Analyzing Recommender Systems' effects on filter bubbles

Yaning Xu
McMaster University
Hamilton, ON, Canada
xuy200@mcmaster.ca

1 Introduction

Recommender systems have played an important role in everyday digital experiences by providing us with personalized content such as videos, articles and products [13]. They improve our social media experience while providing potential business benefits for companies. However, in recent years there has been increasing attention on the potential detrimental effects of over-personalization, commonly referred to as "filter bubbles"[1].

The term filter bubble describes the phenomenon where excessive content provided by recommender systems reinforces users' pre-existing perspectives and beliefs, reinforcing users' beliefs in a feedback loop that may lead to increased bias, intellectual isolation or polarization [7]. Moreover, these effects are often embedded within algorithmic personalization mechanisms, making them invisible and difficult to detect or quantify [1]. Therefore quantifying filter bubbles allows us to evaluate the performance of personalization systems, identify flaws in the algorithms and system design, and propose proper actions to counteract their effects so users can be exposed to a wider range of perspectives, reducing ideological isolation, improving community engagement and social media environment [2, 9].

Despite increasing attention drawn to this field, several challenges remain in addressing the connection between recommender systems and filter bubble effects. Although various metrics have been proposed to measure filter bubbles, there is no universally accepted method to quantify their severity and long-term effects [4]. Additionally, the opinions on whether recommender systems cause filter bubbles are very mixed, some claim that recommender system especially those with collaborative filtering(CF) embedding can reinforce filter bubbles [10], whereas others argue that they have very little impact or even reduce the effect of filter bubbles[11, 13]. Moreover, due to the interactive nature of recommender systems, in order to get a comprehensive understanding of filter bubbles, we need to analyze both the system performance and user behavior, which makes it a complicated research problem [2, 13]. Additionally, despite the influence of recommender systems, user's opinions are also impacted by their social group's dominating perspective [2], and personal factors such as short attention spans, cognitive biases, and subconscious information processing, making it even more challenging to measure filter bubbles [9].

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This research primarily examines biases and fairness in AI systems, with a focus on how recommendation algorithms contribute to the exposure of ideological content and its broader social implications. We intend to answer the following two questions:

- **RQ1**: Do recommender systems based on collaborative filtering reinforce or mitigate the effects of filter bubbles?
- **RQ2**: How does user behavior impact the system performance in a personalized news recommendation setting?

2 Related Work

There have been numerous studies conducted to explore the effect of recommendation systems on filter bubbles. However, the conclusion is somewhat divided. Through analyzing CF-based recommendation systems in a specific field such as Movielens [5], Noordeh et.al. [12] found that CF reinforces filter bubbles and echo chambers. They also stated that once the echo chamber is established, it is difficult for a user to escape it only by manipulating their own actions. Moreover, Nguyen et.al. argued that while recommender systems do lead to a slightly narrower range of content over time, their effect is relatively small, especially for those who actually follow the recommendations instead of neglecting them [11]. They also suspected that purely content-based recommenders would push users into a much narrower content consumption than CF does. Vancompernolle and Fouss [13], on the other hand, claimed that without any human interaction, CF algorithms by themselves do not create filter bubbles. The study found that both user choices and algorithms collectively influence content diversity. However, without the user's feedback loop, the algorithms did not self-reinforce a bubble, further highlighting the challenges of the complex interactivity nature of recommender systems.

Similarly, when analyzing general social media feeds on broader content, some researchers believe that the recommender-driven environment can contribute to information segregation, although this occurs through an interplay between the algorithm and the social group to which users belong [2]. Additionally, Kandula [7] mentioned that personalization algorithms used in social media based on user behaviors and emphasis on performance accuracy have contributed significantly to filter bubbles. However, the focus of his work was primarily on implementing diverse algorithm traits and features into system design to mitigate the effect of filter bubbles, rather than proving such reinforcement exists.

On the other hand, numerous studies and experiments have been conducted to demonstrate that social media can actually help mitigate the effects of filter bubbles. The study conducted by Jones-Jang and Chung [6] found that social media use did not reinforce filter bubbles or polarization in the COVID-19 context, instead it actually mitigated them. One interesting finding they mentioned was that individuals who relied more on social media (two-way communication) for COVID-19 news were less polarized in their attitudes, while those relying on traditional media such as television or radio (one-way communication), were more polarized.

In news-specific domains, by analyzing Brazilian news during its 2018 presidential election, Lundardi [10] found that recommender systems with CF algorithms can create and reinforce filter bubbles, especially when they are used for news recommendation and focus too narrowly on accuracy. Additionally, the experiments conducted through stochastic simulation by Curmei and Dean also supported the claim that recommendation accuracy can strengthen the effects of filter bubbles [4]. Similarly, Liu et.al. [9] found that the filter bubbles effects in news recommendation are real but heterogeneous, as they depend strongly on the users' political profiles and the algorithm used. However, in the literature review, Arguedas et.al [1] argued that algorithmic recommender systems on average increase content exposure. They also claimed that search engines or other social media feeds lead to slightly more diverse news use, and user self-selection, rather than algorithmic design, is the primary driver of echo chambers.

There is considerable disagreement in the literature regarding the impact of recommender systems with different algorithms on filter bubbles in many social contexts. Therefore our research focuses on CF-based recommender systems for news recommendation, with additional focus on how users' behavior impacts the system performance.

3 Methodology and Study Design

For this study, we require a sufficiently large set of news articles annotated by both opinion stances and topics to analyze the performance of the personalization algorithm on users' feeds in news recommendation settings. In this section, we will walk through the data processing and annotation process, as well as the proposed study design and methodology.

3.1 Data Source & Annotation

In our study we used the MIcrosoft News Dataset MIND-small [14] for news recommendation research comprising 50,000 users and their behavior logs. We analyzed real-world user interactions, as simulations may not fully capture the complexities of actual behavior [3].

For the classification step, we first defined a keyword dictionary and used it to determine if an article is relevant to the selected topics. We originally extracted articles that belong to 10 chosen topics, but in the end we decided to keep only two topic datasets - gun rights and environment - to enable more tractable cross-topic comparisons given our limited participant pool. After topic classification was completed, we then used a pre-trained classifier model **facebook/bart-large-mnli** for the data annotation process to determine an article's underlying opinion stances in $\{-2, -1, 0, 1, 2\}$, ranging from strongly oppose -2 to strongly support 2 based on the topic context. After the annotation process, we extracted 1189 and 259 articles related to Gun Rights and Environment, and their stance distributions are presented in Tables 1 and 2.

3.2 System Setup

The CF-based recommendation engine was implemented using LightFM with real user interactions from the MIND-small dataset [8]. There are a total of 5 user interfaces designed for this study, all of which can be found in the appendices:

- Pre-survey: We gather participants' news consumption habits, as well as their stances on one(1) chosen topic, which are defined more precisely.
- Topic Selection: Participants selected the same topic they selected during the pre-survey to receive news recommendations from.
- Recommendation List: A panel that displays a list of 10 recommended news article titles each time. Articles that are rated will be marked, and the list can be refreshed at any time. Participants are asked to rate a total of 20 articles before proceeding to the post-survey
- Rating Panel: For the scope of this project and rapid prototyping, we are only displaying the news title and abstract to users. After reading through them, users will be asked to provide feedback on the following two questions:
  (1) If the article aligns with or contradicts their personal views?
  (2) Would they like to see more content like this in their feeds?
  The feedback for question 2 was used to update the recommendation model for personalization purposes.
- Post-survey: We collect users' feedback on the quality, relevance, and stance diversity of the recommended articles. Additionally, we also ask them to restate their stances on the chosen topic to see if there is any shift in perspective after news consumption.

We also set up screen recordings and a logger to automatically log user interactions, details of which are included in the appendices.

stance	interpretation	# articles	% articles
-2	Strongly support gun rights	3	0.3%
-1	Somewhat support gun rights	849	72.2%
0	No strong opinion on guns	0	0.0%
+1	Somewhat support gun control	331	28.1%
+2	Strongly support gun control	6	0.5%

Table 1: Stance distribution for Gun Rights news articles.

stance	interpretation	# articles	% articles
-2	Strongly oppose environmental action	1	0.4%
-1	Somewhat oppose environmental action	91	36.1%
0	No strong opinion on climate change	0	0.0%
+1	Somewhat support environmental action	156	61.9%
+2	Strongly support environmental action	10	4.0%

Table 2: Stance distribution for Environment news articles.

During the study, each user interacts with a personalized instance of the same underlying recommendation model. This model is updated every five user interactions (i.e., after every five article ratings). These updates are performed individually for each user and are not accumulated across users — that is, the model is reset for each participant and learns only from that user's behavior during their session. Each case study lasted on average 30 minutes, a total of 23 user studies were conducted, and 12 of them were included in the final data analysis. Half of the cases were discarded due to system updates on the model re-training process, but their suggestion in the post-survey are still included in the analysis. Participants were primarily graduate students at McMaster, with two additional working professionals and one undergraduate student. All of them were compensated with snacks and drinks for their time.

4 Experimental Metrics and Results

4.1 Metrics

In this study, we will evaluate both the performance of our recommender system and user agency. This includes both the algorithm's ability to deliver relevant content and the extent of user agency—defined as user control and engagement with diverse content. For each user u, let N denote the total number of articles recommended to the user, and for each recommended article i, let $r_i = 1$ denote the user rated this article, and $r_i = 0$ if they didn't. To analyze the system as well as its effect on filter bubbles, we propose the following metrics:

- Click-Through-Rate(CTR): CTR is the proportion of the number of recommended articles that the user rated. A high CTR in this setting indicates the CF algorithm can deliver recommendations that the user is interested in.

$$\text{CTR} = \frac{\sum r_i}{N}$$

- Average Document Stance: This refers to the average stance score of the articles recommended to the users. It reflects the average ideological position of content users are exposed to. Let $s(a_i) = \{-2, -1, 0, 1, 2\}$ be the stance score for article a_i, we then have

$$\text{Average Document Stance} = \frac{\sum s(a_i)}{N}$$

- Normalized Stance Entropy: Let p_i denote the fraction of articles recommended to the users that have stance i. As we have five values for our stance score, the entropy is calculated as follows:

$$\text{entropy} = \frac{-\sum_{i=1}^{5} p_i \log p_i}{\log 5}$$

  A high value of normalized stance entropy would indicate a smaller filter bubble effect, as the stances of the news articles recommended to the user are more diverse.
- Maximum Rank Gain: The maximum rank gain for an article a is the largest position change for a recommended article before and after personalization updates
- Counter-Perspective Exposure: The number of occurrences where user actively chooses to engage more with content that opposes their beliefs indicated in the pre-survey. This captures how often users engage with content that challenges their existing views.
- Like-Minded Exposure: The number of occurrences where user choose to engage more with content that aligns with their beliefs indicated in the pre-survey. This captures how often users engage with content that confirms their existing views.

4.2 Results

4.2.1 ***User engagement patterns reveal varied news screening behavior.*** Among the 12 participants, 7 selected *Environment* and 5 selected *Gun Rights* as their topic of interest. The number of recommended articles browsed prior to completing the required 20 ratings varied substantially. While most participants viewed between 40 and 90 articles, two outliers scanned as many as 150 and 170 articles.

This disparity highlights the differences in user-level screening strategies. Some participants demonstrated high selectivity by carefully filtering through a large pool before engaging, whereas others rated articles earlier in the sequence. This behavior is also reflected in the click-through rate (CTR) analysis (Figure 1), which shows a median CTR of 36%, meaning users rated approximately 3.6 out of every 10 articles displayed per batch. Overall, this indicates moderate but consistent user engagement with the recommendation model.

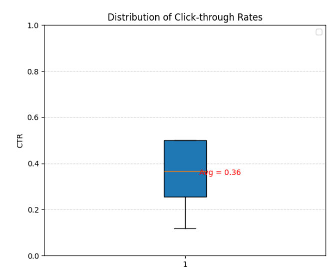

Figure 1: Click-Through-Rate

4.2.2 ***Personalization yielded insignificant content shift in recommended content.*** Despite ongoing model updates during the user sessions, the average article stance of the recommended content remained largely unchanged. As shown in Figure 4 (left), the stance scores of articles recommended to each user exhibited minimal fluctuation around the dataset-wide average, regardless of the participant's initial stance in the pre-survey.

This pattern was observed across both topics, suggesting that the recommender system did not substantially amplify or reinforce user bias through extreme content curation. A potential explanation lies in the dataset's composition: articles with strong ideological stances (i.e., scores of −2 or +2) were underrepresented, comprising less than 1% of the *Gun Rights* articles and under 5% of the *Environment* set. In both sets, articles with neutral stances were also missing. Additionally, the interaction weight in the model was set to 3, which may have limited the extent to which user preferences influenced subsequent recommendations, therefore restricting the personalization effect.

4.2.3 ***Moderate ideological diversity and adaptive model behavior***. The diversity of content exposure, as measured by normalized stance entropy, ranged from 0.39 to 0.60 across participants, with an average of 0.48 (on a scale from 0 to 1) (Figure 2). This indicates that users were exposed to a mix of ideological viewpoints, with moderate concentration toward the dataset's central stance. The entropy scores suggest that while filter bubble effects were not dominant, neither was full ideological balance achieved.

In parallel, the system exhibited signs of adaptation in response to user feedback. Across four rounds of interaction, the average maximum rank gain for an article was 3.48 positions within a 10-article recommendation batch (Figure 3). This indicates that articles aligned with user preferences were increasingly prioritized in the recommendation list over time, reflecting the model's capacity to respond to user behaviors.

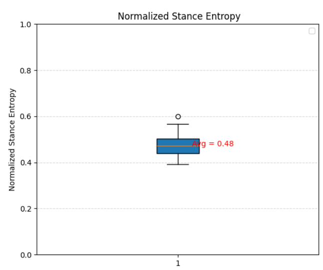

Figure 2: Normalized Stance Entropy

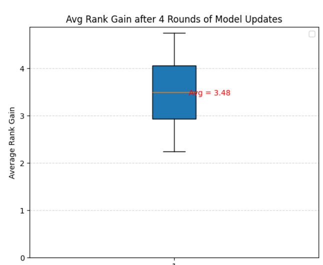

Figure 3: Average Maximum Rank Gain of an Article After Model Updates

4.2.4 ***Shifts in user perspective observed post-interaction***. Post-survey responses revealed significant changes in attitude among a subset of participants. Specifically, three out of the 12 participants—all from the *Environment* topic reported a shift in their stance toward stronger support for environmental actions after the study. While the small sample size limits generalization, this preliminary finding supports the hypothesis that exposure to curated news content can influence users' pre-existing beliefs on sociopolitical topics.

4.2.5 ***Engagement skewed toward like-minded content, with some exceptions***. Engagement data revealed that participants generally preferred content aligned with their personal views. However, several individuals also engaged meaningfully with articles expressing opposing viewpoints. This suggests that users did not passively receive content, but rather they are navigating perspectives to fit in for their personal reading habits (Figure 4, right).

Additionally, a portion of article ratings were marked as neutral or uncertain, as represented by gray bars in the visualization. These reflect users' difficulty interpreting article stance based on limited context (title and abstract) or indifference toward the content presented. This diversity in interaction suggests that user agency played an important role in moderating content exposure within the personalized recommendation environment.

5 Discussion

The results of this study indicate that the collaborative filtering (CF) recommendation model used did not heavily reinforce users' existing beliefs. Instead, it exposed users to a moderately diverse range of perspectives. This finding challenges the common assumption that CF-based recommenders reinforce filter bubble effects, and instead suggests that they may actually contribute to mitigating them.

The system's responsiveness to user feedback is shown by the consistent increase in article rank gain across model updates, indicating that personalization occurred dynamically over the course of the session. At the same time, the average normalized stance entropy of 0.48 suggests that the content presented was not highly polarized, though it was not fully balanced either. This reflects a partial breakdown of filter bubble effects, where users are exposed to a mix of viewpoints, but not in an ideal evenly distributed pattern.

Additionally, while many participants predominantly engaged with like-minded content, a subset of users actively chose to explore opposing perspectives. This voluntary engagement with counter-attitudinal content suggests that some participants were consciously aware of potential bias in personalized recommendations and actively sought broader informational coverage to gain a more balanced understanding.

Moreover, a measurable shift in opinion was observed in 25% of participants—specifically within the environment topic—following exposure to the personalized recommendation stream. Although the sample size limits the generalizability of this finding, it provides preliminary evidence that recommendation systems, when coupled with diverse content, can influence user attitudes over time.

In conclusion, these findings highlight the complex interplay between algorithm design and user agency. Rather than acting as a deterministic force, the CF algorithm in this study appeared to offer a framework that users could navigate and influence. Therefore the mitigation of filter bubble effects depends not only on the algorithmic logic but also on the behavioral patterns and intentions of individual users.

6 Limitations and Future Work

Several limitations emerged during the development and evaluation of our study, both from the system setup and participant feedback.

First, many participants noted that the article abstracts extracted from the MIND dataset were too brief and lacked explicit subjective viewpoints. As a result, users found it difficult to assess the intent of the content based solely on the title and abstract.

"The data is not big enough and the abstract is too little." – U88457

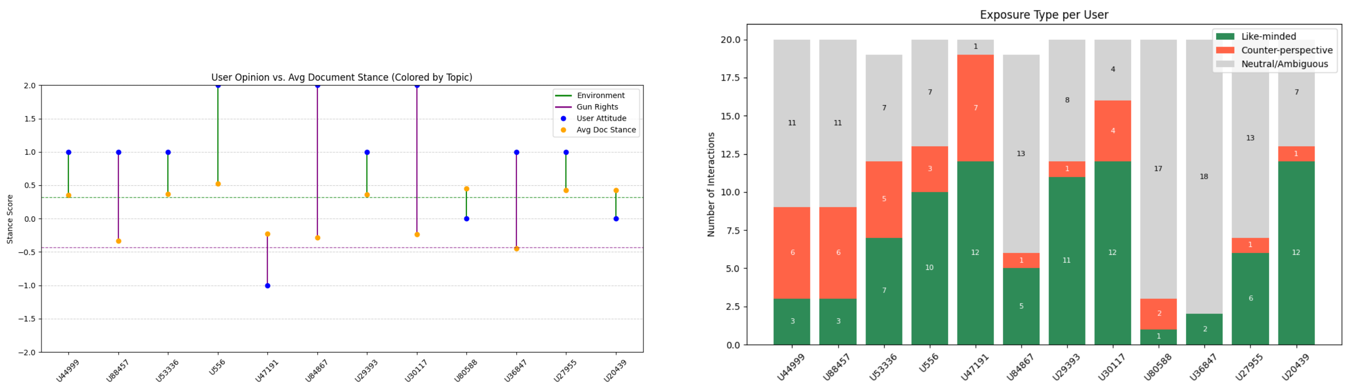

Figure 4: (Left) Comparison between user opinions and average article stance recommended. (Right) Content exposure type distribution.

"The length of the abstracts are fairly short, so although the piece could be discussing something that occurred (a suspected shooting), the abstract could cut off before actually telling me any outcomes or findings." – U33692

Additionally, the dataset appeared to lack articles with strong ideological stances, particularly at the extremes. This imbalance likely stems from limitations in the stance annotation process. While we initially planned to use Media Bias/Fact Check to annotate articles based on their original news source, the URLs provided in the MIND dataset had expired, and therefore we are unable to trace back to their publisher for annotation purposes. Consequently, stance annotation relied solely on text classification, which may have limited the diversity of ideological content. For future work, we aim to adopt alternative datasets that include both user interaction logs and traceable publisher information, or find an alternative news-specific classifier model that annotates articles based on their intents.

Furthermore, participants also expressed difficulty in discerning article intent from titles and abstracts alone. The decision to exclude full-text articles was made to enable rapid prototyping and to accommodate the 30-minute session constraint for each case study. However, this tradeoff may have reduced the expressiveness and evaluative depth of participant feedback.

"Hard to know how to answer because the article is either written objectively and/or there are multiple opposite viewpoints." – U91853

"The articles provided didn't really offer opinions on my chosen topic of gun rights; they were just news articles related to anything with the word 'gun' or 'shooting' involved... There wasn't really anything discussing the pros or cons of gun ownership, regulations, and laws." – U33692

"Have a detailed section to let the user explain why they support their stances." – U53336

Lastly, several participants provided suggestions to improve the user interface. These include displaying article publication dates, allowing users to mark or hide articles they choose to skip, and implementing a more interactive rating mechanism such as a draggable visual scale. Incorporating these improvements could enhance user experience and support more accurate feedback collection in future studies.

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A System Interface

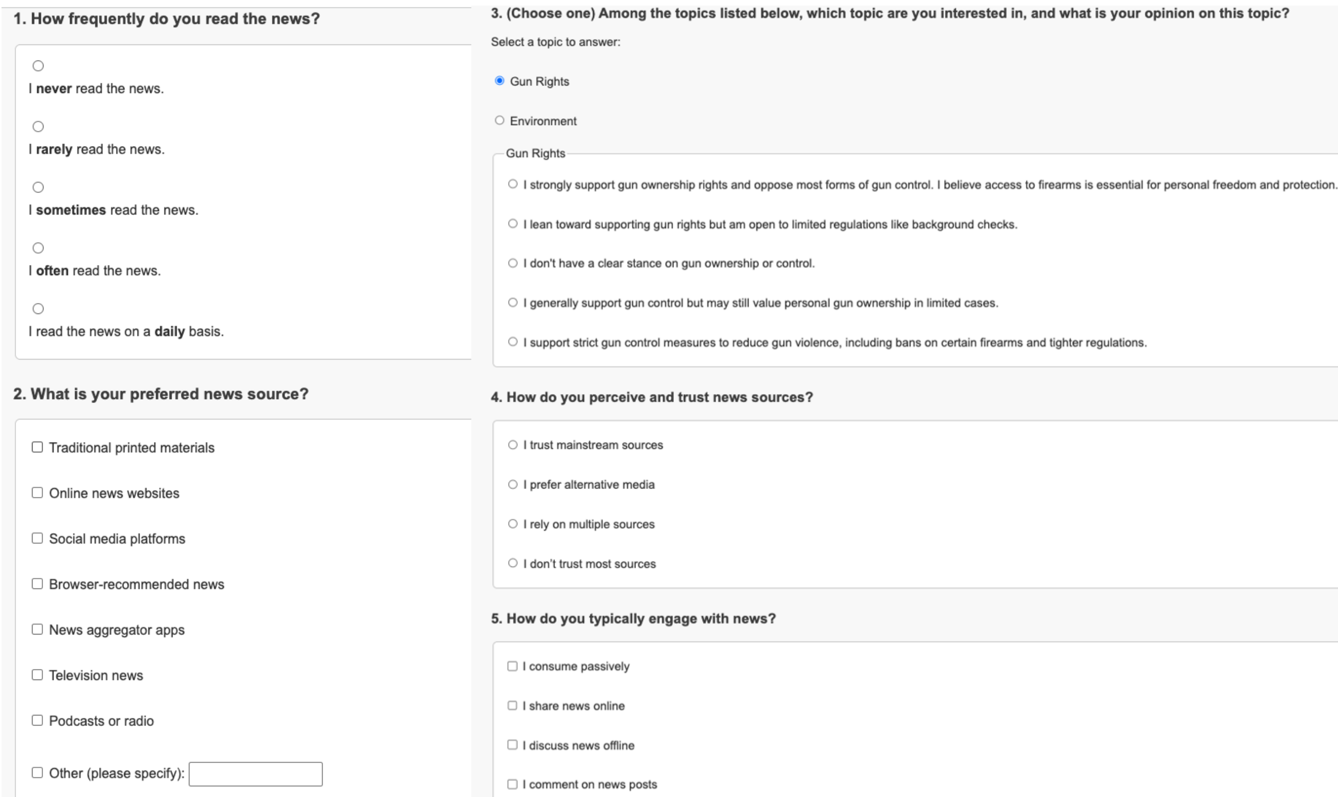


Figure 5: Pre-survey stage.

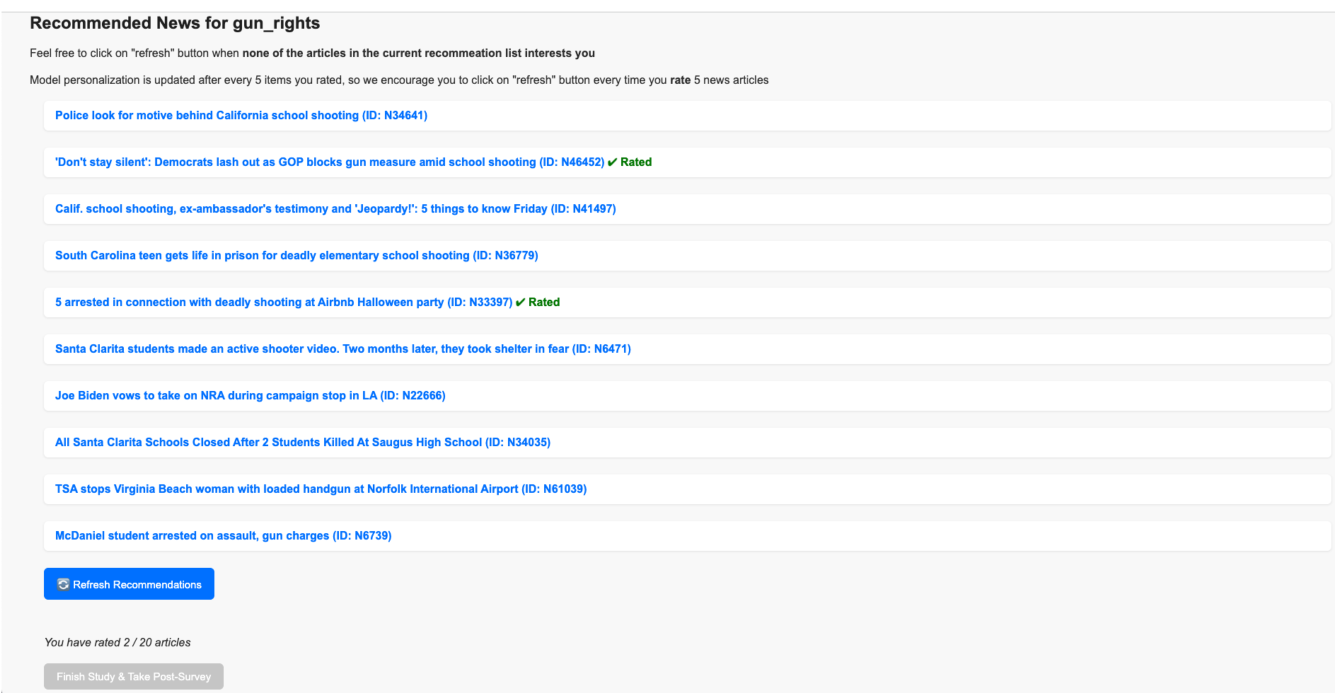
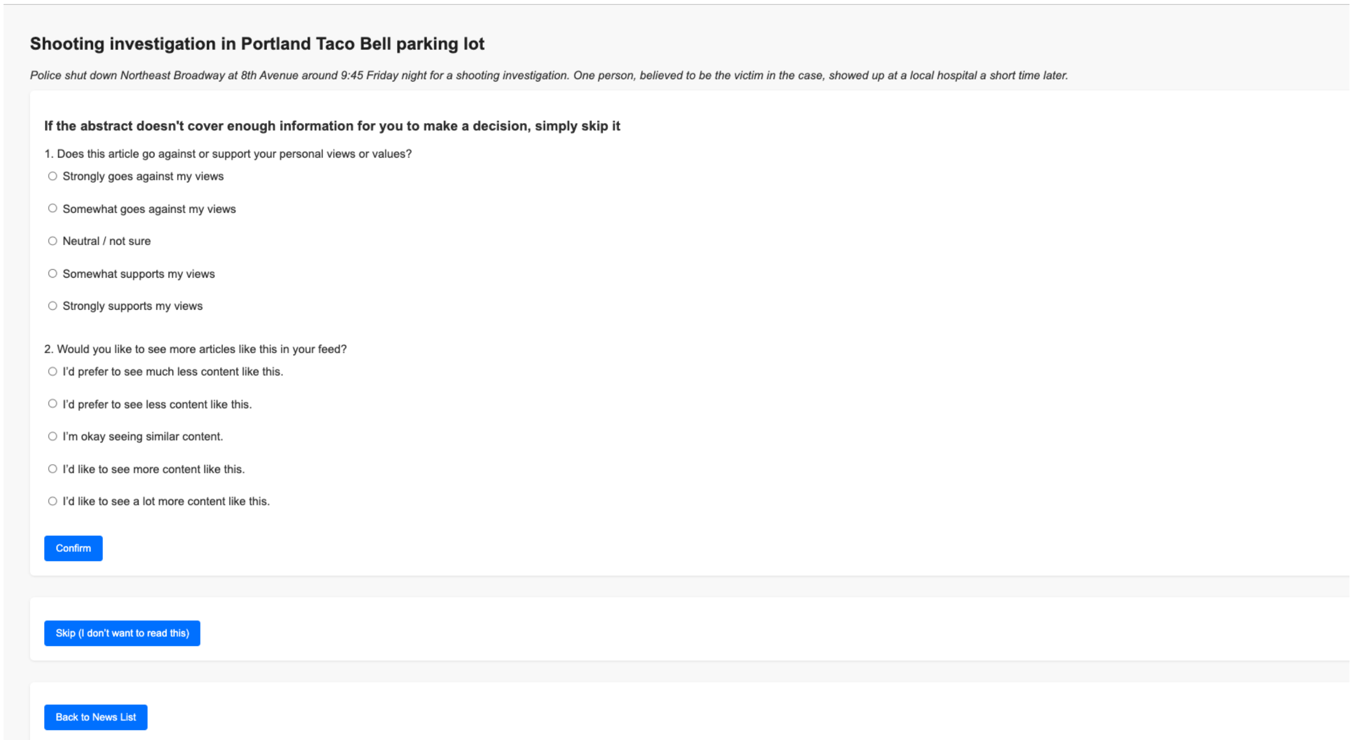


Figure 6: News recommendation panel


Shooting investigation in Portland Taco Bell parking lot

Police shut down Northeast Broadway at 8th Avenue around 9:45 Friday night for a shooting investigation. One person, believed to be the victim in the case, showed up at a local hospital a short time later.

If the abstract doesn't cover enough information for you to make a decision, simply skip it

1. Does this article go against or support your personal views or values?

- ○ Strongly goes against my views
- ○ Somewhat goes against my views
- ○ Neutral / not sure
- ○ Somewhat supports my views
- ○ Strongly supports my views

2. Would you like to see more articles like this in your feed?

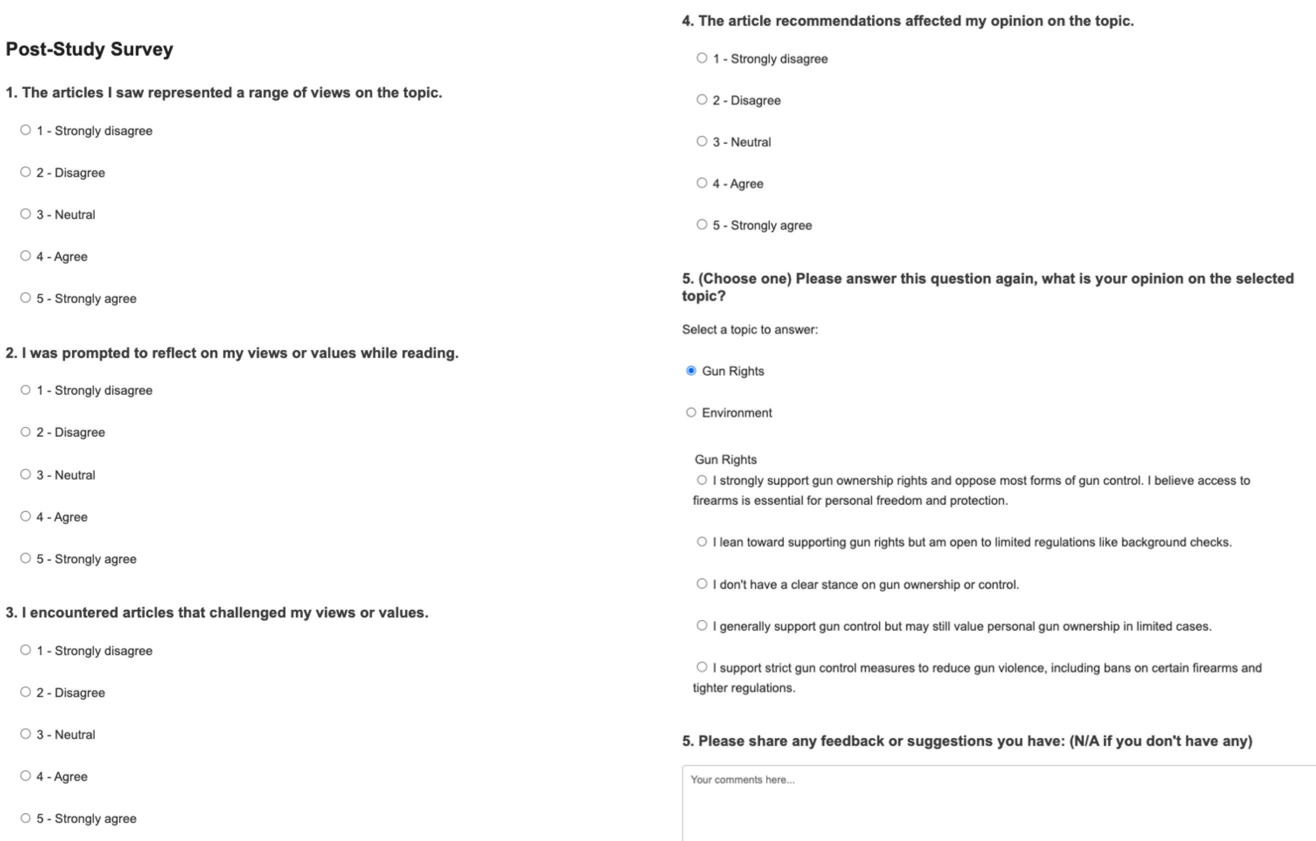
- ○ I'd prefer to see much less content like this.
- ○ I'd prefer to see less content like this.
- ○ I'm okay seeing similar content.
- ○ I'd like to see more content like this.
- ○ I'd like to see a lot more content like this.

Confirm

Skip (I don't want to read this)

Back to News List

Figure 7: Rating panel


Post-Study Survey

1. The articles I saw represented a range of views on the topic.

- ○ 1 - Strongly disagree
- ○ 2 - Disagree
- ○ 3 - Neutral
- ○ 4 - Agree
- ○ 5 - Strongly agree

2. I was prompted to reflect on my views or values while reading.

- ○ 1 - Strongly disagree
- ○ 2 - Disagree
- ○ 3 - Neutral
- ○ 4 - Agree
- ○ 5 - Strongly agree

3. I encountered articles that challenged my views or values.

- ○ 1 - Strongly disagree
- ○ 2 - Disagree
- ○ 3 - Neutral
- ○ 4 - Agree
- ○ 5 - Strongly agree

4. The article recommendations affected my opinion on the topic.

- ○ 1 - Strongly disagree
- ○ 2 - Disagree
- ○ 3 - Neutral
- ○ 4 - Agree
- ○ 5 - Strongly agree

5. (Choose one) Please answer this question again, what is your opinion on the selected topic?

Select a topic to answer:

- ◉ Gun Rights
- ○ Environment

Gun Rights

- ○ I strongly support gun ownership rights and oppose most forms of gun control. I believe access to firearms is essential for personal freedom and protection.
- ○ I lean toward supporting gun rights but am open to limited regulations like background checks.
- ○ I don't have a clear stance on gun ownership or control.
- ○ I generally support gun control but may still value personal gun ownership in limited cases.
- ○ I support strict gun control measures to reduce gun violence, including bans on certain firearms and tighter regulations.

5. Please share any feedback or suggestions you have: (N/A if you don't have any)

Your comments here...

Figure 8: Post Survey

```
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  "pre_survey": {
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    "news_sources": [
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      "browser"
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      "diverse"
    ]
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  "recommendation_list": [
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      "article_stance": -1
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    "rank": null,
    "max_lift": {
      "news_id": "N4267",
      "initial_rank": 9,
      "new_rank": 4,
      "rank_gain": 5
    },
    "article_stance": 1
  },
  {
    "news_id": "N6406",
    "label": 0,
    "rating": null,
    "timestamp": "2025-04-07T12:18:05.668802",
    "batch_id": "N14159,N6406,N52104,N53984,N59494,N60092,N48022,N27539,N58545,N42974",
    "article_stance": -1
  },
  "post_survey": {
    "diverse_views": "2",
    "self_reflection": "4",
    "challenged_views": "4",
    "system_influence": "2",
    "selected_topic": "5b",
    "stance_value": "4",
    "open_feedback": "It'd be nice to ask the user's stance in detail
  }
}
```


Figure 9: Logger