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Automating the News: How Personalized News Recommender System Design Choices Impact News Reception

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Abstract

This study investigates the impact of personalized news recommender system design on selective exposure, elaboration, and knowledge. Scholars have worried that proliferation of personalization technologies will degrade public opinion by isolating people from challenging perspectives. Informed by selective exposure research, this study examines personalized news recommender system designs using a communication mediation model. Recommender system design choices examined include computer-generated personalized recommendations, user customized recommendations, and full or limited news information environments based on recommendations. Results from an online mock election experiment with Ohio adult Internet users indicate increased selective exposure when using personalized news systems. However, portals recommending news based on explicit user customization result in significantly higher counter-attitudinal news exposure. Expected positive effects on elaboration and indirect effects on knowledge through elaboration are found only in personalized news recommender systems which display only recommended headlines. Lastly, personalized news recommender system use has a negative direct effect on knowledge.

Keywords: Internet news, personalization, selective exposure, news information processing, news knowledge

Automating the News: How Personalized News Recommender System Design Choices Impact News Reception

Internet users are interacting with personalized information systems every day. Web search results, social network site status updates, and web advertisements are all common examples of web content tailored individually for users based on a wealth of profile information gathered and managed by online content providers such a Google and Facebook (Parsier, 2011). Online news headlines are also frequently personalized based on geography, political preferences, and past user behavior. The diffusion of personalized news systems has public opinion scholars concerned that citizens will not be exposed to necessary information to make informed civic decisions (e.g., Sunstein, 2007). The ability to selectively filter information based on user preferences allows newsreaders to more easily ignore stories that they deem irrelevant or counter-attitudinal, thereby eroding editorial control of news information by traditional gatekeepers in the news industry. This study will test several personalization system designs in an experiment to examine their impact on political news exposure, political news processing and political knowledge.

Selective Exposure

Selective exposure research has a long history of demonstrating that people prefer to view information that supports their own perspective (e.g., Sears

& Friedman, 1967; Frey, 1986; Sweeney & Gruber, 1984; Garrett, 2009a, 2009b; Knobloch-Westerwick & Meng, 2009; Iyengar & Hahn, 2009; Hart et al. 2009; Stroud, 2010). The primary mechanism of selectively choosing information, cited widely in selective exposure research, is taken from Festinger's (1957, 1964) cognitive dissonance theory. This theory posits people are more likely to attend to information that is attitude-consistent rather than attitude-dissonant. Dissonant information will increase uncertainty and psychological discomfort, while attitude-consistent information will lead to reinforced confidence in pre-existing attitudes and decisions. Therefore, people are likely to selectively choose messages that confirm their perspective while filtering out messages that challenge their perspective.

However, recent empirical research has argued that selective exposure is not necessarily tied to selective avoidance (Garrett, 2009a; Brundidge, 2010; Hart et al., 2009). Brundidge (2010) argued selectivity could provide an easier path for people to engage in civic discourse. This increased engagement could then lead to inadvertent exposure to counter-attitudinal information. Garrett (2009a) showed that people using the Internet for election news were more likely to view stories favoring their candidate but also show knowledge gains for both pro-attitudinal and counter-attitudinal candidates. In a meta-analysis of selective exposure research Hart et al. (2009) found support for increased selective exposure to pro-attitudinal compared with counter-attitudinal information. However, they found counter-attitudinal information was more likely to be selected and processed when people were highly motivated to accomplish a goal judged as important and relevant. In sum, selective exposure may actually provide a path to engage in counter-attitudinal information acquisition rather than counter-attitudinal avoidance.

Cognitive Mediation

This paper will investigate information processing and knowledge outcomes in varying personalized news environments utilizing an O-S-R-O-R communication mediation model of indirect media effects on learning (Cho et al., 2009; McCloud, Kosicki, & McCloud, 2009). Specifically, reception orientation (O1), such as the degree of information system personalization use should be positively related to selective exposure to a message (S), internal reasoning (R1) and outcome orientations (O2), and response (R2). The O-S-R-O-R model (Cho et al.) expands the O-S-O-R communication mediation model (Markus & Zajonc, 1985, McCloud, Kosicki, & McCloud, 2002) by adding reasoning (R1) as a mediator between information exposure and outcome orientations and response. This added mediator is consistent with the cognitive mediation model (Eveland, 2001; Eveland, Shash, & Kwak, 2003). When a person is motivated to acquire information for a specific purpose, such as making a vote choice, she will be more likely to have increased cognitive elaboration, or internal deliberation, about news information related to that goal. Therefore, increased cognitive elaboration should mediate gains in topical knowledge by use of personalized news systems.

Information Processing

Dual-process theories from cognitive psychology offer detailed mechanisms for understanding elaboration and modeling information processing (e.g., Petty & Cacioppo, 1986; Chaiken, 1987). These models broadly comprise a thoughtful centrally processing route or heuristically processing peripheral route for information (e.g., Chaiken & Trope, 1999; Kahneman, 2011). The central processing route requires cognitive resources for elaborative internal deliberation of information when forming an attitude or making a decision. The peripheral processing route occurs when a person minimizes the amount of cognitive effort to form an attitude or make a decision. These theories broadly state elaborative central processing is most likely to occur when high motivation and ability to thoughtfully process information are both present. Higher elaboration is generally preferred when evaluating the quality of an outcome decision because systematically processed messages tend to be more stable over time (Eagly & Chaiken, 1993). Also, higher elaboration has been demonstrated as a key mediator leading to learning, or knowledge gain, for people viewing online news (Eveland, Marton, & Seo, 2004; Cho et al., 2009). Crafting messages that are personally relevant to message receivers is a strategy often used to boost motivation and ability to process information.

Personalized Information Systems

Personalized information systems are made possible by the mass diffusion of digital technology. Economic and technological constraints of mass production in the broadcast and print news media constrained media producers to creating a single message to be distributed on any given channel to viewers. In digital media, content information can be stored in a database, allowing users to access or be presented different messages based on software algorithms. This allows for mass messages to be cheaply and easily personalized to the information consumer based on that user's preferences and profile information. Research has demonstrated personalizing messages could be more effective at engaging and persuading an audience compared with generic mass messages (Rimer & Kreuter, 2006; Roberto, Krieger, & Beam, 2009). Indeed, digital technology, and the Internet in particular, has seen businesses effectively personalize advertisements and messages in a multi-billion dollar digital content industry (MacMillian, 2010; Pariser, 2011). Despite a large literature articulating the relationship between the news information environment and public opinion, little empirical work has yet to focus on information processing and reception in personalized news environments.

Personalization and customization. Personalization and customization are closely linked concepts. The terms have been used synonymously in some studies, but others keep them conceptually distinct. In health communication research, personalization is often referred to as information tailored to a specific information consumer (e.g., Skinner et al., 1999). In marketing research, personalization is often referred to as a product or message changed in regards to a specific customer (e.g., Wind & Rangaswamy, 2001; Vesanen, 2007). Customization, in marketing research, is often defined as when the user is explicitly involved in the process of changing the product (Vesanan, 2007). This distinction is useful when distinguishing between types of tailoring in communication (see also Sundar & Marathe, 2010). This paper will adopt Blom's (2000, see also Blom & Monk, 2003) conceptualization of personalization as a higher order concept in relation to customization. That is, *personalization* occurs in an information system modified to closely align with the preferences of a user. *Customization* defines the amount user involvement in the process of personalizing the system. Customization is the degree to which a user explicitly interacts in the personalization process. A "customized recommender system" refers to a personalized system with high customization or explicit user input determining recommendation rules. A "computer-generated recommender system" refers to a personalized system with no customization.

Computer-generated personalized recommender systems, like Google News, Amazon.com, iTunes, Google's search engine or Google AdSense, use profile and behavioral data collected implicitly from the user without user input into the recommendations (Parsier, 2011). On the other hand, customized recommender systems, such as Feedly or Google Reader, have high levels of customization including allowing users to specify specific sources and topics of news. People interact with computer-generated and customized recommender systems such as these examples every day. In 2009, about half of Internet users accessed personalized web portals, which use personalized information to display a starting point for links and content on the web (Rainie, 2009). In fact, in the 2008 election, over 20% of online political information users under 65 and 32% of online political information users under 30 utilized personalized political information (Smith, 2009).

Personalized news systems are inherently selective. When recommendations are given to users, they should be more likely to engage in that content. Based on previous studies demonstrating users prefer to selectively choose content that more closely matches with their previously held attitudes and beliefs,

H1a: People using personalized news recommender systems will be less likely to be exposed to news headlines from counter-attitudinal sources

H1b: People using personalized news recommender systems will be less likely to be exposed to news stories from counter-attitudinal sources

Past studies have demonstrated personalized information systems increase users' perceived relevance, involvement, engagement, and positive attitudes about message content compared to generic messages (Beam & Kosicki, in press; Sundar & Marathe, 2010; Kalyanaraman & Sundar, 2006). As outlined earlier, dual-processing theories predict higher elaboration will occur when messages are more personally relevant. People using personalized systems should demonstrate increased content elaboration through increasing the motivation of the user to engage with personalized content.

Compared with a generic information system, personalized systems also reduce the amount of cognitive surveillance effort required to select personally relevant stories, which increases the cognitive capacity available for a user to process the content by reducing cognitive load. Indeed, Kalyanaraman and Sundar (2006) argued that users spend more time with recommended stories in a personalized condition because they are more likely to centrally process that information. In generic information portals, users have less motivation and ability to process the message content and are more likely to peripherally process that information. Research also demonstrated that users are more likely to spend more time with and centrally process attitude-consistent stories compared with counter-attitudinal stories (Knobloch-Westerwick & Meng, 2009). Therefore,

H2: People using personalized news recommender systems will show higher elaboration on news stories

Users who engage more fully in news content should also be more likely to also elaborate on counter-attitudinal information that is inadvertently included in selectively chosen news stories (Garrett, 2009a). Selective exposure research has arrived at competing conclusions about overall knowledge gain when selecting information, depending on selective approach and selective avoidance motivations (Beam & Kosicki, in press; Hart et al., 2009; Garrett, 2009a). It is unclear whether using selective personalization technologies will result in greater overall knowledge gain compared to using general information technologies. Lastly, in the cognitive mediation model, higher elaboration predicts greater content knowledge (Eveland, 2001). Therefore, an indirect effect of increased content knowledge indirectly through higher elaboration should occur when using a personalized information system. Based on the previously discussed theory and research, several differences between generic and more personalized web news systems in an online experiment can be expected. Therefore,

RQ1: Does using a personalized news recommender system have a direct effect on news knowledge?

H3: Using a personalized news recommender system will have a positive indirect effect on news knowledge through news elaboration.

Recommender system design. This study will manipulate two distinct dimensions of personalized news recommender systems. First, the source of the recommendations will be varied between implicitly computer-generated personalized recommendations or user-generated customized recommendations. That is, computer-generated personalized recommendations based on user profile information will be compared to customized news story recommendations with explicit user input. Next, the amount of information displayed in the recommender system will be varied. That is, in a limited information recommender system only the recommended news stories will be displayed compared to a full information recommender system displaying all news stories, both recommended and not.

As mentioned earlier, personalized news systems will allow for various levels of customization. In computer-generated personalized news recommender systems, implicit algorithms will generate news headlines utilizing the user profile information such as geographic location and news reading behaviors. In customized recommender systems with user input, a newsreader can explicitly control the recommendation algorithm by selecting sources and topics of news to view. For example, she might choose top headlines from the national online newspaper The New York Times, her local newspaper, and headlines from a popular political blog, Red State. The system would then generate headlines from these specific sources.

The amount of information available to the user is another design choice manipulated in this study. Some systems, such as popular news aggregator sites like Reddit.com and Digg.com, allow for users to access all available content while highlighting recommended content. In these systems, the more highly rated or recommended stories are moved to a more prominent place on the website.

Other news aggregator sites, such as Feedly, Newsblur, or Google Reader, can be setup to *only* display recommended stories to users. In these cases, the users do not have access to the non-recommended news stories.

There is little published research that investigates the impact of these design choices on information processing and reception. Therefore, this study will investigate a series of research questions comparing personalized system design choices on the process of information exposure and reception outlined earlier.

RQ2a: Does personalized news recommender system design influence exposure to news headlines from counter-attitudinal sources?

RQ2b: Does personalized news recommender system design influence exposure to news stories from counter-attitudinal sources?

RQ3: Does personalized news recommender system design influence news elaboration?

RQ4: Does personalized news recommender system design influence news knowledge?

RQ5: Does personalized news recommender system design influence indirect effects of news knowledge through elaboration?

Method

Data in this experiment were collected from a convenience sample of 490 Ohio adult Internet users who agreed to participate in the mock gubernatorial election. Participants were recruited from an online panel managed by Survey

Sampling International (SSI), a leading firm known for its expertise in survey sampling. Participants in SSI's online panel agree to a standard set of rewards for participating in qualified studies, including this online experiment. Members of the opt-in panel receive standard arranged rewards for participating including being entered into raffle drawings and receiving points, which can be redeemed for prizes or money.

Procedure

Participants were randomly assigned to one of five experimental conditions described in detail below. Participants in all conditions were asked an identical series of pre-news viewing questions. Immediately before viewing the election news page, participants viewed an informational web site describing the election news page and news sources. Participants viewed between 2 and 6 news stories on their election news page. Participants spent between a minimum 3.5 and maximum 7 minutes on the election news page. After leaving the election news page, participants in all conditions were asked a series of identical post-news questions.

Mock election. Participants were asked to participate in an online Ohio mock gubernatorial election. Content for the mock election was gathered from the 2010 Wisconsin gubernatorial election. Wisconsin was chosen because it is a nearby Midwest state. This election had no incumbent running for office. Both candidates had previous political experience. The Democratic candidate, Tom

Barrett, was the mayor of Milwaukee, the largest city in Wisconsin. The Republican candidate, Scott Walker, was the Milwaukee county executive. Similar to Ohio's 2010 gubernatorial election, the Republican candidate was challenging to win the election after a Democratic governor, Jim Doyle, controlled the office for the preceding term. Like Ohio, the state's top issue in the election was economic policy due to a high rate of unemployment and economic recession.

Both states eventually elected the Republican candidate in the 2010 election, resulting in a controversial reduction in power of public employee unions. While these state employee issues garnered considerable press coverage after the legislation was passed in 2011, there was little debate during the gubernatorial election and subsequent election news focused on these issues. Therefore, it was unlikely that Ohio participants will recognize Wisconsin gubernatorial election coverage with changed names. A manipulation check detailed below confirmed participants did not recognize the original source of the news.

Candidate's names were changed in the mock election news stories to Democratic candidate "Walter Smith, former Cleveland Mayor" and Republican candidate "George Williams, Cuyahoga County Executive." Both candidates hold their party's stances on economic policy: Smith supports keeping current tax levels to help reign in the statewide deficit while Williams supports cutting taxes across the board and more drastically slashing state programs that he claimed would stimulate the economy.

Election news stories. Mock election news coverage focused on different aspects of a debate between candidates. Four real-world mainstream print news stories were selected and modified. Each story contained information about both candidates and were similar in length. Additionally, the, The Associated Press, a non-partisan wire service, published all the stories. Each article contains several quotes from both candidates supporting their side and attacking their opponent. Each article discusses the candidates' fiscal policy, the central policy debate in the campaign. Stories were modified to reflect the fictitious candidate names. Names of cities were changed to reflect the state of Ohio. Lastly, each of the stories was modified so they were purportedly covering the second debate and an undated election.

In addition to the four news stories, two political blog posts were selected to feature a non-partisan editorial stance on the debates. One blog post argues the debate "was not a debate" because it did not cover new ground and "most of the talking points I'd heard before." The second blog post argues, despite "genuine and substantial differences between the two candidates," their campaigns are tarnished by negative and untruthful claims.

Source effects. The key personalization and information manipulations in this experiment vary the sources of news recommended and available to participants. Scholarship on selective exposure has demonstrated an increase in polarized news sources affects the way news consumers select, evaluate, and process news information (e.g., Bennett & Iyengar, 2008; Iyengar, Hahn, Krosnick, & Walker, 2008; Iyengar & Hahn, 2009,). Therefore, to avoid confounded information effects and source effects, the four mainstream news stories were randomly displayed under the recommended sources. The two editorial political blog posts were also randomly distributed between the two recommended news blog sources.

The mock election consisted of an information universe of 6 news sources. There are two mainstream news source types represented: newspapers and cable news networks. Lastly, two blog sources are also represented. For each of the news source types there was a left-leaning and right-leaning option, resulting in 6 total sources. The two newspaper source options available included a liberal-leaning local paper (The Cleveland Plain-Dealer) and a conservative-leaning local paper (The Cincinnati Enquirer). Two cable news network news feeds were available: the conservative Fox News service and the liberal MSNBC service. Lastly, a liberal blog, the Daily Kos, and a conservative blog, RedState, were used.

Pre-News Viewing Variables

*Screening questions***.** Participants were first screened with questions confirming that they are residents of Ohio over the age of 18.

Media use. Participants were asked a series of questions about their media use. These questions were used to create a recommendation profile for participants in the computer-generated recommender conditions. Users answered questions about the frequency they viewed online and offline newspapers, cable news and cable news websites, and news blogs.

Political variables. Participants were then asked a series of questions about their personal political views including their political party affiliation and political party preference, political ideology and political news interest.

Experimental Conditions

Participants were randomly assigned to one of five conditions. The first condition is a generic news page condition (*N* = 101). The four experimental personalized news system conditions were comprised of a 2x2 design manipulating customized or computer-generated recommendations and recommended stories only or all stories. The four personalized news system conditions are as follows: 1) computer-generated news recommendations and all 6 news stories (*N* = 96); 2) customized news recommendations, and all 6 news stories (*N* = 90); 3) computer-generated news recommendations and recommended stories only (*N* = 103); and 4) customized news recommendations and recommended stories only (*N* = 100). Figure 1 illustrates different experimental manipulations to the personalized news portal pages described in detail below.

[Figure 1 Here]

Control condition. First, participants randomly assigned to the non-personalized, generic news page were used as a control group. These participants had access to headlines from all 6 news sources. There was no indication that any of the news stories were recommended to them.

Computer-generated recommendations. Participants in the computer-generated recommender conditions received recommended news sources that shared their political party affiliation or political ideology. That is, self-identified Republicans or conservative participants were recommended stories from *The Columbus Dispatch, Fox News,* or *RedState.* The self-identified Democratic or more liberal participants were recommended stories from *The Cleveland Plain-Dealer, MSNBC,* or *Daily Kos*. If participants did not indicate any party affiliation preference, sources were recommended based on political ideology. Next, participants were recommended news sources from specific media types based on their current news consumption habits. That is, participants who said they never read newspapers online or offline were not recommended a newspaper source, while those who indicated they read a newspaper were recommended a newspaper source. Participants who selected a party affiliation or political ideology but reported viewing all the news media types as “never,” were recommended their ideologically similar newspaper and cable news sources. All participants in the personalized conditions were recommended a minimum of 2 sources.

Participants in the machine-based recommended conditions who did not report any ideological preference and do not affiliate with either political party were recommended both sources of the news media they prefer. If these participants did not indicate they view any media types, then both liberal and conservative newspaper sources were recommended. The full code for the recommendation algorithm can be found in Appendix 1 posted online at http://mabeam.net/research/a5. Descriptive statistics for the number of recommendations are presented in table 1.

[Table 1 here]

Customized recommendations. Participants randomly assigned to the explicit user customized recommender conditions were able to select their preferred news sources from the list of news sources and news types before entering the news page. Participants were asked to choose 2 news sources at a minimum and may have chosen any number of sources up to the full 6 sources available. Descriptive statistics for the number of recommendations are presented in table 1. Further descriptive statistics showing partisanship, media source headlines, and stories viewed can be found in Appendix 2 posted online at http://mabeam.net/research/a5.

Recommended stories. Participants in the recommended-all conditions viewed a personalized news page with of all six sources of news. The recommended sources of news recommended were placed towards the top of the list with blue headlines and a star. Non-recommended stories appeared in black. Participants in the recommended-only conditions only had access to their recommended sources of news. Again, these sources displayed blue headlines and were starred to indicate they are recommended by the personalized recommendation system.

Pre-News Viewing Information

Following the pre-news viewing questions, participants viewed a page describing their election news page. First, participants were asked to pay careful attention to the news page containing stories about a gubernatorial election. They were told they would be asked to vote after they viewed the news. Participants in the generic news system were told they would be viewing 6 sources of news coming from a variety of news companies. Participants in the computer-generated recommender conditions were told their personalized news system will contain # sources of news coming from a variety of news companies. Participants in the customized recommender conditions were asked to select their preferred sources from a list of sources coming from a variety of news companies. They were told they must choose at least 2 sources and may choose all 6.

All participants were then given a list of the sources they were about to view. Participants received the media company's name (e.g., Daily Kos), media type (e.g., News Blog), and political perspective (e.g., Strongly Liberal). Each newspaper was labeled as "slightly" partisan, each cable news channel was labeled as partisan and each blog source was labeled as “strongly” partisan. Partisanship was also labeled with one, two, or three Republican Party logos, for conservative media outlets, or one, two or three Democratic Party logos, for the liberal media outlets. Again, see Figure 1 for example pages.

Election News System

Participants were required to stay in the election news system for 3.5 to 7 minutes. Instructions at the top of the page read, “Please spend a few minutes reading the news stories below about the Ohio election for governor. To view a story, click on the news headline.” Users in personalized conditions also saw instructions at the top of the page that read, “Stories recommended to you are denoted with a star (★) and the headlines are blue, while other stories headlines are black.” At the bottom of the page, instructions read, “After a few minutes of reading the news stories above, you will see a link appear just below this text. When clicked, this link will allow you to proceed to make your vote.” Participants were told they could view the news page for a maximum of 7 minutes before being asked to vote in the mock election.

News source logos were placed just above news headlines. When a participant clicked on the news source logo or the news headline, the news story content would appear below the headline. When a participant clicked on a different news source logo or news headline, the previous story would disappear and the new news story would appear under its' news headline. Again, see Figure 1 for example news portal screenshots.

Election news system variables. The election news system unobtrusively tracked the number of counter-attitudinal source headlines displayed and stories viewed.

Post-News Viewing Variables

Vote choice. After viewing the election news page, participants were first asked to participate in the mock election by voting. These measures are not used in the analyses.

News elaboration. A validated 12-item elaboration scale (Reynolds, 1997) asked participants a series of questions with the prompt "While reading the news items were you:" Examples of items include "Doing your best to think about what was written," "Not very attentive to the ideas," "Deep in thought about the message." The scale was coded on from "Strongly Disagree" (1) to "Strongly Agree" (5). An average of a balanced number of 6 positively coded and 6 reverse-coded items were computed for an overall elaboration score where a low score represents low elaboration and a high score represents high elaboration (M = 3.65, SD = .56, N = 490, α = .87).

Knowledge. Participants were asked a series of 6 questions about the candidate's positions to test their knowledge of the election news. Response options for these questions included George Williams, Walter Smith, both candidates, or neither candidate. The participants were asked which candidate supports cutting taxes (Williams), increasing education spending (neither), funding stem cell research (Smith), shares the same party as the incumbent (Smith), proposes cutting government spending (Williams), and says he will create jobs (both). The total number of correct answers was calculated to generate a score from 0 through 6 ($M = 2.57$, $SD = 1.53$, $N = 490$).

Manipulation Check Variables

Participants were asked a series of Likert-scale statements to verify the manipulations were effective. The questions asked if participants felt like the news sources "were recommended for me, individually," if they had input into the news source recommendations, and if they only saw recommended news sources. Lastly, participants were asked, "If this were a real-world election for governor, where would it be from?" No participants accurately identified Wisconsin as the state where the election news originated. Participants responded with incorrect states including Ohio, California, Florida, Texas, and Kentucky.

Control Variables

Internet skill. Skill using Internet technology has been demonstrated as an important predictor of online user behavior (e.g., DiMaggio, Hargittai, Celeste, Shafer, 2004; Hargittai, 2010). A 10-item Internet skill measurement was measured as a control variable in the analyses (Hargittai & Hsieh, 2012). Participants were asked to respond on a scale from 1-5 for each item where 1 represented “no understanding” and 5 represented “full understanding” (M = 3.13, SD = 1.13, N = 490, α=.94).

[Table 2 here]

Demographics. A series of demographic questions are used for both descriptive purposes and as control variables in analyses. The ages of the Ohio adult participants in this study ranged from 18-85 years old (M = 45.65, SD = 14.84). Table 2 shows the descriptive results and a comparison of the sample compared with the population of Ohio.

Analysis Plan

This study utilized a series of OLS regression models to test the hypotheses and research questions. Cases with missing values were omitted from the analyses. Conditions were coded with binary dummy variables using the control group as a reference.

As mentioned above, the models also tested the indirect effect of using personalized news systems through increased elaboration on knowledge. An indirect effect, often called mediation, can be quantified by taking the product of the coefficients of the indirect paths from the predictor variable to the mediator variable and from the mediator variable to the outcome variable. When this indirect effect is added to the direct effect of the predictor variable on the outcome variable in the same model, the total effect of the predictor variable on the outcome variable can be specifically quantified (Hayes, 2009). This analysis utilized the MEDIATE macro created by Hayes & Preacher (2013), which quantifies indirect effects and provides confidence intervals using a bootstrap method. Lastly, sample size analysis confirmed this sample was sufficient to conduct mediation analysis ($N > 437$). This was calculated using the *R* package *powerMediation*, which conducts mediation sample size calculations based on Vittinghoff and his colleagues' (2009) formulas (Qiu, 2013).

Results

Manipulation Checks

A series of independent groups *t*-tests were conducted to verify expected differences in the news viewing experience based on the experimental manipulations. As expected, participants in the personalized news systems (M = 3.16, SD = .99) were more likely than those in the generic news systems (M = 2.79, SD = .89) to agree with the statement, "The news sources I viewed were recommended for me, individually," $t(170) = -3.65$ (Welch-Satterthwaite), $p < .001$. Participants in the user customized news systems (M = 3.17, SD = 1.07) were more likely than those in non-customized systems (M = 2.79, SD = .93) to agree with the statement, "I had input into the news sources that were recommended to me," $t(359) = -4.125$ (Welch-Satterthwaite), $p < .001$. Lastly, the participants in the news systems with only recommended sources visible (M = 3.20, SD = .92) were significantly more likely than participants who viewed all news sources (M = 2.83, SD = 1.01) to agree with the statement, "I only saw news stories from sources recommended for me, individually," $t(447) = -4.18$ (Welch-Satterthwaite), $p < .001$. These results confirm the expectations of the experimental manipulations.

Analyses

The first two columns in table 3 show the OLS regression models predicting counter-attitudinal headlines and counter-attitudinal clicks from the personalized news system conditions, using the generic news condition as a reference group. As predicted, personalized news system use significantly reduced the display of news headlines from counter-attitudinal sources, $b = -.298$, $t(457) = -2.59$, $p < .05$. H1a is supported. Recommended-only news system design further reduced the number of news headlines from counter-attitudinal sources, $b = -2.21$, $t(457) = -25.13$, $p < .05$. However, customized recommender system design was related to seeing more news headlines from counter-attitudinal sources compared to computer-generated recommendations, $b = .37$, $t(457) = 4.16$, $p < .05$. These results indicate differences between recommender system design choices (RQ2a). Interestingly, this model also indicated both Republican and Democratic partisans are more likely to view more counter-attitudinal stories than those not affiliated with a party.

[Table 3 here]

Personalized news systems also significantly reduced the number of news stories viewed from counter-attitudinal sources, $b = -.57$, $t(457) = -4.41$, $p < .05$.

H1b is supported. Again, there were also significant differences between the personalized news system designs. Recommended-only news systems resulted in an additional reduction in views of news stories from counter-attitudinal news sources, $b = -1.02$, $t(457) = -10.30$, $p < .05$. Customized news recommender system design resulted in increased news story views from counter-attitudinal sources compared to computer-generated recommendations, $b = .32$, $t(457) = 3.22$, $p < .05$. These results show differences between recommender system designs (RQ2b). Again, Republican and Democratic partisans were more likely to click on counter-attitudinal stories compared with those not affiliated with major parties. Increased income was also a significant predictor of additional counter-attitudinal story viewing.

The third column in table 3 shows the OLS regression model predicting news elaboration from personalized news system conditions, using the generic news system control group as a reference group. There was no significant increase in elaboration for personalized news systems, $b = .06$, $t(455) = .91$, $p = .36$. However, using personalized news systems with the recommended-only design resulted in significantly increased elaboration, $b = .24$, $t(255) = 2.91$, $p < .05$. Customized news system design did not impact elaboration, $b = -.05$, $t(455) = -.92$, $p = .36$. While these results do not show support for H2, a significant increase in elaboration for recommended-only system design indicates conditional support in the predicted direction. This indicates that system design does matter when promoting elaboration (RQ3). The model also showed higher counter-attitudinal headlines, participant internet skill, education and being female resulted in significantly higher elaboration. Minority status and political interest were negatively related to elaboration.

The fourth column in table 3 shows the OLS regression model predicting candidate knowledge from elaboration. As predicted, higher elaboration was significantly related to higher candidate knowledge, $b = .75$, $t(454) = 5.75$, $p < .05$. H3 is confirmed. Users in the personalized news recommender systems reported significantly lower candidate knowledge, $b = -.50$, $t(454) = -2.56$, $p < .05$. However, no differences in system design choices provided significant levels of candidate knowledge (RQ4). Therefore, results show personalized system use has negative direct effects on knowledge (RQ1). Additionally, participant Internet skill level was positively related to candidate knowledge. Minority status and politically liberal ideology has a negative relationship to candidate knowledge.

[Table 4 here]

Lastly, the results of testing indirect effects on knowledge from news system design through elaboration are available in table 4. There was no indirect effect on knowledge when using personalized news systems through elaboration, as the bootstrapped confidence interval contains 0. H4 is not supported. However, there were specific positive indirect effects found from recommended-only news system design on knowledge through elaboration, as the bootstrapped confidence intervals were greater than 0. This result indicates personalized system design choice does matter. Limiting content to only the recommended stories is related to a positive indirect effect on increased knowledge through elaboration (RQ5).

Discussion

Personalized messages and information systems are proliferating throughout the communication industries. Public opinion scholars have worried that increased selectivity and automated personalization system use may lead to a more fragmented electorate (Sunstein, 2007, Prior 2007, Parsier, 2011). This research contributes to our understanding of selective information systems made possible by the Internet and the expanding wealth of personal information accrued by content providers by providing empirical results.

The goal of this study was to contribute to our understanding of the impact of personalized news system design on news information processing and news reception. The experimental design specifically focused on information processing and news reception differences between news recommender system designs. Theoretically informed by the O-S-R-O-R mediation model and dual-processing theories of information, personalized news systems were expected to influence news processing and reception. A key contribution of this study is demonstrating that specific design choices of personalized information systems have differential impacts on news processing and reception.

As predicted, personalized news systems were related to selectivity both in the news headlines displayed and the news stories viewed. However, when users explicitly customized their news recommendations, they viewed significantly more counter-attitudinal headlines and stories. This is unsurprising given the computer-generated recommendations algorithm was informed by the users' political preferences. However, this indicates that computer-generated recommendation algorithms would better align with users' preferences by displaying some counter-attitudinal news sources. It is also a hopeful sign for people worried that personalization fosters total ignorance of counter-attitudinal viewpoints. While these results confirm previous selective exposure research studies that show users will more often choose news stories that align with their own preferences (Garrett, 2009a; Knobloch-Westerwick & Meng, 2009), results also indicated that users do also choose to see some counter-attitudinal news sources when choosing for themselves. These results also confirm research showing specific design attributes of personalized recommender systems are important when evaluating their impact on a user's experience (Sundar & Marathe, 2010).

Contrary to expectations, personalized news did not increase news elaboration or show specific indirect effects on knowledge gain. Elaboration was a strong predictor of knowledge gain, as expected based on previous dual-processing theories of information. However, personalized news systems usage had negative direct effects on knowledge gain. These results confirm that scholars worried about negative consequences of using personalized news systems are founded (Sunstein, 2007; Parsier, 2011).

However, a more nuanced look at the results indicates that personalized recommender system design choices matter. News systems that only displayed the recommended stories led to higher elaboration and positive indirect effects on knowledge gain through increased elaboration. This shows that news recommender system designers may be better served to limit the amount of information displayed to their users when trying to promote careful attention to the content. This result confirms an expected increase in elaboration guided by dual-process theories of information for this personalized news system design (e.g., Chaiken & Trope, 1999; Petty & Cacioppo, 1986).

Taken together, these findings also confirm Parsier's (2011) sentiment that not all personalized systems lead to similar effects. Indeed, he argued that research should compare different personalized design choices to help inform system designers on how to optimize systems with pro-social benefits and alleviate rampant polarization envisioned by Sunstein (2007). This experiment succeeded in providing this guidance about specific design choices.

Strengths and Limitations

This experimental study was conducted with a sample of Ohio adult online panel members viewing news in different information systems. Compared to undergraduate subjects often used in social science experiments, these volunteer respondents better matched the demographic diversity of Ohio adults. While the study lacked the strict control found in a traditional laboratory experiment, it did confront real people with experimental stimuli in a natural online environment. Therefore, while not meeting the formal requirements to be representative of and generalizable to the population, the results here offer a number of benefits compared with traditional laboratory experiments. Participants were randomly assigned to their news system conditions and this study does indicate evidence for changes in news information processing and reception through specific personalized news recommender system designs.

This study examined a short news cycle in an artificial mock gubernatorial election. This evidence indicates the relationship between specific personalized design choices on elaboration is worthy of further study. The proposed theoretical model relies on increased motivation through increased personal relevance created by personalized filters. It is possible that motivation remained low in this study due to the artificiality of the mock election task. The cognitive mediation model (Eveland, 2001) specifies that goal-oriented use of information is likely to increase elaboration and knowledge. Therefore, one might expect more pronounced effects would exist in a real-world personalized election news portal.

On the other hand, news in an externally valid environment is considerably messier than in this controlled experiment. This experiment utilized a relatively small information universe: only a maximum of 6 news stories were displayed to users in the mock election. In most of the popular personalized news portals, election news would be presented side-by-side with other news categories such as entertainment and local news. In a real world environment, newsreaders may more easily tune out of election news altogether. Newsreaders may also be less apt to elaborate and study election news in this context. Or, additional environmental factors may minimize the effect of personalized and customized information. Furthermore, this study enforced a minimum and maximum time limit for users to spend in the information portal. In the real world participants may spend more time than allotted to elaborate on news information. However, this experiment was designed to specifically study the impact of personalization and customization in a particular decision-making context. The experiment was not designed to test the impact of personalized news portals on selecting news stories relevant to public opinion decisions in a real-world news environment comprised of news less relevant to the public sphere and unlimited time constraints.

Future Research

Evidence provided in this study indicates future research should focus on specific design choices when investigating personalized systems (see also Sundar & Marathe, 2010). The outcomes of how filtering technologies impact the public sphere may be shaped, in large part, by the design choices of popular personalized system designers (Pariser, 2011). Web portal designers would benefit from collaborating on future personalization research in order to create personalization systems that meet stated design goals as well as promote a positive user experience and positive democratic outcomes.

The personalized portal software developed for the experiment presented in this study or packages similar to it can be useful for future research. Due to the fact that this study was in a small controlled information environment, results should be replicated and tested in an externally valid environment to provide confirmation of the findings. For example, in a future real-world election, real news stories could be piped in to various recommender system conditions to test differences in portal use over-time with participants. Modifying the recommendation algorithm logic in the system to promote specific outcomes could further test implicit computer-generated recommendations. For example, collaboration with information-based researchers focused on diversity-promoting algorithms could provide fruitful insight into attitudes and behaviors of users (e.g., Munson, Zhou, & Resnick, 2009).

There were several significant socio-demographic controls that predicted counter-attitudinal information exposure, elaboration, and knowledge. While this study did not address these controls as theoretical predictors of the dependent variables, the findings suggest that those aligned with political parties are more likely to survey counter-attitudinal news sources. Also, these results point to

Internet skill as an important predictor of information processing in online news. In sum, personalized system designers may want to further optimize their algorithms based on these socio-demographic characteristics. Future research could replicate these findings in a theoretical context to help better our understanding of personalized systems.

Lastly, an expansion of this research should focus on the rapidly expanding importance of social recommendations. Research has demonstrated that the “bandwagon-heuristic” of popular stories viewed and recommended by others is a significant predictor news exposure (e.g., Sundar, Knobloch-Westerwick, Hastall, 2006; Knobloch-Westerwick, Sharma, Hansen, & Alter, 2005). Popular personalized web portals like Google Reader, Twitter, and Facebook integrate social network contacts as recommenders of news alongside computer-generated or explicit user customized recommendations. Continued research should focus on the expanding world of popularly used recommendation options as well as strive to contribute to system designers’ understanding of new recommendation options.

Conclusion

Staggering numbers of Internet users are relying on personalized information to make important health, political, and behavioral decisions. Often, users are not made aware that information presented is being personalized and targeted to them individually. While content providers and campaigns are investing resources in personalized communication, research should continue to focus on the evolution of these technologies to help understand their impact on the modern world. Empirical results testing theory are needed to help us understand positive and negative consequences of the evolution of information distribution systems. Ultimately, these results can help inform designers on how to minimize negative consequences and maximize positive consequences in their deployed systems. This project contributes to this goal by beginning to parse the impact of personalized news system use on information processing and reception.

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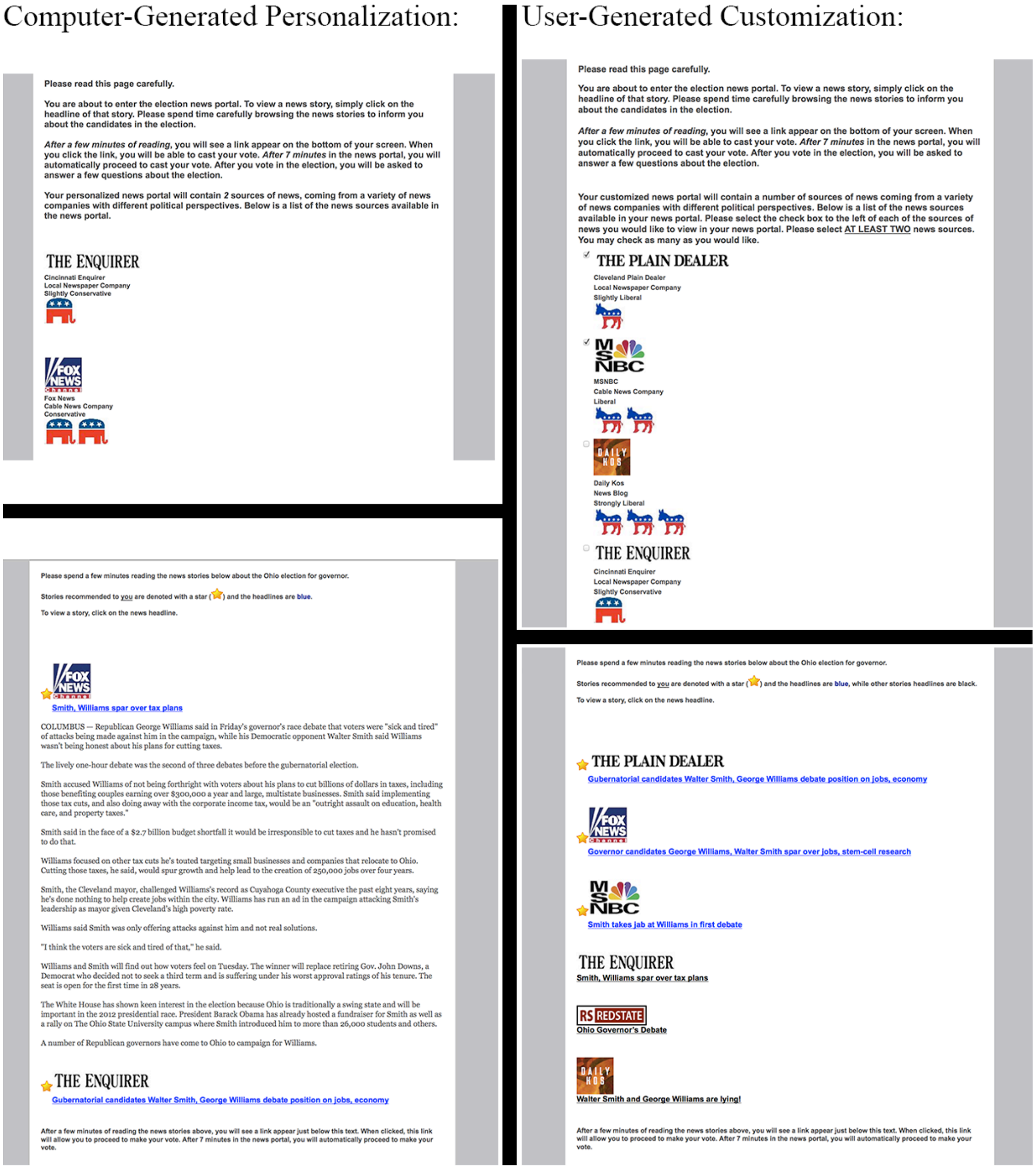

Figure 1. Example experimental portal page layout. Users in the computer-generated personalized conditions (left) are automatically generated recommendations while users in the user-generated customized conditions (right) select their preferred sources by checking the box to the left of the source on the pre-message page (top). Users can view a single story at a time by clicking on the headline located under the source on the message page (bottom).

Table 1.

Number of Recommendations by Experimental Condition

Condition	Mean Recommendations	*SD*	*N*
Computer-generated Recommendations / All Stories	2.90	1.11	96
Customized Recommendations/ All Stories	2.24	.567	90
Computer-generated Recommendations / Recommended Stories Only	2.71	.775	103
Customized Recommendations / Recommended Stories Only	2.27	.694	100
Total	2.53	.787	389

Table 2.

Experimental Demographic and Ohio Demographic Summaries

Variable	Experiment	Ohio
Sex: Female[a]	52.1%	51.2%
Age[b]	47	38.8
Hispanic[a]	1.6%	3.1%
Race: White[a]	83.1%	87.2%
Race: African-American/Black[a]	13.8%	12.2%
Race: Asian American/Asian[a]	0.8%	0%
Race: Native American[a]	1.8%	0.2%
Race: Other[a]	1.4%	2.1%
Education[b]	Some College	Some College
Income[b]	30-under $40k	$45,467

Note: Ohio data based on 2010 Ohio Census Results.
[a] Proportion
[b] Median

Table 3.

OLS Regression Models [a]

	Counter-attitudinal Headlines	Counter-attitudinal Story Views	Elaboration	Knowledge
Personalized News Systems[b]	-.298* (.115)	-.568*** (.129)	.064 (.070)	-.499* (.185)
Customized Recommendations[b]	.366*** (.088)	.322** (.099)	-.049 (.053)	.065 (.149)
Recommended Stories Only[b]	-2.21*** (.088)	-1.014*** (.098)	.239** (.082)	.100 (.230)
Elaboration	-	-	-	.752*** (.131)
Sex (F)	.107 (.080)	.006 (.090)	.143** (.048)	-.155 (.134)
Age	.003 (.003)	.000 (.003)	.003* (.002)	.005 (.005)
Income	.017 (.020)	.060** (.022)	-.020 (.012)	.058 (.042)
Education	-.017 (.025)	-.011 (.028)	.050** (.015)	.053 (.042)
Minority	.026 (.105)	-.137 (.118)	-.156* (.063)	-.653*** (.176)
Political Ideology (Liberal)	.018 (.048)	.065 (.053)	.001 (.028)	-.180* (.079)
Democrat	.769*** (.093)	.342** (.104)	-.053 (.060)	.284 (.166)
Republican	.712*** (.111)	.294* (.124)	-.045 (.069)	.021 (.193)
Political News Interest	-.076 (.042)	-.051 (.047)	-.158*** (.025)	-.013 (.072)
Internet Skill	.030 (.037)	.013 (.042)	.066** (.022)	.131* (.062)
Counter-attitudinal Headlines	-	-	.124*** (.035)	-.016 (.099)
Counter-attitudinal Story Views	-	-	-.020 (.031)	.120 (.087)
Constant	1.945*** (.352)	1.273** (.395)	2.999*** (.216)	-.341 (.718)
R^2	.661	.323	.229	.207

Notes: *p < .05 **p < .01 *** p < .001, two-tailed. Unstandardized coefficients with standard error in parentheses.

[a] $N = 470$

[b] Control group used as reference

Table 4.

Indirect Effect of Personalized System Design on Knowledge through Elaboration

	Indirect Effect[a]	Indirect Effect CIs[b]
Personalized news recommendations	.048 (.053)	-.058 - .151
Customized recommendations	-.038 (.053)	-.120 - .040
Recommended-only	.180 (.069)	.056 - .325

Note. N = 470.

[a] Unstandardized coefficients with bootstrapped standard error in parentheses

[b] Bias-corrected 95% confidence intervals with 5000 bootstrap resamples.