between those elicited with *NewsViz* and those elicited with the slider-based prototype. We further uncover relations among results by using a structural equation model (SEM). Finally, to answer *RQ3*, success rates and task completion times of the second task are presented.

5.1 Comparing *NewsViz* to a Slider-based Prototype

Descriptive results of *NewsViz* and the second prototype based on sliders, can be found in Table 1. As can be seen, results for all items are relatively high. For those items that we formulated ourselves to measure *overview*, we calculated Cronbach's alpha in order to assess the internal consistency, which led to an effect of $\alpha = .59$.

In order to test for statistical differences, we compared results for all our six dependent variables between conditions using one-way MANOVA. The multivariate effect with $F(6, 56) = 2.59$, $p = .028$, *Wilk's* $\Lambda = 0.783$, $\eta_p^2 = .217$ for *condition* was statistically significant. The individual dependent variables were subject to ANOVAs in order to assess whether there were any differences of perceived *overview*, *transparency*, *control*, *system effectiveness*, *recommendation quality*, or *overall satisfaction* between conditions. Analyzing the between-subject effects, we could observe that *condition* has

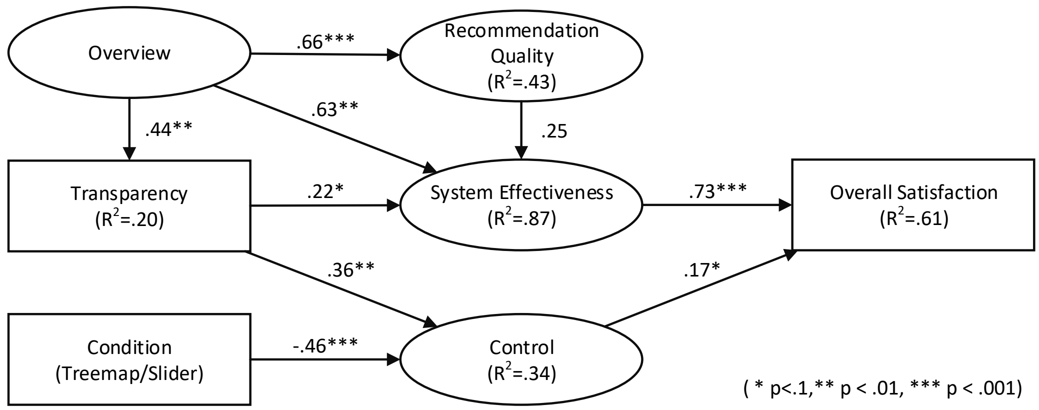

Figure 4: Structural Equation Model revealing causal dependencies between variables of our experiment. Rectangles represent manifest (observed) variables, while latent (unobserved) constructs are depicted as ellipses. R^2 values are given inside the nodes and denote the explained variance of the corresponding variable. Edges of the graph show standardized parameter weights.

a significant effect on *control*, $F(1, 61) = 9.01$, $p = .004$, $\eta_p^2 = .129$. Apparently, *NewsViz* was perceived as easier to control by participants. Other than that, there were no differences with statistical significance.

In order to reveal further dependencies among the aspects measured for both prototypes, we hypothesized a SEM based on the results of our questionnaire (see Section 4.3). The resulting model showed a good fit with the data ($\chi^2(200) = 205.959$, $p = .371$, $CFI = .988$, $TLI = .986$, $RMSEA = 0.022$) and is presented in Figure 4. For setting the SEM up, we used the *R* package *lavaan* [49].

Overview and *condition* acted as exogenous variables, while all other variables of our model were endogenous. *Transparency* and *overall satisfaction* are observed questionnaire items (displayed as rectangles in Figure 4), while *overview*, *recommendation quality*, *system effectiveness*, and *control* are latent composite variables (displayed as ellipses in Figure 4). In order to not overload the graph, we omitted observed manifest questionnaire items for these latent constructs.

One of the most central variables is *overview* as it influences *transparency*, *system effectiveness*, and *recommendation quality*. While not as influential as *overview*, *transparency* shows impact on *system effectiveness* and *control*. *Control* was the only variable that was affected by *condition*. We coded conditions in our experiment with "1" for the condition with *NewsViz* and "2" for the condition with the slider-based variant. In this sense, the negative weight on the edge *condition* $\longrightarrow$ *control* indicates a higher degree of control in the condition using *NewsViz*, which is in line with our findings using ANOVA stated above. *Control* itself had an effect on *overall satisfaction* indicating that users prefer being in control over their recommendations, though the effect was rather small. Together with *system effectiveness*, *control* was able to explain 61% of the variance of *overall satisfaction*, whereas *system effectiveness* showed the larger extent of. *System effectiveness* was the variable with most entering paths, i.e. it was influenced by other variables the most. It also had the highest amount of explained variance. *Recommendation quality*, as well as *transparency* and *overview* were the predictors for *system effectiveness*. Note, that the regression *recommendation quality* $\longrightarrow$ *system effectiveness* was not significant ($p = .155$)[6].

5.2 Prevention of Filter Bubbles

In task 2, participants were presented with depictions of different preference profiles and were asked to estimate what the most influential source of the profile is. With this task we address *RQ3* and thus how easy it is to assess biases such as unilateral news consumption and, as a result, how high the risk of filter bubbles is. Screenshots of both conditions for one of the profiles are depicted in Figure 5. The source that objectively had the highest influence in this case was "*Der Freitag*" (45.9%), which was also answered by 100% of participants in the treemap condition and 77.4% in the slider condition. Over all three profiles[7] shown, 87.5% of participants in the treemap condition and 68.8% of participants in the slider condition were able to spot the source with the highest influence. Task 2 took on average 02:16 minutes (SD = 00:55) in the treemap condition and 03:08 minutes (SD = 01:35) in the slider condition. Multivariate effect for *condition* was statistically significant ($F(2, 60) = 10.1$, $p = .000$, *Wilk's* $\Lambda = 0.748$, $\eta_p^2 = .252$). *Condition* had a significant effect on success rate ($F(1, 61) = 9.62$, $p = .003$, $\eta_p^2 = .136$), revealing that treemap users could find the most influential source better than users of the slider-based version. The same accounts for task completion times, which were significantly shorter in the treemap condition ($F(1, 61) = 6.96$, $p = .011$, $\eta_p^2 = .102$).

6 DISCUSSION

When examining descriptive results of our experiment in Table 1, they confirm that treemaps can effectively be used as interactive input panel for news RS. In qualitative answers, this was further underlined as participants gave statements such as "*Well-grounded,*

[6] We hypothesized this path for logical reasons and thus report it in the SEM, even though it is not significant. We believe, however, that this influence would become stronger in real-world scenarios, where the recommendation quality is more important when assessing the effectiveness of a RS.

[7] Note, that the first profile was shown to introduce the task and thus had no clear most influential source. Consequently, we omitted this profile in analysis of results.

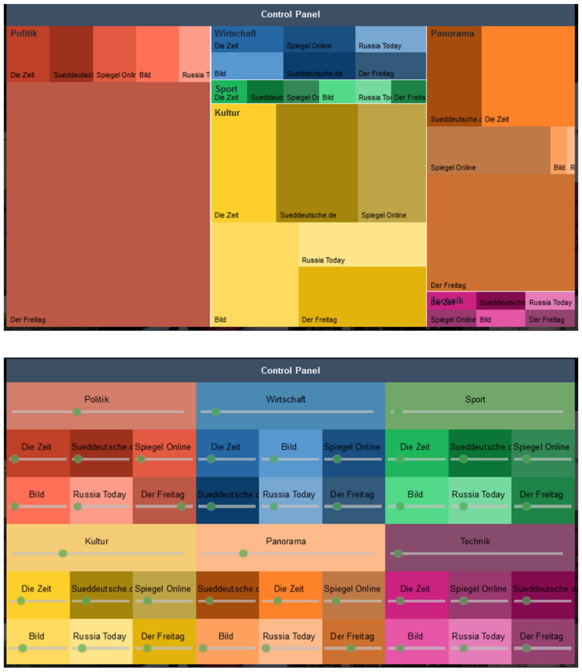

Figure 5: Screenshot of a preference profile that was shown to participants during task 2. The source with the highest influence is in both cases "*Der Freitag*".

interesting system. I absolutely miss something similar on the Internet." (P34) or "*Very innovative and [the system] increases the spectrum of visible online news.*" (P59).

6.1 Comparison of *NewsViz* to a Slider-Based Version

In our second research question, we asked ourselves how *NewsViz* performs in comparison with another system that is not dependent on sophisticated visualizations but uses common slider widgets. Therefore, we deliberately designed the second prototype as equally powerful in terms of interaction modalities. Regarding the results, it became apparent that participants perceived to obtain a higher degree of control with *NewsViz*. We assign this observation to a stronger directness between interaction, visualization and recommendations: Users in the condition with *NewsViz* were able to comprehend more naturally how their interaction with one category or source influenced siblings on the same hierarchical level. When examining sub items of the construct *interaction adequacy*, which we used to measure control, answers most saliently differ for the question "*The system allows me to tell what I like/dislike.*" (*NewsViz*: $M=4.47$, $SD=0.62$; Slider condition: $M=3.65$, $SD=1.17$). Apparently, participants in the slider-based condition did not feel able to express their preferences adequately. In line with prior research [19], we ascribe this to a confusion due to an overcrowded interface. This assumption is also backed up by qualitative statements of participants, which, for instance, experienced the system as "*confusing and irritating*" (P49).

Another reason for this confusion may originate from the slider behavior: When one slider position was changed, the other sliders adjusted themselves to result in an overall distribution that sums up to 100%. Even though adjusting the size of treemap cells also affected the other cells on the same level in *NewsViz*, we assume that this behavior was perceived as more natural. The total size of the treemap gives users a point of reference, making it thus more comprehensible that cells have to arrange themselves in order to fit into the given frame.

Apart from the perceived degree of control, we did not find any statistically significant differences in the results. This is especially noteworthy in terms of the perceived degree of overview. While this indicates that overview in RS is not necessarily tied to complex visualizations, we assume that some potential for overview in RS was left unused in our approach. When comparing screenshots of both prototypes (see Figure 1, Figure 3 and Figure 5), it can be seen that the slider variant is already rather crowded, while *NewsViz* still appears comparable tidy. This is in line with aforementioned prior work about slider elements [19].

Results of task 2 show that participants of the treemap condition were able to spot the most influential source more easily. This became visible through success rates and task completion times (see Section 5.2), which were both significantly better for the treemap condition. As a consequence, we deem treemaps to be superior in conveying a natural sense of the entirety of news items, in relating proportions of own preferences to the rest of the space, and thus in raising awareness for possible biases due to overrepresented sources. This could especially become relevant when users are presented with preference profiles elicited implicitly in the past. With help of the treemap visualization they could rapidly apprehend their preference model, spotting possible biases and adjusting it to resolve these biases or regarding current preferences. We, though, note that users could still create profiles that neglect inconvenient sources and thus self-reliantly creating a filter bubble. Yet, our approach would make it harder to become unaware of such sources.

6.2 Dependencies Among Quality Aspects of RS

In Section 5.1, we introduced a SEM in order to uncover otherwise hidden relations between the different quality aspects of RS that we elicited in our study. As this model shows, *overview* was the most influential variable, influencing *transparency* as well as *system effectiveness* and *recommendation quality*. The influence over the path *overview* → *transparency* appears rather natural: when users perceive a sense of overview of the underlying item space, they understand the data used for recommending better and thus perceive the entire RS as more transparent. While the opposite relation is imaginable too (i.e. degree of transparency accounts for the perception of overview), our understanding of overview follows basic literature on information visualization that treats the notion of overview as *awareness* of an item space [26], which happens *first* [52] in human-computer-interaction. Our self-invented items reflect this understanding (see Section 4.3).

Not all influences emerging from *overview* are that easy to interpret, though. The path *overview* → *recommendation quality* reveals a direct influence of the perceived degree of overview on the quality of recommendations. Note, that this regression even yields a rather high amount of explained variance in *recommendation quality* (43%). That we found a causal relation between such ostensibly isolated variables, emphasizes the complexity of measuring the quality of recommendations with user studies. Recently, we made a similar observation [36] and found that the perceived quality of a recommendation is significantly influenced by how well the system explains its reasons for recommending this particular item. Apparently, users take a lot more aspects into account when assessing the quality of a system's recommendations than solely the suggested items.

Besides *transparency* and *recommendation quality*, *system effectiveness* was influenced by *overview* as well. Deconstruction of the composite variable *system effectiveness* in its latent components can yield some insights into the rationale of this regression. Especially two items help to understand the influence of *overview* on *system effectiveness*: "*The system makes me more aware of my choice options.*" and "*I make better choices with the system.*" In this light, experience with our RS appears to form an arc that begins with a general overview, which then leads over awareness of choice options, to better decisions, and finally to a general perception of system effectiveness. This sequence can also be found in general literature on decision making, e.g. in [53].

The regression *transparency* → *control* also underlines that variables in user studies should not be treated independently of each other. Apparently, control in RS is positively influenced by how transparent the system lays out its inner workings and reasons for recommending to the user. We think this causal relation is naturally comprehensible: to control a complex system (such as a RS), a user needs to some degree understand how the system works and thus where or how to interact with it. Our observation here adds to evidence found by other authors who also underline the importance of transparency to foster control in RS [22, 58].

6.3 Limitations

There were also some limitations to our experiment. First, the sample is comparatively small—especially in terms of performing structural equation modeling. As a result, the model lacks robustness to some degree and interpretations need to be made with care. However, since some of our deductions are not only relying on the SEM but also on comparative analysis and prior observations, we are confident that the trends in our model are valid and would become even stronger with more data. We also acknowledge that further studies with a more representative sample (e.g. in terms of education) should be conducted.

Second, the value for Cronbach's alpha calculated for our construct to measure overview, indicates that there are some inconsistencies within the answers. Nonetheless, we believe that the wording of items is rather clear and that the assessment of overview is reliable.

A third limitation pertains to the number of cells currently displayed in *NewsViz*. In our experiment both prototypes used six categories and six sources, resulting in a total of 36 cells. When applied to real news aggregation portals, the number of categories and sources would probably be higher than this. Also the hierarchy of categories would be more sophisticated (e.g. splitting *politics* into *local* and *global*). While our experiment shows that the slider-based variant was already experienced as cluttered and confusing, we deem the treemap visualization to yield potential for adding several further categories and sources (see, for instance, the large number of articles displayed in *Newsmap*[8]). Nonetheless, the treemap visualization would at one point become overcrowded too. To encounter this, only a small part of the entire profile could be visualized at a given time. When combined with *overview+detail* visualizations [7] (e.g. in form of a minimap) users would still be able to keep awareness of their entire profile.

7 CONCLUSIONS AND OUTLOOK

In this paper, we introduce a novel interface for controlling news recommender systems. The resulting system, *NewsViz*, utilizes a treemap to display the domain space of news as hierarchy composed of news categories and sources. By adjusting cell sizes of this treemap, users can interactively control the influence of the corresponding category or source, respectively. In an empirical user study, *NewsViz* was compared to a baseline system using slider widgets for interaction. Results indicate that *NewsViz* scored as good as the slider-based system in dimensions such as perceived overview, transparency and user satisfaction. The degree of control, however, was perceived as higher for *NewsViz*. By applying structural equation modeling to our results, we were able to identify additional interesting causal influences of overview on transparency, system effectiveness and recommendation quality.

This observation underlines how complex quality assessments of recommendations are and we conclude that more research is necessary about relations between quality aspects of recommender systems. User study results that at first seem isolated should be put into context (e.g. by structural equation modeling) before making reliable assertions about their meaning. In this sense, our structural equation model reveals that the degree of *overview* significantly influenced other quality aspects of the system. Yet, how much overview of the item space is perceived by users is rarely used as means for assessing a system's quality. In future research we thus plan to investigate this aspect in greater depth. Thus far, for instance, a reliable instrument for measuring the perceived degree of overview is missing.

In the future we also plan to test *NewsViz* in other situations. At the moment, for instance, users always start with a neutral treemap, corresponding to cold start situations. In upcoming research, however, we plan to record implicit user feedback, e.g. by logging clicks and dwell times, and visualize the resulting profiles to users. Their reactions could be insightful in two ways: 1) how users react, when they are presented with their implicitly recorded behavior; and 2) whether they will appreciate it when their otherwise hidden profile is not only shown but also made controllable to them.

We further believe that attributes of treemaps can be used more extensively in *NewsViz*. For instance, the inherent ability to depict several levels of hierarchy bears so far unused potential. In our setting, we depicted two hierarchical levels. In practical settings, however, especially categories are typically organized in more than one categorical layer. With such an advanced interface we also plan further user surveys, in which we will also compare *NewsViz* to other baseline systems (e.g. even simpler ones with less interaction modalities).

[8]http://www.newsmap.jp/

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