MITIGATING SELECTIVE EXPOSURE IN SOCIAL MEDIA FORUMS

BY

MINGKUN GAO

DISSERTATION

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Doctoral Committee:

Professor Hari Sundaram, Chair
Professor Alex Kirlik
Professor Karrie Karahalios
Dr. Anbang Xu, LinkedIn

ABSTRACT

This dissertation focuses on designing social media interfaces to help people explore diverse social opinions and mitigate selective exposure - a tendency that people actively seek attitude-consistent information and avoid attitude-inconsistent information. Diverse information consumption has potential benefits, including but not limited to helping individuals form accurate viewpoints, facilitating better decision-making processes, cultivating people's tolerance and mutual understanding with others, which is essential for a thriving democratic society.

Both actively seeking congenial information (i.e., selective exposure) and passively being in a congenial information environment (i.e., *de facto* selective exposure) can impair people's exposure to diverse social opinions. Meanwhile, people can play a significant role in shaping others' information environments by sharing information on social media. Thus, we break our general research problem down to two sub-problems: 1) designing interfaces to mitigate selective exposure for individual information consumption, which focuses on the effect of interface design on people's active information-seeking behavior; 2) understanding humans' role as the information filter for others, which is the first step towards a better interface design to tackle potential problems caused by information sharing among people.

We first proposed organizing and showing categorized social opinions based on emotional reactions to mitigate selective exposure for individual information consumption. Our evaluation indicated that such a design could motivate people to explore diverse social opinions. Next, we designed and implemented a system that can provide novel visual hints with new recommendation mechanisms to improve people's awareness of diverse opinions and mitigate selective exposure. Finally, we studied the effect of the stance label and the credibility label on people's information selection and perception on a two-column news feed. We found that the stance label can exacerbate selective exposure and make people agree more on fake news. And the credibility label has a limited effect on mitigating selective exposure and combating fake news. Our work expanded the design toolbox of mitigating selective exposure and gave interface/system designers more choices when using these tools.

To better understand people's role as the information filter, we conducted a simulated online experiment to figure out how the attitude distribution of the recipient group affects people's information-sharing behavior in the anonymous scenario. We observed that the attitude distribution of the recipient group has an impact on people's sharing behavior even though various factors (e.g., topics, people's attitudes, etc.) may be related to such effect.

People tend to cater to the majority's attitudes by selectively sharing more information consistent with the majority's attitudes in some specific context, which creates the filter bubble for others. This result indicated the necessity to study interface design to motivate people to share more balanced information to help break the filter bubble for those recipients.

To my parents and my wife.

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CHAPTER 1: INTRODUCTION

1.1 OVERVIEW

Social media have gained tremendous popularity among people. According to Pew research [1], seven-in-ten Americans used some type of social media platform in 2021. For many people, social media have become part of their lives, and more than half of Facebook, Snapchat, Instagram, and YouTube users use the platform daily. In addition, social media have become people's primary source of information. More than half (53%) of U.S. adults get news from social media sometimes or often [2], indicating the importance of social media as people's information (e.g., news) consumption hub. Even though there are many benefits of using social media (e.g., building relationships with others, sharing expertise, increasing one's visibility, etc.), social media also negatively affects our society. According to Pew research [3], 64% Americans believe that current social media had a mostly negative effect on our community, including online hate, harassment, extremism, polarization, and echo chamber. These all indicate that social media have many complex problems that need to be solved. We can improve social media design to make it a better place for people to consume information online.

Diverse social opinion consumption is crucial for individuals to comprehensively perceive the spectrum of different opinions and facilitate decision-making with accurate beliefs. Lack of such exposure to diverse viewpoints always leads to problematical decision-making processes and misjudgment in various scenarios [4], including but not limited to valuation/appraisals in the financial market [5], emergency medicine [6], and criminal investigations [7]. In addition, exposure to diverse information or opinions, especially political views, is essential for a prosperous, democratic society [8, 9].

However, selective exposure [10] - the phenomenon that people always seek attitude-consistent information and avoid attitude-inconsistent information - is quite common in our daily lives, ranging from news media selection [11] to travel purchase decisions [12]. Selective exposure can limit people's exposure to diverse information and reinforce their pre-existing beliefs and attitudes [10, 13, 14]. Previous research suggested that people actively select agreeable information and keep away from contradictory information to avoid cognitive discomfort caused by attitude-inconsistent information [10]. In the Internet era or even the social media era, people are overloaded with information and opinions from others with different attitudes and stances. Stroud [15] found that selective exposure still exists, and people's political beliefs influence their online media exposure. In addition, on the contrary to the expectation that social media can expose more diverse opinions to people, the poor design of the social media forum interface (e.g., simply showing comments in a paginated long, tedious list) can not help people explore diverse opinions and get global insight into some controversial topics [16]. Furthermore, some research [17, 18] showed social media might have the opposite effect, i.e., they may play a role in encouraging individuals' selective exposure, even to more attitude-consistent fake news [19].

In addition to actively seeking supportive information, simply being in an environment with more attitude-consistent information is another cause of the overexposure to or the overconsumption of supporting information or opinions. This is called *de facto* selective exposure [20]. Even though there may be different causes of the *de facto* selective exposure, one key factor is the information filter. Compared to automatic personalized algorithms, humans' role as the information filter stands out these days. People are more connected in the social media era, and information sharing has become much easier than before. The impact of such casual sharing behavior is perhaps more extensive than people initially expected. In social media, everyone is the information filter for others around, and people can decide what information will appear on their friends' news feeds.

No matter actively seeking attitude-consistent information (selective exposure) or being in an environment with congenial information(*de facto* selective exposure), the deficiency of attitude-inconsistent information consumption and the overexposure to attitude-consistent information may lead to adverse effects on our society including social fragmentation and social polarization [9, 21].

Thus, the goal of this dissertation is modestly narrowed down to this scope – designing social media interface to mitigate selective exposure and help people explore diverse opinions. Since people's information exposure relates to both active exposure - actively selecting information on social media to consume (selective exposure), and passive exposure - passively being in an information environment shaped by others around (*de facto* selective exposure), to achieve this goal, we need to solve these two sub-problems:

- **Designing interface to mitigate selective exposure for individual information consumption:** For this problem, we are particularly interested in how novel interface design can mitigate selective exposure and help people explore diverse social opinions when they consume information on social media.

- **Understanding humans' role as the information filter for others:** For this problem, we aim to get a better understanding of human's role as the information filter for others. This can help us understand any negative effect (e.g., impairing others' exposure to diverse information) caused by humans' information-sharing behavior.

This will also be the first step towards designing the interface to mitigate such negative effects (e.g., *de facto* selective exposure) in the future.

Figure 1.1 shows the connection between different parts of the dissertation regarding consuming information and sharing information. First, we studied mitigating selective exposure for individual information consumption through showing social opinions based on emotional reactions and recommending diverse opinions with visual hints. In addition, we explored the effect of labels on people's information consumption. Second, since people may shape others' opinion space by sharing information, we studied humans' role as the information filter for a group of recipients.

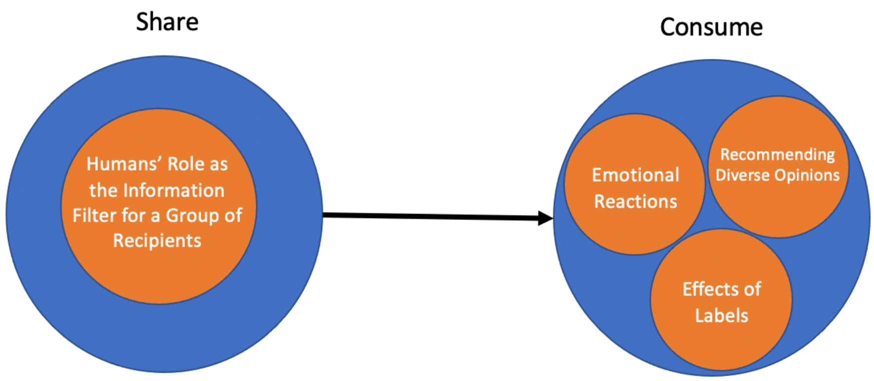


Figure 1.1: The connection between different parts of the dissertation regarding consuming information and sharing information. Chapter 3, chapter 4, and chapter 5 introduce studies about designing the interface to mitigate selective exposure for individual information consumption. Chapter 6 introduces the study about how people share information with a group of recipients.

1.2 LANDSCAPE OF THE PROBLEM

Given that consuming diverse information brings indispensable benefits to individuals and our society, the topic of mitigating selective exposure and helping people explore diverse social opinions through interface design has attracted researchers and scholars' attention.

Over the past 15 years, researchers implemented information systems and designed novel interface features to mitigate selective exposure for individual information consumption.

To be more specific, information systems and novel interface design features that can help people explore diverse information or social opinions [22] mainly include but are not limited to:

- Information aggregation systems [23, 24] which can aggregate information (e.g., news articles) by classifying, extracting, and grouping technologies. Such systems aim to show people different aspects and facets of information so that people can consume and perceive information from diverse perspectives.

- Information visualization systems [25, 26] which can visualize miscellaneous information or social opinions (e.g., comments) to increase people's awareness of different viewpoints and assist people in navigating through information on different stances.

- Interface design features (e.g., information indicators on the interface) [27, 28] which can increase people's tendency to look for more contradictory information and motivate people to explore diverse information or social opinions online.

On the one hand, overconsumption of congenial information can be caused by actively seeking attitude-consistent information. On the other hand, it can also be the result of *de facto* selective exposure - a phenomenon that might be related to humans' role as the information filter. Realizing the (potential) significant role humans can play to filter information for others in the social media age, some researchers joined the force of studying how humans can filter information for others intentionally or unintentionally. These work mainly include but are not limited to:

- Analyzing data from real-world users of social media to identify how people share information with others [29, 30]. Researchers who have access to large-scale user data (e.g., data from Facebook) can conduct such analyses.

- Conducting the experiment to figure out how people filter information for others in a specific context (e.g., one-to-one information sharing scenario) [31].

For this dissertation, to mitigate selective exposure for individual information consumption, we follow the general direction of previous work to expand the design toolbox with novel system and interface designs. Our work enriches interface or system designers' choices to mitigate selective exposure for individual information consumption. In terms of understanding humans' role as the information filter, there's still a lack of research on group sharing scenarios. Thus, we focus on how people share information with a group of recipients with various attitude distributions. This shall give us a clearer insight into humans' role as the information filter and provide more references for future research on interface design to mitigate any corresponding adverse effects on people's information consumption.

1.3 PROBLEMS ADDRESSED

In the following sections, we will introduce motivations for our solutions to design interfaces to mitigate selective exposure for individual information consumption and understand how humans share information with others.

1.3.1 Designing Interface to Mitigate Selective Exposure for Individual Information Consumption

Previous work [23, 27] indicated that systems or interfaces with sophisticated and effective design could help to mitigate selective exposure and expose people to diverse information. For example, information systems, like NewsCube [23], Poli [24], the searching system which can tag results with political leanings [32], and the clustering system which can aggregate diverse patients' comments into different aspects [33], focus on organizing information from various aspects and showing multiple facets of information to help people explore diverse opinions. Meanwhile, visualization systems, e.g., Opinion Space [25], Reflext [34], and data portraits [26], applied interactive visualization technologies to motivate people to explore opinions from different sides. In addition, for interface design features, Liao and her colleagues focus on how different information indicators, e.g., position indicator [27], aspect indicator [28], and source indicator [35], can nudge people into exploring opinions on the opposite side. Furthermore, Munson et al. [36] studied how the browser widget Balancer can motivate people to consume information in a more balanced way.

To expand the toolbox of interface designs to mitigate selective exposure for individual information consumption, motivated by current practical solutions of organizing online information (e.g., organizing online information based on semantic features, the use of visual hints and recommendation in social media, and the use of labels on news feed), we propose the following novel interface designs:

- **Organizing and showing categorized social opinions (comments) based on emotional reactions.** Previous studies on organizing online social opinions (e.g., online comments) to help people gain insight from information mainly focus on semantic features [16, 37, 38]. Semantic features are also widely used in our daily life to organize information (e.g., categorizing information based on topics). Our approach to organizing online social opinions could complement previous work, fulfilling people's demands to see others' emotional reactions.

- **Recommending diverse opinions with visual hints.** Traditional social media lack an effective structure to organize information, and they only list social arguments (e.g., comments) with long and tedious linear list format. Such a structure may not help mitigate selective exposure, especially when people are in the filter bubble [9] with all the agreeable information. Our approach can help people explore diverse social opinions with a novel recommendation mechanism and visual hints.

- **Exploring the effect of stance labels and credibility labels for news feed design.** Labels are widely used in our daily life. However, in the context of social media or news feed interface design, there's a lack of research on how stance labels and credibility labels affect people's information selection and perception. Our study intends to figure out the effect of these labels.

1.3.2 Understanding Human's Role as the Information Filter for *De Facto* Selective Exposure

Even though it emphasized the effect of people's active information selection, one Facebook study [29] gave us a chance to glimpse how much impact humans can have in shaping others' opinion space. According to their research with the large-scale Facebook data, ideological cross-cutting friendships only counted a small portion (roughly 20%) on Facebook, which means that people mainly connect with like-minded others on Facebook. In terms of sharing hard news (e.g., political-related news), most news articles (roughly more than 65%) shared by Facebook friends are ideologically consistent. In addition, Earl [31] mentioned the concept of vicarious selective exposure, which means people tend to select information or opinions which align with the recipient's attitude, especially when they like the recipient. According to their study, for issues that people don't have a preferential attitude towards (e.g., being neutral), they tend to share information relying on the recipient's attitude if they like the recipient, which will create a congenial information environment for the recipient and increase the recipient's exposure to attitude-consistent information. However, the recipient's attitude has no impact on the selector if the selector has a clear stance.

Earl [31] focuses on a one-to-one information sharing scenario where one person shares information with another person. However, how the information selector shares information with a group of recipients still lacks research, especially for groups with various attitude distributions. These days, many people like to use anonymous social media forums (e.g., SubReddit) or anonymous chat rooms (e.g., 321Chat, Talk.chat). Anonymity can give people more freedom to express themselves [39]. Thus, observing how people share information with others in an anonymous scenario would be meaningful. In addition, considering that impression management is one of the primary goals people use social media [40], studying whether and how much people will cater to others' attitudes in a group if they want to leave good impressions will be fascinating. Therefore, to better understand humans' role as the information filter, we conduct (simulated) experiments to figure out how the information selector, to leave good impressions to others, shares information to a group of recipients with various attitude distributions in the anonymous scenario.

1.4 DISSERTATION CONTRIBUTION

Before summarizing the dissertation's contribution, we want to emphasize that we do not assert that selective exposure is absolutely negative in all circumstances [22]. Some research [41] also showed the benefits of selective exposure in some scenarios (e.g., involvement and passion for civil activities). We want to emphasize that this dissertation focuses on designing tools or finding design implications that can help mitigate selective exposure rather than discussing the applicable scenarios of using these designing tools.

In general, this dissertation expands the design toolbox of mitigating selective exposure for individual information consumption and advances people's knowledge of humans' role as the information filter that may create a congenial information environment for others around.

To be more specific, my main dissertation contributions include:

1.4.1 Expanding the Design Toolbox of Mitigating Selective Exposure

First, we proposed a new way to organize online social opinions with emotional reaction information instead of commonly used semantic features. We developed a novel interface/system that showed categorized social opinions (comments) about controversial topics based on emotional reactions. Our interface/system allowed interactive visualization and categorization of original posts based on emotional reactions collected from crowd workers in different stances. We evaluated the interface using Reddit posts about U.S. presidential candidates in an in-person user study. We found that our interface can promote people's curiosity about others' reactions and help users adopt a broader spectrum of diverse social opinions.

Next, we designed and implemented an intelligent system that improved people's awareness of diverse social opinions and mitigated selective exposure by providing visual hints and recommendations of opinions (e.g., news articles and comments) on different sides with different indicators. We evaluated our system with news articles about the Obamacare repeal issue and their corresponding user comments from Facebook in an in-person user study. The evaluation indicated that our system could increase people's awareness of their stances and opinion selection preferences, which mitigates selective exposure and thereby leads to a more balanced perception of social opinions.

Labels are widely used in our daily lives, and the effect of labels is not very clear in individual information consumption. Furthermore, to systematically understand the effects of stance and credibility labels on online news selection and consumption, we conducted a controlled experiment to study how these labels influence news article selection, perceived level of extremeness, and perceived level of agreement of news articles. We found that stance labels may intensify selective exposure and make people more vulnerable to polarized opinions, even fake news. We found, however, that the effect of credibility labels on reducing selective exposure and recognizing fake news is limited. Although initially designed to encourage exposure to opposite viewpoints, stance labels can make fake news articles look more trustworthy. They may lower people's perception of the extremeness of fake news articles. Our results have significant implications on the subtle effects of stance and credibility labels on online news consumption.

1.4.2 Understanding Humans' Role as the Information Filter

We studied how people share information with a group of recipients to conduct impression management in the anonymous scenario. To have relatively accurate experiment controls on the attitude distribution of the recipient group, we adopted simulation in our experiment. We conducted a simulated group study on the Amazon Mechanical Turk (MTurk) platform, where participants played the role of sharing information with other fictitious group members. We successfully designed mechanisms to convince participants from the MTurk platform that other group members were actual. According to our experiment results, we found that for the scenario where a considerable proportion of people don't have preferential attitudes towards a topic, people's information-sharing behavior was heavily influenced by the attitude distribution of the recipient group even though people's own attitudes might also impact their information-sharing behavior. People would cater to the majority's attitude when sharing information, especially those with a neutral attitude. However, for the scenario where most people have preferential attitudes (i.e., support or oppose), their information-sharing behavior differed according to their attitudes. It might be related to various factors (e.g., how convinced people are to their beliefs or position, etc.), which need to be validated in further studies. In general, we did observe the phenomenon that people follow the majority's attitude of the recipient group to share information in some specific contexts when they intend to leave a good impression. Such results indicate that people play the role of information filter in some circumstances and can create the filter bubble for others around. Understanding such behavior is the first step towards designing novel interfaces to mitigate such negative effects of humans' information filtration.

1.5 ORGANIZATION OF THE DISSERTATION

The rest of the dissertation is organized as follows:

- In chapter 2, we will review the related literature of this dissertation work.
- In chapter 3, we will introduce our work on helping people explore diverse social opinions for individual information consumption by organizing and showing categorized social opinions (comments) based on emotional reactions. We will discuss our interface design and how such design can help.
- In chapter 4, we will introduce how the novel recommendation mechanism with visual hints can help to improve people's awareness of diverse social opinions and mitigate selective exposure for individual information consumption.
- In chapter 5, we will introduce our work on exploring the effect of the stance label and the credibility label on a two-column news feed design. We will discuss how these labels affect people's information selection and perception.
- In chapter 6, we will introduce how people share information with a group of recipients with different attitude distributions in the anonymous scenario when they intend to leave good impressions to others, which will give us a better understanding of humans' role as the information filter for others around.
- In chapter 7, we will present our conclusions and discuss some future research directions.
- In the end, we list the references.

CHAPTER 2: LITERATURE REVIEW

In this chapter, we will review relevant previous work which motivated my dissertation research work. First, we will check the theory of selective exposure for individual information consumption. Next, we will introduce related work in organizing online information or social opinions, which inspired our first three studies in mitigating selective exposure for individual information consumption. Finally, we will introduce related work about understanding humans' role as the information filter, which motivated our research on how people share information with a group of recipients with various attitude distributions.

2.1 SELECTIVE EXPOSURE FOR INDIVIDUAL INFORMATION CONSUMPTION

According to [42], information is crucial for people's effective operation and decision-making at all levels in our daily life. Previously, people obtained information mainly from traditional media, such as television programs, newspapers, and magazines. This didn't give people many options in seeking information. With the arrival of the information age and the rise of social media, information and opinions spread mainly via the Internet. This increased the number of information people could reach drastically and gave people more options to obtain information. For example, people can get information worldwide by simply opening the web browser and searching for information they are interested in with Google, or by logging in to Facebook or Twitter to see what is trending in the world on the curated news feed at no cost.

When people enjoy the advantage of the information age where the Internet and social media accelerated the information flow in human society and promoted the efficiency of our community, a phenomenon called selective exposure [14] in social psychology started to attract more and more research interests in academia.

For individual information consumption, selective exposure, also called congenital bias, is the phenomenon that people tend to seek attitude-consistent opinions and avoid opinions that challenge their pre-existing attitudes [14].

According to [10], selective exposure can be explained by cognitive dissonance theory. Cognitive dissonance theory suggests that people may experience discomfort when they encounter conflicting opinions, breaking their internal psychological consistency. People's self-defense mechanism to reduce the discomfort of being exposed to attitude-inconsistent views motivated them to select more agreeable opinions. Furthermore, Zaller [43] suggested that biased assimilation [44] commonly existed among people because attitude-consistent opinions were more acceptable than attitude-inconsistent opinions. For example, [45] showed that cognitive dissonance made patients hostile toward beneficial but unpleasant medical screenings. This may negatively influence patients' medical decision-making process. Tanford and Montgomery [12] indicated that while deciding a travel destination between a green and nongreen resort, people with solid pro-environmental attitudes would feel dissonance when making a nongreen choice. They may actively avoid those conflicting beliefs and attitudes [10] to reduce the discomfort or dissonance. Consequently, people may mentally or physically stay in their comfort zone, losing opportunities to experience and understand the outside world.

While selective exposure is considered an essential and natural human behavioral tendency, researchers always treat it as a negative-outcome-inducing bias. It limits people's exposure to diverse social opinions and impairs the benefits brought by such diverse-opinion exposure. According to [22], being exposed to various views can help people make better decisions [4], prevent social polarization [46], and foster individuals' understanding of different viewpoints [47].

Given these, such bias (i.e., selection bias), together with the echo chamber effect [35, 48, 49] and the filter bubble effect [9], can push people's pre-existing beliefs or attitudes to a polarizing level. Consequently, a polarized society seems inevitable [50], and there will be less room to exchange opinions from people with different stances rationally.

2.2 DESIGNING INTERFACE TO MITIGATE SELECTIVE EXPOSURE FOR INDIVIDUAL INFORMATION CONSUMPTION

As realizing the importance of diverse information consumption for a healthy society, researchers have been working on designing solutions to mitigate selective exposure for individual information consumption. These designing solutions [22] include but are not limited to information systems [23, 25] and interface features [27, 35]. In terms of information systems, people usually built the whole system with the backend functionalities and the corresponding interface (e.g., information aggregating system, visualization system, etc.). Meanwhile, interface feature solutions mainly focus on discussing the effect of one or a couple of specific design features (e.g., information indicators, interface widgets, etc.) on user interfaces.

2.2.1 Information Systems

Information aggregating systems [23], which aim at helping people explore diverse social opinions, are typical system-level solutions. For example, to mitigate the information consumption bias caused by media with different political stances, Park et al. [23] created NewsCube, a news browsing system classifying/grouping news articles based on various aspects and presenting news articles with multiple aspect categories on the interface. Semaan et al. [24] built the system Poli to help people explore diverse social opinions. Poli can automatically aggregate comments about controversial topics from various social media platforms and support information filtering on topics, geographic locations, and so on. Oh et al. [32] implemented a blog searching platform, tagging the retrieved results with automatically predicted political stance labels (Liberal vs. Conservative). Their evaluation indicated that users preferred their system over typical search systems. Jiang et al. [33] created a clustering system to aggregate diverse personal comments of patients from social media into different aspects so users can view various aspects of the medical issues.

Opinion Space [25], as a visualization platform, is also an information system solution to mitigate selective exposure. Opinion Space can visualize diverse opinions and help users browse online comments to understand the whole picture better. The system integrated deliberative polling, dimensionality reduction, and collaborative filtering techniques, allowing information consumers to visualize and navigate comments with different opinions. In addition, Opinions Space is not the only visualization platform with the same design goal (to mitigate selective exposure). Graells-Garrido et al. [26] developed a system to visualize the political distance among Twitter users based on their user profiles to encourage people to explore user profiles with different stances. Baumer et al. [34] developed Reflext, an interactive visualization system that applied natural language processing to broaden users' exposure to diverse opinions.

2.2.2 Interface Features

In addition to information systems, some researchers also focus on how specific interface design features can help to mitigate selective exposure.

For example, Liao and Fu [27] explored how the position indicator, including the valence (pro/con) indicator and the corresponding magnitude (moderate/extreme) indicator, could affect opinion selection for people with different levels of accuracy motives –i.e., the motivation to learn about a topic or an issue accurately. They found that these position indicators can mitigate selective exposure for users with high accuracy motives but had no effect on users with low accuracy motives. Next, Liao and Fu [35] extended the previous work [27] by considering the impact of the source expertise indicator in mitigating selective exposure. They found that the source expertise indicator motivated people to select information from sources with high expertise and discouraged them from choosing from sources with low expertise for both attitude-consistent and attitude-inconsistent information. In addition, their study indicated that the source expertise indicator and the position indicator mentioned in [27] could help mitigate selective exposure to information from expert sources together. Furthermore, Liao and her colleagues [28] studied how the aspect indicator can affect people's information selection by experimenting with the scenario where people need to seek information about drugs to make medical decisions. The aspect indicator suggested whether the corresponding comment was regarding effectiveness or side effects. Their analyses found that aspect indicators can help mitigate selective exposure in selecting information on side effects, which can reduce their decision bias in general. In line with Liao et al. [28], Munson et al. [36] illustrated how a browser widget called Balancer could affect people's information consumption behaviors. Balance is a Google Chrome extension that can indicate the level of balance of users' information consumption in terms of ideology (liberal vs. conservative). They found that the use of Balancer could nudge biased readers into making minor but real improvements in their information consumption balance.

2.2.3 This Work

In general, in chapters 3 - 5, we propose and study three solutions to encourage people to explore diverse social opinions online, following the general direction of previous work to expand the design toolbox of mitigating selective exposure for individual information consumption. To be more specific, for chapter 3 and chapter 4, we propose and implement systems to reduce selective exposure; for chapter 5, we study the effect of a particular interface feature on mitigating selective exposure. We discuss the corresponding related work which motivated these three studies below.

2.3 ORGANIZING ONLINE SOCIAL OPINIONS WITH SEMANTIC CONTENT

As social media becomes more and more pervasive, leaving comments and exchanging opinions on the Internet or social media has been quite common these days. For some news articles, posts, or blogs about controversial topics, since there are always so many people participating in the discussion, the comment list can become very long in a short time, which is hard for people to digest and gain insights from the conversation. Previous research on organizing online social opinions focused on indexing and categorizing social opinions based on semantic content to solve this problem.

For example, Hoque and Carenini [16] designed and implemented the ConVis system to organize online blog conversations and help people get better insight from these long, tedious conversations. Their design principles include showing relevant data (e.g., comment length, comment position, etc.) and providing multi-facet exploration (e.g., topics and authors) with a multi-granularity overview (e.g., topic summaries, sentiment information) and lightweight interactions. They used topic segmentation [51] and topic labeling [52] on the Fragment Quotation Graph [53] for topic modeling. In terms of sentiment analysis, they applied the Semantic Orientation CALculator (SO-CAL) [54]. They found that ConVis can help people find insightful comments and those comments that people are interested in reading.

Given that users had the demand to have greater control over the topic modeling process, Hoque and Carenini extended the ConVis system by incorporating users' feedback in the topic modeling loop. The new system was called ConVisIT [37]. It is crucial to identify the minimal set of operations that would be intuitive and effective to support users' topic revision tasks [55]. To fulfill this requirement, referring to previous research work [56, 57, 58, 59] on interactive topic modeling, Hoque and Carenini identified several topic revision operations ranked based on the priority. Furthermore, Hoque and Carenini extended ConVis [16] and built the MultiConVis [38] system, supporting interactive exploration of blog comments for multiple conversations. However, as the number of conversations increased, users needed to deal with more data with various levels of granularity. Since some of these topics were similar from the semantic perspective, they proposed a hierarchical topic modeling framework to group them into a hierarchical topic organization, facilitating users' understanding and navigating across different topics more effectively.

2.3.1 This Work

Hoque and Carenini [16, 37, 38] tried to help users gain insight from long and staggered asynchronous online conversations by organizing online comments with semantic features. However, they may have neglected that people also had emotional reactions when providing those comments or social opinions. In addition, to have users obtain a global insight into some controversial topics, a fundamental goal of an intelligent social opinion platform is to mitigate selective exposure. In chapter 3, we design and implement an interactive interface/system that categorizes social opinions based on emotional reactions and shows social opinions in such emotional reaction categories to mitigate selective exposure for individual information consumption. Our interactive interface/system can also fulfill people's demands to know others' reactions and help people get more insight into social opinions about controversial topics. This work could complement Hoque and Carenini's approaches by exposing peoples' reactions from different stances to users for controversial topics, which are known to influence the selection process as much as semantics [28].

2.4 PERSONALIZED ALGORITHMS

Personalized searching and recommendation algorithms can cause or intensify the filter bubble - an information isolation phenomenon [9]. Personalized searching and recommendation algorithms can curate the results for each person and show people the information they like. According to [9, 60, 61, 62], the filter bubble has the potential negative impact of limiting people's access to diverse opinions and aggravating overconsumption of agreeable information, isolating people, and exacerbating social polarization and social fragmentation.

From the perspective of personalized algorithms (e.g., personalized searching or recommendation), some of the previous research work [63, 64, 65] supported the filter bubble hypothesis. For example, Flaxman et al. [66] studied whether social media news consumption would cause ideology segregation and filter bubble; they analyzed news browsing data of 1.2 million users in the United States for three months, from March 2013 to May 2013. They found that users showed a higher level of segregation when consuming ideology-related or political news articles recommended by social media platforms or search engines, and their results were consistent with the filter bubble concerns.

As an online video sharing and social media platform, YouTube has a robust recommendation system running in the backend to help people find videos they like based on their browsing history. This recommendation mechanism drew researchers' attention to the corresponding potential filter bubble effect. For example, O'Callaghan et al. [63] focused on how YouTube recommends video content about the extreme right. They first developed a categorization of this type of content based on a different schema. Next, they used two sets of English and German extreme right-wing video channels as the data in their project. According to their observations, YouTube is likely to recommend excessive right-wing video content to users further after users access such a video. Their study suggested that only a few clicks of a specific type of YouTube video content could help YouTube conduct personalized content curation and recommendation, which would create an ideological political bubble for users.

Kaiser and Rauchfleisch [64] conducted another study of YouTube and filter bubbles. They studied the filter bubble effect from how YouTube created online communities (e.g., communities consisting of similar channels) and recommended channels to people by its algorithms. They focused on the channel recommendation mechanism of YouTube in the United States and Germany to figure out whether and how YouTube's channel recommendation algorithm worked to create online homophily and isolation. They compared the online channel community created by YouTube's algorithm with random networks. According to their analysis, YouTube's channel recommendation algorithm facilitated the formation of highly homophilous communities in the United States and Germany. To be more specific, they found that the YouTube political channels seem to be more extreme than people expected and were often leaning toward right-wing ideologies or conspiracies. In Germany, the algorithm would recommend extreme right-wing channels to people who were interested in German politics. Meanwhile, the algorithm would rarely recommend channels from mainstream media if users were interested in the extreme right-wing content. Similar patterns were also found on YouTube in the United States. Their study indicated that YouTube's channel recommendation could foster the creation of the filter bubble potentially.

Another adverse effect people are concerned about is social polarization, one of the adverse outcomes of the personalized algorithms and filter bubble. In Chitra and Musco's [65] research work on filter bubbles and their impact, they applied a mathematical framework to evaluate the effect of the filter bubble. They adopted the Friedkin-Johnsen opinion dynamics model [67], which was successfully used to study polarization in social networks [68, 69], to study the impact of the filter bubble. To mimic the modern recommendation system [70] that can increase users' engagement, they modified the model by adding the network administrator, connecting users with agreeable information. They applied their modified opinion dynamics model to real-world social network data of Twitter and Reddit. They found that the information filtering conducted by the network administrator can significantly increase social polarization, even though the filtering interference of the network administrator was weak. This result suggested that social networks are pretty sensitive to the interference by the content filter and personalized recommendation, and a soft content filter and recommendation by the network administrator can foster significant information filter bubbles and polarize society.

However, some other research work [71, 72, 73] also cast doubt about the magnitude of the filter bubble effect. Nguyen at el. [71] studied the impact of a collaborative filtering-based recommendation system (MovieLens). They found that even though those top-recommended results were similar, the reduction of diversity among the items users consumed was relatively small. Meanwhile, users taking recommendations perceived a more positive experience than those who didn't take recommendations. Courtois et al. [72] researched to figure out whether Google search results contributed to the formation of the filter bubble. Their findings didn't support such a claim in the social and political information retrieval scenario. Nechushtai and Lewis [73] studied the impact of recommendation when people searched for news articles about Hillary Clinton and Donald Trump for the 2016 U.S. presidential election on Google News. Even though they observed homogeneity and concentration in news recommendations, they found that Google News recommended similar news for users with different political stances, which didn't support the assumption that personalized algorithms fostered the filter bubble.

Even though the magnitude of the impact of personalized algorithms on the filter bubble is controversial, according to [63, 64, 65, 66], the personalized recommendation mechanism shows a pretty substantial impact on fostering the filter bubble on social media platforms (e.g., YouTube, Facebook), especially for ideological or political information consumption. In addition, Dylko et al. [62] found that system-driven personalized recommendation (customizability) substantially facilitated the filter bubble and exacerbated people's overexposure to congenial information in the scenario of online political news consumption.

Furthermore, previous research [74, 75, 76, 77] showed that unconscious bias is common, and sometimes people do not realize that they have implicit attitudes towards social issues, specific organizations, or groups of people. Unconscious bias could affect people's social behaviors. For example, [75, 76, 78] showed that unconscious bias influenced people's social behaviors in various scenarios, such as recruiting people from different races and evaluating public sector performance. The lack of awareness of implicit attitudes implies that people are often unaware of why personalization algorithms (e.g., the news aggregators from YouTube or Facebook) recommended certain information. Given that these algorithms are often not transparent, people are also unaware of how the information is selected. As a result, users may often form an inaccurate impression of other people's opinions.

2.4.1 This Work

In chapter 4, we aim to mitigate implicit bias in information selection and break the filter bubble for people when consuming political news articles and comments on social media. We design novel visual hints to improve people's awareness of their stances and information selection preferences, and create a novel recommendation mechanism to mitigate selective exposure. To conduct the novel recommendation mechanism, we applied sentiment analysis technology. Sentiment analysis has been widely studied [79, 80, 81] in different languages. Given that this study focused on interface design, we simply used the famous χ^2 statistic (*CHI*) test [79, 82] to identify the importance of features and trained the random forest model [83, 84] on the comment data we crawled from Facebook for sentiment analysis.

2.5 EFFECT OF LABELS AND FAKE NEWS

2.5.1 Effect of Labels

Labels are widely used in our daily life to provide information and have drawn attention from many researchers in academia.

Researchers have been investigating the effect of labeling on people's perception of different products [85, 86]. In [85], Jeddi and Zaiem studied how the quality labels of food products could affect consumers' purchase intention. In the field of food products, people have raising uncertainties and concerns about the quality. They found that labeling the quality of food products was an effective marketing tool and positively impacted consumers' purchase intention. Furthermore, they pointed out that as the perceived risk of food quality went higher, the impact of quality labels became more vital for consumers' purchase intention.

Beltramini [86] studied how warning labels of varying presenting forms on cigarette package influenced young adults' perceived belief that smoking was harmful to health. He found that warning labels indicating specific dangerous consequences of tobacco and specific remedial actions may be more believable than other warning labels. In addition, he showed that people's "mushiness" levels, namely how firm a person sticks to his/her positions, also impacted their perceived believability. In another study about warning labels on cigarette packages, Bansal-Travers et al. [87] suggested that more prominent, pictorial, and loss-framed warning labels could raise people's awareness of the risks of smoking on health.

Kriplean et al. [88] proposed ConsiderIt, which separated diverse social opinions into pro and con lists with corresponding labels of "Pros" and "Cons" based on users' stances and the stance of the views in each column. They showed that such a design could encourage people to adopt opinions contributed by others and enhance public deliberation.

Epstein and Robertson [89] showed that the Search Engine Manipulation Effect (SEME) was powerful, and biased search rankings could affect undecided voters' preference. Meanwhile, this ranking manipulation may not be realized by people if the manipulation was somewhat masked. Epstein et al. [90] conducted experiments and argued that the voting shift towards the favored candidate caused by biased search rankings could be effectively mitigated by labeling and alerting the biased rankings and news in the search result.

According to an NPR (National Public Radio) article [91], political labels may trigger people to identify their own stances and consolidate their pre-existing beliefs. To reduce the possibility that people's self-identified beliefs or viewpoints to be even more biased by external political labels, politicians and social activists initiated a movement called "No Labels" to create a political force between the left-wing and the right-wing, establishing a "common ground" to solve critical issues. Political labels, such as Democratic and Republican, may encourage people to identify their core values and make people less tolerant to opposing opinions, which could polarize the society.

As an example of helping people exploring diverse social opinions, the Wall Street Journal proposed a novel feed design, "Blue Feed, Red Feed" by presenting liberal and conservative labeled news articles in side-by-side columns. Such design aims to promote awareness of news articles with different standpoints to readers and help people explore diverse social opinions. However, how the stance labels will affect people's news article selection and perception is unclear.

2.5.2 Fake News

Fake news is flooded on social media these days. With the help of the Internet, fake news spread at an extraordinary speed from one's news feed to another's the news feed. Two Buzzfeed articles [92, 93] mentioned that social media platforms are vulnerable to fake news for the lack of effective methods to distinguish between fake and true stories. One article [92] claimed that during the 2016 presidential election campaign, among the most popular counterfeit stories from hoax websites and true stories from mainstream media, fake stories were shared more than true stories on Facebook. The other [93] reported that many people believed those fake news was trustworthy, which may impact people's voting, according to a Guardian report [94].

In [95], Allcott and Gentzkow intended to figure out how much impact the fake news had on the 2016 presidential election theoretically and empirically. Their research showed that fake news was widely shared through Facebook, and all U.S. adults may have been exposed to one or several pieces of fake news before the election. However, people were less likely to trust information from social media than information from national or local news organizations. Thus, they cannot provide a concrete assessment about whether fake news was the deciding factor in the 2016 presidential election.

To help users recognize fake news, initially, Facebook allowed users to label disputed flags to fake stories. However, in an announcement [96] from Facebook, they admitted that the disputed flag was not so effective in preventing people from sharing fake news, possibly for the reason that the intensely disputed flag with strong wordings and visualization may strengthen one's belief [97].

2.5.3 This Work

There is the uncertainty of the label's (i.e., stance labels and credibility labels) effect on people's information consumption from social media feed. In chapter 5, we study how stance labels and credibility labels affect people's news article selection and perception on a two-column news feed containing real and fake news articles.

2.6 UNDERSTANDING HUMANS' ROLE AS THE INFORMATION FILTER

Passively being in the congenial information environment is another possible cause of people's overexposure to attitude-consistent information. This phenomenon is called *de facto* selective exposure [20]. In the social media era, the densely connected social network and the large volume of information exchange online by mutual information sharing enhance people's role as the information filter. People can (partially) shape the information space where others around will (passively) face.

Some research work [29, 31] studied humans' role as the information filter. For example, previous research [29], based on a large amount of Facebook users' data, showed that only about 20% of individual's friends on Facebook have the opposite ideological leaning, which means that people on Facebook are mainly surrounded by friends with the same or similar political stance. Further analysis [29] indicated that people with political leanings (liberal or conservative) always received hard news articles (e.g., political news articles) with identical or similar stances shared by their friends on Facebook. Among all the hard news articles shared by liberals' friends, only 24% have a different ideological stance. Meanwhile, only 35% of articles shared by conservatives' friends are cross-ideology.

In addition, Earl [31] mainly focused on information-sharing behavior in the one-to-one model. Their study showed how the information-sharing behavior of the selector was influenced by the likability and the attitude congeniality between the selector and the recipient. They observed vicarious selective exposure when these social opinions are about a novel issue that the selector has never heard about previously (with a hypothetically neutral attitude). The selector selects the information that aligns with the recipient's attitude if the selector likes the recipient. Meanwhile, attitude-inconsistent information is chosen for the recipient if the selector dislikes the recipient. This result indicates that the selector will create a congenial information environment for the likable recipient for novel issues, verifying that vicarious selective exposure exists between amicable partners. However, for familiar topics that the selector has the pre-existing attitude bias (e.g., supporting gun control vs. opposing gun control), their study finds that the selector selects information for the recipient according to his/her own attitude instead of mainly curating congenial information environment for the recipient based on the recipient's attitude.

The previous study [31] about humans' role as the information filter focused on the one-to-one information-sharing scenario. However, there's still a lack of thorough research on how people share information with the group of recipients.

These days, since people have concerns about their privacy and don't want to expose their personal information to others, online anonymous information-sharing groups (e.g., Reddit/SubReddit Group) or online anonymous chat rooms (e.g., 321Chat, Talk.chat) have gained more and more popularity. These online groups can attract like-minded people to get together and exchange information anonymously. People in these anonymous groups may mainly share information following the majority's will. Thus, group members may play the role of an information filter for others. This may create a filter bubble/echo chamber for people in the group and exacerbate selective exposure for group members. In addition, according to [40], impression management is one of the most critical goals people stay on social media (e.g., Facebook). Social media is always portrayed as a platform for selective performance with some specific contexts [98]. Thus, we propose to study how people with the goal of impression management share information with a group of recipients with various attitude distributions in an anonymous scenario.

2.6.1 This Work

In chapter 6, to better understand humans' role s the information filter, we generally study how the selector will select information for a group of recipients in the one-to-many scenario. Specifically, we designed and conducted experiments to explore how the selector's attitude and different attitude distributions of the recipient group affected the selector's information-sharing behavior when the selector was asked to leave a good impression on the group through an online anonymous simulation study.

CHAPTER 3: MITIGATING SELECTIVE EXPOSURE THROUGH SHOWING SOCIAL OPINIONS BASED ON EMOTIONAL REACTIONS

3.1 INTRODUCTION

Increased information access has enabled the public to use online social platforms to express their opinions. Most of these platforms use various forms of semantic content (e.g., [26, 53]) to index and categorize these social opinions. To a large extent, this kind of organization treats social opinions as other information sources such as news items or articles. While it is helpful for information access, it is not designed to facilitate users' understanding, exchange, and appreciation of public social opinions. For example, Reddit, a popular social forum where people express their opinions about different topics, presents posts to users mainly based on semantic features. Users need to read through hundreds of comments when reading one post to appreciate the broad spectrum of reactions and emotions embedded in an arguably random. There is clearly a need to improve the organization of social opinions by going beyond semantic contents.

In this chapter, we focus on two essential characteristics for better organization of social opinion platforms. First, in addition to knowing the social topics, people are often curious about the opinions of others on these topics, such as why and how other people think positively or negatively about the issues, what are the "dominant" or "mainstream" opinions, how likely someone from different backgrounds may agree or disagree with these opinions, what are the alternative opinions and who expressed these opinions, etc. Second, social opinions, especially those on controversial topics (e.g., presidential election), often have polarizing emotions and reactions from people who have opposite stances. Showing these reactions will help users get a better sense of the general sentiment of the public and help them selectively attend to those that are more relevant to them. Another important consideration in the design of such a platform is to mitigate selective exposure to information, or at least not to exacerbate polarization of opinions [25, 28, 36, 50]. In fact, previous research has found that structures that help people easily see opposing views or highlight different aspects of the issues can mitigate the otherwise pervasive selective exposure phenomenon [23, 28]. On the other hand, the lack of such an organization often nudges people to attend only to those that are consistent with their own views.

To overcome the drawbacks of existing online social opinion platforms, we design and evaluate a prototype of an intelligent social forum interface that allows people to more easily visualize and better understand and appreciate people with diverse attitudes and opinions on controversial topics. The interface provides interactive visualization of social opinions with reactions of various stances and a clustering summarization of overall reactions based on emotion labels. We derived a set of design principles and performed a user study evaluating the interface using a set of controversial posts about the 2016 US presidential candidates and obtained promising results. In this proof-of-concept study, we focus on interface design. Reactions and the corresponding emotion labels for posts were collected from Turkers on Amazon Mechanical Turk (AMT).

3.2 DATA

To build an interface where users could explore controversial opinions with access to others' stances and reactions, we need to obtain controversial social opinions and people's reactions to these controversial opinions. To collect data for the study, in general, there are two steps: first, we need to collect posts about controversial topics from Reddit; Second, we need to obtain reactions with emotional labels to the corresponding Reddit post by crowdsourcing on Amazon Mechanical Turk (AMT).

In the current prototype, Reddit posts about *Donald Trump* and *Hillary Clinton* were used as data. In election, many expressed opinions as supporters of either candidate, but seldom (if any) both. Opinions about the two candidates also tend to be highly polarized – there is a wide spectrum of opinions, reactions, and emotions about each candidate in a large number of posts on Reddit, making the dataset ideal for the current study. We first crawled posts about each candidate from Reddit submitted before Mid-March 2016. Next, we filtered out posts with profanity and selected 50 posts based on popularity (using Reddit score + num. of comments) for each candidate. We also performed pilot studies to ensure that most posts had readable textual content (*e.g.*, not just an external link) and had similar length, relevant to the topic, and in general understandable to people with a general level of reading skill.

Next, we collected reactions to the selected 50 posts using workers recruited from AMT crowdsourcing platform. In each Human Intelligence Task (HIT), two posts were presented. One was about Donald Trump and the other was about Hillary Clinton. First, we asked Turkers to select their preferred candidate between these two. After they read each post, they were asked to select one or more explicit emotion tags among 17 emotions [99]. Meanwhile, Turkers also needed to describe their reactions using at least 25 words after they finish reading each post. To reduce Turkers' reaction bias, each Turker read posts in a randomized order. Ultimately, 1,000 Turkers participated into our study with a reimbursement of \$0.40 per HIT from June 8th 2016 to June 19th 2016. We collected reactions and sets of emotions from 10 Donald Trump supporters and 10 Hillary Clinton supporters for each post on average to avoid opinion bias caused by the amount of responses in different sides. However, the number of overall selected emotion tags in different sides may be uneven for each post since the number of emotions to select was totally at each participant's will.

3.3 INTERFACE DESIGN AND IMPLEMENTATION

3.3.1 Design Principles

The goal is to increase exposure to diverse opinions to users. Based on results from previous studies [16, 23, 26, 27, 35, 36, 37, 50, 88, 100, 101, 102], we derived our design principles (*DP*) below:

1. **Show people's different stances for each topic**: The interface should split people's reactions based on different stances. That would help users to know what reactions are generated from people in different stances.

2. **Provide users with reactions to each topic in different granularity**: Users should be able to view others' reactions in different levels of generalization. This novel interface provide users with high level emotional cluster labels and the corresponding reactions.

3. **Provide the degree of controversy of each topic**: Users should be able to infer how controversial a topic is, which allows users to easily prioritize their selection depending on their goals.

4. **Provide social opinion filters for different stances and emotional reactions**: To facilitate the exploration of social opinions with different stances and (emotional) perspectives, users should be able to filter social opinions based on emotional reaction labels in different stances (rather than semantic labels as in traditional interfaces).

3.3.2 Visual Encoding and Implementation

This novel interface is designed to expose diverse opinions to users in order to mitigate selective exposure. In addition, it helps users to extract information, obtain insight of controversial topics and capture others' stances and reactions for controversial social opinions more easily.

We implemented our interface with 50 Reddit posts about each candidate and the corresponding responses (emotion labels and reactions) collected from Turkers.

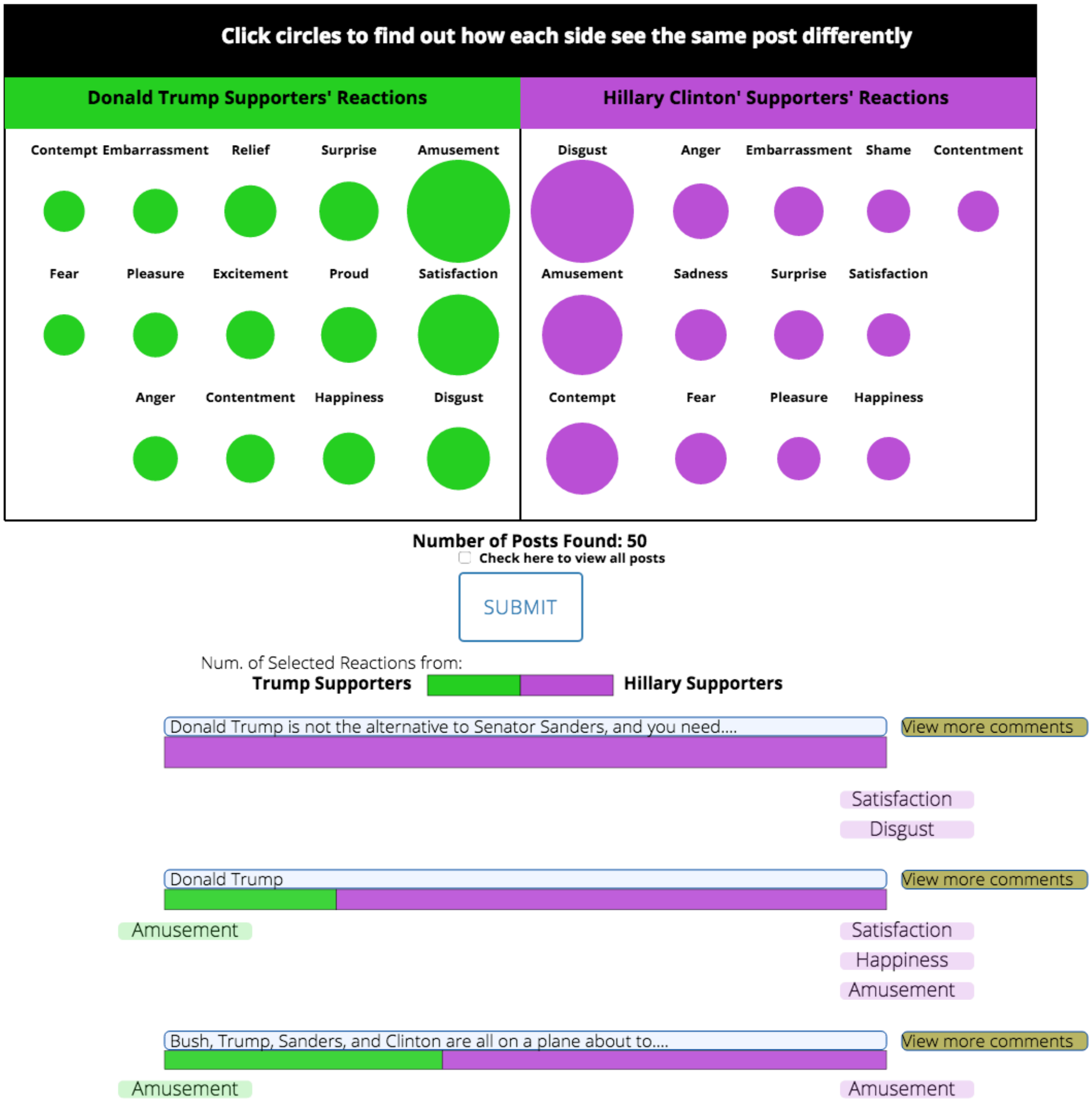


Figure 3.1: A snapshot of the overview of the novel system/interface. The novel system/interface provides emotion labels from each side below each post. If the user put the mouse over an emotion label, the actual reactions collected from Turkers for the emotion will pop up and the user could read these reactions (DP-2)

Figure 3.1 shows the overview of the system. For presidential election, we set two stances: Trump supporters and Hillary supporters. By using different colors, we split reactions generated by people with different stances. Green is for Trump supporters and purple is for Hillary supporters. For each post, we list the dominant emotions which received votes above threshold (4) from Turkers. The threshold is the turning point between picking out significant emotions and covering most of the emotions, including insignificant ones. Users can view the different stances for each posts (*DP-1*) and know how controversial a topic is (*DP-*

3) by comparing the length of the green bar and purple bar below each post. The length of bar indicates how many supporters on the corresponding side made emotional comments on the post.

Even though we discard some unrelated features on Reddit interface *(e.g. upvotes and downvotes)*, we use the thickness of the bar under the post title to show how many comments the post has on Reddit. In Figure 3.1, the bubbles on the top panel represent emotion types of reactions to each stance. The radius of each emotion bubble is positively correlated to the number of that emotion existing in that stance for all posts. Here, users could click the emotional bubble to select emotions and search for posts based on their curiosity for specific emotional reactions generated by people in different stances (*DP-4*). The system will return posts with the corresponding emotional reactions. Users can read reactions (collected from Turkers) for different emotions in a pop up window by putting the mouse over the corresponding emotion label listed below each post. This provides users with different levels of granularity of people's reactions (*DP-2*).

Figure 3.2 shows the different granularity of people's reactions. Basically, emotion labels from each side under the post were provided. If the user put the mouse over an emotion label, the actual reactions collected from crowd workers for the emotion will pop up and the user could read these reactions (DP-2).

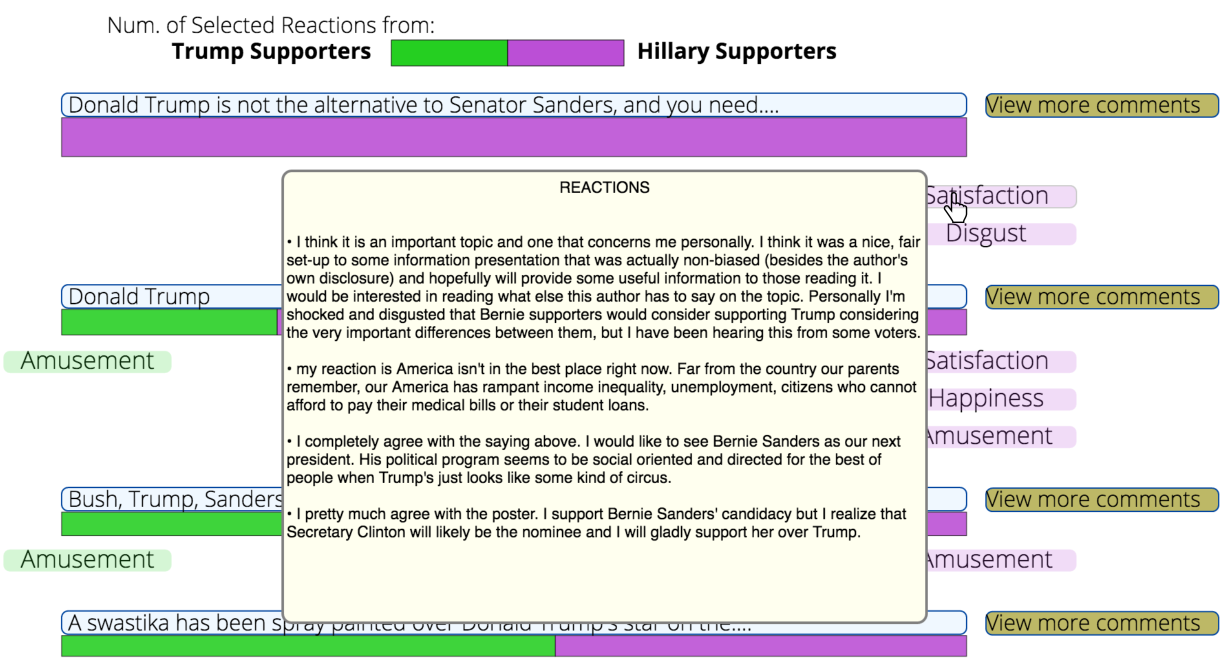


Figure 3.2: A snapshot of actual reactions.

3.4 METHODOLOGY

To evaluate the novel interface, we conducted human subject user study to compare the novel interface with the traditional Reddit interface.

3.4.1 Participants

Eight participants were recruited from the Midwest of the United States (age range 18 to 34, five females). They held a balanced sample of potential users regarding familiarity with the traditional Reddit interface: two stated that they use Reddit almost every day, three said seldomly (one day per week), and three said they do not use Reddit. Moreover, participants showed the diverse attitudes towards the presidential candidates, including four Hillary Clinton supporters, one Donald Trump supporter, and three neutral.

3.4.2 Procedure and Task

To compare between our interface to the traditional Reddit interface where users could browse posts' titles with the number of comments and select post to read in the actual Reddit platform, we provided a platform that a user could select between traditional Reddit interface in a controlled setting and our interface. A within-subject design was used for this study with the user interface as the within-subject factor. We changed the order and contents *(e.g. posts about Hillary Clinton or posts about Donald Trump)* for each interface to reduce the carryover effect. After a short tutorial which helped participants understand the meaning of each interface component, a pre-study questionnaire was given on Reddit, and their opinions on reading controversial posts. Next, we asked the participant to freely explore the posts according to their own interest within 10 minutes. After reading each post, they were asked to answer open-ended questions that ask about the reason why they chose the post and summarize overall opinions (or reactions) of other people. Participants then performed short usability questionnaire on a 5 point Likert scale regarding the usefulness, ease of use, enjoyable, effectiveness, discovering diverse opinions, and satisfaction. After exploring the two interfaces, we conducted another short questionnaire that asks about components of this novel interface in 5 point Likert scale. For the last task, recorded interviews were administered regarding the overall preference, helpfulness of interface to explore diverse opinions, interface components, and suggestions. The interviews were transcribed, and the user behaviors were logged throughout the experiment.

3.5 RESULTS

Based on the result of pre-study questionnaire, all participants agreed that they wanted to know how controversial the post is when reading online opinions, which supports the need of our interface. In addition, 4 participants used Reddit before and 2 of them complained about Reddit's UI design and they said: *"UI is too bad.", "The interface is complicated."*

3.5.1 Mitigating Selective Exposure

While reading the posts in each interface, participants carried out a task that asked their observation about the overall discussion of each post they read.

In average, 2.75 posts were read in Reddit interface and 3.25 posts were read in our interface. More posts were read in our interface than the Reddit interface. This is consistent with our idea that the novel interface facilitates users to find and read a post. After a user read one post, the user was asked why he/she chose the post. Based on their answers, we discovered common motivations of reading posts: 1) posts shown on the top, 2) posts that are simply curious when reading the title, 3) posts with topics that interest the user, 4) posts related to their prior knowledge/opinion/stance, 5) posts selected because of their curiosity of others' reactions.

Table 3.1: Distribution of different motivations to choose posts on Reddit and our interface.

Motivation Type	1	2	3	4	5
Reddit (%)	27	27	27	14	**5**
Our Interface (%)	15	35	8	12	**30**

Table 3.1 shows the distribution of different motivations to choose a post on different platforms. Comparing with Reddit, the percentage of the Type 5 motivation (curiosity of others' reactions) was promoted significantly from 5% to 30% through this novel interface. The result clearly demonstrates that the novel interface helps users to explore others' opinions that is otherwise difficult, if not impossible, to do using the traditional interface.

To be more specific, on Reddit interface, the most common motivations were type 1(27%), 2(27%), and 3(27%), whereas on the novel interface, the most common reasons were type 2(34%) and 5(30%). In both interfaces, many users clicked to read posts that they were simply curious about when reading the title (type 2, *e.g. "I selected the post about the swastika over Trump's star because the word "swastika" jumped out at me."*). While many users were simply choosing the posts based on the semantic information or the position of the post (*e.g. "It was the top post"*) in Reddit interface, type 5 (*e.g. "I want to hear other's* *reactions"*) was especially high on the novel interface and this clearly demonstrates that our interface leads users to explore other's opinions compared to the traditional Reddit interface.

The analysis showed that the users with the neutral stance showed different behavior of using the filtering panel against the ones who support one of the candidates. Specifically, neutral users selected emotions only from one side (e.g. only Clinton supporter's happiness) or the same emotions for both sides (e.g. Trump supporter's happiness vs Clinton supporter's happiness). On the contrary, all the supporters were interested in contrasting emotions expressed by the opponents (e.g. Trump supporter's sadness vs Clinton supporter's happiness). Interestingly, all supporters looked for positive emotions expressed by the opponents and negative emotions expressed by those who were supporting the same candidate. For example, Clinton supporters were interested in posts that Trump supporters were proud and Clinton supporters were sad. This partially support our expectation that the novel interface mitigates selective exposure as people are motivated by the cues to read opinions for both sides.

6 out of 8 participants reviewed the reactions by putting the mouse over the emotional label. 3 of them showed clear supportive stance for Hillary Clinton and the remaining 3 are neutral about election candidates. Using our system, 2 of the 3 Hillary supporters spent more time reading reactions from Trump side than Clinton side, which means they want to know how people in different stances think about the topic.

In addition, we asked all participants the following questions: 1) whether our interface help users to explore posts supported by people in diverse stances; 2) whether the emotion clusters help users to get insight across different opinions. For the first feature, all participants agreed that our interface makes it better to seek for posts supported by people in different stance. P2 said: "*I can easily find which are the controversial posts and which are not. Controversial posts are more interesting to me. So I think that is a good feature.*" P4 said: "*I could know what's pro-Trump or pro-Clinton before I click on it.*" P6 said: "*The interface has drawn like green bar and purple bar so I can easily find which are the controversial posts and which are not. Controversial posts are more interesting to me. So I think that is a good feature.*" For the second feature, 6 out of 8 participants agreed that cluster posts based on emotional reactions helped them to gain global insight for a topic in a short time. P8 said:"*I really liked it. It's easy to use. It's nice to have visuals.*"

3.5.2 Usability Improvement

The results of usability questions given to the participants are shown in Figure 3.3. People found the novel interface easy and useful for browsing posts *(usefulness)*, enjoyable

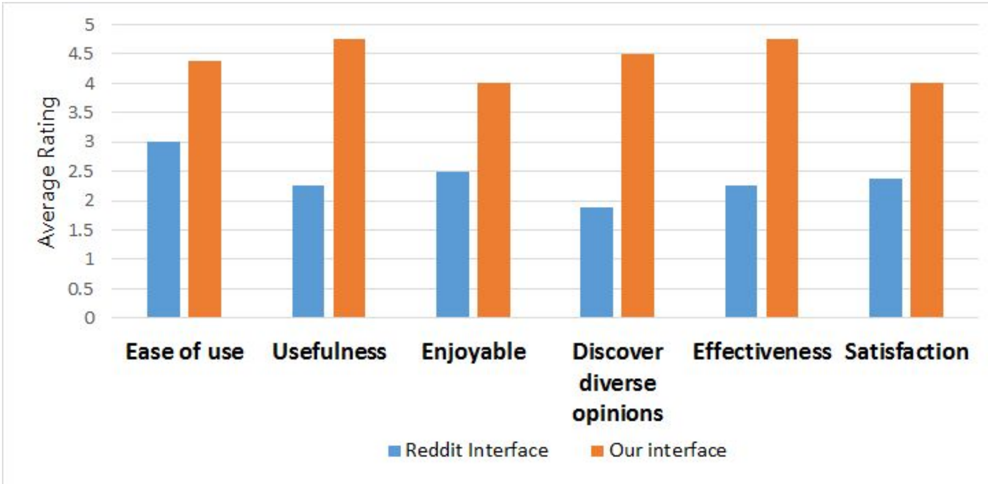


Figure 3.3: Comparison of average ratings between interfaces based on the usability measures. Longer bars indicate better rating and our interface have higher ratings compared to Reddit.

to use *(enjoyable)*, and effective in helping them complete the tasks *(effectiveness)*. Most importantly, participants agreed that the novel interface enabled them to discover diverse opinions *(Discover diverse opinion)* than Reddit that may lead to global insight of controversial topics. Overall, participants were more satisfied with our interface than the counterpart *(satisfaction)*.

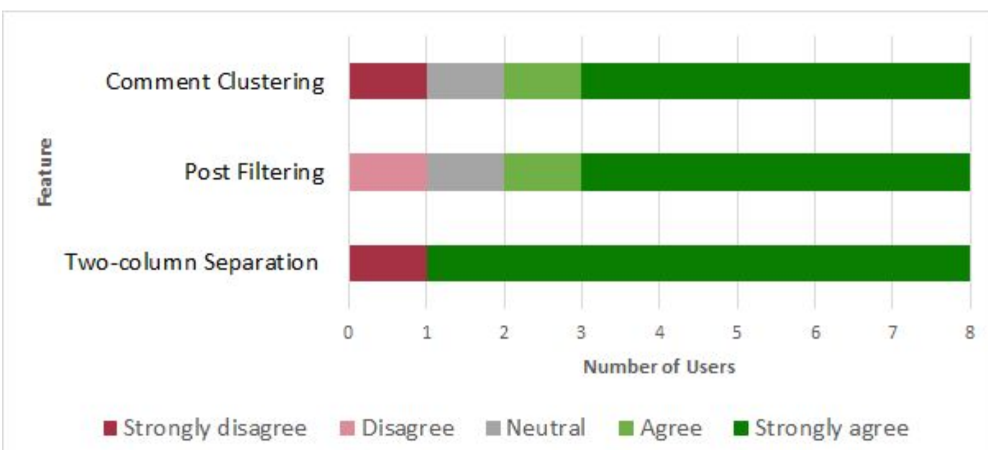


Figure 3.4: Evaluation for specific interface features in our interface. Most of the users agreed that each feature is useful.

Furthermore, Figure 3.4 shows the result of evaluating key visualization features in our interface. We found that the two-column design of separating different supporters was the most useful to find the other side's opinion. Also, the feature of filtering the posts and clustering the comments based on the emotion labels were reported to be useful when analyzing the post. As the response to which interface they prefer, 6 of 8 participants showed a clear overall preference to our proposed interface compared to the Reddit interface. For example, P2 said :"*I prefer your interface because it has more features. So it's easier to use to find some interesting posts, especially if you want to find a specific type of posts. For the basic (Reddit) UI, you have to browse all the titles to pick up which one you want to read.*"

3.6 DISCUSSION

What is the role of online forums in society? People post their opinions to openly discuss and get feedback from others who may or may not share the same views or beliefs in ways that allow people to understand and appreciate each others' values. From this perspective, online social forums should be designed to enable users to develop and share their own views while browsing and understanding the collective opinions and reactions of others. Thus, an online space that promotes appreciation of diverse opinions and understandings of various emerging social issues can play a crucial role in healthy online communications and thereby facilitate societal agreement. With the same goal, my research motivates users to explore opinions from different stances and thereby helps them interact with online social opinions on controversial topics in ways that are believed to facilitate understanding and reduce selective exposure and opinion polarization. The experimental results of this study demonstrated that people proactively searched for opinions and reactions of opposite stances using the novel interface. A promising future direction is to extend the current interface so that it can automatically categorize new posts as a user type, such that the user can receive immediate feedback on how their posts are similar to and different from existing ones. We expect that this will further mitigate selective exposure and help users explore more diverse opinions and acquire a more balanced view of a social topic.

The current interface assumes that emotions reflect attitudes in general, because people tend to have positive emotions when they support an idea and negative emotions when they disagree. Although the results provide some support to this assumption, we should point out that more research needs to be done on how such forums should represent the diverse spectrum of opinions and reactions. Nevertheless, we believe that the current study provided important insights to research in this direction.

In addition, we believe that the current approach of using human computation in intelligent user interfaces can be scaled up to larger forums by incorporating it into text and emotion analysis techniques. For example, labels (and reactions) from Turkers can be used as training samples to cluster posts and reactions automatically, and incremental inputs can refine the accuracy of these clusters over time. We did obtain promising preliminary results, but they are beyond the scope of this current chapter and are therefore not studied.

In this chapter, we found that showing categorized social opinions based on emotional reactions can help to mitigate selective exposure and fulfill people's demand to see others' reactions. Previous research [9] shows that recommendation algorithms can create filter bubbles and intensify people's overconsumption of attitude-consistent information. We will study how recommendations with novel visual hints can help to mitigate selective exposure rather than strengthen it in chapter 4.

CHAPTER 4: MITIGATING SELECTIVE EXPOSURE THROUGH RECOMMENDING DIVERSE OPINIONS WITH VISUAL HINTS

4.1 INTRODUCTION

Social media have been playing an increasingly important role in spreading and shaping social opinions. Pew research [103] showed that, in 2016, 62% of U.S. adults get news from social media. Contrary to the expectation that people are exposed to more diverse opinions, some research has shown that social media may have the opposite effect, i.e., they may play a role in encouraging people to be more selective in their information consumption – a phenomenon often referred to as *selective exposure* [10, 13, 14]. Selective exposure to information may prevent people from receiving diverse opinions and cause polarization of social opinions. This effect may be exacerbated by implicit personalization algorithms that selectively guess what information users would like based on their history of information selection. This process that may keep users separated from information that is inconsistent with their beliefs or attitudes. Users are often unaware of this "filter bubble," [9] which may negatively affect their social opinion consumption. For example, the lack of awareness has raised some concerns over how selective exposure to "fake news" on social media has influenced the US presidential election. The current chapter aims to investigate strategies for designing intelligent features that may mitigate this type of implicit behavioral tendencies.

When people are selectively exposed to information, they may not be fully aware that their attitudes are influencing their selection [74]. Some people may have traces of past experiences that mediate their favorable or unfavorable feelings about specific social issues. These feelings may influence their information selection behavior that they may not be aware of. For example, when people are asked whether they support or oppose the repeal of Obamacare, they may think that they are neutral. However, when they encounter information related to various perspectives of the issue, their experiences or beliefs (e.g., their general beliefs about the role of the government) may lead to varying levels of behavioral dispositions that mediate their behavior (e.g., more likely selecting information favoring the repeal) in ways that they are unaware of. Such behavioral dispositions may be magnified as people become selectively exposed, as their beliefs are reinforced by attitude-consistent information, leading to an *echo chamber* effect.

Online interface design often simply presents social opinions (e.g., news article comments) in a linear format. There is a general lack of structure that helps improve people's awareness of their behavioral dispositions and opinion selection preferences. In fact, research shows that the lack of sensitivity to people's attitudes towards different social issues in the design of social information interfaces may aggravate selective exposure, as people have a natural tendency to process information that they agree with.

To address this problem, we proposed a novel intelligent system consisting of design features that aim to improve people's awareness of their stances and selection preferences by encouraging them to attend to more diverse opinions. To be more specific, this novel system provides people with novel visual hints, including showing a trace of people's stances based on previously read news articles and highlighting visually on the interface when people are selectively exposed to one side of opinions. In addition, the system recommends attitude-inconsistent and attitude-consistent comments according to people's stances with different priorities and different recommendation indicators. When first recommending attitude-inconsistent opinions to people, the system will label these opinions as "Recommended." Later, when recommending attitude-consistent opinions, these opinions will be labelled as "Not Recommended." We expect that the recommendation mechanism and the indicators could *nudge* people to attend to the connection between the indicator and the stance expressed in the recommended comments so that they could realize their stances and the existence of the "filter bubble." For example, people may be accustomed to being recommended attitude-consistent opinions by personalization algorithms on the social network. Hopefully, the mismatch of the indicator and stances expressed in recommended opinions in the novel system could motivate people to inspect their own stances and expose diverse opinions to people.

To summarize, we proposed the following research questions:

- RQ1: Can the novel system help people become more aware of their stances and social opinion selection preferences?
- RQ2: Can the novel system mitigate selective exposure when people use it to read social opinions?

4.2 SYSTEM DESIGN AND IMPLEMENTATION

4.2.1 Data

Facebook allows users to select emoticons, among *Like*, *Love*, *Haha*, *Wow*, *Sad* and *Angry*, to express their emotions to the articles. Many Facebook users not only write their comments to articles but also select the emoticons to express their emotional reactions. This gives us cues to know users' emotions when they write their comments. We intended to categorize emotions into positive and negative sentiments. We found that the *Like* emoticon is so general that many Facebook users always selected the *Like* emoticon regardless of the emotions expressed in their comments. In addition, the *Haha* and *Wow* emoticons are too ambiguous. Some of the comments with the *Haha* emoticon expressed the emotion of jeer whereas others may express the emotion of happiness. The *Wow* emoticon is for the feeling of surprise. However, the sentiment of surprise could be either negative or positive. On the contrary, comments with emoticons of *Love*, *Sad* and *Angry* express relatively consistent emotions with their labels in most cases. Thus, in my study, the *Love* emoticon represents positive sentiment whereas the *Sad* or *Angry* emoticons denotes negative sentiment.

We selected the Obamacare repeal issue as a controversial topic in the study. In order to implement the system and mitigate the bias caused by different news sources, we collected CNN and FoxNews news articles with comments from Facebook using Facebook API. We crawled most recent 100 CNN news articles published from May 8th 2017 to August 10th 2017 and 100 FoxNews articles published from May 1st 2017 to August 16th 2017 from Facebook. Note that the time coverage is slightly different because we were not able to collect the same number of articles in the same period of time. But we tried to remove the potential bias stemmed from different collection times by crawling articles in overlapping periods that the median dates are similar. All these articles we collected have the keywords "health care" in their Facebook news messages. We analyzed people's sentiment (positive vs. negative) towards these articles by comparing how many people selected the *Love* emoticon and how many people selected the *Sad* or *Angry* emoticons. On average, the comparison between being positive and being negative is 40.03% vs. 59.97% for CNN news articles and 45.57% vs. 54.43% for FoxNews articles. This suggested that Obamacare repeal issue is a typical controversial topic on social network so that we select this as a representative in our study.

In order to train the sentiment classifier and build the novel system, for each article, we also collected the corresponding Facebook comments. Thus, unlike previous sentiment analysis studies where researchers collected data first and then recruited external annotators to add sentiment labels to their data [80, 104], we only collected Facebook comments provided by people who also selected one or more emoticons to indicate their emotions. For each comment we collected, there could be one or more emotion labels selected by comment providers. Comments with the *Love* emoticon were labelled as positive sentiment whereas those with the *Sad* or *Angry* emoticons were labelled as negative sentiment. These positive and negative labels are treated as gold standard sentiment labels.

Data for Sentiment Analysis 4,000 positive comments and 4,000 negative comments were randomly selected from our dataset to train and test the sentiment classifier. To further evaluate the classifier, we randomly selected extra 200 comments from each side. These extra 400 comments are used as test data for the comparison of performance between our classifier and human annotators (e.g. online crowd-workers).

Data for System Implementation To implement the system prototype, we selected four CNN news articles that oppose to repeal Obamacare and four FoxNews articles that support to repeal Obamacare from our article pool. For each selected article, to obtain diverse opinions, eight comments that support this article and eight comments that oppose this article were picked as the corresponding comments for the article.

4.2.2 Sentiment and Stance Analysis

We trained a classifier to predict people's sentiment to an article from their comments. We worked on the corpus where there are 4,000 comments on each side. We preprocessed the comment texts by stemming and removing stop words, and we converted comments into unigram feature vectors. Since different terms have different levels of importance when used to decide the sentiment, we adopted χ^2 statistic (*CHI*) test [79, 82] on each unique term in the training set of the corpus. The *CHI* statistic measures the degree of association between the term and the sentiment category. The definition of *CHI* statistics between term t and sentiment category c_i is:

$$\chi^2(t, c_i) = \frac{N \times (AD - CB)^2}{(A + C) \times (B + D) \times (A + B) \times (C + D)} \tag{4.1}$$

where A is the number of times t and c_i co-occur, B is the number of times t occurs without c_i, C is the number of times c_i occurs without t, D is the number of times neither t nor c_i occurs and N is the total number of comments. If t and c_i are independent, the value of the χ^2 statistic is zero. For each unique term t, we calculated the χ^2 statistic for each sentiment category and finally we assigned the weight, which shows the importance of the term, to each unique term t with:

$$\chi^2_{max}(t) = \max_{i=1}^{m}\{\chi^2(t, c_i)\} \tag{4.2}$$

where m is the total number of categories. In my case, m equals 2 since there are two sentiment categories (positive vs. negative) in the study.

In the feature vector of each comment, the normalized weight $Weight(t, D)$ of a unique term t in comment D is calculated based on:

$$Weight(t, D) = \frac{tf(t, D) \times \chi^2_{max}(t)}{Total\_Weight(D)} \tag{4.3}$$

$tf(t, D)$ is the term frequency of the unique term t in comment D and $Total\_Weight(D)$ is the total weight of all terms in comment D ($Total\_Weight(D) = \sum_{t \in D} tf(t, D) \times \chi^2_{max}(t)$).

We trained a Random Forest classifier [83, 84] on feature vectors using Python scikit-learn package. We evaluated our sentiment classifier via 10-fold cross validation using the corpus. We calculated the precision, recall and F_1 score for both positive and negative sentiment categories and results are shown in Table 4.1.

Table 4.1: 10-fold cross validation result of sentiment classifier.

	Positive	Negative
Precision	0.742	0.683
Recall	0.638	0.778
F_1 score	0.686	0.727

Furthermore, we compared the performance between our classifier and human annotators on the extra test set which included 200 randomly selected comments in each sentiment category. To evaluate the performance of human annotators, we recruited Turkers on Amazon Mechanical Turk platform (AMT) to annotate sentiment labels (positive vs. negative) to each comment. In each Human Intelligent Task (HIT), we presented 20 comments and we asked Turkers to identify the sentiment expressed in each comment. For each comment, we collected five sentiment labels and used majority vote to determine final sentiment. Ultimately, 100 Turkers participated into the study with a reimbursement of $1.00 per HIT on September 30th 2017. Among the 400 testing comments, 102 comments received either two positive votes and three negative votes or three positive votes and two negative votes from Turkers. This result suggested that among the 400 testing comments, about 25% of them are ambiguous. We compared model-predicted and human-annotated labels with the gold standard respectively and calculated the precision, recall and F_1 score for both methods. Results are shown in Table 4.2. We found that our classifier's performance is comparable to human annotators' performance on this difficult task.

With the predicted sentiment label of the comment to an article, we could predict comment providers' stances as we know the stance of these articles in our study. Here, stance means the opinion (support vs. oppose) towards an issue. For example, if the sentiment classifier predicted a comment to be negative to an article which opposes to repeal Obamacare, we would predict the comment provider's stance as supporting Obamacare repeal.

Table 4.2: Comparison of performance between our classifier and human annotators.

		Positive	Negative
Random Forest	Precicion	0.734	0.678
	Recall	0.635	0.770
	F_1 score	0.681	0.721
Human Annotator	Precision	0.791	0.671
	Recall	0.585	0.845
	F_1 score	0.673	0.748

4.2.3 System Design Principle

The novel system aims to improve people's awareness of their own stances and social opinion selection preferences, and mitigate selective exposure. Based on previous studies about nudging the bias of selection using various visualization techniques [23, 105] and recommendation systems [106, 107], we propose the design principles as below:

1. **Highlight visual difference when opinion selection bias is detected:** The system should provide highlighted difference visually when social opinion selection bias is detected. We expect that visually salient hint is effective to remind people that they may be selectively exposed to a specific side of opinions.

2. **Show the trace of people's stances:** When the system detects stances of users, it should provide explicit feedback to improve users' awareness of their stances. We expect that this feature not only will help them realize their own stances, but also be more conscious of the stances of other people's opinions relative to their own stances.

3. **Recommend social opinions from an opposite stance with positive indicators:** People who are biased towards one side of the opinions may intentionally avoid opinions on the other side, or they may be unintentionally kept in a filter bubble by personalization algorithms. In our study, we investigate whether recommending opinions opposite to a user's stance would help increase the diversity of exposure to social opinions, thereby raising their awareness of their own stances. In the current design, the system will recommend attitude-inconsistent opinions with a positive indicator (i.e. labelling these opinions as "Recommended") to encourage people to attend to these opinions – i.e., we expect that this will help burst the filter bubble.

4. **Recommend social opinions in the same stance with negative indicators:** If the system only recommends attitude-inconsistent opinions to people, people may

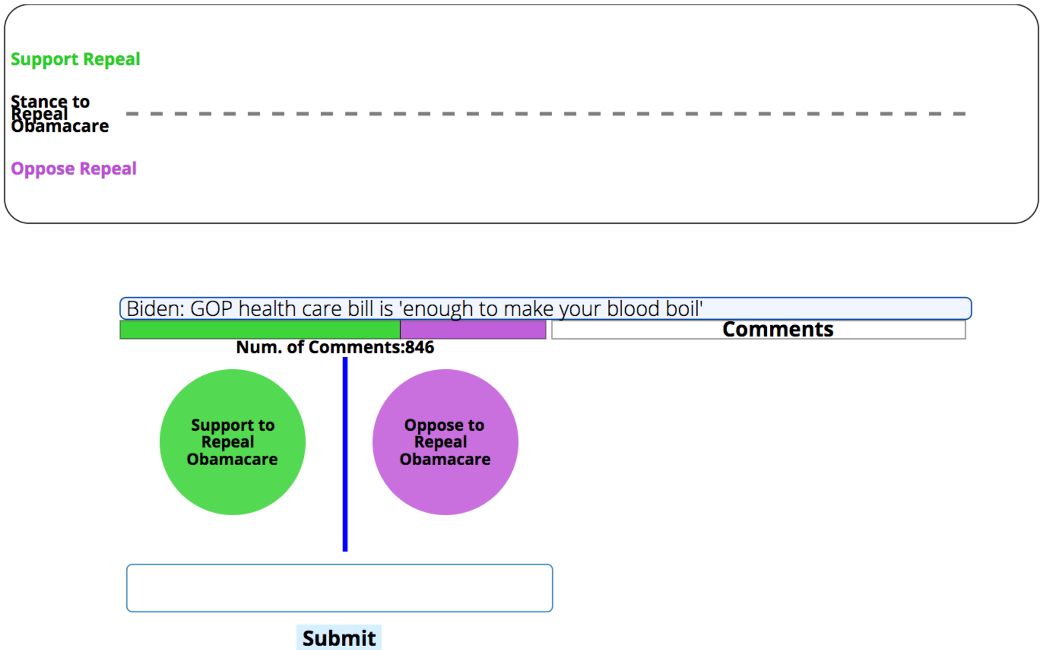


Figure 4.1: An overview of our new interface.

leave the platform when they feel dissatisfied with the recommended information. In the current design, we investigate whether recommending attitude-consistent opinions will fulfill the implicit information needs of users. However, to avoid the effect of a filter bubble, we will provide a negative indicator to the opinions (i.e. labelling these opinions as "Not Recommended"). The negative indicator may also stimulate people's curiosity about why the system shows opinions which are not recommended. By nudging people to figure out the connection between the indicator and the stances expressed in the opinions, the novel system may help people realize their stances.

4.2.4 Visual Encoding and Implementation

To achieve my design goals, the novel system incorporates visual hints and opinion recommendations. There are four articles (two FoxNews articles and two CNN news articles) in the system. The system only shows people one article at a time and recommends the next article based on people's stances to the previous one. Figure 4.1 shows the overview of our new interface. On the top of the article title, there's a panel to trace people's stances on previous articles. The color bar under the article title indicates how controversial the article may be. The length of the green bar indicates the proportion of comments which support to repeal Obamacare and the length of the purple bar indicates the proportion of comments on the other side.

There are two round clickable stance labels under the color bar. Green stance label represents comments which support to repeal Obamacare and purple stance label represents comments in the opposite stance. There's a text entry field under the stance labels where people could write their own comments. For each article, we selected eight comments on both sides respectively. We split comments on each side into two groups and each group has four comments. On each side, the first group of the comments will be presented when people click the corresponding stance label to read comments. The second group of comments will be used as recommended comments when the system makes recommendations based on people's stances.

Visual Hints (DP-1, DP-2) The novel system provides various visual hints to help people realize their opinion selection bias and stances.

The interface highlights the visual difference in terms of the stance label size (*DP-1*). Figure 4.2 shows an example that after a user clicked a stance label to read comments on that side, the stance label became smaller. This could improve the user's awareness of their social opinion selection preference. Under each comment, the interface allows the user to rate the degree of (dis)agreement on the comment in a 5 Point Likert scale ranging from strongly disagree to strongly agree. If necessary, these ratings could be used to evaluate the user's stance after submitted by the user.

Figure 4.3 shows that after the user wrote and submitted a comment, the novel system predicted the user's stance on the Obamacare repeal issue. In case of inaccurate classification, the system gives the user a chance to correct the predicted stance label and confirm. Previous research [108] shows that most people are willing to correct the prediction mistakes caused by auto-systems.

Figure 4.4 shows an example of the function of stance record panel. After submitting the ratings to comments which were selected to read and confirming the stance for the first article, the user moved on to next article. The stance record panel showed the trace of the user's stances on previous article(s) to improve the self-awareness of his/her own stance (*DP-2*). The dashed line in the middle represents the neutral stance. The small round purple label below the dashed line is a user stance indicator showing the user's confirmed stance (oppose the repeal). If the user confirmed the stance as "support to repeal Obamacare", there would be a green user stance indicator above the dashed line. For neutral stance confirmation, a grey user stance indicator would appear on the dashed line. There is a bar colored with green and purple on the right of the user stance indicator. The length of the green part indicates

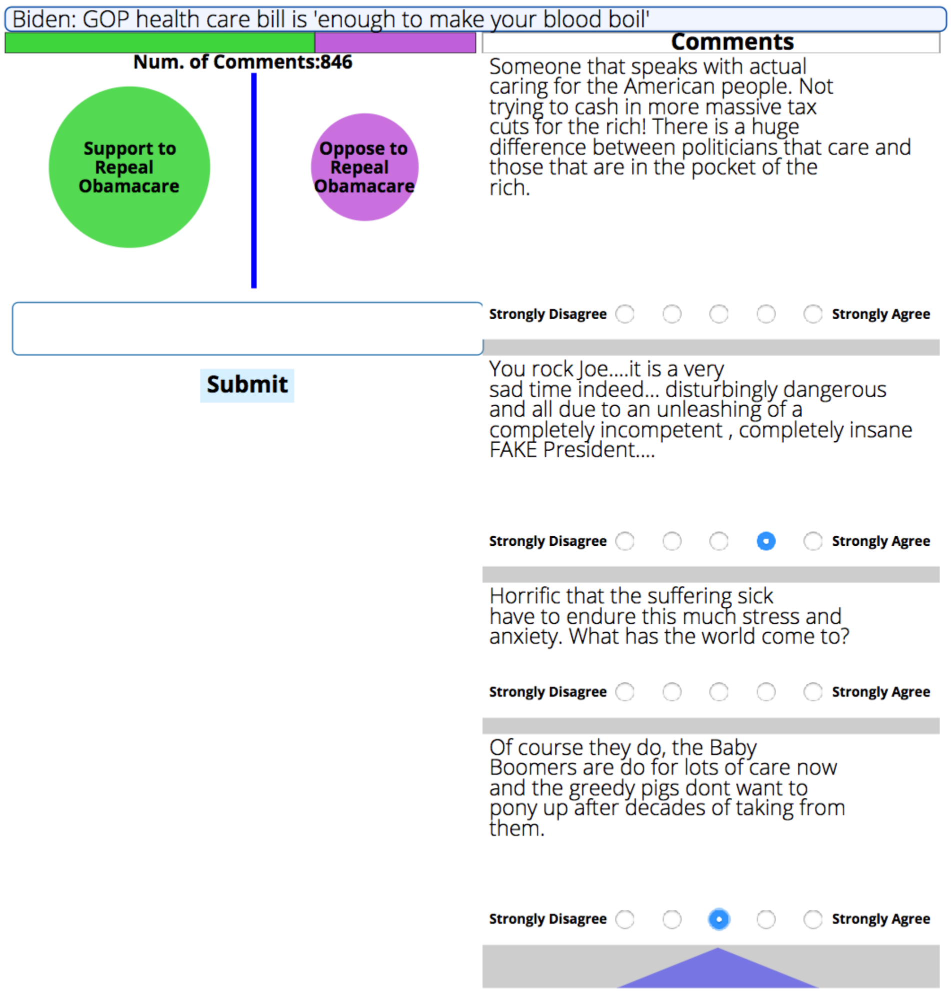


Figure 4.2: An example of size changeable stance labels.

the mean of ratings given to comments which support to repeal Obamacare while the length the purple part indicates the mean of ratings given to comments on the other side. The ratio between the lengths of these two parts indicates the ratio between the average ratings for comments on each side. In the example shown in Figure 4.4, the purple part exceeds the dashed line, which means the user rated comments which oppose to repeal Obamacare higher than comments on the other side.

Social Opinion Recommendation (DP-3,DP-4) The novel system recommends diverse social opinions to mitigate selective exposure. Before recommending articles or comments, the system needs to detect people's stances. If a user confirmed a non-neutral stance expressed in his/her own comment, the user's stance would be the same as the confirmed

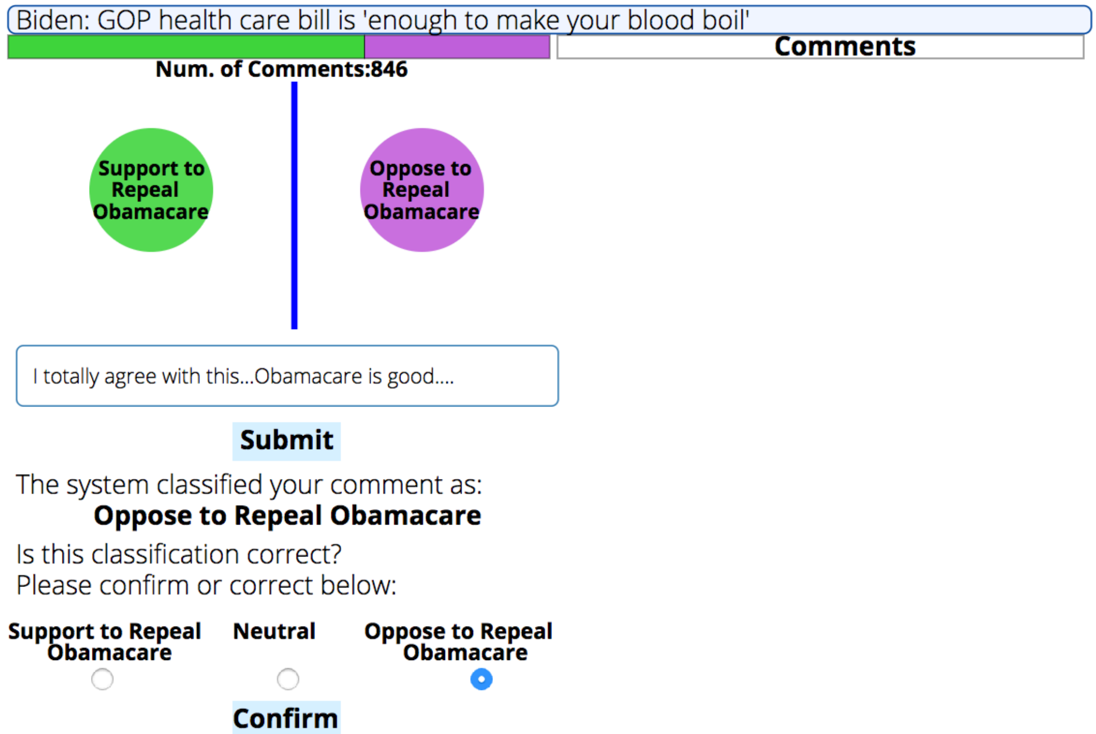


Figure 4.3: An example of our new interface after people write and submit a comment.

one. If the user didn't confirm or confirmed a neutral stance and the mean of his/her ratings given to each side of comments are different, the user's stance would follow the stance of the side with higher average rating. Furthermore, the user's stance would be neutral if he/she confirmed neutral stance and the average rating for comments on each side is the same. If the user confirmed a neutral stance and only rated comments on one side, the user's stance label will be chosen based on the mean of ratings given to the comments on that side. If the mean value was higher than three, the user's stance would be the same as the stance of this side. Otherwise, if the mean value was lower than three, the user's stance would be opposite to the stance of this side. If it's three, the user's stance would be considered as neutral.

In order to recommend diverse opinions to users, the novel system provides two types of recommendations (*Type 1* vs. *Type 2*; See Table 4.3) at both the article and comment level. For both article and comment level recommendations, *Type 1* recommendation has higher priority than *Type 2* recommendation since attitude-inconsistent opinions could make people be conscious of the existence of opinions with different stances, which could mitigate selective exposure. In the novel system, as long as there are attitude-inconsistent opinions available, our system will conduct *Type 1* recommendation. *Type 2* recommendation will

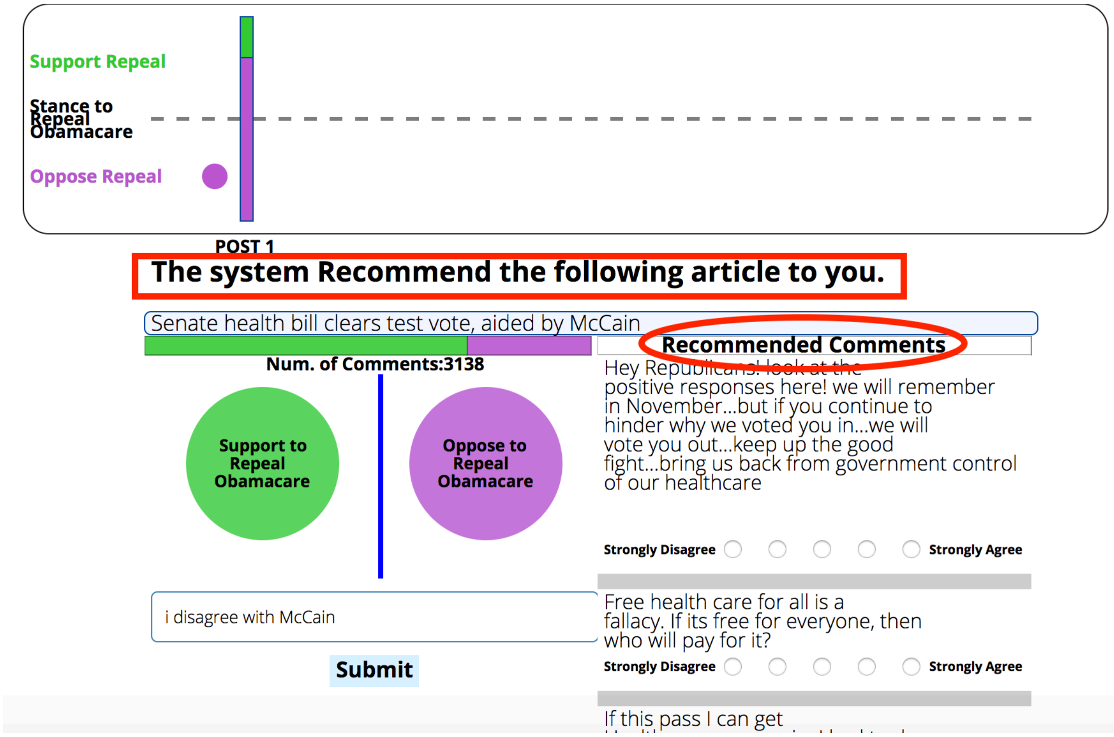


Figure 4.4: An example of our new interface after people move on to the next article and the system conducts *Type 1* article recommendation and *Type 1* comment recommendation.

Table 4.3: Two types of recommendations.

Type	Recommendation Mechanism
Type 1	Recommend attitude-inconsistent opinions with a positive indicator (*DP-3*)
Type 2	Recommend attitude-consistent opinions with a negative indicator (*DP-4*)

be conducted after all attitude-inconsistent opinions (e.g. articles and comments) have been recommended.

Figure 4.4 shows an example of *Type 1* article recommendation. Based on the user's ratings to comments and stance confirmation, the novel system determined his/her stance as opposing to repeal Obamacare. Since there were articles with an opposite stance available in our article database, the system conducted *Type 1* recommendation by recommending an article expressing an opposite stance with a positive indicator "The system Recommend the following article to you" (See the red rectangle in Figure 4.4). However, if at this moment, there were only articles with the same stance available in the system, the system would conduct *Type 2* recommendation by recommending the same-stance article with a negative indicator "The system Doesn't Recommend the following article to you".

Comment recommendation is conducted in the same way as the article recommendation. Figure 4.4 also shows an example of *Type 1* comment recommendation. The user confirmed the stance as opposing to repeal Obamacare. The system recommended four comments which support to repeal Obamacare with a positive indicator "Recommended Comments" (See the red circle in Figure 4.4). After the user clicked the "readmore" button (the upside-down blue triangle at the bottom of the comment list), the system conducted *Type 2* recommendation by presenting four agreeable comments with a negative indicator "Not Recommended Comments" to the user. Last but not least, if the system determines the user's stance as neutral, there's no recommendation for articles and comments. The system will randomly select articles and comments for the user to read.

4.3 METHODOLOGY

We conducted a user study to evaluate how the novel system could improve users' awareness of their stances and selection preferences of social opinions. In addition, we examined how our interface could mitigate selective exposure and encourage users to read more diverse opinions.

4.3.1 Participant

In this study, 12 subjects (age range from 18 to 64, 6 females) from the Midwest of the U.S. were recruited via email. They all reported that they have considerable knowledge about the Obamacare issues. When they were asked about their stances on the Obamacare repeal issue prior to the user study, four of them reported neutral and eight of them reported opposing to repeal Obamacare.

4.3.2 Experimental Design and Task

As shown in Figure 4.5, the control interface shows 16 comments in a linear list format for each article. These comments are shown in a randomized order. To compare the novel interface (system) with the control interface, we designed a within-subject study where the interface is the within-subject factor. To avoid potential carry-over effect caused by the order of exposure to specific interface and group of articles, we first split eight selected news articles into two groups where each group had two CNN news articles and two FoxNews articles. Then, we changed the order of the interfaces and the article groups.

In the beginning of the user study, participants took a background survey about their demographic information and their experience in reading controversial topics. Then, participants did the following tasks for each interface: 1) Participants watched a tutorial video about how to use the interface; 2) Participants were asked to read each article, rate comments they were interested in and to write a comment to the article; 3) After finishing the task, participants worked on a two-part in-study survey. The first part asked about how the interface could help them realize their stances and comment selection preferences, and whether the interface could help them discover diverse opinions easily. The second part asked about usability of the interface, which focused on the following measures: 1) *Usefulness*: "I found this interface to be useful for reading controversial issues"; 2) *Ease of use*: "This interface is easy to use when reading controversial topics"; 3) *Enjoyable*:"I found this interface enjoyable to use"; 4) *Effective*: "The interface is effective in helping me complete the tasks"; 5) *Overall Satisfaction*: "Overall, I am satisfied with this system." All the questions in the in-study survey were measured on a 5 Point Likert scale. Then, after finishing the tasks and in-study surveys for both interfaces, participants were asked to finish a post-study questionnaire about the usefulness of each design feature in the novel system and their perception of how the system recommends articles to them. Finally, we conducted a short interview. The user study lasted about 1 hour and 20 minutes with a payment of $12.

4.4 RESULTS

4.4.1 Improving Awareness of Diverse Opinions (RQ1,RQ2)

Figure 4.6 shows the comparison between two interfaces for the first part of the in-study survey. We performed Wilcoxon Signed Ranks Test to each measure and found that our new interface is significantly more helpful than the control interface in terms of helping people realize their stances ($Z = -2.859$, $p < 0.01$) and their selection preferences in comments ($Z = -1.982$, $p < 0.05$). Furthermore, results indicated that the novel interface is significantly more helpful for users to discover diverse opinions than the control interface ($Z = -2.214$, $p < 0.05$).

Since participants' interface usage behaviors (e.g. which comments they rated, what rating they gave to each comment, participants' stances) were recorded, we conducted analysis on their social opinion browsing behaviors to evaluate whether our system could mitigate selective exposure. During the user study, each participant was asked to read four different articles on each interface. The system recorded which comment(s) they selected to rate with corresponding ratings and their stances to Obamacare repeal issue after reading each

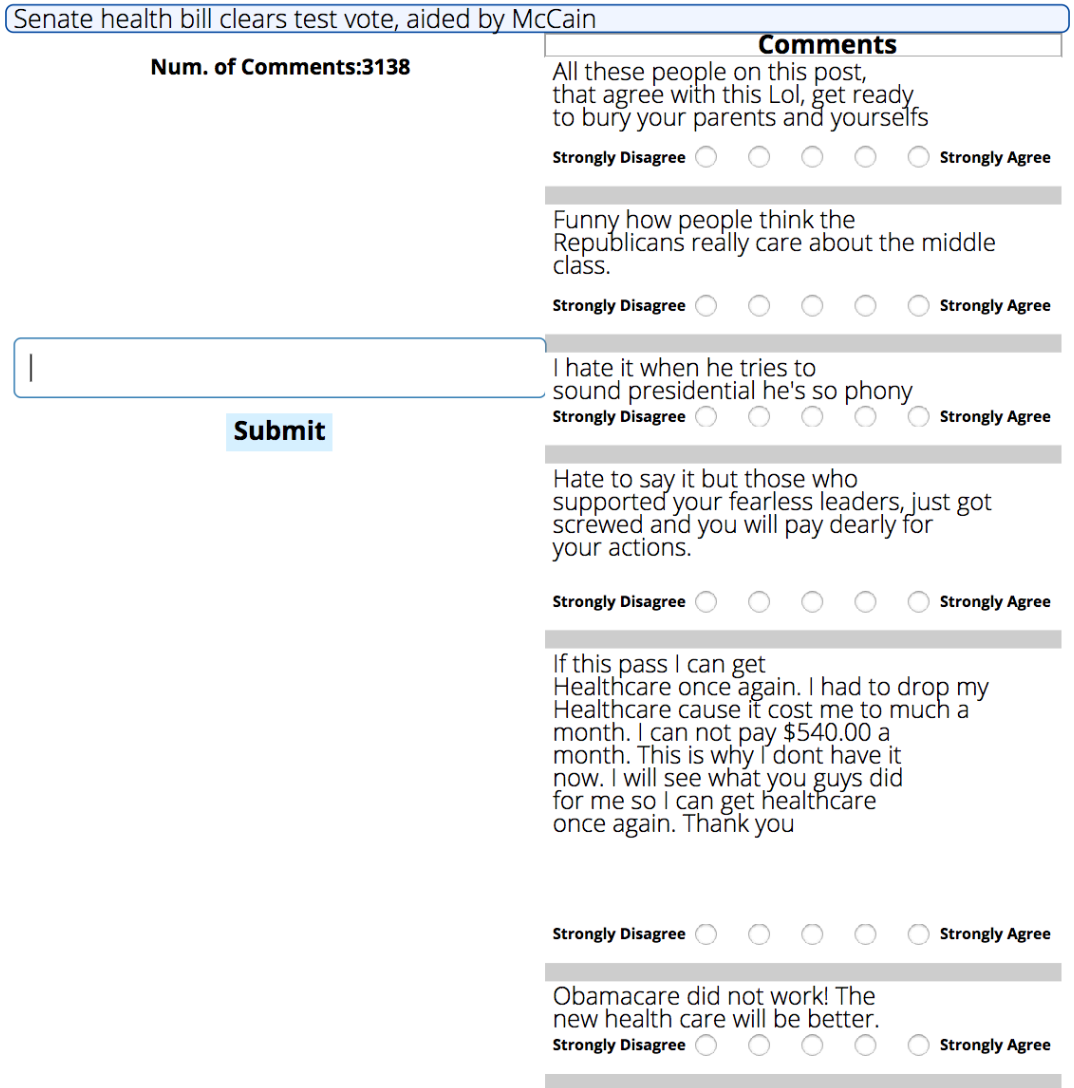


Figure 4.5: An overview of the control interface.

article. Since we asked participants to only select and rate comments they were interested in, we could evaluate how they were selectively exposed to attitude-consistent opinions by comparing the number of comments they selected on different sides. To measure the selective exposure effect, we defined Selective Exposure Index (SEI) for an article as:

$$SEI = \frac{N_{consistent}}{N_{consistent} + N_{inconsistent}} \tag{4.4}$$

where $N_{consistent}/N_{inconsistent}$ is the number of selected comments which are consistent/inconsistent with participants' stances respectively. An SEI higher than 0.50 means the participant tends to be selectively exposed to agreeable social opinions.

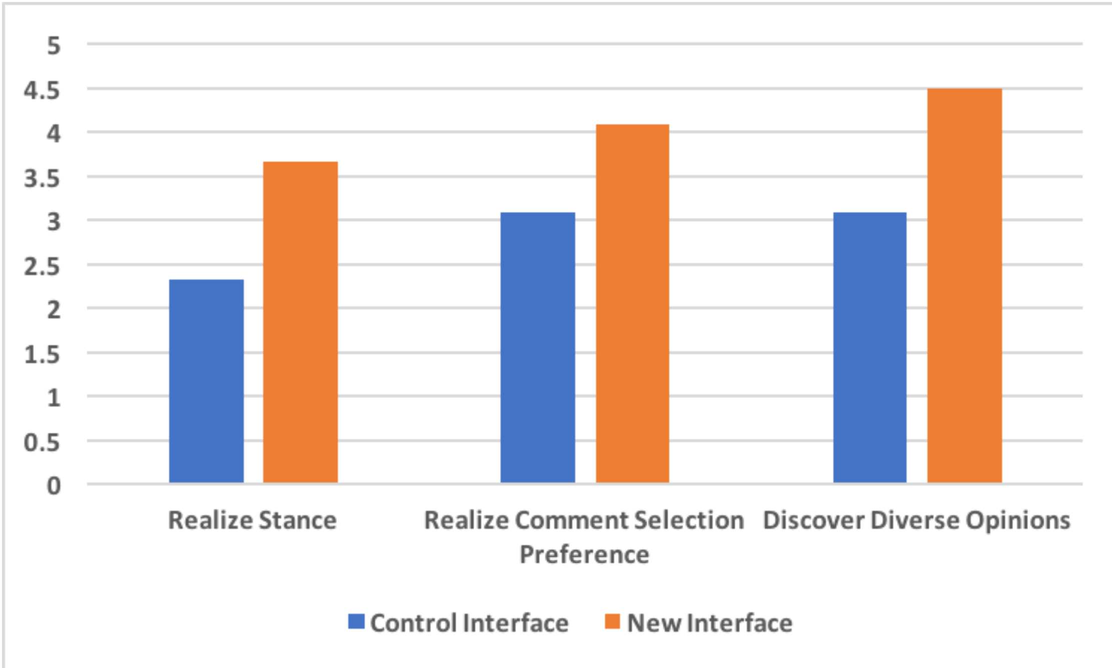


Figure 4.6: Comparison of average ratings between two interfaces in terms of whether the interface could help users realize their stance, comment selection preference and discover diverse opinions.

We counted the total number of comments participants selected for each article and calculated the SEI for each article in both interfaces. Since every participant read four articles using each interface, in total, for each interface, we have 48 data entries collected from 12 participants for each measure. The results of comparison between these two interfaces for each measure are shown in Table 4.4. A two-tailed paired-sample t-test was conducted on each of these measures. The result showed that participants read more comments on the novel interface than the control interface and the difference is significant ($t(47) = 12.717$, $p < 0.001$). In addition, the SEI of the new interface is significantly lower than that of the control interface ($t(47) = -2.280$, $p < 0.05$), which suggests that our new interface motivates participants to read more attitude-inconsistent comments and helps to mitigate selective exposure.

To further investigate the efficacy of the novel interface in mitigating selective exposure on people with different reading behaviors, for each participant, we calculated the average SEI of all four articles he/she read on the control interface and separated participants into High SEI group (with 9 participants) and Low SEI group (with 3 participants). High SEI group participants have an average SEI higher than 0.50 and Low SEI group participants have an average SEI lower than 0.50. We evaluated the effect of the new interface on

Table 4.4: For both interfaces, we calculated the mean and the standard deviation of the numbers of comments rated and SEIs.

	New Interface	Control Interface
Number of comments rated (n = 48)	12.33 (± 3.49)	6.50 (± 2.61)
SEI (n = 48)	0.49 (± 0.08)	0.57 (± 0.21)

Table 4.5: For both High and Low SEI groups, we calculated the mean and the standard deviation of SEIs for both interfaces.

	New Interface	Control Interface
High SEI group (n = 36)	0.50 (± 0.08)	0.61 (± 0.23)
Low SEI group (n = 12)	0.47 (± 0.05)	0.45 (± 0.12)

different groups of participants and Table 4.5 shows the mean and standard deviation of SEIs on different groups and interfaces. A two-tailed paired-sample t-test showed that there is a significant difference between two interfaces ($t(35) = -2.621$, $p < 0.05$) for High SEI group. Meanwhile, no significant difference is found for Low SEI group ($t(11) = 0.457$, $p = 0.657$). This result indicated that High SEI group participants have more balanced comment selection behaviors when using our interface. However, there's no significant difference in comment selection behaviors for Low SEI group participants when using different interfaces.

These results show that the new interface (system) improves people's awareness of their stances and social opinion selection preferences (RQ-1), and mitigates selective exposure (RQ-2).

4.4.2 Usability Improvement

Figure 4.7 shows the comparison between two interfaces for the second part of the in-study survey. We conducted Wilcoxon Signed Ranks Test on each measure of usability (Table 4.6) and found that for the measures of *EaseofUse*, *Enjoyable*, *Effective* and *Overall Satisfaction*, the new interface are rated better than the control interface with a significant difference. However, we only found marginal significant difference in the *Usefulness* measure when comparing the new interface with the control interface. In general, we can see that the new interface has a higher usability level than the control interface. Even though the new interface first recommends attitude-inconsistent information to users, users are still more satisfied with the new interface. This result might indicate that the new interface, which motivates people to explore diverse opinions, especially opinions on the opposite side, didn't trigger hate. People still prefer to use the new interface.

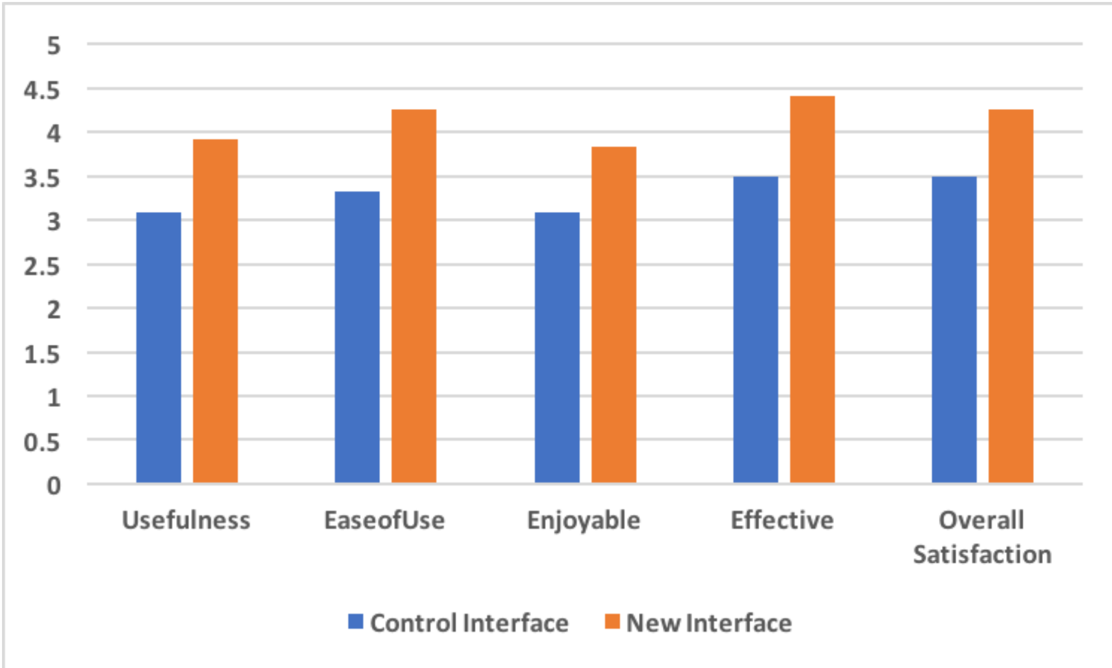


Figure 4.7: Comparison of average ratings between two interfaces in terms of usability measures: Usefulness, EaseofUse, Enjoyable, Effective and Overall Satisfaction. Higher rating means better interface efficacy.

4.4.3 Evaluation of System Features

In the post-study questionnaire, we asked participants how system features (e.g. size-changeable stance labels, stance recorder panel, *Type 1*/*Type 2* recommendations of articles/comments) help them realize their stances and comment selection preferences.

Figure 4.8 and Figure 4.9 show participants' evaluation about these system features. Based on the result, we found that the stance recorder panel is the most important feature to help participants realize both of their stances and opinion selection preferences with an agreement rate of 9/12 and 11/12 respectively. In addition, all other features have an agreement rate equal to or higher than 50%, which means participants found the proposed features useful in general.

Unlike the control interface where all comments are shown together at once, there are two types of comments in the novel interface: stance label comments (comments which are presented after people click the corresponding stance label) and recommended comments (comments which are recommended by both *Type 1* and *Type 2* recommendations). We compared participants' comment selection behaviors in the measure of SEI among different comment browsing scenarios: 1) browsing comments on control interface; 2) browsing stance

Table 4.6: Wilcoxon Signed Ranks Test on Usefulness, EaseofUse, Enjoyable, Effective and Overall Satisfaction.

Measures	New Interface vs. Control Interface
Usefulness	Z = -1.831; p = 0.067
EaseofUse	Z = -2.598; p <0.01
Enjoyable	Z = -2.460; p <0.05
Effective	Z = -2.428; p <0.05
Overall Satisfaction	Z = -2.165; p <0.05

Table 4.7: We calculated the mean and the standard deviation of SEIs in each comment browsing scenario.

	SEI (Mean ± SD)
Control Interface	0.57 (± 0.21)
Stance Label Comments	0.50 (± 0.14)
Recommended Comments	0.48 (± 0.11)

label comments on the novel interface and 3) browsing recommended comments on the novel interface. Table 4.7 shows the mean and standard deviation of SEIs in each scenario. A repeated measures ANOVA (with Greenhouse-Geisser correction for sphericity) found that the SEI differs significantly between scenarios ($F(1.708, 80.280) = 4.176$, $p < 0.05$). Post-hoc tests using the Bonferroni correction indicated that there's a significant difference between scenario 1) and 3) ($p < 0.05$) but no significant difference between 2) vs. 3) ($p = 0.968$) and 1) vs. 2) ($p = 0.242$). This result indicates that the recommendation feature mitigates selective exposure more effectively than the size-changeable stance label feature when comparing with the control interface. This result is mesmerizing. Initially, we expect that the size-changeable stance label could motivate people to explore comments on both sides. However, the result indicates that the size-changeable stance label might not be that effective in helping people explore diverse opinions. But the recommendation feature is handy in mitigating selective exposure.

4.4.4 Qualitative Analysis

We asked participants about their perception of how the system recommends articles to them. Specifically, we asked 1) whether they could figure out why sometimes the system showed a "Recommended" article but sometimes showed a "Not Recommended" article, 2) whether they thought the recommendation was related to their stances, and 3) how the system recommended articles to them. As a result, 10 out of 12 participants agreed to the

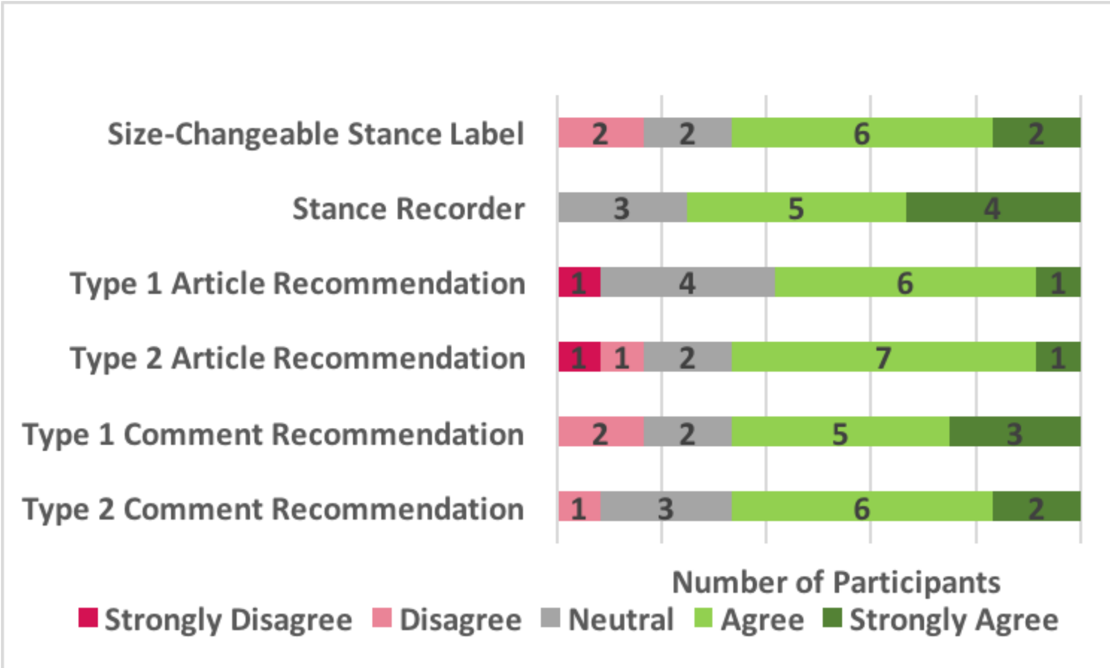


Figure 4.8: Evaluation for specific system features in helping participants realize their stances.

first question, saying that they could figure out how the system made recommendations. For the second question, 8 out of 12 participants agreed, which illustrates that most of the users thought the recommendations were made based on their stances. For the third question, 6 out of 12 participants correctly described how the system made recommendations. For example, participant *U7* reported "I think that the recommended articles are trying to get you to see different perspectives on the issue" and participant *U12* reported "The counter-recommendation mechanism is there to provide an opportunity to 'burst your bubble' so the reader is exposed to opposing points of view...This whole mechanism that was implemented is interesting considering the buzz around the whole notion of being trapped in a bubble of one's own opinions: as in everyone they talk to or read from agrees with them and only reinforces their beliefs." These results show that our recommendation mechanism nudged participants to figure out the connection between the indicator and stance expressed in recommended opinions, which improved self-awareness of their own stances. However, the other 6 participants couldn't accurately describe the recommendation mechanism, which suggests that people's perception of how the system made recommendations may vary. In addition, all participants showed an overall preference to our system and 11 out of 12 participants agreed our system helped them to get global insight across different opinions during our short interview.

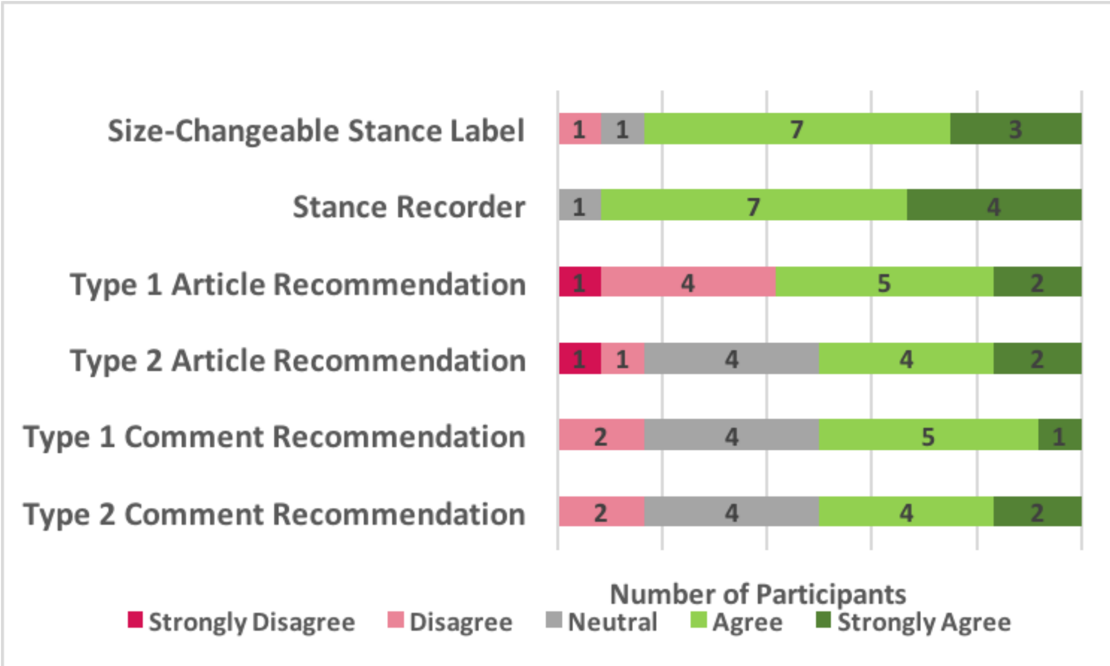


Figure 4.9: Evaluation for specific system features in helping participants realize their comment selection preferences.

4.5 DISCUSSION

Past research has pointed out the need to design informational structures or personalization algorithms for the vast amount of user-generated contents on online social media platforms. These informational structures or algorithms often focus on helping users find and select information they desire. There is, however, a general lack of attention to how these structures may lead to undesirable effects, such as selective exposure to information and social polarization. The design goal of the novel system is different from these approaches: Instead of *only* helping users find information they desire, the novel system *also* aims to help user correctly perceive and understand different perspectives expressed by other users. In this chapter, we showed how the general techniques of sentiment analysis and opinion recommendation can be repurposed to satisfy this design goal.

4.5.1 Analyzing People's Sentiments for Controversial Topics

Sentiment analysis technique is typically used to find emotional reactions to a topic. However, we utilized the technique to infer people's stances, whether they support or oppose a controversial topic. Specifically, in my study, we wanted to infer people's stances on

Obamacare issue using a classifier that predicts sentiment labels of people's comments about Obamacare issue. We conducted feature engineering with the χ^2 statistic test on each unique term. We found some terms, such as "president", "Trump" and "McCain" were assigned a very high weight. These terms are highly related to the topic of the issue and people's stereotypes of political figures related to the issue. However, they are not the common terms people use to express sentiments. This indicates that when analyzing people's sentiments on controversial issues, we should consider not only their emotional expressions but also their stereotypes of the topic and people related to the issue.

4.5.2 Social Opinion Recommendation

Traditional personalized recommendation systems select and recommend agreeable information or opinions to people based on their records of information selection. This mechanism aims to increase people's satisfaction with the system but it often separates people from attitude-inconsistent information and may further aggravate the selective exposure effect. We designed our recommendation mechanism differently. Although the novel system we designed recommends opinions on both sides, the system recommends attitude-consistent opinions (*Type 2* recommendation) after the attitude-inconsistent opinions (*Type 1* recommendation). We found that our new recommendation mechanism could mitigate selective exposure. We should point out that, in more realistic situations where there are a large amount of opinions on each side, the system may need to use an appropriate ratio between *Type 1* recommendation and *Type 2* recommendation. We believe that the question of how to set this ratio will be an interesting research topic in the future.

4.5.3 Limitations

In our study, we tested user behavior using only four articles and a limited number of comments on Obamacare topic. In the future, we plan to investigate people's social opinion browsing behavior with more articles and comments on other controversial topics over a longer period of time in a larger-scale user study. This would generate a richer set of data to achieve more comprehensive evaluation and inform better design of such interfaces.

In addition, we only considered positive and negative sentiments when designing and implementing the system. However, people may have other types of emotions when browsing social opinions. Also, people may get a better understanding of comments by checking scores or ratings about sentiments. We plan to improve the sentiment classifier to support multi-category emotion classification as well as generating numeric sentiment scores in the future.

Lastly, although users could be motivated to inspect both stances at the same time, we decided to present opposite viewpoints asynchronously for the sake of testing our design ideas more effectively and conveniently. However, we will consider this alternative design in our future studies.

4.6 CONCLUSION

In this chapter, we presented an intelligent interactive system that organizes social opinions using a combination of novel visual cues and recommendation mechanisms to increase self-awareness of users' stances and to mitigate the effects of selective exposure. Compared to a control interface in which opinions are organized in a linear format, the novel system was found to help users become more aware of their own stances and their selection preferences of opinions. We also found that users attended to more diverse opinions and showed less selective exposure to attitude-consistent information in the new interface. We concluded that the proposed new system is promising in raising users' awareness of their own stances and preferences and mitigating selective exposure to information.

Chapter 3 and chapter 4 focus on using design with emotional reactions and recommendations to mitigate selective exposure. However, given that labels are widely used elements in social media interface design, we will study the effect of labels (e.g., stance labels and credibility labels) on people's information consumption in chapter 5.

CHAPTER 5: EFFECT OF STANCE AND CREDIBILITY LABELS ON MITIGATING SELECTIVE EXPOSURE

5.1 INTRODUCTION

As an example of helping people explore diverse social opinions, the Wall Street Journal proposed a novel feed design "Blue Feed, Red Feed" by presenting liberal and conservative labelled news articles in side-by-side columns. The purpose of such design is to promote awareness of news articles with different standpoints to readers. However, it is unclear how much they can truly reduce attitude polarization and lead to productive cross-ideological dialogue. For example, theories of motivated reasoning [109] suggest that when presented with attitude-inconsistent arguments or opinions, people may engage in counter-arguing and will likely dismiss or downplay them as a way to reduce the psychological stress caused by cognitive dissonance [10]. As a result, people may become even more entrenched in their original beliefs and polarized than before [110]. This kind of "anticonformity boomerang effect" [111] may affect people's perception of these labelled news articles and lead to undesirable news browsing behavior. For example, when people who are self-identified as supporting gun control encounter an anti-gun control article on their news feed, they will expect a certain degree of cognitive conflict if they read the news article. The presence of the "conservative" label on the article may trigger people's previous stressful memory of reading other conservative news articles, which in turn aggravates their expectation of the level of cognitive conflict. People may simply discontinue reading to avoid such an unpleasant experience, which incubates potential selective bias.

For the sake of preventing the dissemination of fake news, Facebook proposed a user-self-report mechanism that allows users to label news articles with a disputed flag to indicate potential misleading information in a news article. However, after a year of testing, a Medium article [96] found that the dispute flag label didn't work effectively to prevent fake news from spreading. One reason is that the strong wording or visuals of the label may backfire and consequently reinforce users' belief in fake information [97]. According to a TechCrunch article [112], people who wanted to believe these false stories were found to share them even more when they were labelled. What's more, when only some news articles are flagged, those that are not flagged (but contain false stories) are often presumed to be trustworthy. These unintended consequences of labels prompted the use and testing of new strategies to combat the spread of misinformation.

Given the aforementioned efforts by the Wall Street Journal and Facebook in helping people explore diverse opinions and combating the spread of fake news, understanding the effect of these stance and credibility labels is crucial to learning how designs of news feed platforms could be further improved. However, to the best of our knowledge, questions about the effect of stance labels and credibility labels have not been well examined in the social opinion, selective exposure, and fake news literature. Since people's social opinion selection and perception (i.e., perceived level of agreement and extremeness on social opinions) may be relevant to the extent of their opinion polarization [50, 113] and their judgment on public opinions [114], we are interested in how stance labels and credibility labels impact people's social opinion selection and perception. Thus, we ask the following research questions:

- RQ-1: How do stance labels and credibility labels impact people's news article selection when browsing news for controversial topics?
- RQ-2: How do stance labels and credibility labels impact people's perception of news articles regarding perceived extremeness and level of agreement?

Even though labels are commonly used in social media design to categorize content and facilitate people finding information, little has been known about the effect of labels beyond facilitating information seeking. Previous research [109] suggests people are driven by two motives when seeking information: the defense motive for directional goals and the accuracy motive for accuracy goals. People tend to seek more supportive information for a desired and directional goal while they would expend more cognitive effort and seek objective information for an accurate conclusion. Regarding the effect of labels, stance labels may trigger people's defense motive and push people away from opinions on the opposing side. Meanwhile, credibility labels may ignite people's desire for the accurate and objective truth and pull people to more opposing views. We are motivated by the dual motives theory in information seeking and conducted an experiment to figure out the effect of these labels on social media.

Our analysis suggests that stance labels may exacerbate selective exposure while increasing people's agreement level and decreasing their perceived extremeness on fake news articles from different sides. Thus, stance labels may have some negative effects on people's social opinion consumption and mislead people to give incorrect judgment on the credibility of fake news. Unlike stance labels, credibility labels may have more positive effects in our experiment, even though those effects might be limited. We found that credibility labels could mitigate selective exposure, especially for people with liberal stances, and marginally decrease people's level of agreement to news articles on their own side, which, as a result, could have the potential to weaken social polarization. Our results modestly suggest that labels may have complex effects on people's news article browsing behavior and their perception of social opinions. Social media designers should be cautious about these complex effects when designing novel news feeds.

5.2 METHODOLOGY

5.2.1 Interface Design

We used 2 × 2 full factorial experiment design to see how stance labels and credibility labels affect participants' preferential selection and perception of news articles. Our design elicited four interfaces, see Table 5.1 and Figure 5.1 (On the screenshot, the top two news articles on the feed are disputed. Their credibility are not labelled due to the experiment design).

Table 5.1: Experiment settings.

	No Stance Label	Stance Label
No Credibility Label	Interface A	Interface B
Credibility Label	Interface C	Interface D

Based on established research on social media design [88, 105] and the Blue Feed, Red Feed website, our basic interface template for all four interfaces adapted a two-column layout where each column only listed news articles with similar political leanings. To control for the potential bias from people's reading habits (e.g. people may tend to start from left), the left-and-right position of those two columns was randomly assigned to each participant. The order of news articles within each column was randomly assigned initially but kept the same for all participants. To highlight the two-column design and meanwhile to control for people's color preference, the background colors of each column were grays with two different shades.

Since our study was focused on labels' effects, all interfaces were based on the same two-column template and had exact same news articles. A total of 14 news articles with clear political leanings were selected one day prior to the experiment. The number of news articles with conservative or liberal leanings was balanced, i.e. 7 news articles with conservative leanings in one column and 7 news articles with liberal leanings in the other. Since news articles were collected from different news sources, for the sake of design consistency we created our own page for each article. We also removed the source media to control the effect of users' existing knowledge of media's political leanings. More details about news article selection process will be described in the later section.

5.2.2 Experiment Procedure

The study procedures were approved by IRB and included three major steps,

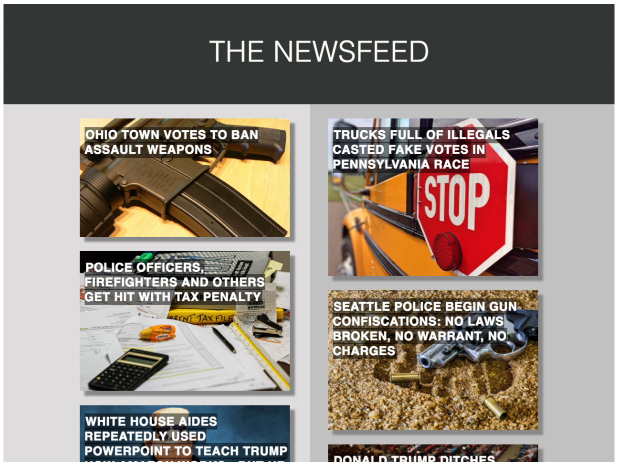
- 1) Pre-study Survey. Upon participants consented to join our study, they first took a pre-study survey of demographics including age, gender, political leaning and social media usage.
- 2) News Browsing Task. Participants were randomly assigned to one of our four interfaces. To ensure participants actually read the news, before the news reading starts, participants were told that there would be a follow-up task about the news articles they read. Next, participants were asked to select and read at least five different news articles to their most interest. Once participants finished news reading, they were asked to write a short paragraph to express their opinions of the news articles they just read. Then, participants were asked to rate those news articles accordingly in terms of level of agreement and level of extremeness.
- 3) Post-study Survey. The post-study survey contains a questionnaire measuring participants' level of state anxiety.

After all steps, participants were thoroughly debriefed with the purpose of the study and a list of fake news articles they might read during the study. All data we collected were anonymized and stored locally. The study was published on Amazon Mechanical Turk and framed as a task to gather information from news articles. Each participant was paid $6/hr as compensation.

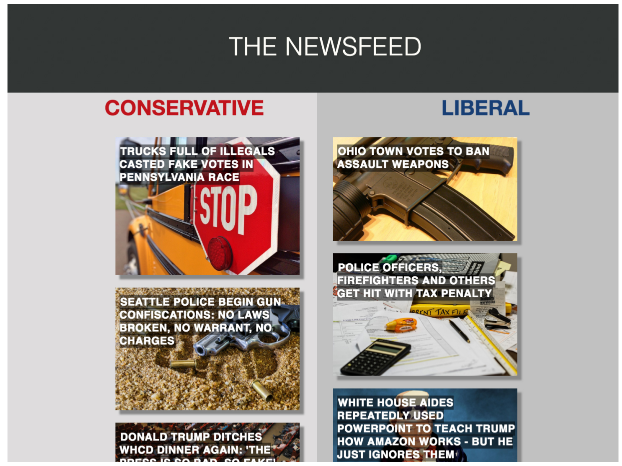
5.2.3 Selected News Articles

Due to the scope of the study, articles on our news feed interface covered two major trending and controversial topics, President Trump and Gun Control. The number of articles about those topics appeared in our interfaces were balanced.

To mimic the mundane world where we are often exposed to both real and fake news articles, our news feed contained both real and fake news articles as well. In our study, "fake news" denotes news articles which contain false or misleading information with political implications [95, 115]. 6 out of 14 news articles on our news feed were fake news articles directly collected from Snopes.com's and Politifact.com's fake news archive or modified from other news articles. We manually changed people's name and location and exaggerated numbers appeared in the original article to ensure those articles contain false information. All the fake news articles have a clear political leaning and related to either President Trump or Gun Control. The stance labels of those news articles were assigned independently and verified by authors.

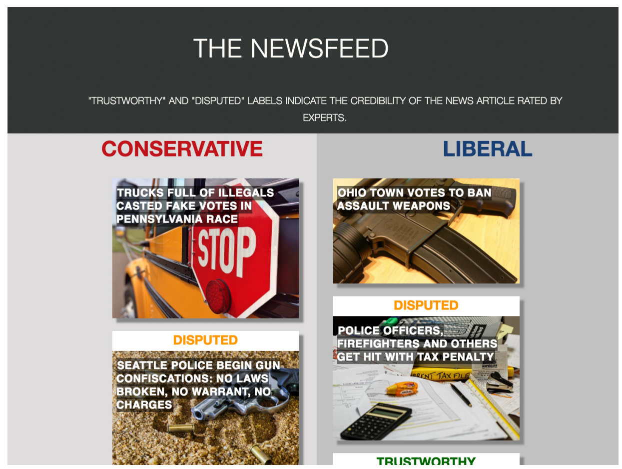


(a) Interface A, Without Stance Labels and Credibility Labels



(b) Interface B, With Stance Labels but no Credibility Labels

(c) Interface C, With Credibility Labels but no Stance Labels



(d) Interface D, With both Stance Labels and Credibility Labels

Figure 5.1: Screenshots from the 4 interfaces in our 2x2 experimental design.

The rest eight news articles were collected from Wall Street Journal's Blue Feed, Red Feed. The stance label of each news article follows Blue Feed, Red Feed's category (liberal or conservative), which is based on self-described political leanings of article-sharers on Facebook [29], and was verified independently by authors.

5.2.4 Credibility Label

There were two kinds of credibility labels on Interface C and Interface D, e.g. "Trustworthy" and "Disputed". To best mimic real world scenarios where even on a credibility-labelled news feed, such as Facebook, not all news articles were clearly labelled, therefore, on Interface C and Interface D, only 4 of the 8 real news articles were labelled as "Trustworthy", and 4 of the 6 fake news articles were assigned with label "Disputed". All those credibility labelled news articles were chosen randomly. The rest 6 news articles had no credibility label. The credibility label assignment was also balanced regarding political leanings and topics.

5.2.5 Measures

For the purpose of fair comparison among conditions, we defined the following measures for later analyses.

Independent Variables

- **Stance Label.** A binary categorical variable, 1) with stance label 2) without stance label, indicating if participants were assigned to an interface where there are stance labels.

- **Credibility Label.** A binary categorical variable, 1) with credibility label 2) without credibility label, indicating if participants were assigned to an interface with credibility labels.

- **Self-Reported Political Stance.** Participants' pre-existing political stances were collected from a five-point Likert scale from "Very Liberal" to "Very Conservative" with "Neutral" in the middle. Based on the participant's response, he/she was coded as a member of the liberal group if he/she selected "Very Liberal" or "Liberal", as a member of the conservative group if he/she selected "Very Conservative" or "Conservative", or as a member of the neutral group if "Neutral" was selected.

Dependent Variables

- **Selective Exposure Index.** The selective exposure index (SEI) is defined as:

$$SEI = \frac{N_{consistent}}{N_{consistent} + N_{inconsistent}} \tag{5.1}$$

  where $N_{consistent}$ is the number of stance-consistent news articles that the participant selected to read and $N_{inconsistent}$ denotes the number of stance-inconsistent news articles which were selected and read.

- **Perceived Level of Agreement** After finishing news browsing on the assigned interface, participants were asked to rate their perceived level of agreement of all news articles they just read. The measure of perceived level of agreement is a five-point Likert scale from "Strongly Disagree" to "Strongly Agree" on "How much you agree with the opinion expressed in the news article". The rating was then coded as 1 (Strongly Disagree) to 5 (Strongly Agree).

- **Perceived Level of Extremeness** Similar to Perceived Level of Agreement, after finishing news browsing on the assigned interface, participants were asked to rate their perceived extremeness of each individual news articles they just read. The measure of perceived extremeness is a five-point Likert scale from "Least Extreme" to "Most Extreme" on "How extreme you perceive the news article is". The rating was then coded as 1 (Least Extreme) to 5 (Most Extreme).
- **The Level of Cognitive Dissonance.** The level of cognitive dissonance measured by a Six-Item State Anxiety Scale derived from the State-Trait Anxiety Inventory [116, 117]. The State-Trait Anxiety Inventory has been examined and widely used in cognitive psychology and marketing research as a measure for accessing the level of cognitive dissonance [118, 119]. While the original State-Trait Anxiety scale contains 20 items, to prevent the effects of survey fatigue, we decided to use the shorter version which has six items. The six-item scale has been examined as effective as the original scale in terms of reliability and validity [116].

5.3 RESULTS

To answer our research questions, we ran the 2×2 full factorial experiment on Amazon Mechanical Turk. The qualification for participants to join our study was a 90% approval rate. In a period of 3 days, a total of 132 participants joined our study. 62 of them self-identified as members of the liberal group and 60 of them self-identified as members of the conservative group. Since the study focused on people who have an explicit political leaning, 10 participants' data were removed due to their self-identified neutral leanings or incomplete data. The number of participants in the liberal and the conservative group is roughly balanced for all interface conditions (see Table 5.2). Of those 122 participants in the analysis, 40% were male and 60% were female. 79.51% of participants were between 25 and 54 years old, 4.10% of participants were between 18 and 25 years old, and 16.39% of participants were above 54 years old. All participants used Facebook and 98.36% of them reported Facebook as an frequent source for reading news and opinions. On average, participants spent 11.25 minutes on our interface. Participants followed the instructions, clicked and read at least five news articles ($M = 5.5$, $SD = 1.29$). Across all four interfaces, there was no significant difference in the number of clicked news articles ($F = 1.25$, $p = 0.29$). Additionally, a logistic regression on news article clicks showed participants had no significant preference between fake news articles and real news articles ($\beta = 0.10$, $z = 1.01$, $p = 0.31$).

Table 5.2: Number of participants under each interface condition.

	Interface A	Interface B	Interface C	Interface D	All
Liberal	16	18	16	12	62
Conservative	18	13	15	14	60
All	34	31	31	26	122

In the following subsections, we will present the effects of stance labels and credibility labels on participants' preferential selection in 4.1 and on their perception of news articles in 4.2.

5.3.1 The Effect of Stance Labels and Credibility Labels on News Article Selection (RQ-1)

To measure participants' selective exposure, we calculated the selective exposure index for each participant, which is defined as the percentage of news articles the participant read that align with his/her pre-existing political stance [120].

The two-way ANOVA showed significant main effects of both stance labels and credibility labels on participants' selective exposure but no interaction effect, see Table 5.3. Therefore, in the following analyses, we will discuss the effect of stance labels and the effect of credibility labels on selective exposure separately.

Table 5.3: Two-way ANOVA results on selective exposure index.

Source	df	MS	F	p	Cohen's F
Stance Label(A)	1	0.57	17.14	0.00**	0.38
Credibility Label(B)	1	0.19	5.64	0.02*	0.22
A x B	1	0.00	0.06	0.81	0.02
Residuals	118	0.03			

The Effect of Stance Labels on Selective Exposure The ANOVA results (Table 5.3) suggested the presence of stance labels significantly affected participants' opinion selection preference (Cohen's F = 0.38, $p < 0.01$**). Participants ($N = 57$) who saw the news article with a stance label exhibited a significantly higher selective exposure bias ($M = 0.65$, SD

= 0.19) than participants (N = 65) who saw the news article without a stance label (M = 0.51, SD = 0.18). In other words, participants were more likely to click and read news articles from their own side if political leanings of news articles on their assigned interfaces were labelled. The effect held for both participants in the liberal group and participants in the conservative group, see Figure 5.2.

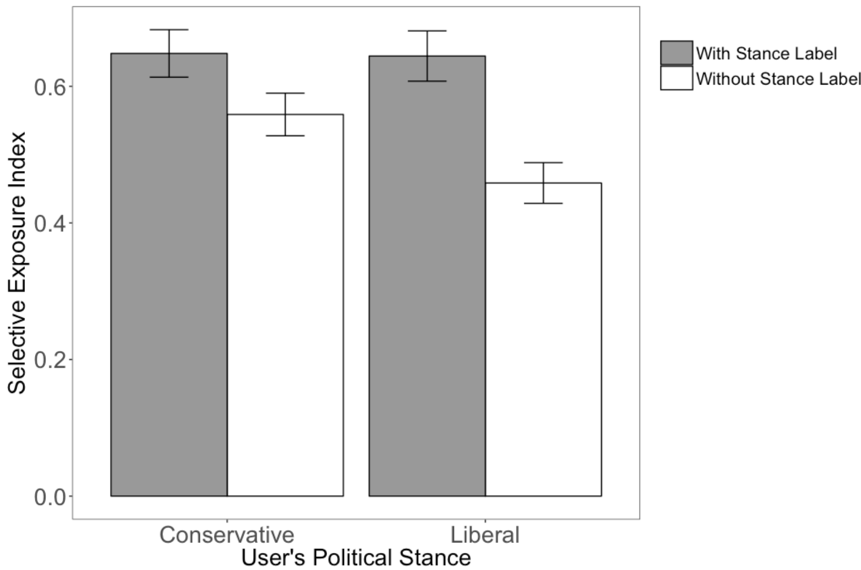


Figure 5.2: The effect of showing stance labels on users' selective exposure index.

These results support our hypothesis that even though news articles from both sides have equal opportunity to appear on a user's screen, the user exhibits a higher-level of selective exposure bias if news articles' political leanings are labelled. In stance label conditions (Interface B and D), on average, 65% of the news articles that one participant read were stance-consistent.

To further understand the result, we looked into users' level of state anxiety [116] after using our interfaces. The level of state anxiety indicates the level of cognitive dissonance users experienced after they read news articles through our interfaces. We found users who used the interface with stance labels (M = 1.18, SD = 0.28) had a higher level of state anxiety than those who used the interface without stance labels (M = 1.08, SD = 0.27). A two-sample t-test showed the difference was statistically significant (t = 2.10, p = 0.03*). Cognitive dissonance is considered the potential cause of people's avoidance of attitude-inconsistent information and may lead to selective exposure in general. The difference between interfaces with and without stance labels suggested that the presence of the stance label might trigger a higher level of cognitive dissonance that may affect participants' preferential selection processes.

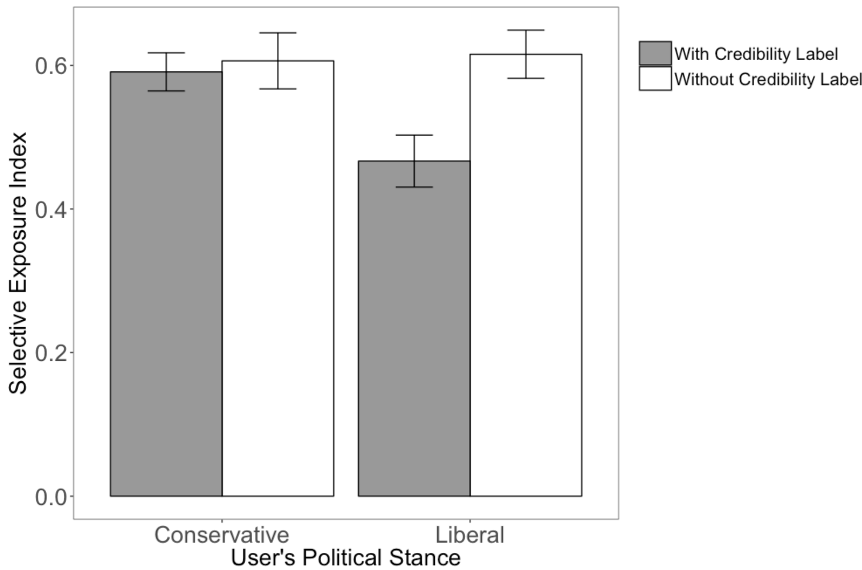


Figure 5.3: The effect of showing credibility labels on users' selective exposure index.

The Effect of Credibility Labels on Selective Exposure From Table 5.3, we found that showing the credibility label of news articles significantly reduced participants' selective exposure (Cohen's F = 0.22, p= 0.02*). Participants ($N = 57$) who used interfaces (Interface C and D) with credibility labels showed a significantly lower level of selective exposure bias ($M = 0.53$, $SD = 0.18$) than users ($N = 65$) who used interfaces (Interface A and B) without credibility labels ($M = 0.61$, $SD = 0.20$). When considering participants' political stances, we found a marginal interaction effect between showing credibility labels and users' political stances (Cohen's F = 0.18, $p = 0.06$). Through a post-hoc test, we found that showing credibility labels to participants in the liberal group significantly reduced selective exposure bias ($M_{\text{w/ credibility label}} = 0.47$, $SD = 0.19$; $M_{\text{w/o credibility label}} = 0.61$, $SD = 0.20$; $p = 0.01$*) while the effect was not significant for participants in the conservative group ($M_{\text{w/ credibility label}} = 0.59$, $SD = 0.14$; $M_{\text{w/o credibility label}} = 0.61$, $SD = 0.21$; $p = 0.98$), see Figure 5.3.

To further understand the effect of credibility labels on news article selection, we divided our news articles into three categories based on their credibility labels. According to our interface design, we had three categories of news articles, 1) Trustworthy news articles, a subset of real news articles that are labelled as "Trustworthy" on interfaces with credibility labels (Interface C and D). 2) Disputed news articles, a subset of fake news articles that are labelled as "Disputed" on interfaces with credibility labels (Interface C and D). 3) Unknown news articles, a mix of real and fake news articles that are not labelled on all interfaces.

Since selective exposure theory suggests users would click and read stance-consistent and stance-inconsistent news articles differently, we further divided each of the three news article categories into two subcategories – stance-consistent and stance-inconsistent. Therefore, in the following analysis, we will look at the composition of what kinds news articles each participant clicked and read in terms of those six categories (Table 5.4).

Since the previous result showed that credibility labels affect participants in the liberal group and participants in the conservative group differently, we placed participants' political stances as an interactive term in the two-way ANOVA analysis for each categories in Table 5.4.

The main effect of showing the credibility label was found in stance-inconsistent trustworthy news articles, where users clicked and read a larger proportion of stance-inconsistent trustworthy news articles on the interfaces with credibility labels (Interface C and D) ($M_{\text{w/ credibility label}} = 0.17$, $SD = 0.14$; $M_{\text{w/o credibility label}} = 0.12$, $SD = 0.11$; $p = 0.03$*). There was no interaction effect from participants' political leanings.

For stance-inconsistent unknown news articles and stance-consistent disputed news articles, the ANOVA analysis revealed a significant interaction effect between credibility labels and participants' political leanings but no main effect of credibility labels. The post-hoc test showed participants in the liberal group read significantly more stance-inconsistent unknown news articles ($M_{\text{w/ credibility label}} = 0.27$, $SD = 0.13$; $M_{\text{w/o credibility label}} = 0.18$, $SD = 0.14$; $p = 0.02$*) and a significantly lower proportion of stance-consistent disputed labelled news articles ($M_{\text{w/ credibility label}} = 0.08$, $SD = 0.12$; $M_{\text{w/o credibility label}} = 0.16$, $SD = 0.12$; $p = 0.03$*) if they used the interfaces with credibility labels (Interface C and D).

No significant effect was found in stance-consistent trustworthy news articles, stance-consistent unknown news articles or stance-inconsistent disputed news articles.

The results from above analyses provide insights on how credibility labels mitigate selective exposure bias, especially for users with liberal stances. Showing credibility labels nudged users to read more stance-inconsistent trustworthy news articles. For users with liberal stances, showing credibility labels helped them avoid disputed news articles from their own ideology and nudged them to explore stance-inconsistent news articles without any credibility labels. The result is consistent with previous studies on the individual difference between people with conservative and liberal stances that found people with liberal stances in general might be more curious [110, 121, 122]. Users with liberal stances may select news articles driven by curiosity. They may be less familiar with conservative news articles and fake news articles in general, but showing credibility labels may have made them more curious about the conservative "no label" articles and want to understand these news articles' credibility by reading them. However, they may be less curious about the disputed news articles on their own side because of the potential cognitive conflicts of reading fake news articles that supported their beliefs. The change in the proportion of different types of news articles (see Table 5.4) between conditions with and without credibility labels indicates how credibility labels of news articles influenced people's selections.

Table 5.4: 6 types of news articles based on credibility and stance-consistency.

	Stance Consistent	Stance Inconsistent
Trustworthy	Stance Consistent Trustworthy	Stance Inconsistent Trustworthy
Disputed	Stance Consistent Disputed	Stance Inconsistent Disputed
No Label	Stance Consistent Unknown	Stance Inconsistent Unknown

5.3.2 The Effect of Stance Labels and Credibility Labels on Perceived Extremeness and Level of Agreement (RQ-2)

We tested the effects of stance labels and credibility labels on people's perception of extremeness and their level of agreement on all news articles with a mixed effect model, in which we used Stance Label, Credibility Label, and whether news articles were stance-consistent as independent variables (details of these variables were described in the Method section). In general, people expressed higher level of agreement on stance-consistent news articles ($M_{\text{stance-consistent}} = 3.57$, $SE = 0.08$; $M_{\text{stance-inconsistent}} = 2.58$, $SE = 0.09$; $p < 0.01$*) and perceived stance-consistent news articles as less extreme ($M_{\text{stance-consistent}} = 3.10$, $SE = 0.07$; $M_{\text{stance-inconsistent}} = 3.51$, $SE = 0.07$; $p < 0.01$*). This shows the general trend for existing attitudes to influence their perception of news articles. The more interesting result was the effect of labels on their perception – we found that stance labels had a significant effect on increasing people's level of agreement on news articles ($M_{\text{w/ stance label}} = 3.50$, $SE = 0.20$; $M_{\text{w/o stance label}} = 3.12$, $SE = 0.13$; $p = 0.02$*), suggesting that the mere presence of the stance labels could increase their level of agreement of news articles, regardless of whether they were stance-consistent or not. We also found that credibility labels had a marginal effect on decreasing people's level of agreement, but the effect was only found in stance-consistent news articles ($M_{\text{w/ credibility label}} = 2.10$, $SE = 0.52$; $M_{\text{w/o credibility label}} = 3.08$, $SE = 0.25$; $p = 0.09$). This could be because people had lower level of agreement with stance-inconsistent articles in general, and therefore credibility labels did not lead to significantly lower level of agreement (i.e., there could be a floor effect). Interestingly, we did not find stance labels and credibility labels had any effect on participants' perceived extremeness of news articles, regardless of their stances. There was also no significant interaction effect among those three independent variables on the level of agreement and perceived extremeness of articles.

Motivated by the idea that large amounts of fake news can influence people's general perception of public opinion, and worse still, encourage the formation of extreme and polarized viewpoints [123], we further investigated how the labels affected people's perception of fake news articles using the same mixed effect model with the same independent and dependent variables only on fake news articles. In general, we found that people agreed more on stance-consistent fake news articles ($M_{\text{stance-consistent}} = 3.25$, $SE = 0.12$; $M_{\text{stance-inconsistent}} = 2.15$, $SE = 0.12$; $p < 0.01$*) and a marginally significant effect of people perceiving stance-inconsistent fake news as more extreme ($M_{\text{stance-consistent}} = 3.47$, $SE = 0.11$; $M_{\text{stance-inconsistent}} = 3.82$, $SE = 0.10$; $p = 0.08$). Our results showed that the presence of stance labels led to a significantly higher level of agreement on fake news articles ($M_{\text{w/ stance label}} = 3.44$, $SE = 0.27$; $M_{\text{w/o stance label}} = 2.72$, $SE = 0.18$; $p < 0.01$**) and led to a significantly lower level of perceived extremeness of fake news articles ($M_{\text{w/ stance label}} = 2.13$, $SE = 0.21$; $M_{\text{w/o stance label}} = 3.66$, $SE = 0.14$; $p < 0.01$**) regardless of news articles' political stances. We did not find that credibility labels had any effect on people's perception of fake news, suggesting that, surprisingly, stance labels might have a stronger impact on people's perception of fake news than credibility labels. There was no interaction effect among those three independent variables on people's level of agreement and perceived extremeness on fake news articles.

Similar analysis was conducted on real news articles as well. People agreed more on stance-consistent real news articles ($M_{\text{stance-consistent}} = 3.81$, $SE = 0.09$; $M_{\text{stance-inconsistent}} = 2.84$, $SE = 0.11$; $p < 0.01$*) and perceived stance-consistent real news articles as less extreme ($M_{\text{stance-consistent}} = 2.82$, $SE = 0.09$; $M_{\text{stance-inconsistent}} = 3.24$, $SE = 0.10$; $p < 0.01$*). Neither stance labels nor credibility labels had significant effects on participants' level of agreement and perceived extremeness of real news articles. No interaction effect was found.

Our results indicate that stance labels have an effect on people's perception of fake news articles. In general, stance labels increase people's level of agreement on fake news, regardless of whether those news articles are consistent with their political stances. This indicates that stance labels may have the undesirable effect of increasing the perceived trustworthiness of fake news. In addition, stance labels lower people's perceived extremeness of fake news on both sides. These effects of stance labels may be potentially dangerous since people might be misled by extreme and polarized opinions in fake news when they are categorized under different stance labels. Meanwhile, credibility labels could marginally decrease people's level of agreement on news articles on their own side, which may lead to a more moderate opinion space. However, consistent with previous findings, the effect of credibility labels was in general limited. Interface designers may not expect that credibility labels can play a significant role in combating fake news. They should also be very cautious when using stance labels on their news feed designs, especially if the news feed might host any fake news or misinformation.

5.4 DISCUSSION

We want to address several limitations of the study. First, news articles in our study cover only two topics, President Trump and Gun Control. Even though during the time of the study, those two topics were trending and controversial, users' news feed often bombards with a massive amount of stories. Therefore, including more topics can further benefit our study's ecological validity. Second, our study only demonstrates how the presence of labels affects readers' news article preferential selection and perception in the short term. However, people's opinions can be affected by information in the long run. For example, if people repeatedly encounter misinformation in a long term, misinformation may retain even though people have been informed with the correction [124, 125]. Therefore, a future long-term field study on social media websites can best help us understand how labels may affect people's viewpoints in a long run.

There are many possible directions for future work. For example, although the design of our news feed is directly adapted from Blue Feed, Red Feed, the popular news feed, more research needs to be done in other contexts. For example, friends' activities may also affect users' behavior on news feed [126]. Although a news article is labelled with opposite political leanings, users may still be willing to read the news article because their friends commented on it. Another important research direction is to study the effects of labels as their positions, colors, fonts or background colors are changed [127, 128]. These design choices may also influence readers' behavior in ways that nudge them to read opposite viewpoints and eventually become more open-minded and less polarized.

5.5 CONCLUSION

Overall, our results suggest that stance and credibility labels can affect people's news article selection and perception in ways that deviate from their original intended effects. As a result, such effects are often neglected in online news platform designs. Thus, social media designers should be cautious about using labels. Our results show that, consistent with previous studies, assigning credibility labels to articles (such as "Disputed") is not effective for combating fake news. Interestingly, stance labels, which are often designed to help people find information, may have undesirable effects on facilitating the spread of fake news. Specifically, we found that stance labels can make fake news articles look more trustworthy, and they seem to lower people's perception of the extremeness of fake news articles. Without systematic evaluation, those unintended yet undesirable effects of stance labels could not have been detected. In fact, our results suggest that stance labels may reinforce users' existing beliefs and indirectly exacerbate the polarization of social opinions.

At a higher level, our results demonstrate the importance of studying the role of readers' pre-existing stances on online news platform designs, as seemingly benign design choices, such as stance labels, could lead to complex interactions among people's stances, their perception of the news articles, as well as how much they agree with and consequently influenced by the news articles, including fake news articles. Social and behavioral theories that study these complex interactions are therefore important to guide the designs of online social information platforms. In general, one important message from decades of social behavioral research is that humans should not be treated as simple information processors that search for and consume information using indices as machines do. Instead, humans have complex internal traits and states, such as their existing beliefs, attitudes, and opinions, that influence how they look for relevant information react to information that deviates from their existing beliefs.

Our results show that news articles' stance labels may exacerbate selective exposure. There are multiple possible causes of the effect. First of all, showing stance labels helps people quickly target stance-consistent news articles in their areas of interest, thus paving the way for them to only read articles to their interest. Another possible explanation could be that stance labels elevate people's cognitive dissonance and trigger people's defense motives for desired and directional goals, making them look for more stance-consistent news articles. Even though no causal relationship between showing the stance label and the level of cognitive dissonance can be derived from the current experiment design, our analyses showed that the state anxiety level of people who used the stance-labelled interfaces is significantly higher than those who used interfaces without stance labels. The results are consistent with the idea that stance labels may induce uncomfortable feelings, prompting people to adapt reading strategies to resolve them.

On the other hand, our results also suggest that credibility labels might mitigate people's selective exposure, especially for people with liberal stances; furthermore, our findings indicate that people tend to read more stance-inconsistent news articles that are labelled as trustworthy. It is possible that people read more trustworthy news articles from the opposite side since credibility labels could trigger people's accuracy motives for objective and accurate information. To further understand the underlying mechanism for the effect of labels, more sophisticated studies and evaluations are needed. In order to figure out whether different types of labels could ignite different types of motives and thus alter people's news article reading behavior, future studies could measure the level of accuracy and defense motives in different labelling conditions and then analyze the relationship between motives and social opinion selection and/or perception.

From the perspective of information-seeking strategies, Munson and Resnick [50] proposed that both challenge-averse and diversity-seeking people exist. Challenge-averse people tend to avoid disagreeable social opinions, while diversity-seeking people are open-minded for opinions with different stances. It would be fruitful to address and explore how stance and credibility labels affect social opinion selection and perception for challenge-averse and diversity-seeking people, respectively. Labels may have different effects on people with different social opinion reading behavior. For example, showing stance labels may facilitate challenge-averse people avoiding opposite opinions but help diversity-seeking people to find different opinions more easily. Further studies need to be conducted to figure out the exact effect of labels on people with different social opinion reading behaviors, which could help design a better news feed to mitigate selective exposure across different groups of people in terms of social opinion consumption traits.

In general, we studied how to mitigate selective exposure for individual information consumption through showing social opinions based on emotional reactions and recommending diverse opinions with visual hints in chapter 3 and chapter 4, respectively. In addition, we explored the effect of stance labels and credibility labels on mitigating selective exposure and combating fake news for individual information consumption in chapter 5. People may shape others' opinion space by sharing information. Thus, we will study how people share information with others to understand humans' role as the information filter in chapter 6.

CHAPTER 6: UNDERSTANDING HOW PEOPLE SHARE INFORMATION WITH A GROUP OF RECIPIENTS

6.1 INTRODUCTION

Selective exposure [10, 13, 14, 129], a phenomenon that people tend to look for attitude-consistent information and avoid attitude-inconsistent information, may bring negative outcomes (e.g., increasing social polarization) to our society. According to [10, 130, 131, 132], to avoid the cognitive discomfort brought by attitude-inconsistent information, people's active forage for attitude-consistent information is the cause of selective exposure. However, this may not be the only reason why people are exposed to more attitude-consistent information. In addition to actively seeking congenial information, simply being in an environment with more attitude-consistent information for any reason is another cause of congenial information exposure. This phenomenon is called *de facto* selective exposure [20, 133]. Even though there might be various causes for *de facto selective exposure* of people, one factor that we cannot neglect is the information filter. For example, Pariser [9] mentioned that personalized algorithms could filter information automatically after they detect people's preferences and place people in the filter bubble where attitude-inconsistent information is filtered out. In addition to these automatically personalized algorithms, people around us can also play the role of information filter, especially in the social media age.

According to the Pew research [134], from 2005 to 2015, social media users increased from 7% to 65% among adults in the United States. As more and more people use social media, social media have become the hub for people to share and receive information [135]. Social media make it easy for people to share information, amplifying people's role as the information filter. Previous work [20] indicated that information selection on behalf of others is one possible way to create a congenial information environment for other people. Recently, Earl [31] proposed the concept of vicarious selective exposure - a phenomenon that people tend to filter out attitude-inconsistent information and share attitude-consistent information with others, especially for those they like. Their study showed that for novel topics the selector doesn't have a preferential attitude towards, the selector will share information that aligns with the recipient's attitude if the selector likes the recipient. In addition, Bakshy et al. [29] showed how people's friends on Facebook shape their opinion space. They found that most of people's Facebook friends have a similar political stance or ideological leaning. Furthermore, most of the political information shared by one's Facebook friends has identical or similar political leaning as with that person. This suggests that most liberals' Facebook friends are liberals and most political articles liberals received from their Facebook friends have liberal political leanings. So as conservatives. All these indicated that people are (potentially) playing a significant role of information filter for others, intentionally or unintentionally.

These days, online anonymous social media groups (e.g., SubReddit) or online anonymous chat rooms (e.g., 321Chat, Talk.chat) get more and more popular. Huang and Yang [39] illustrated why people like anonymous expressions with the example of the Tencent QQ Group (a popular group chat platform in China). First, people can be freed from the limitation of their identity, especially when the topic is sensitive. For example, many people on 321Chat anonymously discuss sensitive issues. In addition, people also wanted to find a place to vent their thoughts, feelings, and emotions freely and do not need to take responsibility if there are any. Online anonymous social media are just the answer to people with such demand. In such anonymous social media groups or online chat rooms, in addition to receiving information from others, people also play the role of information selector for other group members who have various attitudes. However, previous work neglected such information-sharing scenarios where one shares information with a group of recipients with different attitudes anonymously.

This chapter focuses on how people share information with a group of recipients with different attitude distributions anonymously. We are particularly interested in the scenario where people's goal and strategy of using social media is to conduct good impression management among others [40] since social media have the functionality as the performance region for people's context-specific selective "performance" to achieve impression management [40, 98, 136, 137]. Thus, to be more specific, in this work, we summarize our research questions as:

RQ1: How do people's attitudes affect their sharing behavior when sharing information with a group of recipients anonymously with the goal of impression management to the group?

RQ2: How does the attitude distribution of the recipient group affect people's sharing behavior when people share information with a group of recipients anonymously with the goal of impression management to the group?

We designed a simulated online group study with fictitious recipients to mimic the scenario where the participant needed to share articles with others to answer these research questions. We provide incentives through a lottery to motivate participants to share information with others to leave a good impression. In addition, similar to [31], we studied participants' information-sharing behavior for two different topics, which varied in inducing preferential attitudes among participants. We expect that participants or at least a considerable proportion of participants have no preferential attitude (i.e., being neutral) for one topic and have preferential attitude (i.e., support or oppose) for another topic.

Contribution: This work helps people better understand humans' role as the information filter in the anonymous group sharing scenario. This is the first step towards designing better interfaces to reduce any adverse effect of the information filtration conducted by humans.

6.2 RELATED WORK

6.2.1 *De Facto* Selective Exposure

De facto selective exposure is the phenomenon that people are exposed to more attitude-consistent information by simply being passively in an environment that contains more congenial information. According to [31], the possible ways of contributing to *de facto* selective exposure include: 1) people just happen to be in an environment with more congenial information (e.g., people accidentally enter a SubReddit or an online chat room full of supportive points of view); 2) other people play the role of information filter and shape our information space by sharing information with us, especially when they know our attitudes and know what we want to hear.

In this chapter, we focus on the second possible path to *de facto* selective exposure and explore how people share information with a group of recipients to have a better understanding of humans' role as the information filter.

6.2.2 Humans' Role as the Information Filter

Social media make it easier for people to share information with others. Research work indicated that people share information on social media or social networks generally to support their social-networking activities, such as connecting with others and engaging in online communities [138]. These information-sharing behavior may intentionally or unintentionally filter information for others.

Previous research [29, 30, 31] showed that people could play the role of information filter for others around. Meanwhile, others around can also affect people's behavior. This was even quite common before the social media era. Zimmerman and Bauer [139] suggested that the audience can influence how people organize the presentation that they make to it. For example, people may organize their speeches to fulfill audiences' expectations when introducing a travel destination to different audiences (e.g., the League of Women Voters or the Chamber of Commerce). In addition, people were always more reluctant to share bad news with others than sharing the good news with the consideration of others' feelings [140, 141].

In terms of sharing information on social media, An et al. [30] found that people tend to share information aligning with their political stances. In addition, Bakshy et al. [29] found that Facebook users always connected with people with the same political ideologies, and most information shared by their friends was consistent with their political leaning. Earl [31] conducted experiments to explore how people share information with others in the one-to-one sharing mode. They found that the selector would filter out attitude-inconsistent information but share more attitude-consistent information with the liked recipient for the topic in which the selector had no preferential attitude (i.e., being neutral). However, the selector tended to share information based on their attitudes for the topic in which the selector had a preferential attitude (i.e., support or oppose).

These days, anonymous online information-sharing groups or online chat rooms, which give people more freedom to share information [39], gain more and more popularity. In addition, since impression management is one of the essential goals of using social media [40], we focus on how people share information with a group of recipients with various attitude distributions to leave a good impression on the group in the anonymous scenario. This study is complementary to the study [31] about the one-to-one information-sharing scenario to some extent.

6.3 METHODOLOGY

To study how people's attitudes (RQ1) and the attitude distribution of the recipient group (RQ2) affect people's information-sharing behavior in the anonymous online group scenario, we designed a between-subject simulation experiment. Participants in the experiment played the selector's role in sharing information with the alleged group of eight recipients to leave good impressions on others. Similar to the paradigm of [31] to experiment on one topic which people don't have preferential attitudes towards (i.e., being neutral) and on another topic which people have preferential attitudes towards (e.g., supporting or opposing) respectively, we also included two topics in our study: 1) a fictitious intelligence test (the SAA intelligence test) for the condition where people don't have preferential attitudes (i.e., being neutral on the topic); 2) a (fictitious) strict gun control law (only individuals who are older than 21 and have served in the United States armed forces for at least two years are allowed to purchase guns) for the condition where people have preferential attitudes (i.e., being supportive or opposed to the topic). The full name of the SAA intelligence test is Standard Accurate Assessment Intelligence Test. During the study, the full name will not be shown to participants. For these two scenarios, the experiment procedure kept the same except for the topic.

In terms of attitude distributions of the recipient group, we had three conditions: 1) six support the topic and two oppose the topic (75% Support and 25% Oppose); 2) four support the topic and four oppose the topic (50% Support and 50% Oppose); 3) two support the topic and six oppose the topic (25% Support and 75% Oppose).

6.3.1 Participant Recruitment

We recruited participants from the Amazon Mechanical Turk (AMT) platform from August 11th, 2021, to August 29th, 2021. Only Turkers located in the United States with a HIT (Human Intelligence Task) approval rate higher than 95% and had at least 100 approved HITs were allowed to participate in our study. Previous research [142] indicated that low-education respondents were underrepresented and young people were overrepresented on the AMT platform. Thus, to include people across all ages and educational levels in our study, we recruited participants following the age and education level distribution mentioned in the latest available United States census statistics in 2020 [143] at our best effort. Participants were randomly assigned to the topic and attitude distribution groups. Each participant was paid $10/hour for joining our study.

6.3.2 Experiment Procedure

The experiment consisted of five steps: 1) Experiment Entry; 2) Role Assignment and Task Instruction; 3) Attitude Distribution Disclosure; 4) Article Selection; 5) Post-Study Survey and Debrief.

Step 1: Experiment Entry In this step, we needed to convince participants that our simulated group study was real and that other participants were actual group members. In addition, participants needed to finish two surveys. One is the demographic survey, and the other is about their attitudes towards some controversial topics.

To convince participants that our simulated online group study was a real group study, we described our study as a scheduled recurring event (e.g. occurring every three minutes) for a fix time frame (e.g. 8 AM - 11 PM) of each day on the HIT information panel of the AMT platform. To be more specific, in the HIT introduction, we showed participants this message "Since this is a group study, to have enough participants for each study session, each study session is scheduled every 3 minutes and each session will start on time. The study is available from 8 AM CT to 11 PM CT every day and for each hour, we will have 20 session starting times (For example, for 1 - 2 pm, starting times will be 1:00 pm, 1:03 pm, 1:06 pm,...1: 57 pm). You will not be able to join the current session if that session has already started. You will need to wait till the next available session starts to join our study." To coordinating with this experiment design, our experiment system was only opened from 8 AM CT to 11 PM CT every day during the period of our online data collection. In addition, only participants who entered the system at the correct session starting time could participate in the study. Otherwise, the participant would be asked to wait for the next session to begin in our system. For example, if a participant logged into our system at 1:03 PM, the participant would directly enter our study. However, if a participant logged into our system at 1:04 PM, the participant would be directed to wait for the next session starting at 1:06 PM in our system. When it is 1:06 PM, the participant would have access to the study. We framed the study as a scheduled recurring event because it made more sense for Turkers to perceive it as an actual group study if all participants came to the study at the same (scheduled) time.

In this step, participants would also sign the consent form and finish the demographic survey, which asked about participants' gender, age, education level, household income, and social media usage.

Next, participants would complete the survey about their attitudes towards some controversial topics. For the SAA intelligence test condition, we asked participants to answer questions about their attitudes towards the validity of the SAA intelligence test and the validity of intelligence tests in general. Here, for the SAA intelligence test, participants only knew the test's name at this moment. We didn't expose any other information about the SAA test until the participants moved to Step 4 to select articles for others. To hide the actual topic we wanted to study and get participants' honest attitudes towards it, we also asked participants to provide answers about their attitudes towards legalizing abortion and Obamacare. For the strict gun control law condition, we asked participants' attitudes towards the strict gun control law and gun control laws in general instead. However, for this condition, we showed participants the strict gun control law - only individuals who are older than 21 and have served in the United States armed forces for at least 2 years are allowed to purchase guns. The other two questions were identical to the SAA intelligence test condition. We asked for participants' attitudes towards the general concepts (e.g., intelligence tests in general and gun controls laws in general) because we intended to check whether and how much participants' attitudes towards a general concept related to participants' attitudes towards a corresponding specific concept (i.e., the SAA intelligence test and the strict gun control law), especially when participants knew nothing about the specific concept except for the name (e.g., the SAA intelligence test). All these questions were in the 7-point Likert Scale format ranging from 1 (strongly oppose) to 7 (strong support).

Step 2: Role Assignment and Task Instruction First, given that we framed this study as a group study in Step 1, we informed the participant that there were eight other participants in the research, and the system has assigned the role of the information selector to the participant to share information with other group members. In addition, we organized a lottery and provided monetary incentives to participants to set the goal of their information selection to leave good impressions for other group members by showing the message "Your goal is to leave a good impression to others in the group by selecting and sharing articles for them. If your general impression rating is among the TOP 20% of all experiment subjects, you will be included in the lottery where researchers will randomly select 5 subjects from this set to win an extra $5 bonus."

When the participant proceeded to the next step, the participant was told to wait for others to finish reading the instruction by showing the message "We are waiting for all group members to finish reading the introductions on the last page. Please be patient and wait..." and the participant would wait there for 6 seconds. According to previous work of pseudo-dyadic interactive experiment on AMT platform [144], to mimic the real-world scenario where it's not possible that every participant took actions at the same time in a group study, asking the participant to wait for other participants for several seconds was effective to convince the participant that other participants were actual. After waiting for 6 seconds, the participant would proceed to the next step of attitude distribution disclosure.

Step 3: Attitude Distribution Disclosure In this step, we disclosed the attitude distribution of the recipient group by showing the participant how many recipients support the topic and how many recipients oppose the topic. Then participant proceeded to the step of selecting articles for others.

Step 4: Article Selection In Step 4, participants selected articles for others from a single column feed with 8 articles about the topic in random order. Participants were told that other members would wait for about 15 minutes on the site. Figure 6.1 showed the news feed for articles on the SAA intelligence test. If participants hovered the cursor on the article block, the corresponding block would expand to show the full article. Figure 6.2 showed an example of the expanded block showing the full article when a participant hovered the cursor over the article block. For the SAA test condition, participants were shown eight short articles about the validity of the test. Four of them supported the validity of the

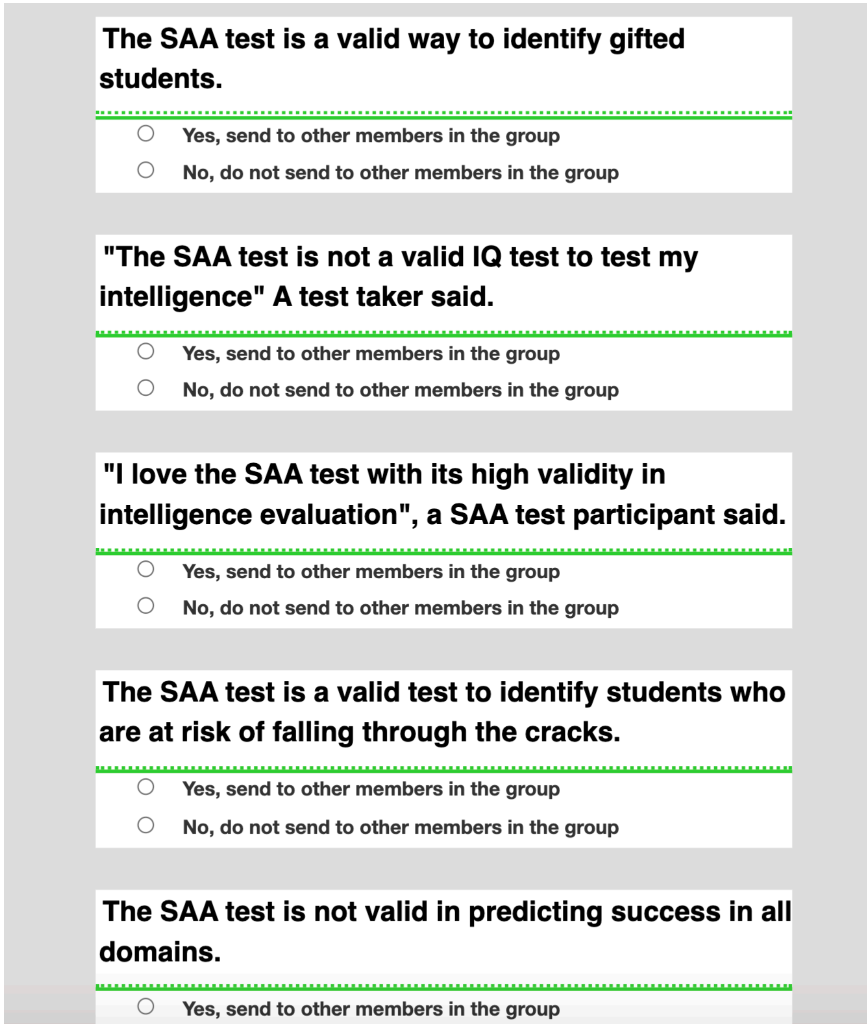
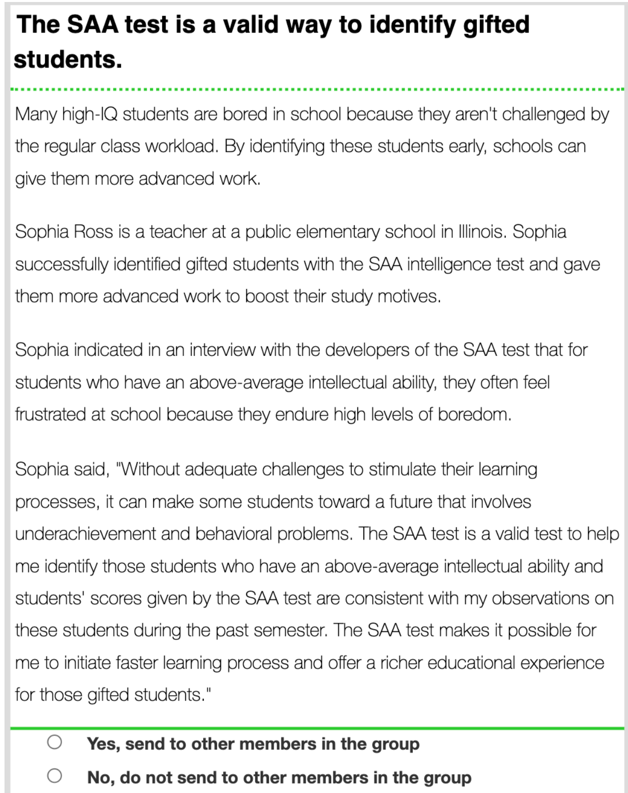


Figure 6.1: An example of the single column article feed.

SAA test, and four of them opposed the validity. Researchers created these eight articles by referring to IQ test reviews (e.g. [145, 146, 147, 148, 149]). For the strict gun control law condition, same as the SAA test condition, participants were shown eight articles about the strict gun control law (four with a supportive attitude and four with an opposed attitude). These eight articles about the strict gun control law were revised from online articles about gun control on ProCon.org [150]. Participants can share however many articles they want.

Step 5: Post-Study Survey and Debrief In this last step, we asked the participant how much they felt they had accomplished the goal of leaving a good impression to others by sharing articles using a 1 (Not at all) to 5 (Extremely) 5-point Likert Scale. Next, following the previous pseudo-interaction study [144], we conducted a funnel debriefing to



The SAA test is a valid way to identify gifted students.

Many high-IQ students are bored in school because they aren't challenged by the regular class workload. By identifying these students early, schools can give them more advanced work.

Sophia Ross is a teacher at a public elementary school in Illinois. Sophia successfully identified gifted students with the SAA intelligence test and gave them more advanced work to boost their study motives.

Sophia indicated in an interview with the developers of the SAA test that for students who have an above-average intellectual ability, they often feel frustrated at school because they endure high levels of boredom.

Sophia said, "Without adequate challenges to stimulate their learning processes, it can make some students toward a future that involves underachievement and behavioral problems. The SAA test is a valid test to help me identify those students who have an above-average intellectual ability and students' scores given by the SAA test are consistent with my observations on these students during the past semester. The SAA test makes it possible for me to initiate faster learning process and offer a richer educational experience for those gifted students."

- **Yes, send to other members in the group**
- **No, do not send to other members in the group**

Figure 6.2: An example of the expanded article block after the participant put the cursor over the article block.

ask participants' thoughts about what the study was about and if participants felt anything odd or suspicious in the study. Finally, participants were debriefed that other participants were fictitious and the assigned topic was also fictitious.

6.4 RESULTS

In total, 120 participants joined the study for the SAA intelligence test condition and 124 participants for the strict gun control law condition. According to the funnel debriefing responses, we removed 7 participants and 10 participants from the analysis of the SAA intelligence test condition and the analysis of the strict gun control law condition, respectively, since they found out that other participants were not actual or figured out our study purpose.

In the following analyses, in terms of the attitude distribution of the recipient group, *Group 1* represented the condition of 75% Support and 25% Oppose (6 support the topic and 2 oppose the topic); *Group 2* represented the condition of 50% Support and 50% Oppose

(4 support the topic and 4 oppose the topic); *Group 3* represented the condition of 25% Support and 75% Oppose (2 support the topic and 6 oppose the topic);

Demographics We hired participants to align with the demographic distributions of the United States [143] in 2020 in terms of age and education level. Table 6.1 showed participants' demographic distribution for the SAA intelligence test condition and Table 6.2 showed that for the strict gun control law condition.

Table 6.1: The demographic information (age and education levels) of participants for the SAA intelligence test condition.

Demographics	**Group 1**	**Group 2**	**Group 3**	**All**	**Census**
Education Level					
High School or Lower	33.3%	28.6%	35.9%	32.7%	36.5%
College Associate	28.2%	31.4%	28.2%	29.2%	28.2%
Bachelor's Degree or Above	38.5%	40.0%	35.9%	38.1%	35.3%
Age					
18–24	12.8%	11.4%	12.8%	12.4%	13.5%
25–39	30.8%	34.3%	30.8%	31.9%	31.1%
40–54	30.8%	31.4%	28.2%	30.1%	27.6%
55–69	25.6%	22.9%	28.2%	25.7%	27.8%

Table 6.2: The demographic information (age and education levels) of participants for the strict gun control law condition.

Demographics	**Group 1**	**Group 2**	**Group 3**	**All**	**Census**
Education Level					
High School or Lower	29.7%	33.3%	34.2%	32.5%	36.5%
College Associate	29.7%	30.8%	28.9%	29.8%	28.2%
Bachelor's Degree or Above	40.6%	35.9%	36.9%	37.7%	35.3%
Age					
18–24	13.5%	12.8%	13.2%	13.2%	13.5%
25–39	35.2%	33.3%	31.6%	33.3%	31.1%
40–54	29.7%	28.2%	26.3%	28.1%	27.6%
55–69	21.6%	25.7%	28.9%	25.4%	27.8%

For participants of the SAA test condition, 39% were female, 60% were male, and 1% preferred not to disclose their gender information. The median household income was within the range of $40,000 - $49,999. All participants indicated that they had used social media before, such as Facebook or Twitter, in terms of social media usage. In addition, 59%

Table 6.3: Participants' attitude distribution for the SAA test condition.

Attitude Distribution	Oppose	Neutral	Support	All
The SAA Intelligence Test				
Group 1	2	12	25	39
Group 2	3	12	20	35
Group 3	0	14	25	39
All	5	38	70	113
Intelligence Test in General				
Group 1	2	8	29	39
Group 2	3	6	26	35
Group 3	2	8	29	39
All	7	22	84	113

reported that they used social media to browse news articles all the time or frequently, 37% used social media to browse news articles rarely or occasionally, and 4% never used social media to browse news articles.

For participants of the strict gun control law condition, 50% were female, 49% were male, and 1% preferred not to disclose their gender information. The median household income was within the range of $40,000 - $49,999. Regarding social media usage, 96% of participants indicated that they had used social media before, such as Facebook or Twitter, 3% stated that they didn't use social media before, and 1% preferred not to say. In addition, 62% reported that they used social media to browse news articles all the time or frequently, 32% used social media to browse news articles rarely or occasionally, 5% never used social media to browse news articles, and 1% preferred not to disclose this information.

Participants' Attitudes We asked for participants' attitudes towards the validity of the SAA intelligence test and the validity of intelligence tests in general for the SAA test condition. Meanwhile, we asked for participants' attitudes towards the strict gun control law and gun control laws in general for the strict gun control law condition. Table 6.3 shows participants' attitude distribution of the SAA test and intelligence tests in general. Table 6.4 shows participants' attitude distribution of the strict gun control law and gun control laws in general. To code participants' attitudes, 1 - 3 (strongly oppose, oppose, somewhat oppose) are coded as opposing the topic, 5 - 7 (somewhat support, support, strongly support) are coded as supporting the topic, 4 (neutral) is coded as neutral.

According to [31], the experiment paradigm of using a fictitious intelligence test was to simulate the scenario where people didn't have preferential attitudes (i.e., being neutral) towards the topic since participants didn't know what the test was except for the name of

Table 6.4: Participants' attitude distribution for the strict gun control law condition.

Attitude Distribution	Oppose	Neutral	Support	All
The Strict Gun Control Law				
Group 1	16	7	14	37
Group 2	15	1	23	39
Group 3	13	4	21	38
All	44	12	58	114
Gun Control Laws in General				
Group 1	3	5	29	37
Group 2	5	5	29	39
Group 3	6	3	29	38
All	14	13	87	114

the test. To validate whether such a paradigm really worked in our experiment, we compared the SAA intelligence test condition and the strict gun control law condition to figure out whether the proportion of participants with neutral attitudes (towards the SAA test and strict gun control law) were different. Table 6.5 shows the number of participants with neutral attitudes and non-neutral attitudes towards the SAA intelligence test and the strict gun control law, respectively. We conducted χ^2 test, and we found that the proportion of participants with the neutral attitude significantly differed between the SAA intelligence test condition and the strict gun control law condition. The SAA test condition have significantly more participants with the neutral attitude ($\chi^2(1, N = 227) = 16.315$, $p < 0.01$, odd ratio is 4.31). This indicates that such a paradigm of only exposing the name of some novel fictitious topic can create a scenario where a considerable proportion of people would have neutral attitudes.

Table 6.5: Participants' attitude distribution in term of being neutral or non-neutral towards the SAA intelligence test and the strict gun control law, respectively.

Attitude Distribution	Neutral	Non-Neutral
The SAA Intelligence Test	38	75
The Strict Gun Control Law	12	102

In addition, we investigated participants' attitude strength distribution for supporters and opponents for each topic. For the SAA intelligence test condition, among those 70 supporters, 26 of them somewhat supported, 35 of them supported, and 9 of them strongly supported. For those 5 opponents, 3 of them somewhat opposed, 2 of them opposed, and none of them strongly opposed. There's no significant difference between the attitude strength distribution between the SAA test supporters and opponents ($p = 0.82$). For the strict gun control law condition, among those 58 supporters, 23 of them somewhat supported, 20 of them supported, and 15 of them strongly supported. For those 44 opponents, 10 of them somewhat opposed, 15 of them opposed, and 19 of them strongly opposed. There's no significant difference between the attitude strength distribution between the strict gun control law supporters and opponents ($p = 0.11$).

Attitude Correlation We collected participants' attitudes towards both general concepts (e.g., validity of intelligence tests in general and gun control laws in general) and specific concepts (the SAA intelligence test and the strict gun control law) to figure out whether these attitudes between the general and the specific concept have any correlation. We conducted the Spearman correlation test on participants' raw inputs (1 - 7) for these questions.

For the SAA test condition, the result indicates that participants' attitudes towards the validity of the SAA test were highly correlated with participants' attitudes towards the validity of intelligence tests in general ($\rho = 0.63$, $p < 0.01$).

For the strict gun control law condition, the result indicates that participants' attitudes towards the strict gun control law were moderately correlated with participants' attitudes towards gun control laws in general ($\rho = 0.40$, $p < 0.01$).

Such a result indicates that the correlation of the strict gun control law condition is weaker than the correlation of the SAA test condition. The reason behind this could be that for the strict gun control law condition, participants may have a more independent attitude towards the strict gun control law because we showed the strict gun control law to participants (We showed participants the exact law "Only individuals who are older than 21 and have served in the United States armed forces for at least 2 years are allowed to purchase guns."). However, participants in the SAA test condition knew nothing but the name of the intelligence test (We only showed participants this message before they read articles about the SAA test "SAA test is an intelligence test."). That might make participants rely more on their attitudes towards intelligence tests in general when indicating their attitudes towards the SAA test.

Measures for Further Analyses Here, we defined the following measures for further analyses on how participants' attitudes towards a specific topic (i.e., the SAA intelligence test or the strict gun control law) and the attitude distribution of the recipient group affect participants' information-sharing behavior. In addition, we included participants' perceived level of goal accomplishment in analyses to measure to what degree they set the goal of leaving a good impression when sharing information with others.

Independent Variables

- **Participants' Attitudes.** A categorical variable that has three classes. According to participants' responded attitudes towards the SAA test or the strict gun control law, we categorized their attitudes into 1) Oppose (including strongly oppose, oppose, somewhat oppose), 2) Neutral, 3) Support (including somewhat support, support, strongly support).

- **Attitude Distribution of the Recipient Group.** A categorical variable with three classes, 1) Group 1 (75% Support and 25% Oppose), 2) Group 2 (50% Support and 50% Oppose), 3) Group 3 (25% Support and 75% Oppose).

Dependent Variables

- **Information Sharing Index (ISI).** The information sharing index (ISI) is defined as:

$$ISI = \frac{N_{support}}{N_{support} + N_{oppose}} \tag{6.1}$$

  where $N_{support}$ is the number of articles that supported the topic and were shared by the participant. Meanwhile, N_{oppose} denotes the number of articles that opposed the topic and were shared by the participant. Thus, if ISI is 0.50, that means the participant shared in a balanced way in terms of the stance of these articles; if ISI is greater than 0.50, that means the participant shared more articles that supported the topic; otherwise, the participant shared more articles which opposed the topic if the corresponding ISI is less than 0.50.

- **Goal Accomplishment Index (GAI).** This was participants' responses to the 5-point Likert Scale question on how much they believed they had accomplished the goal of leaving a good impression to others at the end of the study (1 for not at all, 2 for slightly, 3 for moderately, 4 for very, and 5 for extremely).

Before diving into further analyses, we checked whether participants' attitudes towards the general concept (intelligence tests in general or gun control laws in general) impacted their information-sharing behavior. The linear regression model indicates that even though participants' attitudes towards the general concept can predict their information sharing indexes (ISI) ($\beta = 0.07$, $t(111) = 2.65$, $p < 0.05$ for the SAA intelligence test condition and $\beta = 0.06$, $t(112) = 3.51$, $p < 0.05$ for the strict gun control law condition), the effect was very small (adjusted $R^2 = 0.05$ for the SAA intelligence condition and adjusted $R^2 = 0.09$ for the strict gun control law condition). In addition, since those articles to be selected by participants were about specific topics (i.e., the SAA intelligence test or the strict gun control law), we would focus on participants' attitudes towards the specific topics for further analyses.

6.4.1 Analysis for the SAA Test Condition

Descriptive Statistics about ISI First, we showed the descriptive statistics about ISI in different conditions regarding the attitude distribution of the recipient group and participants' attitudes towards the SAA intelligence test.

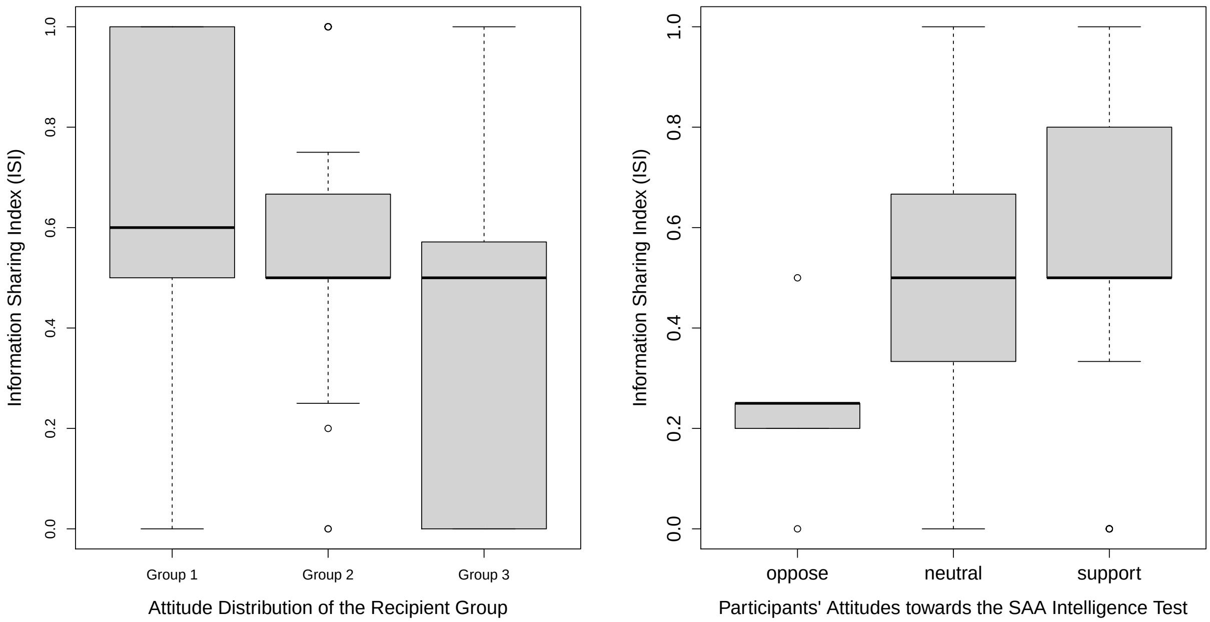
Table 6.6: Mean and standard deviation of ISI for different attitude distributions of the recipient group and for participants with different attitudes towards the SAA intelligence test.

	Attitude Distribution of the Recipient Group		
	Group 1 (75% Support, 25% Oppose)	Group 2 (50% Support, 50% Oppose)	Group 3 (25% Support, 75% Oppose)
ISI	0.66 ($\pm$ 0.27)	0.58 ($\pm$ 0.27)	0.40 ($\pm$ 0.32)
	Participants' Attitudes towards the SAA Intelligence Test		
	Support	Neutral	Oppose
ISI	0.59 ($\pm$ 0.28)	0.49 ($\pm$ 0.34)	0.24 ($\pm$ 0.18)

From Table 6.6 and Figure 6.3(a), we observed the phenomenon that the attitude distribution of the recipient group may affect the information sharing bias (ISI) of the participant. We can see that when the majority's attitude of the recipient group was biased towards one side, the selector tended to select more articles from the corresponding side. In addition, from Table 6.6 and Figure 6.3(b), we also observed that participants' attitudes towards the SAA intelligence test seemed to have an impact on their information-sharing behavior as well. However, these observations need to be validated by statistical analyses.

Statistical Analyses about ISI (RQ1 and RQ2) On average, participants shared around five articles in total with others ($M = 5.05, SD = 1.86$). There was no significant difference in terms of the number of shared news articles across different conditions ($F = 0.76, p = 0.47$).

To further analyze the effect of how participants' attitudes towards the SAA intelligence test and recipients' attitude distributions affect participants' information-sharing behavior,



(a) The boxplot of ISI on the attitude distributions of the recipient group.

(b) The boxplot of ISI on participants' attitudes towards the SAA intelligence test.

Figure 6.3: Boxplots of ISI for different conditions.

we conducted a two-way ANOVA analysis where independent variables were: 1) participants' attitudes towards the SAA intelligence test (support vs. neutral vs. oppose); 2) attitude distribution of the recipient group (Group1 vs. Group 2 vs. Group 3); and the dependent variable was participants' ISI.

Table 6.7: Two-way ANOVA results on information sharing index for the SAA intelligence test.

Source	df	MS	F	p	η^2
Participants' Attitudes towards the SAA Test (A)	2	0.36	4.75	0.01*	0.11
Attitude Distribution of the Recipient Group (B)	2	0.84	10.90	0.00***	0.17
A $\times$ B	3	0.05	0.61	0.61	0.02
Residuals	105	0.08			

Table 6.7 shows the result of the two-way ANOVA analysis. We find that participants' attitudes towards the SAA intelligence test and the attitude distribution of the recipient group had significant main effects on participants' ISI. No interaction effect was found.

In terms of participants' attitudes towards the SAA intelligence test, our post-hoc analysis indicates that participants ($N = 70, M_{ISI} = 0.59, SD_{ISI} = 0.28$) who supported the

SAA test shared significantly more supportive articles than participants ($N = 5, M_{ISI} = 0.24, SD_{ISI} = 0.18$) who opposed the SAA test ($p < 0.05$). There was no significant difference on the information sharing index (ISI) between participants ($N = 70, M_{ISI} = 0.59, SD_{ISI} = 0.28$) who supported the SAA test and participants ($N = 38, M_{ISI} = 0.49, SD_{ISI} = 0.34$) who were neutral ($p = 0.18$), and between participants ($N = 5, M_{ISI} = 0.24, SD_{ISI} = 0.18$) who opposed the SAA test and those ($N = 38, M_{ISI} = 0.49, SD_{ISI} = 0.34$) who were neutral ($p = 0.13$). This result indicates that participants' attitudes towards the SAA test might have an impact on participants' information-sharing behavior, and participants may tend to share more articles with the same attitudes as their own (**RQ1**).

In addition, for the effect of the attitude distribution of the recipient group, our post-hoc analysis indicates that participants ($N = 39, M_{ISI} = 0.66, SD_{ISI} = 0.27$) in Group 1 (75% Support, 25% Oppose) shared significantly more supportive articles than participants ($N = 39, M_{ISI} = 0.40, SD_{ISI} = 0.32$) in Group 3 (25% Support, 75% Oppose) ($p < 0.001$), and participants ($N = 35, M_{ISI} = 0.58, SD_{ISI} = 0.27$) in Group 2 (50% Support, 50% Oppose) also shared significantly more supportive articles than participants ($N = 39, M_{ISI} = 0.40, SD_{ISI} = 0.32$) in Group 3 (25% Support, 75% Oppose) ($p < 0.01$). No significant difference was found between participants ($N = 39, M_{ISI} = 0.66, SD_{ISI} = 0.27$) in Group 1 (75% Support, 25% Oppose) and participants ($N = 35, M_{ISI} = 0.58, SD_{ISI} = 0.27$) in Group 2 (50% Support, 50% Oppose) ($p = 0.50$) on ISI. This result indicates that the attitude distribution of the recipient group had impact on participants' information-sharing behavior and participants tended to follow the majority's attitude in the recipient group to select information for others (**RQ2**). The possible reason that Group 1 and Group 2 had no difference could be that there were many participants supporting the validity of the SAA test in both conditions, so they tended to select more supportive articles for others. Given that only a few (five) participants opposed the SAA intelligence test, we dropped those who opposed the SAA intelligence test, and conducted statistical analyses. Appendix A shows the analysis results, which also support our main findings mentioned above.

Given that the SAA intelligence test condition was to create the scenario where participants didn't have preferential attitudes, we were particularly interested in how attitude distributions of the recipient group affected the information-sharing behavior of participants with the *NEUTRAL* attitude towards the SAA intelligence test. Thus, we only used data from participants with the neutral attitude and conducted an ANCOVA analysis where the independent variable was the attitude distribution of the recipient group, the control variable was participants' attitudes towards intelligence tests in general, and the dependent variable was the information sharing index (ISI). According to the analysis result, we found that the attitude distribution of the recipient group had an impact on the information sharing index

($F(2, 34) = 3.671, p < 0.05, \eta^2_{partial} = 0.18$). Post-hoc analysis was performed with a Bonferroni adjustment and we found that there was a significant difference between Group 1 (75% Support, 25% Oppose) ($N = 12, M_{ISI} = 0.66, SD_{ISI} = 0.09$) and Group 3 (25% Support, 75% Oppose) ($N = 14, M_{ISI} = 0.32, SD_{ISI} = 0.08$) ($p < 0.05/3$). No significant difference was found between Group 1 (75% Support, 25% Oppose) ($N = 12, M_{ISI} = 0.66, SD_{ISI} = 0.09$) and Group 2 (50% Support, 50% Oppose) ($N = 12, M_{ISI} = 0.53, SD_{ISI} = 0.09$) , and between Group 2 (50% Support, 50% Oppose) ($N = 12, M_{ISI} = 0.53, SD_{ISI} = 0.09$) and Group 3 (25% Support, 75% Oppose) ($N = 14, M_{ISI} = 0.32, SD_{ISI} = 0.08$). This indicates that when participants had a neutral attitude towards the topic, their information-sharing behavior was influenced by the attitude distribution of the recipient group, especially when there was a majority attitude in the recipient group (**RQ2**).

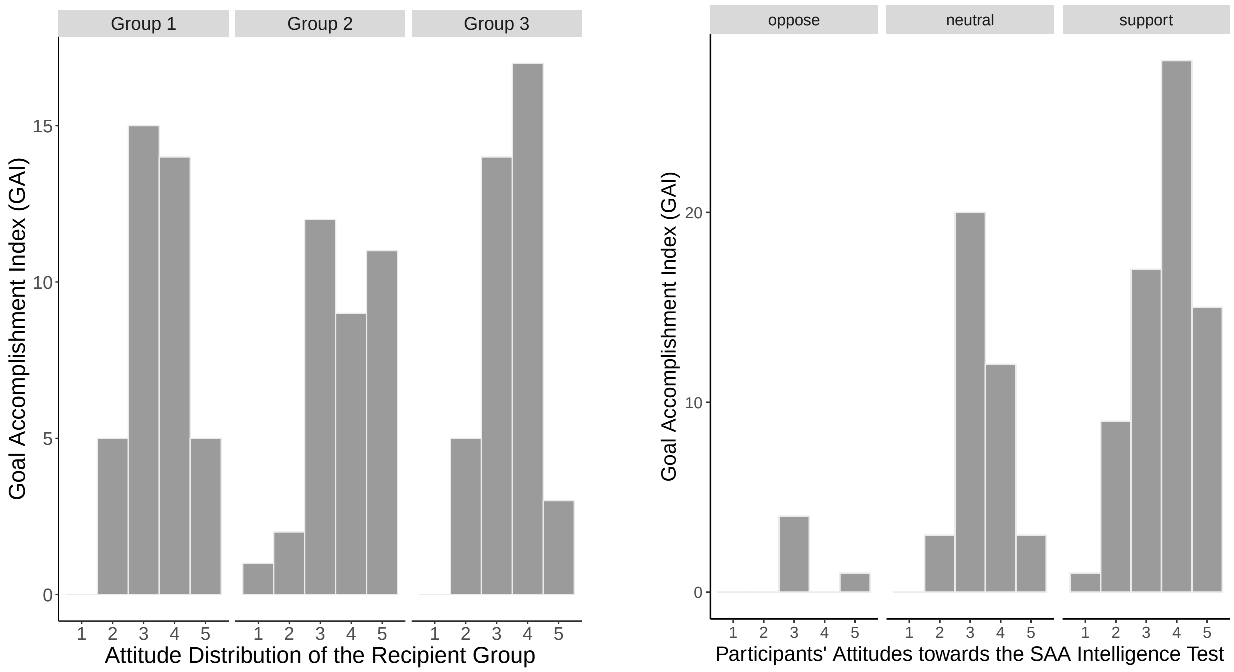
Descriptive Statistics about GAI We measured how participants felt they had accomplished the goal of leaving a good impression to others using a 5-point Likert Scale (1 for not at all and 5 for extremely). Table 6.8 and Figure 6.4 showed the descriptive statistics of the Goal Accomplishment Index (GAI) for different attitude distributions of the recipient group and participants' attitudes towards the SAA intelligence test. We didn't observe significant differences across different conditions in terms of the GAI.

Next, we conducted statistical analyses to validate.

Table 6.8: Mean and standard deviation of GAI for different attitude distributions of the recipient group and for participants with different attitudes towards the SAA intelligence test.

	Attitude Distribution of the Recipient Group		
	Group 1 (75% Support, 25% Oppose)	Group 2 (50% Support, 50% Oppose)	Group 3 (25% Support, 75% Oppose)
GAI	3.49 (± 0.88)	3.77 (± 1.06)	3.46 (± 0.82)
	Participants' Attitudes towards the SAA Intelligence Test		
	Support	Neutral	Oppose
GAI	3.67 (± 1.00)	3.39 (± 0.75)	3.40 (± 0.89)

Statistical Analyses about GAI To analyze the effect of how participants' attitudes towards the SAA intelligence test and the attitude distribution of the recipient group affect participants' perceived level of goal accomplishment, we conducted a two-way ANOVA analysis where independent variables were: 1) participants' attitudes towards the SAA test (support vs. neutral vs. oppose); 2) attitude distributions of the recipient group (Group 1 vs.



(a) The histogram of GAI on the attitude distributions of the recipient group.

(b) The histogram of GAI on participants' attitudes towards the SAA intelligence test.

Figure 6.4: Histograms of GAI for different conditions for the SAA intelligence test.

Group 2 vs. Group 3); and the dependent variable was participants' goal accomplishment index (GAI).

Table 6.9 shows the analysis result (Appendix B shows the analysis result based on data excluding those who opposed the SAA test). The result indicates no significant difference on the goal accomplishment index (GAI) between different conditions in terms of the attitude distribution of the recipient group and participants' attitudes towards the SAA test.

Table 6.9: Two-way ANOVA results on goal accomplishment index for the SAA intelligence test.

Source	df	MS	F	p	η^2
Participants' Attitudes towards the SAA Test (A)	2	1.02	1.17	0.31	0.03
Attitude Distribution of the Recipient Group (B)	2	1.24	1.43	0.24	0.03
A $\times$ B	3	0.11	0.13	0.94	0.00
Residuals	105	0.87			

6.4.2 Analysis for the Strict Gun Control Law Condition

Descriptive Statistics about ISI First, we showed the descriptive statistics about ISI

Table 6.10: Mean and standard deviation of ISI for different attitude distributions of the recipient group and for participants with different attitudes towards the strict gun control law.

Attitude Distribution of the Recipient Group			
	Group 1 (75% Support, 25% Oppose)	Group 2 (50% Support, 50% Oppose)	Group 3 (25% Support, 75% Oppose)
ISI	0.68 ($\pm$ 0.26)	0.51 ($\pm$ 0.27)	0.41 ($\pm$ 0.30)
Participants' Attitudes towards the Strict Gun Control Law			
	Support	Neutral	Oppose
ISI	0.59 ($\pm$ 0.24)	0.51 ($\pm$ 0.33)	0.46 ($\pm$ 0.34)

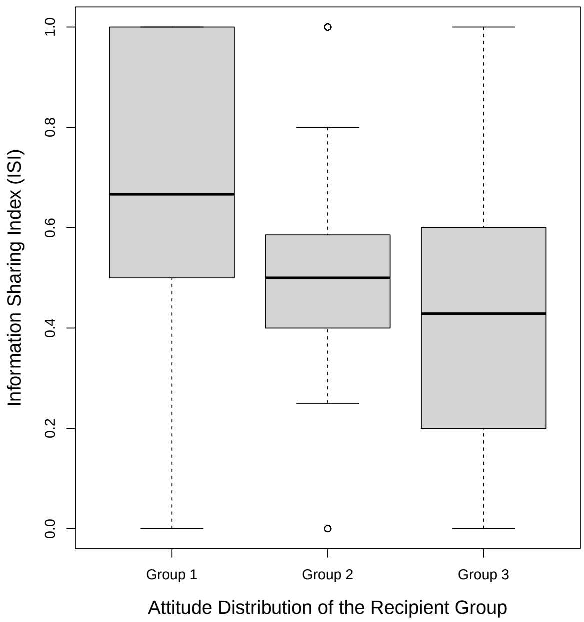
in different conditions regarding the attitude distribution of the recipient group and participants' attitudes towards the strict gun control law.

Table 6.10 and Figure 6.5(a) show that the attitude distribution of the recipient group had an impact on the information sharing bias (ISI) of the participant. There was the seeming trend of following the majority's attitude to sharing information with the group. In addition, from Table 6.10 and Figure 6.5(b), we also observed that participants' attitudes towards the strict gun control law seemed to affect participants' information-sharing behavior. However, again, these observations need to be validated by statistical analyses.

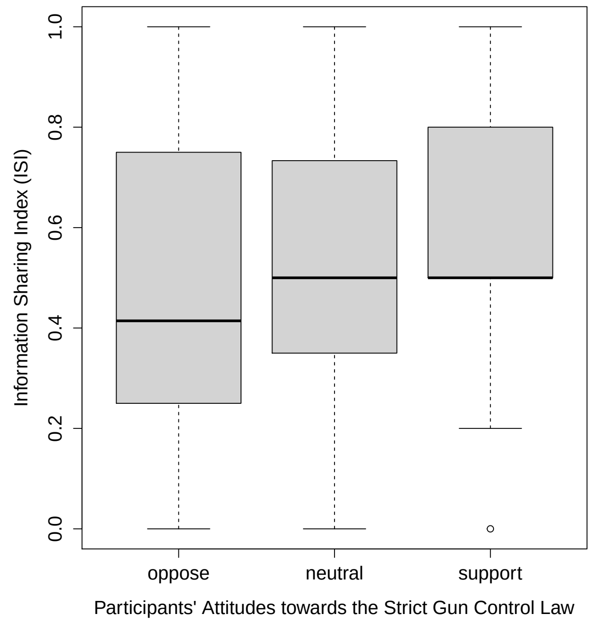
Statistical Analyses about ISI (RQ1 and RQ2) On average, participants shared around five articles in total with others ($M = 4.91, SD = 1.88$). There was no significant difference in the number of shared news articles across different conditions ($F = 0.55, p = 0.58$).

To further analyze the effect of how participants' attitudes towards the strict gun control law and the attitude distribution of the recipient group influence participants' information-sharing behavior, we conducted a two-way ANOVA analysis where independent variables were: 1) participants' attitudes towards the strict gun control law (support vs. neutral vs. oppose); 2) the attitude distribution of the recipient group (Group1 vs. Group 2 vs. Group 3); and the dependent variable was participants' information sharing index (ISI).

Table 6.11 shows that participants' attitudes towards the strict gun control law and the attitude distribution of the recipient group had significant main effects on participants' ISI. Our post-hoc analysis finds that participants ($N = 58, M_{ISI} = 0.59, SD_{ISI} = 0.24$) who supported the strict gun control law shared significantly more supportive articles than participants ($N = 44, M_{ISI} = 0.46, SD_{ISI} = 0.34$) who opposed the strict gun control law ($p < 0.05$) (**RQ1**). There was no significant difference on ISI between participants who



(a) The boxplot of ISI on the attitude distributions of the recipient group.



(b) The boxplot of ISI on participants' attitudes towards the strict gun control law.

Figure 6.5: Boxplots of ISI for different conditions in the strict gun control law condition.

supported the strict gun control law and participants ($N = 12, M_{ISI} = 0.51, SD_{ISI} = 0.33$) who were neutral on the strict gun control law ($p = 0.59$), and between participants who were neutral on the strict gun control law and participants who opposed the strict gun control law ($p = 0.79$). In terms of the attitude distribution of the recipient group, our analysis shows that participants ($N = 37, M_{ISI} = 0.68, SD_{ISI} = 0.26$) in Group 1 (75% Support, 25% Oppose) shared significantly more supportive articles than participants ($N = 38, M_{ISI} = 0.41, SD_{ISI} = 0.30$) in Group 3 (25% Support, 75% Oppose) ($p < 0.0001$), and participants ($N = 37, M_{ISI} = 0.68, SD_{ISI} = 0.26$) in Group 1 (75% Support, 25% Oppose) also shared significantly more supportive articles than participants ($N = 39, M_{ISI} = 0.51, SD_{ISI} = 0.27$) in Group 2 (50% Support, 50% Oppose) ($p < 0.01$) (**RQ2**). No significant difference was found between participants ($N = 39, M_{ISI} = 0.51, SD_{ISI} = 0.27$) in Group 2 (50% Support, 50% Oppose) and participants ($N = 38, M_{ISI} = 0.41, SD_{ISI} = 0.30$) in Group 3 (25% Support, 75% Oppose) (p= 0.19) on ISI.

In addition, Table 6.11 shows that there was a significant interaction effect between participants' attitudes towards the strict gun control law and the attitude distribution of the recipient group.

Table 6.11: Two-way ANOVA results on information sharing index for the strict gun control law.

Source	df	MS	F	p	η^2
Participants' Attitudes towards the Strict Gun Control Law (A)	2	0.22	3.47	0.03*	0.10
Attitude Distribution of the Recipient Group (B)	2	0.82	12.85	0.00***	0.20
A $\times$ B	4	0.27	4.21	0.00**	0.14
Residuals	105	0.06			

Next, we conducted post-hoc analyses. First, we found that for participants who supported the strict gun control law, the attitude distribution of the recipient group had no impact on their information selection for others ($F(2, 55) = 1.10, p = 0.34$) and there was no significant difference on ISI among Group 1 (75% Support, 25% Oppose) ($N = 14, M_{ISI} = 0.66, SD_{ISI} = 0.20$), Group 2 (50% Support, 50% Oppose) ($N = 23, M_{ISI} = 0.60, SD_{ISI} = 0.24$), and Group 3 (25% Support, 75% Oppose) ($N = 21, M_{ISI} = 0.54, SD_{ISI} = 0.26$) (**RQ2**). For participants who were neutral on the strict gun control law, there was no significant difference ($F(2, 9) = 2.75, p = 0.12$) on ISI among Group 1 (75% Support, 25% Oppose) ($N = 7, M_{ISI} = 0.57, SD_{ISI} = 0.26$), Group 2 (50% Support, 50% Oppose) ($N = 1, M_{ISI} = 1.0$), and Group 3 (25% Support, 75% Oppose) ($N = 4, M_{ISI} = 0.29, SD_{ISI} = 0.34$). This may be caused by the small amount of participants with such a neutral attitude (**RQ2**). However, for participants who opposed the strict gun control law, the attitude distribution of the recipient group had significant impact on participants' information-sharing behavior ($F(2, 41) = 15.05, p < 0.001$) (**RQ2**). In addition, we found that participants ($N = 16, M_{ISI} = 0.75, SD_{ISI} = 0.30$) in Group 1 (75% Support, 25% Oppose) shared significantly more supportive articles than participants ($N = 15, M_{ISI} = 0.34, SD_{ISI} = 0.21$) in Group 2 (50% Support, 50% Oppose) ($p < 0.001$) and participants ($N = 13, M_{ISI} = 0.24, SD_{ISI} = 0.28$) in Group 3 (25% Support, 75% Oppose) ($p < 0.001$). There was no significant difference between Group 2 and Group 3 ($p = 0.59$).

In addition, we analyzed how participants' attitudes towards the strict gun control law affect their information sharing index for different conditions in terms of the attitude distribution of the recipient group. For Group 1 (75% Support, 25% Oppose), we didn't find significant difference on ISI ($F(2, 34) = 1.22, p = 0.31$) among participants who supported the strict gun control law ($N = 14, M_{ISI} = 0.66, SD_{ISI} = 0.20$), participants who opposed the strict gun control law ($N = 16, M_{ISI} = 0.75, SD_{ISI} = 0.30$), and participants who were neutral towards the law ($N = 7, M_{ISI} = 0.57, SD_{ISI} = 0.26$) (**RQ1**). For Group 2 (50% Support, 50% Oppose), there was significant difference among participants with different attitudes towards the strict gun control law ($F(2, 36) = 8.44, p < 0.001$). To be more specific, participants ($N = 23, M_{ISI} = 0.60, SD_{ISI} = 0.24$) who supported the strict gun control law shared significantly more supportive articles than participants ($N = 15, M_{ISI} = 0.34, SD_{ISI} = 0.21$) who opposed the strict gun control law ($p < 0.01$) (**RQ1**). In addition, even though the participant ($N = 1, M_{ISI} = 1.0$) who was neutral shared significantly more supportive articles than participants ($N = 15, M_{ISI} = 0.34, SD_{ISI} = 0.21$) who opposed the strict gun control law ($p < 0.05$), and there was no significant difference between the participant who was neutral and participants who supported the strict gun control law, these results may not be stable because there was only one participant with the neutral attitude. For Group 3 (25% Support, 75% Oppose), we only find that participants ($N = 21, M_{ISI} = 0.54, SD_{ISI} = 0.26$) who supported the strict gun control law shared significantly more supportive articles than participants ($N = 13, M_{ISI} = 0.24, SD_{ISI} = 0.28$) who opposed the strict gun control law ($p < 0.05$) (**RQ1**). There was no significant difference between participants ($N = 21, M_{ISI} = 0.54, SD_{ISI} = 0.26$) who had supportive attitudes and participants ($N = 4, M_{ISI} = 0.29, SD_{ISI} = 0.34$) who were neutral ($p = 0.24$), and between participants who were neutral and participants ($N = 13, M_{ISI} = 0.24, SD_{ISI} = 0.28$) who had opposed attitudes ($p = 0.95$).

We also dropped neutral participants (12 participants) on the strict gun control law and conducted statistical analyses. Appendix C shows the result.

These analyses indicate that the attitude distribution of the recipient group had no impact on participants if they supported the strict gun control law. However, participants who opposed the strict gun control law tended to follow the majority's attitude in the group to share information with others.

Descriptive Statistics about GAI For the strict gun control law condition, we also measured how participants believed they had accomplished the goal of conducting impression management for others using a 5-point Likert Scale (1 for not at all and 5 for extremely). Table 6.12 and Figure 6.6 show the descriptive statistics of the Goal Accomplishment Index (GAI) for different conditions, and we don't see significant differences among conditions in terms of the GAI.

Next, we conducted statistical analyses to validate.

Statistical Analyses about Goal Accomplishment Index (GAI) To analyze the effect of how participants' attitudes towards the strict gun control law and the attitude distribution of the recipient group affect participants' perceived level of goal accomplishment, we conducted a two-way ANOVA analysis where independent variables were: 1) participants'

Table 6.12: Mean and standard deviation of GAI for different attitude distributions of the recipient group and for participants with different attitudes towards the strict gun control law.

	Attitude Distribution of the Recipient Group		
	Group 1 (75% Support, 25% Oppose)	Group 2 (50% Support, 50% Oppose)	Group 3 (25% Support, 75% Oppose)
GAI	3.43 (± 0.77)	3.33 (± 0.77)	3.61 (± 0.89)
	Participants' Attitudes towards the Strict Gun Control Law		
	Support	Neutral	Oppose
GAI	3.59 (± 0.86)	3.42 (± 1.00)	3.30 (± 0.67)

Table 6.13: Two-way ANOVA results on goal accomplishment index for the strict gun control law.

Source	df	MS	F	p	η^2
Participants' Attitudes towards the Strict Gun Control Law (A)	2	1.07	1.62	0.20	0.03
Attitude Distribution of the Recipient Group (B)	2	0.73	1.10	0.34	0.02
A × B	4	0.31	0.47	0.76	0.02
Residuals	105	0.66			

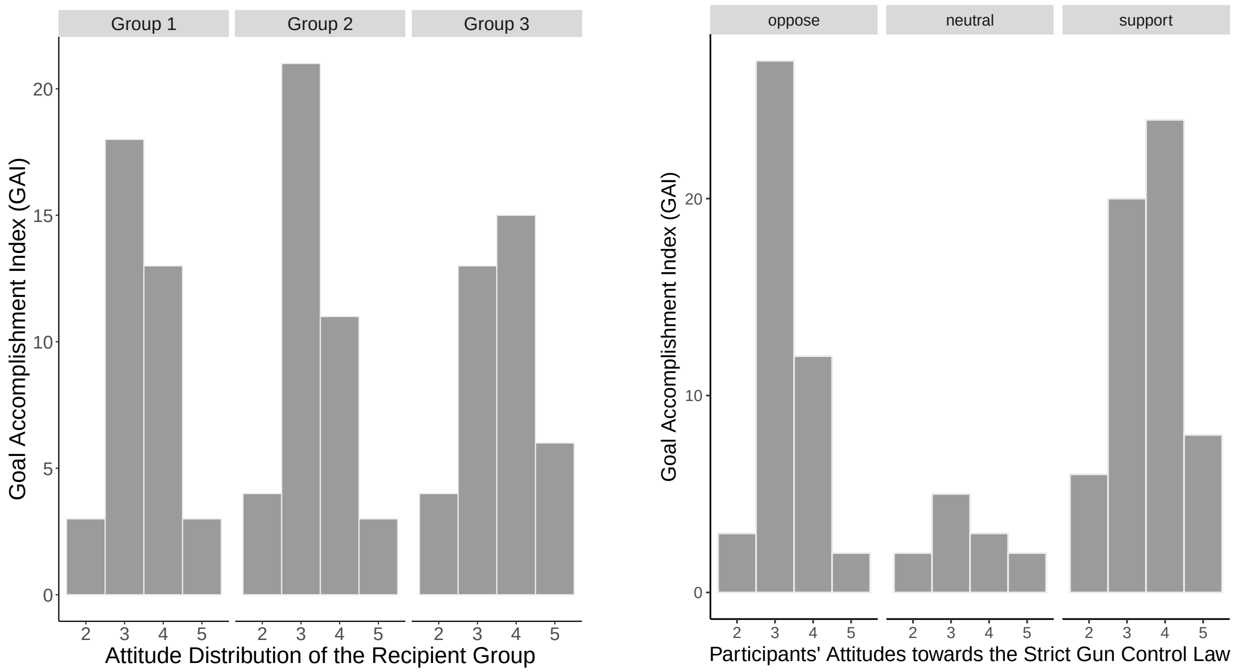
attitudes towards the strict gun control law (support vs. neutral vs. oppose); 2) the attitude distribution of the recipient group (Group 1 vs. Group 2 vs. Group 3); and the dependent variable was participants' goal accomplishment index (GAI).

Similar to the SAA test condition, Table 6.13 shows that there was no significant difference in the goal accomplishment index (GAI) between different conditions in terms of the attitude distribution of the recipient group and participants' attitudes towards the strict gun control law (Appendix D shows the analysis result based on data excluding those neutral participants).

6.5 CONCLUSION AND DISCUSSION

6.5.1 Experiment Design

In this study, we designed a simulated online group experiment framework to mimic the real-world scenario of sharing information with a group of people. Our experiment results indicated that few participants perceived other group members as fictitious partners, which showed that our experiment framework could successfully simulate the group study sce-



(a) The histogram of GAI on the attitude distribution of the recipient group.

(b) The histogram of GAI on participants' attitudes towards the strict gun control law.

Figure 6.6: Histograms of GAI for different conditions for the strict gun control law.

nario. Our experiment framework gives researchers more options when conducting online group studies, especially when they want accurate and better control on different conditions or if it's difficult to recruit many actual participants online. In addition, our results showed that the paradigm of only offering a novel topic with limited information (e.g., only showing participants the name of the SAA intelligence test) could create a scenario where a considerable proportion of participants would have a neutral attitude towards the topic.

6.5.2 People's Information-Sharing Behavior

Both of the two research questions are about how people share information with others. RQ1 focuses on the effect of people's attitudes towards the topic, and RQ2 focuses on the impact of the attitude distribution of the recipient group. Next, we will discuss the result of the SAA intelligence test condition and the strict gun control law condition, respectively.

SAA Intelligence Test For this condition, a considerable proportion of participants were neutral and didn't exhibit a preferential attitude towards the topic. Participants' attitudes towards the SAA test (i.e., support vs. oppose) may affect their information-sharing behavior (**RQ1**). Future studies might use a novel topic with sufficient participants with both supporting and opposed attitudes to make a more concrete conclusion. In addition, participants' information-sharing behavior was found to be heavily affected by the attitude distribution of the recipient group, especially for those who were neutral (**RQ2**). To be more specific, participants, including those who were neutral, would follow the majority's attitudes of the recipient group to share information with others to leave a good impression on the group. This result indicated that for novel topics that fewer people have a preferential attitude towards (e.g., the SAA intelligence test), people, especially neutral ones, would select more information with the stance aligning with the majority's attitude in the recipient group. This will create a congenial information environment for most group members and further exacerbate the echo chamber effect in the group.

Strict Gun Control Law For this condition, most participants had preferential attitudes (i.e., oppose or support) towards the topic. For participants who supported the strict gun control law, they tended to stick to their own attitudes when sharing information with others (**RQ1**). Meanwhile, those participants who opposed the strict gun control law tended to follow the majority's attitude of the recipient group to share information (**RQ2**). It seems strict gun control law supporters are more convinced to their beliefs or position when sharing information, and this need be validated in further studies.

6.5.3 People's Perception on Goal Accomplishment

In terms of the goal accomplishment index, we can see that neither the attitude distribution of the recipient group nor participants' own attitudes influence participants' perceived level of completing the task to leave a good impression on others. The average GAI for all conditions is between 3 (moderately) and 4 (very). This indicated that participants believed that they had accomplished the goal of leaving a good impression to some degree for all conditions. Previously, we assumed that people would feel hard to complete the impression management task for conditions where 50% of recipients support and 50% of recipients oppose since it's difficult for people to decide which side to cater to or follow. However, our results showed that participants just simply shared information based on their own attitudes in such attitude distribution conditions. That made them feel they had completed the impression management task to a considerable extent (at least half of the recipients would like what they share).

6.5.4 Possible Design Implication

For the strict gun control law condition, if the attitude distribution of the recipient group was 50% vs. 50% (Group 2), we can see a clear tendency that the participant would select information based on their own attitudes. This might give us important design implications to mitigate *de facto* selective exposure for the recipient group. For those online anonymous chat rooms or subreddit groups, they should try to attract people with different attitudes to join the group. The simplest way to avoid the filter bubble in the group information-sharing scenario is to have a relative balanced distribution of people with different attitudes. In addition, even if the actual attitude distribution is biased, we may inform those group members that the attitude distribution of people in this group is roughly balanced so that members would prefer to share information based on their own stances rather than following the majority's attitude in the group. For example, for an online chatting group where 70% participants support a topic and 30% participants oppose the topic, if those 30% with opposing views can share information based on their own attitudes, that would have significant effects to expose attitude-inconsistent information to those who support the topic in the group, which can further break the information filter bubble.

6.5.5 Limitation

In this chapter, we conducted a simulation study to mimic the anonymous group sharing scenario. In reality, people also always share information with others they know. Studying how people share information with a group of acquaintances is another fascinating research topic. However, it's hard for the participant to build a close relationship with fictitious partners during a short-term online experiment. Simply conducting an online simulation experiment may not create a scenario where everyone knows each other or where there are ties among the information selector and recipients. Thus, we need to build an actual social media platform to study how people share information in a group where they know each other. We need to have people use the platform for a long time to cultivate their friendship or directly invite people with their acquaintances to participate in such experiments and observe their information-sharing behavior.

6.5.6 Summary

As a summary, we found that for novel topics in which a considerable proportion of people have a neutral attitude to, the attitude distribution of the recipient group will affect people's information-sharing behavior, and people, including those who are neutral, tend to select more information which supports majority's attitude in the recipient group to leave a good impression. Meanwhile, people's attitudes may also affect their information-sharing behavior, and they tend to share more information on their side if they have an attitude. However, for topics which most people have a preferential attitude towards (i.e., support or oppose), the effect of the attitude distribution of the recipient group is subtly related to people's attitude towards the topic. People with some attitudes (e.g., supporting the strict gun control law) might be more convinced about their beliefs and position when sharing information, which requires further studies to validate.

In general, in this experiment, we did observe the phenomenon that the attitude distribution of the recipient group affects people's information-sharing behavior in the anonymous scenario when people aim to leave a good impression to those recipients, and people tend to cater to the majority's attitude of the recipient group in some specific contexts. This should alarm us that people may play the role of information filter to create filter bubbles for others around. Future studies on interface design should explore how to mitigate such negative effects.

CHAPTER 7: CONCLUSIONS

In this chapter, we summarize the contributions of this dissertation and discuss potential future work.

7.1 RESEARCH CONTRIBUTIONS

Selective exposure and *de facto* selective exposure can limit people's exposure and access to diverse information or social opinions, which impairs those benefits of diverse information exposure, including facilitating people's decision-making process with accurate beliefs and cultivating mutual understanding among people with different attitudes.

This dissertation focuses on designing the interface to mitigate selective exposure and help people explore diverse social opinions. One perspective of solving this problem is to mitigate selective exposure for individual information consumption through the novel interface or system design. Another perspective is to understand people's role as the information filter and learn corresponding adverse effects if there's any, which can be the first step towards designing the intervention to mitigate any potential negative impact related to information-sharing behavior among people (e.g., intentionally or unintentionally creating the filter bubble for others).

7.1.1 Designing Interface to Mitigate Selective Exposure for Individual Information Consumption

We introduced three studies on designing the interface to mitigate selective exposure for individual information consumption.

In chapter 3, we first proposed organizing and showing categorized online social opinions based on people's emotional reactions. We implemented a novel system with this design. People can browse Reddit posts with corresponding comments organized based on comment providers' emotional reactions and interact with the system when exploring different posts. Our evaluation suggested that our novel system can promote people's curiosity about others' reactions and help people explore diverse social opinions compared to Reddit. People also showed higher satisfaction with our interface/system from different aspects, including ease of use, usefulness, enjoyment, etc.

Next, in chapter 4, we introduced our study of designing an interface/system, which provided people with novel visual cues (e.g., showing a trace of people's stances, highlighting people's information selection bias, etc.) and a novel recommendation mechanism to improve people's awareness of diverse social opinions and motivate people to explore diverse opinions online. Compared with the traditional way of organizing online social arguments (e.g., comments) with a linear list format, our interface/system can improve people's awareness of diverse social opinions and mitigate selective exposure when they consume information.

Finally, in chapter 5, we explored the effect of the stance label and the credibility label on a two-column news feed design with real and fake news articles. Our experiment found that the stance label has primarily negative effects on people's article selection and perception. For example, on the interface with the stance label, people selected news articles with a significantly stronger selective exposure tendency. In addition, when people consume information on the interface with the stance label, they agreed more with those fake news. However, the effect of the credibility label in combating fake news seemed to be limited even though it may have some effect of mitigating selective exposure.

7.1.2 Understanding Humans' Role as the Information Filter

In addition to selective exposure, *de facto* selective exposure is another cause of people's lack of exposure to diverse information. In the social media age, people have the potential to shape the opinion space of others around. By sharing information with others or a group, people can play the role of the information filter and partially decide what information others will see. Thus, understanding humans' role as the information filter is crucial for further studies which aim to create a better information consumption environment on social media.

For this perspective, chapter 6 focuses on how people share information to a recipient group with various attitude distributions anonymously to leave a good impression on others. We found that for the topic to which a considerable proportion of people didn't have a preferential attitude (i.e., being neutral), people would follow the majority's attitude of the recipient group and share more information that aligns with the majority's attitude, especially for those people with a neutral attitude. For people who had an attitude (i.e., support vs. oppose), their attitudes might also impact their information-sharing behavior. However, for the topic to which most people have preferential attitudes (i.e., support or oppose), people with different stances exhibited different information-sharing behavior. People with some attitudes (e.g., opposing the strict gun control law) tend to follow the majority's attitude of the recipient group to share information. Meanwhile, people with other attitudes (e.g., supporting the strict gun control law) would like to share information according to their own attitudes. The possible reason might be that people with some attitudes (e.g., supporting the strict gun control law) are more convinced about their beliefs or position, and further studies are needed to figure this out.

In general, these results indicate that the attitude distribution of the recipient group does have an impact on people's information-sharing behavior (even though it may be related to various factors, such as topics, people's attitudes, etc.) in some specific contexts, and people may play the role of creating the filter bubble for others around.

7.2 FUTURE WORK

There are different directions of future work which can improve the interface or system design to mitigate selective exposure and help people explore diverse social opinions.

7.2.1 Personalized Interface Design

One interface cannot solve problems for everyone. Dey et al. [110] showed that simply showing attitude-inconsistent information about some stigmatized topics may backfire, and it would reinforce people's pre-existing attitudes. Since people have different personalities [151] and information-seeking traits [50], offering the same design to all may not be the best practice to mitigate selective exposure for individual information consumption in such scenarios (e.g., the topic is stigmatized). Instead, for people with different personalities (e.g., open-minded vs. close-minded), the interface or system may need to adopt different strategies to show information with various stances. For example, the interface may simply show diverse opinions to open-minded people but should be very careful when offering these diverse opinions, especially information with an opposite point of view, to people with a close-minded personality since it may cause the backfire. Thus, for people who are less tolerant of new ideas or have obstinate attitudes, the interface may need to show opinions on the opposite side with a mild tone with particular designs accordingly.

7.2.2 Applying New Technologies

There are many new forms of interface emerging these days. Chatbots, as one of the most famous novel interfaces, gain attention from both academia and industry [152, 153, 154, 155]. Zarouali et al. [156] showed using chatbots to deliver news with conflicting views can improve people's agreement on these counter-attitudinal opinions compared with the articles offered on traditional websites. In addition, people also perceived news articles delivered by the chatbot as more credible. This indicated the massive potential of chatbots as an information hub where people can consume diverse information. Perhaps, one day, people can build a companion chatbot delivering diverse opinions to have long-term exposure to information from different sides or make a bot to share miscellaneous information in the group information-sharing scenario.

7.2.3 Exploring New Aspects to Improve Social Media Interface Design

My dissertation focuses on designing the interface to mitigate selective exposure and help people explore diverse opinions. However, social media research is rapidly changing and in flux all the time. As new research in social media emerges all the time, researchers can explore other aspects of social media design. For example, emotions are important factors affecting people's information consumption on social media [157]. Emotional content could increase people's engagement in advertisements [158]; emotional proximity may drive people to share misinformation [159]; and emotional contagion is significant on social media (e.g., anger is more contagious than joy on social media) [160]. In the future, reflecting on these findings, we may need to focus on emotion and have a better social media interface design that can mitigate the spread of emotional content.

7.2.4 Have More Comprehensive Understanding of People's Information-Sharing Behavior

In chapter 6, we found that strict gun control law supporters share information based on their own attitudes and opponents follow the majority's attitude of the recipient group to share information. Even though participants' general goal is to leave good impressions on the group, we didn't consider their intrinsic motivation of sharing information. Starbird et al. [161] showed that people might share attitude-inconsistent information to criticize. For example, people may retweet with their own comments to attack the validity of the information or the author in the original tweet. In our experiment in chapter 6, participants cannot add comments to the information they want to share. In the future, more studies are needed to figure out people's intrinsic motivation to share information.

In addition, it may backfire if we simply show attitude-inconsistent information about some stigmatized topics to people [110]. Thus, we may also study how people share information about stigmatized issues to figure out whether people have any unusual information-sharing behavior in such a scenario.

Furthermore, in chapter 6, we only considered the scenario of sharing information anonymously. In reality, many people share information in a public group where people know each other and have a sense of affinity. Previous research showed that the relationship closeness induction task (RCIT) [162] could help build a close relationship between two strangers quickly. In our experiment, we tried this task to help participants form strong tie strength

Figure 7.1: A possible example of the interface prototype to motivate people to share diverse information with recipients.

with the group of recipients to mimic the scenario where participants have a close relationship with the group. However, it seems that adopting the task in the online scenario is problematic, and this task cannot help build a relationship between participants and the group. In the future, to have more ecological validity, researchers need to study how people share information in scenarios where people know each other and there are social ties among them. In addition, we can also explore how people share information in the offline environment. For example, people need to share their thoughts when they discuss some issues in a face-to-face meeting. Studying how people share information in such scenarios may better help us understand the group decision-making process [163].

7.2.5 Humans' Role in Breaking the Filter Bubble

Earl's work [31] and our work mentioned in chapter 6 indicated that when sharing information with others, people tend to filter out the information recipients don't like and share more information that aligns with the recipient's or most recipients' attitudes in some scenarios. These results showed humans could play the role of the information filter and create a congenial information environment for others. This also gives us the inspiration to consider that perhaps we can reverse humans' position from the information filter to the information disseminator, which can share diverse information and break the filter bubble for others. Previous research [164, 165] showed that a delay before sharing content on social media could help people make wiser decisions on sharing information. We propose a prototype (see Figure 7.1) that may help people share information more balanced. The general design principle is to create a delay and give people more time to think about the information-sharing decision. For example, after people select an article to share, a window will pop up, reminding people that the topic (e.g., gun control) is polarizing and showing the attitude distribution of the recipient group. The system can learn group members' attitudes by conducting surveys or estimating their attitudes by analyzing their information-sharing history. We expect such a design to motivate people to think more about their information-sharing decision and better mitigate information polarization for the recipient group. In addition, the information selector may not perceive the majority's attitude if the recipient group is enormous. Our proposed design can solve this problem by explicitly showing people the attitude distribution of the recipient group. However, there is another possibility that explicitly showing attitude distribution of the recipient group may make it easier for people to cater to the majority's attitude when sharing information. Thus, future studies need to validate the effectiveness of such a design. However, regardless of the efficacy of such a design, studying how to design interfaces to motivate people to share diverse opinions on social media would be an exciting and promising future work.

7.2.6 Have a Better Social Media Ecosystem

Social media make our society more connected and make it easier for people to exchange information. However, most people believe social media negatively affects our community [3], and some doubt whether people should be so connected online [166]. These all indicate that we should have a better ecosystem on social media. We can improve the ecosystem of social media from various aspects. For example, privacy is one of the critical concerns of social media design [167]. A better social media system should focus more on users' privacy and adopt more sophisticated strategies to protect users' data. In addition, the click economy business model [168], which values the number of clicks and online traffic the content (e.g., advertisements, news articles, videos, etc.) can get, has thrived in the digital age. Even though such a business model may help to boom the online market and bring benefits to companies and consumers, some [168, 169] also indicated that the consequence of the click economy might be complicated with some potential negative effects. The click economy might encourage people to create low-quality but clickbait content [168] or even fake content [169]. We might need to upgrade or modify this business model to encourage people to produce high-quality content and better assure the profit of those high-quality content creators rather than the creators of low-quality work.

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APPENDIX A: STATISTICAL ANALYSES ABOUT ISI FOR THE SAA TEST CONDITION (EXCLUDING PARTICIPANTS WHO OPPOSED THE SAA TEST) (CHAPTER 6)

Table A.1: Descriptive statistics of participants for different attitude distributions of the recipient group (excluding participants who opposed the SAA test).

Attitude Distribution of the Recipient Group	Descriptive Statistics
Group 1 (75% Support, 25% Oppose)	$N = 37, M_{ISI} = 0.68, SD_{ISI} = 0.27$
Group 2 (50% Support, 50% Oppose)	$N = 32, M_{ISI} = 0.62, SD_{ISI} = 0.24$
Group 3 (25% Support, 75% Oppose)	$N = 39, M_{ISI} = 0.40, SD_{ISI} = 0.32$

Table A.2: Two-way ANOVA results on information sharing index for the SAA intelligence test (excluding participants who opposed the SAA test).

Source	df	MS	F	p	$\eta^2_{partial}$
Participants' Attitudes towards the SAA Test (A)	1	0.24	3.09	0.08	0.03
Attitude Distribution of the Recipient Group (B)	2	0.82	10.49	0.00***	0.17
A × B	2	0.06	0.71	0.50	0.01
Residuals	102	0.08			

Table A.3: Post-hoc analysis of the effect of attitude distributions of the recipient group on ISI (excluding participants who opposed the SAA test).

Comparisons	Statistical Significance
Group 1 vs. Group 2	p = 0.61
Group 1 vs. Group 3	**p <0.001**
Group 2 vs. Group 3	**p <0.01**

APPENDIX B: STATISTICAL ANALYSES ABOUT GAI FOR THE SAA TEST CONDITION (EXCLUDING PARTICIPANTS WHO OPPOSED THE SAA TEST) (CHAPTER 6)

Table B.1: Two-way ANOVA results on goal accomplishment index for the SAA intelligence test (excluding participants who opposed the SAA test).

Source	df	MS	F	p	$\eta^2_{partial}$
Participants' Attitudes towards the SAA Test (A)	1	1.89	2.18	0.14	0.02
Attitude Distribution of the Recipient Group (B)	2	1.06	1.22	0.30	0.02
A $\times$ B	2	0.08	0.10	0.91	0.00
Residuals	102	0.87			

APPENDIX C: STATISTICAL ANALYSES ABOUT ISI FOR THE STRICT GUN CONTROL LAW CONDITION (EXCLUDING NEUTRAL PARTICIPANTS) (CHAPTER 6)

Table C.1: Descriptive statistics of participants with different attitudes for different attitude distributions of the recipient group (excluding neutral participants).

Attitude Distribution of the Recipient Group	**Descriptive Statistics**
Group 1 (75% Support, 25% Oppose)	
Strict Gun Control Law Supporters	$N = 14, M_{ISI} = 0.66, SD_{ISI} = 0.20$
Strict Gun Control Law Opponents	$N = 16, M_{ISI} = 0.75, SD_{ISI} = 0.30$
Group 2 (50% Support, 50% Oppose)	
Strict Gun Control Law Supporters	$N = 23, M_{ISI} = 0.60, SD_{ISI} = 0.24$
Strict Gun Control Law Opponents	$N = 15, M_{ISI} = 0.34, SD_{ISI} = 0.21$
Group 3 (25% Support, 75% Oppose)	
Strict Gun Control Law Supporters	$N = 21, M_{ISI} = 0.54, SD_{ISI} = 0.26$
Strict Gun Control Law Opponents	$N = 13, M_{ISI} = 0.24, SD_{ISI} = 0.28$

Table C.2: Two-way ANOVA results on information sharing index for the strict gun control law (excluding neutral participants).

Source	df	MS	F	p	η^2
Participants' Attitudes towards the Strict Gun Control Law (A)	1	0.44	7.05	0.01**	0.10
Attitude Distribution of the Recipient Group (B)	2	0.78	12.52	0.00***	0.21
A × B	2	0.36	5.70	0.00**	0.11
Residuals	96	0.06			

Table C.3: Post-hoc analysis of the effect of attitude distributions of the recipient group on ISI for strict gun control law supporters and opponents, respectively.

Comparisons	**Statistical Significance**
Strict Gun Control Law Supporters	
Group 1 vs. Group 2 vs. Group 3	p = 0.34
Strict Gun Control Law Opponents	
Group 1 vs. Group 2 vs. Group 3	**p <0.001**

Table C.4: Post-hoc analysis of the effect of attitude distributions of the recipient group on ISI for strict gun control law opponents.

Comparisons	**Statistical Significance**
Group 1 vs. Group 2	**$p < 0.001$**
Group 1 vs. Group 3	**$p < 0.001$**
Group 2 vs. Group 3	$p = 0.59$

Table C.5: Post-hoc analysis of the effect of participants' attitudes towards the strict gun control law for different attitude distributions of the recipient group.

Comparisons	**Statistical Significance**
Group 1 (75% Support, 25% Oppose)	
Supporters vs. Opponents	$p = 0.34$
Group 2 (50% Support, 50% Oppose)	
Supporters vs. Opponents	**$p < 0.05/3$**
Group 3 (25% Support, 75% Oppose)	
Supporters vs. Opponents	**$p < 0.05/3$**

APPENDIX D: STATISTICAL ANALYSES ABOUT GAI FOR THE STRICT GUN CONTROL LAW CONDITION (EXCLUDING NEUTRAL PARTICIPANTS) (CHAPTER 6)

Table D.1: Two-way ANOVA results on goal accomplishment index for the strict gun control law (excluding participants who were neutral on the strict gun control law).

Source	df	MS	F	p	η^2
Participants' Attitudes towards the Strict Gun Control Law (A)	1	2.12	3.46	0.07	0.03
Attitude Distribution of the Recipient Group (B)	2	0.66	1.09	0.34	0.02
A $\times$ B	2	0.58	0.96	0.39	0.02
Residuals	96	0.61			