# Bridging Viewpoints in News with Recommender Systems

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## ABSTRACT

News Recommender systems (NRSs) aid in decision-making in news media. However, undesired effects can emerge. Among these are selective exposures that may contribute to polarization, potentially reinforcing existing attitudes through belief perseverance—discounting contrary evidence due to their opposing attitudinal strength. This can be unsafe for people, making it difficult to accept information objectively. A crucial issue in news recommender system research is how to mitigate these undesired effects by designing recommender interfaces and machine learning models that enable people to consider to be more open to different perspectives. Alongside accurate models, the user experience is an equally important measure. Indeed, the core statistics are based on users' behaviors and experiences in this research project. Therefore, this research agenda aims to steer the choices of readers' based on altering their attitudes. The core methods plan to concentrate on the interface design and ML model building involving manipulations of cues, users' behaviors prediction, NRSs algorithm and changing the nudges. In sum, the project aims to provide insight in the extent to which news recommender systems can be effective in mitigating polarized opinions.

## KEYWORDS

News Recommender Systems, Behavioural Change, Polarization, Attitude, Nudges, Selective Exposure

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## 1 INTRODUCTION

Personalized recommender systems have been applied daily for years in many areas, such as Politics, Movies, Health and Business [19, 24, 35, 69]. They support people in decision-making and may facilitate the further purchase of the recommended items [24, 28, 71]. Netflix indicates that the proportion of the content people watch from different sorts of recommendations accounts for 75% [3]. Furthermore, a report from YouTube mentions that the proportion of clicking videos from the homepage via the recommender systems was 60% [14]. When applied to news, News Recommender Systems (NRSs) have enabled platforms to deliver news content tailored to users' preferences [33]; various modern media sites adopt personalized news recommender systems to suggest news articles based on users' personalities and preferences. For example, personalized recommender systems increase click-through rates and provide tailored articles on news websites through designed interfaces and algorithms [19, 22].

However, it is important to equally consider the potential risks; one of the fundamental theories in our research is that individuals have attitudes, which are essentially favorable or unfavorable opinions toward specific aspect [18]. These attitudes may influence readers' behaviors on news consumption. Moreover, people tend to seek out and read news that aligns with their pre-existing beliefs or attitudes, a phenomenon known as selective exposure [20, 34, 65]. People being exposed to news that matches their beliefs, selective exposure can also significantly reinforce and intensify polarization among individuals. As a result, their existing attitudes can be further strengthened [11, 23]. Another issue in algorithms used in personalized recommender systems is the filter bubble, which reduces a person's exposure to information that is at odds with their own beliefs and attitudes. Consequently, these theories are essential as they closely link to our research strategies. For example, our recent study explored to what extent manipulations, such as emotional reframing influence user perception and behavior in news recommender systems [30].

Importantly, we chose emotional reframing as one of manipulations because it influences users' attitudes and decision-making process [44, 56]. By manipulating emotional frames of news articles, we can study how different framings affect user attitude and behavior. We also explore the re-framing effect in large language models (LLM) compared with human journalists. Although NRSs deliver personalized content [33], LLMs, such as ChatGPT, may assist newsroom automating or optimizing a broader range of news-related decisions and processes [16, 55]. Additionally, we consider other manipulations, such as re-angling stories for local relevance, to adjust narratives for specific demographics.

A major limitation of these findings is the uncertainty regarding how to mitigate the undesirable effects of polarization through both algorithmic and interface manipulations in a news recommender scenario. Additionally, it is unclear whether these interventions will impact the profitability of the journalism industry. This project aims to propose novel recommender technology that can steer people's choices based on their attitudes, to reduce the adverse effects of polarization (see Figure 1). For our study, we focus on the controversial news topics, such as Gun Control, Abortion and Climate Change [10]. Firstly, this research agenda will focus on the interface design with different cues. Next, the project will observe which cues different people use the most based on their attitudes and profiles. Then, this project will build machine learning models from


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NRSs algorithm and the observations to predict people's choices. We also explore whether the usage of these manipulations will affect readers' engagement and trust in news articles, then, in turn, influence their willingness to pay for news subscriptions. Finally, the project will utilize different kinds of nudges to discover how they can steer users' choices. Moreover, we plan to focus more on the user's perspective with long-term testing in the final evaluation stage [9, 37, 58, 68, 75]. Therefore, this research agenda will consider comprehensive visions, from frontend and backend design to user-system interactions.

- RQ1: To what extent does a user's attitude determine their choices in a news recommender system, compared to traditional user characteristics, such as demographics and personality?
- RQ2: How is cue/nudge usage in a news recommender system related to user attitudes and profiles?
- RQ3: To what extent can we predict user choices in a personalized news recommender system using different attitudes and profiles?
- RQ4: To what extent does the use of cues, NRS algorithms and nudges affect users' engagement and trust in news articles, and consequently, influence their willingness to pay for news subscriptions?
- RQ5: To what extent can we steer user choices in the context of news recommender systems toward different polarized topics in long term and short term effects?

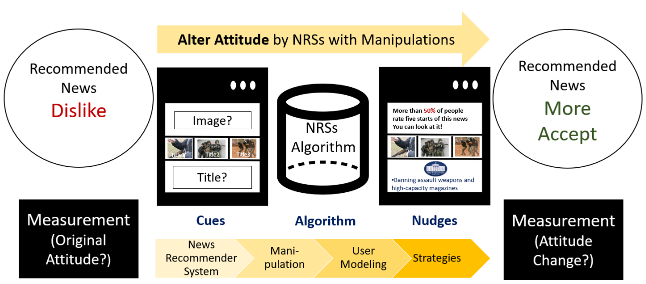


**Figure 1: The overall research flow that aim to alter users' attitude by news recommender system and manipulations from cues, NRSs algorithm and nudges.**

## 2 RELATED WORK

News personalized recommender systems and selective exposure are critical concepts in news media. Given the influence of personalization techniques and selective exposure on user behavior and preferences, it is crucial to address these undesired effects from research and media services arising within the context of recommender systems in news media. The following sections will discuss these concerns, emphasizing the responsibilities of researchers in mitigating the potential undesired effects on users to prevent polarization in distinct groups.

The following sections will introduce and discuss these concepts, beginning with an explanation of news recommender systems and their purposes. Subsequently, the select exposure from personalized recommender systems will be discussed. Finally, we will discuss news polarization and how to mitigate these undesired effects using nudges.

### 2.1 News Recommender Systems

The abundance of news content leads to information overload and this issue increases the complexity that hinders users' capacity to identify content relevant to their interests and benefits [33]. Given this scenario, news recommender systems becomes crucial as they offer personalized recommendations, effectively enabling users to navigate the massive online news and information. By tailoring content to align with user profiles and preferences, these systems accelerate the information-retrieving process, raising the efficiency and relevance of online news consumption [13, 29, 57]. Existing studies indicate that personalized information systems enhance users' perceived relevance, involvement, and engagement with content [6, 53]. In addition, news recommender systems not only facilitate access to content relevant to individual users, but also yield commercial advantages for platform providers [72].

However, the potential drawbacks of news personalized recommender systems also warrant attention. Some researchers have expressed concerns that this level of personalization may lead individuals to make unwise decisions by missing essential information. This is because personalized news recommendation systems may filter content based on user preferences and behavior, potentially causing individuals to ignore stories that they deem irrelevant or contrary to their attitudes. Ultimately, this could result in undesired effects, such as polarization [6].

In personalized news recommendation algorithms, there is a potential risk of filtering out content representing opposing viewpoints or perspectives, an effect known as the filter bubble. The online recommendation system, as a technique, may be particularly prone to this negative consequence. The reason for this susceptibility lies in the system's primary objective, which is to predict and present users with content or products tailored to their preferences [49]. As a result, the filter bubble effect can inadvertently contribute to a narrowed scope of information exposure for users, limiting access to diverse perspectives [19, 71].

Moreover, recent studies suggest that the undesired effects of online polarization may not be attributable to filter bubbles as alone. Instead, selective exposure based on users' pre-existing attitudes may play a significant role in this phenomenon [7, 77]. Furthermore, this selective exposure may interact more closely with our pre-existing perspectives, potentially exacerbating polarization [60]. When it comes to the influence of individuals' attitudes and actions, personalized news recommender systems have a tendency to be selective, resulting in users being leaner to consume articles that correspond with their existing beliefs and spending more time on them [6, 32, 34].

As suggested in multiple studies [6, 40, 48] , this problem has been noticed in many news topics, such as elections, refugee issues, and disease control. Moreover, this problem also occurs on social media platforms where it can increase the division between different online communities with contrasting attitudes [15, 17, 39]. To overcome this issue, researchers should investigate various personalized design choices and adjust algorithms considering multiple factors to decrease the negative impact [6, 53, 66].

Consequently, personalized news recommender systems are increasingly prevalent in news media, utilizing user preferences and the need to deliver customized content. These systems present numerous benefits, such as efficient content consumption and improved user experience. Nonetheless, potential drawbacks should be considered, as present content consistently aligning with users' behaviors and preferences could result in polarization. It is essential for researchers to investigate diverse methodologies and designs to address these issues, achieving a balance between personalization and the various perspectives. As mentioned, potential issues stemming from recommender system algorithms and that users self-select content aligning with their preferences encompass the filter bubble effect, which may exacerbate polarization. From an individual standpoint, selective exposure remains a significant challenge, as users might persistently opt for content that corresponds with their pre-existing beliefs.

## 2.2 Selective Exposure

Selective exposure is when people pay attention to information that agrees with their beliefs and ignores information that goes against them; It avoids feeling uncomfortable or confused when encountering information contradicting their pre-existing thought. In other words, people seek information supporting their beliefs and ignore information that challenges them [6, 20, 74].

*2.2.1 Selective Exposure with Recommender Systems.* Personalization in recommender systems inherently involves selectivity, as individuals tend to consider the recommended context when receiving customized suggestions. Users generally prefer content that aligns with their pre-existing attitudes or beliefs [6]. In the era of digital journalism, online news providers have increasingly adopted personalized news recommender systems to alleviate information overload and tailor content to individual preferences. However, these algorithms may inadvertently reinforce selective exposure among users. Consequently, this phenomenon has the potential to exacerbate polarization and facilitate the spread of misinformation [2].

As a result, the negative consequences associated with personalization in recommender systems can be attributed to both the selective exposure, which is driven by users' attitudes and beliefs, and filter bubble effect, which stems from algorithmic factors and the tendency of readers to choose content that matches their preferences. This essay concentrates on examining the impact of users' attitudes on selective exposure, exploring potential methods to mitigate its undesired effects.

*2.2.2 Selective Exposure with Users.* People's attitudes and behaviors may lead to biased news consumption. Regarding the bias from people's attitude and behavior, personalized news recommender systems tend to be selective, and users tend to spend more time engaging with stories that align with their pre-existing attitudes [6, 32, 34]. Two patterns can be observed in how individuals consume news; some individuals explore multiple news outlets but still prefer a particular viewpoint, while others stick to sources that align with their beliefs and rarely consider different perspectives[21].

*2.2.3 Confirmation bias and Echo Chambers.* The potential risks of selective exposure include cognitive phenomena such as confirmation bias and echo chambers. Confirmation bias represents the underlying psychological cause of selective exposure, whereby individuals tend to interpret or seek evidence that aligns with their pre-existing beliefs or attitudes. In contrast, selective exposure refers to the active decision-making process in which individuals actively select information that aligns with their pre-existing beliefs or attitudes [50, 60]. For instance, one study provides evidence that online news exacerbates confirmation bias more than traditional media in political news. The experiment demonstrated that liberals exhibited confirmation bias only when the users were exposed to online news articles, compared to print media [54]. An additional concern is the formation of echo chambers caused by the recommender system's design rather than user psychology, which can lead to polarization. These chambers contribute to the widening of divisions between opposing groups and tend to amplify the spread of misinformation within isolated environments. Eventually, the recommendation systems employed by these platforms may continuously suggest content that reinforces existing perspectives while omitting irrelevant information based on the user's personality, thereby reducing the likelihood of users encountering diverse opinions from different communities [15, 19, 71]. For instance, a majority of Americans rely on social media platforms as their primary source of news, initially assuming that such platforms offer a diverse range of perspectives. However, growing concerns suggest that such content can lead to increased polarization and isolation from different groups [5].

Thus, selective exposure exacerbates users' tendencies to engage with content that aligns with their pre-existing beliefs or attitudes, potentially giving rise to confirmation bias, echo chambers, and ultimately causing polarization. With the growing adoption of personalized recommender systems in digital news platforms, it is crucial to address these negative consequences. By doing so, individuals may become more open to diverse viewpoints, mitigating polarization in society and reducing risks associated with selective exposure and filter bubbles. Additionally, exploring the potential of cues, NRSs algorithm and nudges to alter existing attitudes may be valuable in addressing the selective exposure problem, increasing the likelihood of users embracing novel perspectives they may have previously overlooked. By achieving this balance, recommender systems can continue to provide valuable services while fostering an inclusive and well-informed digital landscape.

## 2.3 News Polarization

Polarization causes a cyclical process that results in diminished communication between disparate groups. As interactions decrease, polarization is further reinforced, ultimately cultivating an "us-versus-them" mindset. This cycle can undermine the principles of democracy. Moreover, polarization may exacerbate violence in our society; it is imperative to implement strategies that address and mitigate the growth of this adverse effect [64].

*2.3.1 The Impact on Media and Society.* In recent years, digital news media has contributed to disseminating false information and promoting divisive messages, such as the 2016 presidential election in the USA. In essence, individuals tend to spend more time within groups that share similar attitudes or viewpoints, resulting in decreased exposure to distinct perspectives [42]. News consumption could contribute to polarization when individuals discuss with like-minded individuals. As people discuss political topics within groups that share similar beliefs, they tend to develop a greater trust in news sources that align with their viewpoints. Consequently, this can cause opposing groups to experience an increased divide in perceived credibility [76]. Moreover, the fake news and misinformation spread from the internet have contributed to ideological polarization within society, undermining democratic principles and fostering instability. In this context, opposing perspectives on various issues become increasingly polarized. Internet users' beliefs and attitudes are reinforced through communication within insular environments, intensifying extreme and radical viewpoints, while moderate voices are marginalized [4]. Polarization is predominantly driven by algorithms and personalization, mainly through recommender systems. These systems are designed to provide tailored content for users and are widely employed across online news platforms and social media. In contemporary applications, recommender systems deliver content based on users' prior behaviors, preferences, and patterns observed among similar users [1, 64].

Thus, polarization leads to an "us-versus-them" mentality, deepening societal divisions and undermining democracy. With the evolution of digital news and the widespread use of recommender systems, polarization has been exacerbated as individuals are increasingly exposed to like-minded communities, thereby limiting access to diverse perspectives and content from alternative sources. Furthermore, the spread of fake news and misinformation amplifies these polarizing effects. It is evident that personalization within recommender systems contributes to the issue of polarization, and this aspect has recently garnered increased attention as a matter of concern. As a result of these factors, the relationship between news polarization and personalized recommender systems is becoming increasingly intertwined.

#### 2.3.2 *News Personalized Recommender Systems and Polarization.*

Personalized recommender systems are widely applied to deliver customized information, encompassing news, search results, and product recommendations. The effectiveness of these systems is primarily attributed to the underlying algorithms, which are designed based on users' historical behaviors and profiles to predict users' preferences or needs. Moreover, these algorithms recommend extra content that may interest users by analyzing and comparing similar actions or behaviors exhibited by other users with comparable characteristics [13].

The algorithms in these systems are designed to deliver content that matches users' interests, which may exacerbate news polarization. This occurs when the algorithms consider individuals' pre-existing beliefs or attitudes to maximize news consumption, ultimately reinforcing their existing biases. Furthermore, polarization may contribute to the decrease of democracy and the rise of violence. For example, the polarization between different parties during US political elections has sometimes resulted in violence instead of adopting democratic norms, such as resolving differences through public debates. Consequently, there is a growing concern regarding preserving peace and security, particularly in the context of recommender systems that employ personalized algorithms to present a vast amount of news content [64].

The potential detriments engendered by the increasing polarization in personalized recommender systems, three primary factors could be identified: (1) the "filter bubble" phenomenon, which results from excessive personalization and consequently restricts exposure to contrasting perspectives or beliefs; (2) "selective exposure" and the "echo chamber" effect, which can reinforce users' pre-existing attitudes or beliefs by encouraging the selection of news that aligns with their prior perspectives, potentially exacerbating polarization; (3) the dissemination of misinformation and fake news, as personalized recommender systems may inadvertently facilitate the spread of erroneous information, posing a threat to societal stability and potentially widening the rift between opposing groups [6, 19, 42, 60].

Consequently, implementing personalized recommender systems in news dissemination has led to a notable increase in polarization. This phenomenon may exacerbate existing social and political divisions, ultimately threatening democratic principles and potentially escalating violence.

## 2.4 News Recommender Systems with Diversity from Cues, Algorithm and Nudges

To effectively address the negative consequences of recommender systems, there are two primary strategies: algorithmic adjustments and interface modifications. Studies [62, 70] have indicated that reommender systems typically base their suggestions on users' past behaviors, which can result in limited diversity. Enhancing diversity through algorithmic modifications is a crucial approach; incorporating factors such as relevance, serendipity, and novelty may help provide users with more balanced recommendations [19]. Additionally, interface design can contribute to increased diversity [61]. For instance, Netflix's interface employs varied layouts and manipulations to capture user attention and present diverse content [24]. The presentation of distinct cues influences users' decision-making processes, as various user groups demonstrate preferences for specific cues based on their profiles, which may originate from an item's title, description, and image [8, 25, 27, 36, 43]. This preference can be anticipated through a combination of these cues [12, 59]. Consequently, the interface modifications may be worth minimizing adverse effects.

Based on this, utilizing nudges from the interface to influence user choices is an emerging area of interest within personlization research. Nudges have been identified as a potentially effective means of altering attitudes and behaviors by providing various perspectives across numerous domains, such as politics, commerce, and health [24, 46, 52, 63, 73]. However, the extent to which nudges can sway the opinions of staunch believers in political matters remains an open question.

There are two fundamental categories of social influence in nudges: The first is peer pressure, where individuals are driven by a desire to conform to the expectations or preferences of the crowd to avoid disapproval. The second category involves informational influence, whereby individuals observe the behavior or opinions of others to determine the best content or action for themselves [67].

According to [45], social nudges can encourage positive behavior change by leveraging group conformity tendencies. Moreover, informational nudges can serve as a valuable tool in mitigating environmental harm at the individual level [46].

However, despite the potential advantages of nudges in addressing undesired effect within NRSs, it may blur the line between guidance and manipulation, as they can interfere with individuals' decision-making processes without their awareness. This lack of transparency may ultimately undermine personal autonomy [38, 51].Even when nudges are ethically acceptable, their motivations and purposes should be transparent to users [41]. Consequently, it is crucial to consider integrating the principle of informed consent [26, 47]. This integration ensures that recommender systems could fairly employ nudges, ultimately promoting equitable and diverse recommendations.

# 3 ON-GOING WORK

## 3.1 Initial Research

My initial study is Attitudinal Change in News Recommender Systems. During the first year of my doctoral program, I concentrated on the study of news recommender systems and their impact on user attitudes, especially regarding the climate change topic. My objective for my PhD thesis is to explore how selective exposure and personalized content might contribute to polarization and how persuasive technologies could mitigate these effects by adopting nudges and cues. In my initial work [31], I examined the link between users' environmental concerns and their news preferences. The study also analyzed article sentiment to see how it correlates with users' attitudes and preferences. Findings showed a positive correlation between environmental concern and article preference, but no significant link with article sentiment. This suggests users' attitudes influence their preferences more than sentiment does. We recommend analyzing various news types and topics for further insights.

## 3.2 Subsequent Research

I conducted a further study on the emotional framing of news articles in the new topic: Economics [30]. This study explored how different emotional frames (Anger, Fear, Hope) by ChatGPT-4, compared with neutral baseline (Human Journalist) influenced readers' emotional states and their perceived trust in news articles. The results indicated that negative framing (Anger, Fear) triggers stronger negative emotional states, while Hope led to little changes in general. Interestingly, the perceived trust in the news articles varied minimally across different conditions. For the next study, we propose exploring a nuanced analysis of user behavior, including engagement and their intention to pay for a subscription. Additionally, we will investigate whether different cues (text and image) play a crucial role in affecting these factors.

## 3.3 Recent Research

My ongoing research recently focuses on exploring the effects of affective reframing on positive and negative text with congruent, incongruent, and no images in the context of a news recommender system. The system presents news based on their preferred news topics by knowledge-based NRSs: abortion, economics, and gun control topics. This work utilizes Large Language Models (LLMs), specifically ChatGPT-4, to reframe news content to be either positive or negative. We examine the impact of these reframed contexts along with images, on users' emotional states, engagement, and intention to pay for news services.

# 4 FUTURE WORK

Our current study has several limitations. We did not investigate images generated by ChatGPT, potentially overlooking significant differences between the use of real and generative images. Additionally, our focus on a knowledge-based personalized recommender system may ignore biases arising from content diversity, leading to polarized perceptions. A key question that remains is how to effectively recommend news content to individuals and encourage them to read articles from opposing viewpoints, as well as to pay for these articles. Exploring the potential of nudges in this context is critical. Importantly, our research focuses on short-term effects, potentially missing valuable insights from long-term evaluations. Finally, our current study merely focuses on the demographic context of the USA, which is a notable gap in our investigation concerning local demographics.

Based on these insights, our future work will extend the current research in several ways: First, we will not only examine text framed by GPT-4 with real images but also introduce a new condition where news images are generated by GPT-4. Second, we will develop an algorithm to ensure our news recommender system presents diverse content, minimizing the adverse effects of polarization that may caused by selective exposure or filter bubbles. Third, we will design a new interface to explore whether nudges can be used to steer user choices encouraging them to read articles toward different polarized topics from opposing viewpoints, and whether they are willing to pay for these news articles, in both the short term and long term period. Finally, we also plan to run the study in Norway, which could better represent the local population and its news consumption behaviors.

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