Personalized News:
How Filters Shape Online News Reading Behavior

Dissertation

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By
Michael A. Beam, M.A.
Graduate Program in Communication

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Dissertation Committee:
Dr. Gerald M. Kosicki, Advisor
Dr. David R. Ewoldsen
Dr. R. Kelly Garrett
Dr. Andrew F. Hayes
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Abstract

The evolution and diffusion of communication technology has consistently changed interactions between members of the public sphere in forming public opinion. Some democratic scholars have worried recent developments in personalization technologies will degrade public opinion formation. They worry that personalized news allows citizens to only pay attention to news coming from their preferred political perspective and may isolate them from challenging perspectives. Empirical research has shown people with access to more highly selective information technology demonstrate increases in both selectivity and incidental exposure to diverse perspectives.

This dissertation focuses on these behavioral and attitudinal outcomes of using personalized news technologies. Dual-processing theories of information provide the foundation for analyzing opinion formation within the bounded rationality model of public opinion. Personalized news technologies are hypothesized to increase the amount of news exposure and elaboration through increased personal relevance.

Two studies test these broad hypotheses. First, results from a national random sample of adults show users of personalized web portals are more likely to engage in increased news viewing both online and offline. No differences in preference for perspective sharing or challenging sources of news is found between personalized portal users and non-users. Next, results from an online experiment of Ohio adult Internet users show an increase in time spent reading news articles in personalized news portals
compared with a generic portal. An interaction between using customized news portals with source recommendations based off of explicit user preferences and increased time spent reading per news article is found on news elaboration. No differences in news elaboration are found in other personalized news designs including implicitly recommended news sources based on user profile information and only showing users recommended stories. The implications of these results are discussed in terms of the public opinion debate about new communication technologies, selective exposure research, information processing research, and personalized information system design.
Dedicated to Jackie and Adam.
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Vita

1996 . . . . . . . . . . . . . . . . . . . . . . . . . System Administrator, Web Services
1997 – 1999 . . . . . . . . . . . . . . . . . . . . . . . System Administrator, SISCOM
2001 – 2003 . . . . . . . . . . . . . . . . . . . . . . Technician, CNS, Ohio University
2003 . . . . . . . . . . . . . . . . . . . . . . . . . . . . . B.S., Telecommunications, Ohio University
2003 – 2006 . . . . . . . . . . . . . . . . . . . . . . . Network Technologist, University of California, Santa Barbara
2008 . . . . . . . . . . . . . . . . . . . . . . . . . . . . . M.A., Communication, The Ohio State University
2006 – 2011 . . . . . . . . . . . . . . . . . . . . . . Graduate Teaching and Research Associate, The Ohio State University

Publications


Fields of Study

Major Field: Communication
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Chapter 1: Introduction

Daily interaction with personalized digital information systems is rapidly becoming a common reality for information consumers. The transition from analogue mass broadcast media to individualized digital media has been the focus of considerable public opinion research throughout the last two decades. In the old media model, broadcasters sent out broadly appealing messages to the mass public through electro-magnetic waves into the ether. Information consumers would tune in to their local radio and television broadcast stations and receive the important information of the day. As information distribution evolved in the later half of the 20th century, the number of television channels blossomed, first through analog broadcast signals, then cable and satellite technology, and finally through digital distribution. With the arrival of the Internet, information consumers who could access the digital network and who were interested in acquiring information were able to access huge amounts of new and old information from traditional and new types of sources.

These new digital information consumers have been able to selectively filter the important information that appeals specifically to them. This technology allows information consumers to more easily ignore information they find irrelevant. So, while individualized information acquisition might blossom, collectively shared information by all users may actually narrow in the digital information world. In sum, mainstream
adoption of new communication technologies exponentially increases the amount of accessible information and changes the landscape of information options, selection, and exposure (Bimber, 2003; Prior, 2007). This dissertation strives to contribute to our understanding of how the rise of personalized, filtered information systems impacts information selection, exposure, and decision-making.

The revolution in information accessibility presents a new dilemma for information users: how does one make sense of an unmanageable amount of information? One answer comes in the form of personalization technology. Instead of trying to survey and select from a torrent of information, users can harness personalized filtering technologies and enter an individualized information environment that is tailored to their particular preferences. While this technology is a helpful evolution for users struggling to make sense of the information explosion, it poses both challenges and solutions for the democratic notion of a public sphere.

Public opinion and the public sphere are inextricably tied to the birth of democracy (Spier, 1950; Baker, 1987, Habermas, 1989). Public opinion, broadly defined, is “those opinions held by private citizens which governments find it prudent to heed” (Key, 1969, p. 14). Habermas (1989) argues a normatively functioning democracy operates through a discourse environment, the public sphere, where participants reflexively and rationally communicate. It is through the public sphere that legitimate, justified decisions on governance can be made. Public discourse is largely diffused through the mass media. Indeed, Zaret (2000) traces the infancy of democracy to the wake of the printing press. It was the ability to share ideas widely that helped ignite a coherent public debate and help foster a politically informed middle class.
Structural changes in public opinion and politics are tied to changes in the information landscape (Bimber, 2003). Bimber argues innovation through “information revolutions” leads to changes in politics. Scholars are trying to make sense of the democratic impact of the current transformation from a broadcast and mass media environment into an Internet society (Bimber, 2003; Sunstein, 2001, 2007; DiMaggio et al., 2001; Prior, 2007; Benkler, 2006; Brundridge, 2010a).

Sunstein (2007) argues personalized information systems will decay the public sphere. He posits users will polarize in the new information environment because citizens will no longer attend to multiple perspectives during opinion formation. Instead, they will only be aware of arguments coming from voices consistent with their own political preferences.

Freedom properly understood consists not simply in the satisfaction of whatever preferences people have, but also in the chance to have preferences and beliefs formed under decent conditions—in the ability to have preferences formed after exposure to a sufficient amount of information and also to an appropriately wide and diverse range of options (Sunstein, 2007, p. 45).

Research shows that increased television channel availability has coincided with people tuning out of news and politics in general (Prior, 2007). Indeed, there is an over-time trend of decline in political knowledge among the citizenry in the United States (Page & Shapiro, 1992).

Other scholars have a more optimistic view of the information selectivity afforded to users in the wake of the Internet. The Internet, as opposed to the older one-way media technologies, allows for people to interact more easily with content producers and other
users. This interactivity also allows for much easier access to personally relevant political discussion. There is evidence that the Internet provides a new avenue of political participation due to relatively low access costs and higher capacity for personally relevant information and discussion (Benkler, 2006). Additionally, evidence shows Internet users often inadvertently become exposed to cross-cutting political news, ideas, and discussion (Brundridge, 2010b; Wojcieszak & Mutz, 2009). Therefore, there is hope, as well as evidence, that the Internet actually increases citizens’ overall political awareness (Garrett, 2009a). The Internet may actually do more good than harm for the health of the public sphere. Based on this evidence, this dissertation tests the thesis that online personalized news systems increase users’ news exposure and engagement with news.

This dissertation provides a discussion of the dominant models of political behavior found in the public opinion, communication and cognitive psychology literature. These models offer a theoretical lens through which the relationship between personalized communication and political news engagement can be viewed. This discussion centers on evidence that personally relevant information increases the motivation to engage in news. Also, a reduction in extraneous non-relevant information increases a user’s ability to engage in news stories by feeling less overwhelmed. Guided by dual-process theories of information, increased motivation and ability should result in increased news elaboration (e.g., Petty & Cacioppo, 1986; Hastie & Park, 1986; Chaiken & Trope, 1999).

Personalized web portals have become the dominant software used to customize and access personalized information online. These personalized portals provide the platform for researching personalized information in the dissertation studies.
A series of hypotheses and research questions are investigated in two studies. First, nationally representative survey data test the proposal that personalized news use is related to a reduction in feeling overwhelmed by the amount of news information. These data are also used to test the hypotheses that personalized news use is related to an increase in exposure to online news sources and news categories. The relationship between personalized news use and offline news exposure and preferences in the perspectives of news sources is also explored. These analyses provide insight into how users of online personalized information differ in their attitudes and behaviors about news use.

Next, an online mock election experiment with Ohio adult participants tests the hypotheses that increased personal relevance of information provided by personalized news systems results in increased news attention and news elaboration. The experiment also investigates the impact of specific design choices when building personalized news systems. News attention and elaboration are expected to increase when using personalization systems that utilize explicit user input rather than implicit machine-based recommendations. Finally, news attention and elaboration are predicted to increase when personalized news systems show only recommended stories rather than all news stories, recommended and non-recommended. The results from this experiment contribute to our understanding of the mechanisms of how personalized information systems shape the way news users process information used for political decision-making. After providing the details and results of these studies, the dissertation concludes with a discussion of the theoretical and practical implications of the proliferation of personalized news.
Chapter 2: Theoretical Foundation and Hypotheses

Internet technologies provide a low-cost, high information, interactive platform for citizens to engage in news viewing and discussion. Like the many changes in dominant media platforms before it, this new media platform creates structural changes in citizens’ interactions with news. These changes could mean shifts in the power structures that dominate political discourse in the public sphere. Scholars are very interested in discerning changes in political information acquisition and discussion, and elite information gatekeeping because these elements are essential in understanding how the citizenry makes political decisions. This chapter will provide a discussion of previous research on political information acquisition and decision-making.

First, a discussion of the Internet and politics will illuminate Internet users’ behavioral changes in their political information seeking. Recently, public opinion scholars have actively debated how political decision-making processes are changing in the wake of new media technologies made possible through the Internet. Selective exposure research highlights the active debate over how the Internet is changing the quality of political information accessed by Internet users. A discussion of the normative framework for optimal individual political decision-making from public opinion literature follows. This dissertation will contribute to the public opinion literature on new media by providing empirical data testing the impact of personalized information system usage on political information acquisition and political information processing. Information
processing theory provides the theoretical underpinnings of the mechanisms tested herein.

Lastly, a discussion focused on personalized web portals will provide information about the specific technology platform investigated in this dissertation. A series of hypotheses synthesizing these literatures is provided. Broadly, the synthesis of the research and theory reviewed suggests personalized web portal use is likely to increase news information acquisition and information processing due to the increased personal relevance and decreased effort required to find personally relevant news.

*The Internet and Public Opinion*

The Internet has changed the way citizens acquire and process political information, in part, because the flow of political information from elites to the masses has shifted. Political elites have considerable power in mainstream political discourse, regardless of the information delivery system (Entman, 2003). Empirical results indicate the Internet is not an egalitarian information environment. In fact, mainstream news providers and elite actors still appear to be firmly placed as central hubs of news information flows (Benkler, 2006; Dylko, Landreville, Beam, & Geidner, 2009). In every step down in the flow of news from elites to information consumers, biased or faulty information has the potential to harm the citizenry at an aggregate level in properly making political decisions (e.g., Page & Shapiro, 1992; Kuklinski & Quirk, 2000). In discussing the current information regime, Bimber (2003) argues,

> The informed citizen in the age of the Internet is not a rational actor, nor necessarily even one who pursues short-cuts and satisficing strategies in lieu of exhaustive and thorough information-gathering. Instead, informed citizenship
involves the information-rich growing even richer as the cost of information falls, while those in poor in information remain so (p. 25).

Bimber cites the new organizational structure of information brought on by the Internet as the key component to changes in political power. The lowered cost of information will diffuse power among politically interested organizations. Organizations that successfully adapt to the new information resource environment will then indirectly exert influence on individuals.

It is through this theoretical lens that this paper’s view of personalized technologies can be seen. Google, Facebook, and other information aggregating organizations have successfully adapted to the new information environment and command the attention of millions of Internet news readers (Pariser, 2011). Hargittai (2000) argues search engines are powerful new gatekeepers in the information ages. This argument is bolstered by more recent research that finds information seekers rarely move past the first page of results when searching for information (Pan et al., 2007). These Internet information providers have harnessed personalization technologies that will adapt to individuals’ preferences to predict what information users are actually seeking (Pariser, 2011). They have also harnessed customization technologies that allow users to explicitly tailor their information environments. Over time, by automatically tracking a user’s behavior and customization choices, Internet information providers can create potentially lucrative individualized user profiles for personalizing new information products.

Using personalization and customization tools, the cost of information acquisition is significantly lowered to information consumers. Unlike the information regime in the
Internet era, information consumers no longer have to expend large resources to assess the utility of their information options because their information environment is adapted to them. Those actors that utilize personalization tools to acquire information will likely see higher information acquisition than those not utilizing these tools. That is, users of these technologies will engage in their information environment more frequently, process more information centrally, possess a more sophisticated accessible memory structure, and ultimately acquire information more readily.

There is growing concern over the potential harm of personalized technologies. Large Internet information providers hold considerable power over what information a user sees. That is, an Internet information provider can control how the personalization system works. This study will test several different personalization system designs to examine how design choices impact the decision-making processes. In addition to the information providers’ control of profile information and design choices, scholars are concerned about how selectively filtering news information impacts political decisions.

Selective Exposure

Cass Sunstein (2007) warns new information technology fostered by the diffusion of the Internet may limit citizens’ ability to make quality political decisions. He argues the sheer quantity of news and information accessible in the present day allows people to insulate themselves from counter-attitudinal views. This selective exposure limits the conditions necessary to reach a high-quality decision. This contentious view is widely debated and tested in empirical scholarship.

Selective exposure research emphasizes information consumers will likely engage in news that supports their own perspective (e.g., Sears & Friedman, 1967; Frey, 1986;
Empirical evidence establishes that individuals’ preferences guide their information acquisition and information processing. Historically, news information consumers have selectively chosen news that seems to support their own perspective in a balanced mainstream news environment steeped in journalistic norms (Sweeney & Gruber, 1984). In ambiguous information environments citizens are likely to process information favoring their own perspective (e.g., Vidmar & Rokeach, 1974; LaMarre, Landreville, & Beam, 2009). Indeed, information consumers are likely to apply selective filtering to identical news information based on changes in source attribution. That is, identical headlines attributed to different sources of news are rated as more interesting when the news provider is perceived to share the political perspective with the news viewer (Iyengar & Hahn, 2009).

Many formative studies in political information distribution conclude media messages are selectively diffused and attended to by voters (e.g., Lazarsfeld, Berelson, & Gaudet, 1944; Berelson & Steiner, 1964). The primary mechanism of selectively choosing information to attend and process, cited widely in selective exposure research, is taken from Festinger’s (1957, 1964) cognitive dissonance theory. This persuasion 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 his or her attitudes and decisions. Therefore, people are likely to selectively choose messages that confirm their perspective while filtering out messages that challenge their perspective. In a system of absolute selective exposure and selective
avoidance, a spiral of reinforcement is introduced in which people are exposed only to pro-attitudinal messages (see Slater, 2007).

Applying cognitive dissonance in the domain of politics, scholars predict people will seek out, and selectively process information that is consistent with one’s pre-existing political beliefs. Public opinion scholars argue political ideologies are a set of attitudes and beliefs that form a consistent system, shared by a group in the electorate. Ideologies are generally defined by political elites, who have both the time and power to create and distribute these belief systems (e.g., Converse, 1964, van Dijk, 1998). Combining cognitive dissonance theory with political ideology research, selective exposure predicts people will more likely attend to political messages and sources that are consistent with their ideological leaning. Therefore, even if one does not hold a strong attitude about a particular issue, if one self-identifies with a dominant ideology he or she will likely attend to a message from an ideologically consistent source.

Cognitive dissonance theory suggests both approach and avoidance behaviors in communication processes. That is, one is more likely to approach pro-attitudinal information and one is more likely to avoid counter-attitudinal information. Empirical evidence has largely focused on selective approach, rather than selective avoidance (Cotton, 1985). Many scholars agree selectively approaching media has far more influence on information acquisition than selectively tuning out information, or avoidance (e.g., Chaffee, Nichols, Saphir, Graf, Sanvig, & Hahn, 2001; Sears & Freedman, 1967; Garrett, 2009b; Brundridge, 2010b). This power differential is essential in understanding the effects of having access to a nearly limitless number of sources. Brundridge (2010b) argues that selectivity can lead to engagement in civic discourse and
increase inadvertent exposure to cross-cutting opinions. Garrett (2009a) also finds that citizens demonstrating increased selectivity show knowledge gains in both favored and unfavored political candidates. Bennett and Iyengar (2008), conversely, argue that an increasing perception of a hostile media (e.g., a media biased against one’s beliefs) helps motivate people to seek other sources and avoid dominant mainstream sources (see also Iyengar & Hahn, 2009, Iyengar, Hahn, Krosnick, & Walker, 2008). They worry an increasingly polarized media environment will lead to more citizens ill equipped in political discourse and decision-making. In sum, the differential impacts of approach and avoidance mechanisms are still under scholarly debate.

The selective exposure literature contributes to our understanding of political decision-making. Citizens selectively approach pro-attitudinal media. This information offers users easily processed information they can use to make political decisions. It is unclear whether citizens selectively avoid counter-attitudinal media. Counter-attitudinal information also provides utility to the decision-making ability of a citizen, but at the cost of cognitive dissonance and increased cognitive processing. This study will help add empirical evidence to these questions by focusing on differences between users of personalized information systems that selectively filter news content with users who do not use personalization systems.

*Selective exposure and the Internet.* The amount of accessible information in any given media environment governs the ability one has to selectively expose. In a news environment with 3 news channels, one can selectively choose which newscast they prefer, or turn off the television. In a cable news environment, one can tune into the news or one of many other entertainment options (Prior, 2007). Therefore, since the diffusion
of the Internet and other information and communication technologies (ICTs) that access the Internet, the ability to selectively expose has exponentially increased. In the modern ICT environment it is physically impossible to attend to all accessible information, so people are required to selectively expose themselves to specific information. The makeup of this selectivity can certainly be either more or less pro- or counter-attitudinal, but some level of selectivity is required. To understand selectivity in the Internet era, the changes in the political information environment must first be discussed.

The rise of the Internet has led to a shift in the power of news gatekeeping (Beam, 2007). The traditional media environment was largely bounded by traditional journalistic routines of balanced and accurate reporting (Shoemaker, 1991). Now, news information can be diffused through a nearly limitless number of channels, so former traditional media gatekeepers can no longer withhold information from the public (Williams & Delli-Carpini, 2000). Sunstein (2007) worries that this limitless information environment will lead to the polarization of the public sphere (i.e. total selective exposure and isolation from counter-attitudinal information and ideas). Some scholars dispute this claim. Benkler (2006) argues that the rise of the Internet does allow for a more reflexive news environment, but that mainstream news collectors still dominate the flow of political news information. There are several empirical studies that support Benkler’s claim, including a study of the most popular YouTube videos produced in the 2008 election (Dylko, Landreville, Beam, & Geidner, 2009). This content analysis of the most popular videos in the 6 months preceding the election found content produced by mainstream news organizations still vastly outnumbered user-generated videos. On the other hand, the majority of uploaders of this news content were non-elite average Internet users.
Bruns (2005) argues communities of users that moderate news stories (“gatewatchers”) have been given power to help other users select stories with relevant information. Indeed, Sundar & Nass (2001) found online news-readers rate stories selected automatically by a computer agent or by other Internet users more highly than stories selected by news-editors or the news-reader themselves. Also, as discussed earlier, Bimber (2003) argues that the Internet era will allow for shifts in the power structure of communication elites, rather than a polarization due to self-selection.

It is in this new information environment that the renewed interest in selective exposure has been debated. Information-seeking routines are now different on the Internet. Instead of being communication receivers, Internet users are able to actively seek out the information they would like to acquire. Selective exposure would predict this new information environment would lead to a great increase in selectivity. For example, Tewksbury (2003) found Internet users are more selective in the information topics they seek out online compared with offline counterparts. Selective exposure also increases the perceptions of credibility of news (Johnson and Kaye, 2004; Kalyanaraman and Sundar, 2006). Johnson and Kaye found blog readers were more likely to rate blogs as more credible than traditional media.

Prior (2007) argues increased selective exposure leads to political indifference and lack of participation. Using data from cable television viewers, Prior shows strong partisans are more likely to expose themselves to reinforcing political information while moderates are more likely to tune out of political information all together. Others argue the over-time impact of selective exposure leads to polarization and attitude reinforcement (see Sunstein, 2007; Stroud, 2008, 2010). Stroud (2010) finds a
combination of partisanship and partisan selective exposure lead to increased polarization.

Sunstein (2007) is centrally concerned that personalized information environments will create “cybercascades” leading to an increasingly polarized electorate. That is, citizens will no longer be exposed to counter-attitudinal information and will become isolated from opposing viewpoints. On the other hand, Prior’s (2007) concern, empirically based in 30+ years of data, stems from increased avoidance of political information altogether. He argues “there are fewer moderate voters today not because they have been converted by increasingly partisan media, but because they have been lost to entertainment. They are still alive and moderate, but politically less relevant because their tendency to abstain” (Prior, 2007, p. 275).

There is contention about whether the Internet leads to reduced political engagement and increased selective avoidance. Garrett (2009a, 2009b) argues citizens do not selectively avoid political information. He found people using the Internet for campaign news in the 2004 election were more likely to selectively engage in news stories about their favored candidate, but they are also more likely to have higher knowledge about both their favored and non-favored candidate (Garrett, 2009a). Brundridge (2010b) argues the Internet facilitates increased inadvertent exposure to counter attitudinal political information. She found increased selectivity leads to increased engagement in civic news and civic discourse, which in turn leads to increased exposure to both pro- and counter-attitudinal information.

Taken together, there is a possibility that increased selectivity in news selection may facilitate more processing of political news—both pro- and counter-attitudinal. The
process may come through incidental exposure in online postings that are not explicitly political (Brudridge, 2010b; Wojcieszak & Mutz, 2009), or through reduced cognitive costs of accessing explicitly political information (Bimber, 2003). This study is going to investigate this claim in the context of personalized news systems.

A personalized news system is inherently selective because news stories are selected based on the specific user’s profile. The sources of news recommended by a personalization system should allow for easier news information processing because these sources should carry high credibility ratings. This study will provide the empirical evidence needed to sort out the impact of personalized news systems on information exposure and processing. The central thesis being tested in this dissertation is increased selectivity in personalized systems leads to a higher quality political decision-making environment where more elaborative political information is thoughtfully considered through mechanisms of reduced effort required to find personally relevant information and increased utility of easy access to personally relevant information. To understand this argument, the social science literature on political decision-making and cognitive information processing is reviewed.

*Information, Rationality and Opinions*

*Rational Choice*

Public opinion scholars have spent decades building a literature to explain political decision-making. An early dominant paradigm in this social science literature follows the rational choice perspective (see Downs, 1957). Rational choice models posit individuals are constrained by various forces and behave rationally based on their relationship to those constraints. In this system political actors attempt to maximize
utility by minimizing costs and uncertainty. This means individuals try to spend as little time, resources, and effort as required in attaining their political goals. According to this perspective, there exists a threshold where the cost and uncertainty will outweigh the utility of a political goal. In that circumstance, no effort will be spent on attaining those goals because that would be irrational.

In rational choice, information seeking and acquisition occur when both uncertainty and an actor’s motivation to gain utility through forming an opinion are high. Acquiring this information comes at the measureable cost of the time and resources used to find, evaluate and integrate political information (Downs, 1957). Actors are constrained by this system, because it is impossible to attend to all available information about a topic. Forced to limit information acquisition, rational actors will develop ways to quickly acquire enough information to make a decision and then make a reasoned choice based on that information. Therefore, people who are highly motivated in making a decision are more likely to spend the time and resources acquiring necessary information compared with those that have lower motivation. Motivation to make a decision can be driven internally through self-interest or externally from societal pressures such as discussing politics with peers. Rational actors with quality conduits for easy information acquisition have reduced costs in making a decision. These conduits are exemplified by a politically knowledgeable friend, low-cost access to political news channels, or an efficient personalized political news system.

In the rational choice model, actors are unmotivated to make political decisions that yield little utility. So, these actors may forego acquiring any information and avoid political behavior because it is rational to stay ignorant. Unmotivated actors may still
come across political information incidentally through everyday discussion or packaged with other types of communication. This incidental exposure eliminates the cost of information seeking, therefore greatly decreasing the overall information acquisition cost. Downs argues there is nearly always some utility found in making a political decision due to the societal pressures of civic responsibility.

A large body of public opinion research has used rational choice theory as a normative basis for evaluating political decision-making, opinion formation and opinion quality. Focusing on outcome opinions, Converse (1964) argues an ideal citizen should form a stable and consistent opinion. Stability denotes an opinion that should hold over time. A rational decision will hold over time unless there are major changes to an actor’s life circumstances. In a rational system an actor will store his decision in memory and recall it when cued. There is no need to reevaluate the decision unless uncertainty becomes so high the equilibrium with information acquisition is disrupted. Consistency means that diverse opinions should logically fit together to form a belief system, or ideology. Scholars argue that political elites and others in the public that are highly attentive to politics establish dominant cultural ideologies (e.g., Zaller, 1992; Entman, 2003). Less politically attentive citizens should adopt these ideologies through information cues. So, once actors receive signals from elites, they should have a logical system in place that consistently provides utility. Responsibility is a third criterion for outcome opinion quality (Yankelovich, 1991). Responsibility means actors should accept the likely consequences of their opinions. Again, according to rational choice, actors make decisions based on the utility of their outcomes.
Empirical research evaluating individuals’ opinion quality has led to results that dispute rational choice predictions. Converse’s (1964) classic study on “The Nature and Belief Systems in Mass Publics” uses national panel survey data to demonstrate the average citizen’s opinions are not stable or consistent. That is, people do not seem to hold rational opinions when polled. A wide body of decision-making research also disputes the claim that people hold responsible opinions. For example, framing studies by Tversky and Kahneman (1974, 1981) utilize equivalency frames to show framing identical information either positively or negatively can predictably lead to differing decisions. Actors that have high ambivalence (which can be seen as a level of uncertainty) are more highly susceptible to framing effects (Pan & Kosicki, 2005). This research demonstrates the weaknesses of the rational choice model. Rational choice has provided a normative starting point for scholars to model political decision-making processes, but empirical results have demonstrated the need for updated theoretical assumptions (see also Green & Shapiro, 1994).

Heuristics & Bounded Rationality

A set of less restrictive assumptions governing rational political decision-making is found in the bounded rationality model (e.g., Simon, 1957, 1985, 1998). Informed by cognitive psychology, this approach assumes a dynamic relationship exists between information and political decision-making. That is, the goals of information acquisition have a reciprocal relationship with information itself (Bimber, 2003). Kahneman (2003) argues that despite the simple appeal of rational choice modeling, the added psychological dimension of “intuition” makes human decision-making a more complex process to understand. Bounded rationality attempts to solve this problem by
acknowledging the role of automatic psychological factors used as heuristics when making political decisions such as affect, accessibility, and activation in addition to the logical reasoning found in rational choice (Kahneman, 2003). Based on these revised assumptions, different actors, or even the same actor at two time periods, may interpret identical information differently.

Bounded rationality also replaces the notion of actors behaving optimally with the notion that actors are satisficers. Instead of achieving an optimal outcome as theoretically posited in the rational choice model, an adequate outcome requiring minimal effort is reached through the process of “satisficing.” That is, instead of coming to cost-benefit information equilibrium when decision-making, satisficers strive to make decisions in their low-information environments exerting the minimal amount of energy required to make a decision. These decisions are guided by fallible heuristics (e.g., Lupia, McCubbins, Popkin, 2000; Tetlock, 2000). Therefore, the relationship between information and opinion quality operates differently than in a rational choice model. Here, uncertainty and motivation do not necessarily lead to information seeking. Instead, satisficing judgments are often formed using only whatever information is readily available to the actor.

Actors do their best to make accurate decisions but those decisions largely rely on heuristic systems (e.g., Sniderman, Brody, & Tetlock, 1991; Jones, 1999; Lupia, McCubbins, & Popkin, 2000). Lupia (1994) presents convincing survey results exemplifying successful heuristic processing in the 1988 California special election. The election had several complex policy options dealing with automobile insurance. Most citizens had only a small amount of information to utilize in making their voting decision
due to lack of media attention and lack of party cues to those issues. Despite that fact, low-information voters did a reasonably good job in selecting the “correct” choice. That is, the same choice as those who had high information. They found that these voters were able to utilize heuristic cues based on organizational support for the bill (e.g., insurers, lawyers and consumer advocacy organizations).

Heuristic-use studies paint a less dire picture of rational citizens’ ability to make political decisions than the opinion quality studies outlined earlier. People seem to behave in a rational way when making decisions, but generally do so relying on extremely limited information. Rational choice models predict actors will rely on heuristics to maximize their opinion while minimizing the cost of information acquisition. Heuristic-use studies show that rather than maximizing the quality of political decisions, citizens seem to be minimizing their effort by making choices that seem rational at any given time, while not thoroughly maximizing their process of internal deliberation.

In light of the bounded rationality perspective, scholars often focus on understanding the conditions that optimize the quality of political actors’ decisions. The impact of new ways to acquire information, such as using personalized news systems, often create renewed interest in comparing citizen political-decision making with the optimal normative rational citizen. Internal deliberation, or elaboration, is a key variable of focus when evaluating opinion quality and political decisions. As described in more detail below, when integrating new information that may contribute to a political decision, a higher quality opinion will result when that information is deliberatively processed. This study investigates the impact of using personalized news systems
compared with generic news systems on the political decision-making process. As argued below, personalized news systems are likely to increase political actors’ motivation and ability to engage in news information acquisition and ultimately result in increased news elaboration. Therefore, these mechanisms may show using personalization systems contributes to an increase in overall opinion quality.

*Information Processing*

The literature on cognitive information processing highlights various mechanisms for making decisions including relying on an online tally or a memory-based model as well as relying on systematic elaborative decision-making processes compared with less rigorous heuristic peripheral decision-making processes. These various mechanisms of information processing are key considerations in the bounded rationality approach to understanding political decisions. Kahneman (2003) argues perception and intuition both act automatically and separate from logical reasoning. Cognitive psychology research helps make sense of the intuition process. In a networked model of memory, “memory nodes,” or individual items stored in memory, are structured such that certain related concepts may be “activated,” or utilized, simultaneously (Anderson, 1983). When multiple nodes are activated closely in time, a pathway is strengthened between the two nodes. This networked association builds (or declines) over-time as the relationship between memory nodes is recalled repeatedly (or not). In describing the networked activation model, Roskos-Ewoldsen (1997) uses the example of a cockroach and a negative evaluation being associated in memory: “when cockroach is activated, activation would spread to the associated concept of “yuck”” (p. 187).
In addition to the networked associations in memory, cognitive scholars have also demonstrated the dimension of memory accessibility is important when storing and retrieving memory information. In their memory model, Wyer & Srull (1986) conceptualize stored information as a “storage bin.” In this model, when a memory or a schema is accessed it is placed on the top of the bin. The closer a memory node is to the top of the bin, the more highly accessible it is. Newly acquired information is more likely to be encoded into the first related memory node towards the top of the bin. Therefore, new information will likely by integrated with any given memory construct when the construct is both available and accessible (Higgins, King, and Martin, 1982). “Construct availability” refers to whether information about a given construct exists in memory. “Construct accessibility” refers to the readiness that a construct will be used when processing information. Thus, if two individuals have identical construct availability (e.g., information or knowledge) but differing construct accessibility, they may process information in a different context.

Both recency and frequency of memory node activation contribute to its accessibility (Wyer & Ottati, 1993). Recency causes temporary accessibility, as demonstrated through priming studies. For example, Srull and Wyer (1979) measured the accessibility of hostility by asking participants to construct sentences from a bank of words. Participants who scored equally hostile on the word bank task scored higher when they evaluated the fictional character directly after the accessibility measurement compared with those with a 24-hour lag between measurements. Political priming studies show an accessibility effect of a political event can impact future political considerations (e.g., Krosnick & Kinder, 1990). Frequency, on the other hand, can lead to chronically
accessible concepts. Studies show participants with chronic accessibility still tend to encode information within a given schema without any recent concept priming (Higgins et al., 1982; Bargh & Thein, 1985; Shen, 2004).

While accessibility influences the readiness of memory, it only gets used when that memory is activated (e.g., Price & Tewksbury, 2007; Pan & Kosicki, 2005; Tewksbury & Scheufele, 2008). Public opinion framing research started with this automatic cognitive process as a theoretical explanation for how information consumers come to different interpretations of identical information framed with positive or negative connotation (e.g., Tversky & Kahneman, 1981). Framing research subsequently proliferated throughout social science disciplines focusing on various information effects on judgments. Druckman (2001) conceptually clarified two different types of frames commonly used in this literature: equivalency frames and emphasis frames. Equivalency frames are those that carry logically identical information framed in different ways. For example, Tversky & Kahneman (1981) posed two logically equivalent scenarios where participants either chose from a gain (“200 people will be saved”) or loss (“400 people will be saved”) compared to a riskier gain (“1/3 probability that 600 people will be saved”) or loss (“2/3 probability that 600 people will die”) (p. 453). Emphasis framing effects focus on different information considerations. For example, Iyengar (1991) finds differences in attribution of responsibility when experimental participants view stories framed thematically or episodically. Nelson, Clawson, and Oxley (1997) found differences in tolerance when experimental participants viewed a story framing a KKK rally in terms of free speech or in terms of a disruption of public order. In each of these examples the central event discussed in the stories is the same, but peripheral context
information is different. In both equivalency and emphasis frames the process of activation of different memory nodes leads to different responses in assessing the information presented. Two bipolar theoretical models of information processing are often used in political psychology and public opinion research to help integrate and explain cognitive differences in political decision-making: online vs. memory-based processing and central vs. peripheral processing.

Online processing and memory-based processing are two widely used mechanisms to explain political decision-making (e.g., Hastie & Park, 1986; Zaller & Feldman, 1992; Lodge, McGraw & Stroh, 1989). In the memory-based model, various relevant memory nodes are recalled then considered when making a decision. The online model specifies that people keep a running tally of judgment in their mind. In the online model, after new information is integrated into the running judgment, the information is discarded and not stored in memory for a later date.

Dual-process theories from cognitive psychology offer alternative mechanisms for modeling persuasive information processing (e.g., Petty & Cacioppo, 1986; Chaiken, 1987). These models broadly comprise a thoughtful centrally processed route or heuristically processed peripheral route for information (e.g., Chaiken & Trope, 1999). 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). A key component to boost motivation and ability to process when creating a message is to craft messages that are more personally relevant to the message receivers.

Recent scholarship suggests that decision-making tasks are frequently composed of a hybrid of memory-based and online processing (see Mattes, 2007; Kim & Garrett, in press) as well as a mix of elaborative and heuristic processing (Smith & DeCoster, 1999, 2000). That is, when making political decisions, actors rely on both running-tally evaluations and memory-based information, as well as both heuristically processed cues and elaborative thoughts. Recent research also shows that a hybrid of mechanisms including online vs. memory-based and central vs. peripheral processing can help explain information processing (Choi, in press). In sum, these bipolar frameworks are useful for evaluating information processing, but in actuality are likely to occur simultaneously.

Bounded rationality combines the automatic psychological intuition processes outlined above with a deliberate reasoning process when modeling decision-making. This model finds a more complex, but still explanatory, relationship between information and opinion formation compared with the rational choice perspective. Zaller’s (1992) receive-accept-sample (RAS) model of opinion integrates these assumptions into four axioms for opinion formation: 1) increased levels of cognitive engagement lead to high exposure to and comprehension of political information; 2) political information that is inconsistent with one’s predispositions is likely to be resisted; 3) recency of activation of political information will lead to increased accessibility; 4) when asked to make political decisions, people will survey and respond with accessible considerations (p. 58). The first
two steps in this model assume individuals conduct biased information processing based on previously held attitudes. According to the last step in this model, individuals will not retrieve all relevant memory information when asked to make a judgment. Even if one is motivated to centrally process in reasoning, he will sample available accessible considerations to create a judgment based on the average of those sampled considerations. This satisficing is key to the bounded rationality approach. Even when citizens are acting rationally, they cannot act completely rational because they are constrained by automatic cognitive mechanisms.

The rational and bounded rationality approaches both suggest that information acquisition comes at a cost. Scholars argue that the rapid diffusion of a low-cost high-information environment in the age of the Internet will likely change the political landscape (Sunstein 2007; Bimber, 2003; Benkler, 2006). In the rational choice model, cheaper information will likely result in a more informed citizenry, which will, in turn, lead to better opinion quality. The bounded rationality approach, however, does not come to such a clear conclusion about information environments and the quality of information acquisition. In both cases, however, the structural differences in a new information environment can change the mechanisms of cognitive information processing.

Using the bounded rationality framework, this study is broadly based on the assumption that personalized news systems increase personal message relevance and reduce the amount of effort required to engage in political information acquisition. This assumption is also the primary motivation for information technology companies to invest in deploying personalized information technologies in their products. That is, personalized systems increase personal relevance and user engagement, leading to
increased time spent with information portals. This increased time spent in their information portals results in increased revenue for the companies (Pariser, 2011).

Increased message engagement and message relevance made possible by personalized information use should increase the frequency and recency of engaging in political news, so political attitudes and memories should be more accessible. Ultimately, the increased message relevance provided by personalized information systems should result in an increase in message elaboration and cognitive engagement. These propositions indicate personalized information systems containing political news should provide a platform for forming high quality political decisions and easy entry into the public sphere.

**Personalized Information Portals**

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 allowed for a single message to be distributed on any given channel to viewers. In digital media, information can be stored in a single 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. Research has shown personalizing messages can 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 new multi-billion dollar 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 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 often refers to information tailored to a specific information consumer (e.g., Skinner et al., 1999). In marketing research, personalization refers to a product or message changed in regards to a specific customer (e.g., Wind & Rangaswamy, 2001; Vesanen, 2007). Customization, in marketing research, occurs when the user is explicitly involved in the process of changing the product (see Vesanen, 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. An “explicitly personalized” system refers to a personalized system with a high level of customization while an “implicitly personalized” system refers to a personalized system with a low level of customization.

Personalized recommender systems, like amazon.com, iTunes, Google’s search engine or Google AdSense, use data automatically collected from the user in the background without any explicit user interaction (Parsier, 2011). On the other hand,
many personalized news recommender systems, such as Google Reader, have high levels of customization including allowing users to specify specific sources of news. People interact with personalized and customized information systems such as these examples every day. About half of Internet users access personalized web portals which use personalized information (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 utilize personalized political information (Smith, 2009).

*Web Portals*

One of the most pervasive ways to access news online is through a web portal. Indeed, in their explication of web portals Kalyanaraman and Sundar (2008) describe a portal as a gate. Portals provide “a door to access information on the web” (p. 248). A portal page also allows users to start their information seeking online through links or search tools. Kalyanaraman and Sundar (2008) describe several additional functions of web portals. In addition to acting as a gateway, portals also “help increase awareness of—and confidence in—other sites” (p. 248). Taking these two functions combined, it is no wonder Hargittai (2000) argues web portals are important new gatekeepers in the Internet-connected world. Web portals also allow for users to access personalized links, news stories, and other tailored information. This study will focus specifically on the level of personalization in news web portals.

The amount of information accessible through a connection to the Internet greatly reduces the power of traditional gatekeepers. Internet users now have the power to choose to read stories on any number of topics from any number of sources. With access to an overwhelming number of sources online, Internet news consumers must come up with a
strategy to cope with accessing relevant information. Personalized news systems allow users to manage the topics and sources of news with which they are presented. As described earlier, this allows the user to greatly reduce the amount of information and more easily find relevant news. Therefore, it is expected that personalized news users will be more likely to cope with the quantity of news and engage in online news selection. That is, users of personalized news systems will be less overwhelmed by the amount of news available online because their news-gathering systems will automatically filter out less relevant news content (H1).

To understand the impact of personalized news systems, it is important to understand basic differences between a representative sample of users and non-users. Research shows that using multiple types of media (e.g., radio, television, newspapers) is a predictor for news processing outcomes (e.g., Holbert, 2005). Prior (2006) also argues that a subset of the population very interested in political news information is tuning in to news while an increased number of people are tuning out of news all together. Therefore, this study will test if there are differences in the quantity of offline media consumption between users and non-users of online personalized news systems (RQ1).

This study will also harness data to understand how personalized news portal users and non-users differ in their exposure to news information online. Personalized news systems are built to increase the personal relevance of news sources, topics, and headlines compared with generic news portals. Increased personal relevance should reduce the cognitive ability required to selectively find interesting news stories and increase a user’s motivation to engage in news reading. Therefore, personalized news users should be more likely to report viewing a larger number of online news sources
compared with non-users (H2). Also, personalized news users should report viewing a larger number of online news categories than non-users (H3).

Evidence shows users are likely to choose to view news from sources that share their perspectives. It is unclear if users prefer to avoid information that challenges their perspectives. Personalization technology allows users to filter their news sources and topics automatically. This study will examine whether there are systematic differences in preferences for news sources that share or challenge users’ perspectives between personalized news users and non-users (RQ2).

Studies have showed personalized information systems and automatically tailored systems increase users’ perceived relevance, involvement and positive attitude of message content compared to generic messages (Roberto, Raup-Kreiger, Beam, 2009; Kalyanaraman and Sundar, 2006). As outlined earlier, dual-processing theories predict higher elaboration will occur when messages are more personally relevant. Therefore, personalized systems should increase elaboration through increasing the motivation of the user to engage with personalized content.

Compared with a generic information portal, personalized portals also reduce the amount of cognitive surveillance effort required to select personally relevant stories, which increases the cognitive ability for a user to process the content. Indeed, Kalyanaraman and Sundar (2006) argue 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 demonstrates 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). Viewing personally relevant stories increases attitude accessibility and political self-concept. Users who engage more fully in news content may also be more likely to also elaborate on counter-attitudinal information that is inadvertently included in recommended stories. Based on these findings, several differences between generic and more personalized web news portals in an online experiment can be expected.

A process of increased elaboration through increased personalization is outlined below. First, an increase in motivation and reduction in cognitive resources expended to find personally relevant stories should increase a users’ time spent with news articles (H4) and elaboration of the news content (H5). News users will be more invested in reading stories that are personalized for them.

Communication scholars have argued models should test the mechanisms of the process for outcomes (e.g., Hayes, 2009). By testing the process within our models, we are able to more narrowly test our theoretical models. As described above, the extra time spent with news stories in a personalized news system should contribute to the increase in news elaboration due to increased story engagement. Therefore, a significant indirect effect from personalized news is expected on news elaboration through time spent with news articles (H6, see Figure 1).
Figure 1. Experimental Model

*Conditions:
1. Generic Portal
2-5:

<table>
<thead>
<tr>
<th>Condition</th>
<th>Implicit Personalization</th>
<th>Explicit Personalization</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Stories</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Recommended Stories Only</td>
<td>4</td>
<td>5</td>
</tr>
</tbody>
</table>

Hypotheses (all paths same direction):

- H4-H6 Generic (1) < Personalized (2-5)
- H7-H9 Customized (3,5) < Non-Customized (1,2,4)
- H10-H12 Recommended Only (4,5) < All Stories (1,2,3)
Dimensions of Personalized Web Portal

Customization. The level of customization, or explicit personalization, is another dimension when thinking about personalized information system design. In a study investigating customized portal user psychology, Kalyanaraman and Sundar (2006) found a positive relationship between web portal customization and attitudes towards the site. A multiple mediated model including perceived novelty, community, involvement, interactivity and relevance was empirically supported. Many personalized news systems will allow for various levels of customization. That is, users can initially input their broad topical interests and then the personalized system will generate default information options based on those initial selections. For example, on the Google Reader web news portal, a user can select that they would like to subscribe to the top headlines from the national online newspaper The New York Times, the local newspaper The Columbus Dispatch, and/or headlines from a popular political blog Red State. The system would then generate headlines from these specific sources using an automated algorithm.

Again, increased customization in a web portal has been demonstrated to increase personal relevance and involvement just as personalized portals increased these dimensions over generic portals. When users explicitly engage in personalizing their own news sources and stories through customization, they should be more highly motivated to engage in that information, and the cognitive load required to determine if a story is credible or relevant should be reduced. So, again a trend can be expected for highly customized portal content over implicitly personalized portal content similar to that of personalized portal content compared with generic portal content. Personalized portal users who explicitly personalize their news selection filters should spend more time
reading news articles (H7) and elaborating on those articles (H8) compared with users of automated, implicitly personalized portals. Again, the extra time spent with news stories in explicitly customized news portals should contribute a significant indirect effect from portal type to news elaboration through time spent with news articles (H9).

Recommender System Design. When designing news recommendation systems, the amount of information recommended and remaining viewable to the user is another design choice. Some systems, such as the popular websites like Digg.com, allow for a user 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 sites, such as Google Reader, only display recommended stories to users. In these cases, the users do not have access in their news portal to the non-recommended information. There is little research that investigates the impact of information access in a news system. Like the expectation when comparing a personalized to a generic information system, a personalized system that gives a user access to the entire information world should increase the users’ cognitive load when selecting which stories to read compared with a more limited information system with just the recommended stories. When a user is given only their recommended content, the amount of time required to survey headlines and overall information displayed is reduced. Personalized portal users who only have access to their recommended stories should spend more time with stories (H10) and have higher news elaboration (H11) than users who have access to all news stories. There should be a positive indirect effect from viewing a portal with only recommended content to news elaboration through time spent with articles (H12).
Chapter Summary

This chapter discussed the theoretical basis for this dissertation. New communication routines made possible by the Internet and digital technologies have come under intense scrutiny by public opinion scholars. The Internet offers a tremendous increase in the amount of accessible information available to users. How users engage in information exposure and how that exposure shapes attitudes and behaviors is important for understanding public opinion formation and political decision-making in the 21st century. Political decision-making theories found in rational choice and bounded rationality provide the background for determining ideal decision-making conditions. Specifically, bounded rationality allows for more nuanced theories of cognition and information found in the social psychology literature to govern decision-making processes. It is through these information-processing theories that usage of personalized web portals are expected have a positive impact on decision-making conditions by increasing the personal relevance of news. This increased personalized relevance should increase motivation to engage in news exposure as well as thoughtful processing of news information. The next section will provide the details for how these hypotheses and research questions will be tested.
Chapter 3: Survey Study

This chapter will discuss the details of two large-scale, random population surveys used to test the proposed relationships between personalized portal use and information acquisition and attitudes (H1-H3, RQ1-RQ2). This chapter is designed to make externally valid comparisons between personalized portal users and non-users in their online and offline news viewing and attitudes about news. First, the methods employed to conduct the survey analyses will be provided. Next, the results will be discussed beginning with a discussion of the bivariate relationship between the predictor and focal variables, followed by more rigorous multivariate analyses.

Methods

Two survey data sets collected by the Pew Research Center will test the relationship between using personalized news portals and users’ news attitudes and behaviors. These data were chosen because they utilize a large representative landline and cell phone random sample of Americans covering topics about online and offline news use, including usage of customized news portals.

The Pew Research Center’s Internet and American Life Project (PIAL) collected the first nationally representative data set between December 28, 2009 and January 19, 2010. Data were gathered from 2,259 English-speaking adults living in the continental United States including 1,748 landline participants and 580 cell phone participants. The landline response rate is 22% while the cell phone response rate is 20%. This data set is
weighted using a two-stage procedure. The full data collection and weighting procedure is provided at the PIAL (2010) website.

The Pew Research Center for the People and the Press (PPP) collected the second national data set between June 8, 2010 and June 28, 2010. Data were gathered from 3,006 English-speaking adults living in the continental United States including 2,005 landline participants and 1,001 cell phone participants. The landline response rate is 16.9% while the cell phone response rate is 17.5%. This data set is also weighted using a two-stage procedure. The full data collection and weighting procedure is outlined at the PPP (2010) website.

Measures

Personalized news use. In the PIAL survey, Internet users (N=1,675) were asked, “Thinking about all the different ways you might get and share news online, please tell me if you ever customize your homepage to include your favorite news sources or topics.” Participants answered yes, coded 1 (N = 466) or no, coded 0 (N = 1,208). Participants who answered yes to this question are classified as “personalized news users” in the analyses.

In the PPP survey, Internet user participants (N = 2,475) were asked, “How often, if ever, do you get news or news headlines through a customizable web page, such as iGoogle or MyYahoo, or through an RSS reader?” Participants who responded, “regularly,” “sometimes,” or “hardly ever” are coded 1 (N = 965), as “personalized news users” in the analyses, while those who respond “never” are coded 0 (N = 1,489).

Overwhelmed by the news. Participants in the PIAL survey were asked about their attitude towards the amount of news available today. Participants were read the
statement; “the amount of news and information available from different sources today is overwhelming.” They were asked to respond on a Likert-scale if they completely agree (coded 4), mostly agree (coded 3), mostly disagree (coded 2), or completely disagree (coded 1) \( (M = 2.91, SD = .86) \).

**Offline news media use.** The PPP survey asked participants to report on their news consumption habits. For each type of offline news consumption, participants were given response options of regularly (coded 3), sometimes (coded 2), hardly ever (coded 1) or never (coded 0). Some of the questions in this portion of the survey were only collected from a subset of the participants, those randomly assigned to form 1 \( (N = 1,497) \) or form 2 \( (N = 1,502) \). For *nightly broadcast network news*, form 1 participants were asked, “How often do you watch the national nightly network news on CBS, ABC, or NBC? This is different from local news shows about the area where you live” \( (M = 1.54, SD = 1.78, N = 1,488) \). For *cable news networks*, form 1 participants were asked, “How often do you watch cable news channels such as CNN, MSNBC, or the Fox News Channel?” \( (M = 1.93, SD = 1.10, N = 1,493) \). For *local network news*, all participants were asked “How often do you watch local news about your viewing area which usually comes on before or after the national news in the evenings and again later at night?” \( (M = 2.16, SD = 1.04, N = 2,992) \). Lastly, for *newspapers*, all participants were asked, “How often do you read a daily newspaper?” \( (M = 1.86, SD = 1.16, N = 2,995) \).

Participants randomly assigned to Form 2 in the PPP survey were asked about their viewing of specific cable news channels. Again, response options for these questions were regularly (coded 3), sometimes (coded 2), hardly ever (coded 1) or never (coded 0). For *Fox News*, participants were asked, “How often do you watch the Fox
News cable channel?” ($M = 1.36$, $SD = 1.20$, $N = 1,505$). For CNN, participants were asked, “How often do you watch CNN?” ($M = 1.36$, $SD = 1.11$, $N = 1,503$). For MSNBC, participants were asked, “How often do you watch MSNBC?” ($M = 1.08$, $SD = 1.06$, $N = 1,499$).

*Online news sources.* Internet user participants in the PIAL survey were asked to report the number of online sources they rely on for news. They were asked, “Thinking about all of the news and information you get online, how many websites, if any, do you routinely rely on for your news and information?” They were given response options of “just one site” (coded 1), “two to five” (coded 2), “six to ten” (coded 3), and “more than ten” (coded 4) ($M = 1.72$, $SD = .88$, $N = 1,576$). Participants who responded that they don’t rely on any websites regularly for news, a response option not given by the interviewer, were coded 0.

*Online news categories.* Internet user participants in the PIAL survey were asked to report the categories of news they viewed online. Participants were asked “Thinking about news and information you might get online, do you ever use the Internet to get news or information about…”. Participants were then read a list of 12 news content categories including, “developments in your local community; developments in your state; national events; international events; health or medicine; the weather; celebrities or entertainment; arts and culture; business, finance or the economy; science and technology; sports; and traffic.” Participants answered “yes” or “no” to each category. The sum of the number of yes responses was computed for an overall number of online news categories ($M = 6.34$, $SD = 3.25$, $N = 1,664$).
Perspective of news. Participants in the PIAL survey were asked to report the type of perspective they preferred in their news. They were asked, “thinking about the different kinds of news available to you, what do you prefer?” Participants were given response options, “getting news that share your point of view” (coded 1) and “getting news from sources that don’t have a point of view” (coded 0). Participants randomly assigned to form 1 (N = 1,109) and form 2 (N = 1,150) were given slightly different response options for news that differs from their perspective, both coded -1. Form 1 participants were given the option, “getting news from sources that challenge your point of view” (M = .06, SD = .72, N = 1,020). Form 2 participants were given the option, “getting news from sources that differ from your point of view” (M = .22, SD = .64, N = 1,033).

Control Variables

Demographic control variables. Research on digital inequalities has demonstrated that certain people are more likely to have access and skills to use communication technology for specific purposes (Yu, 2006; DiMaggio, Hargittai, Neuman, & Robinson, 2001). Therefore, age, minority race, income, education, and gender are controlled in the survey analyses. A dummy variable for those who use the Internet (coded 1) and those who do not (coded 0) will also be included in RQ1 and RQ2. All other analyses compare Internet users.

Age was measured by asking participants to give their age in years (PIAL M = 45.98, SD = 18, N = 2,212; PPP M = 46.29, SD = 18.12, N = 2,960). Minority race was measured by asking participants to separately answer their race and if they were of Hispanic origin. Non-Hispanic whites were coded 0 (PIAL N = 1,564, PPP N = 2,135),
while others were coded 1 for the variable minority (PIAL N = 664, PPP N = 825).

Income was measured by asking participants, “last year, that is in 2009” (or 2008 for 2009 respondents), “what was your total family income from all sources, before taxes?” Response options available were “less than $10,000” (coded 1), “10 to under $20,000” (coded 2), “20 to under $30,000” (coded 3), “30 to under $40,000” (coded 4), “40 to under $50,000” (coded 5), “50 to under $75,000” (coded 6), “75 to under $100,000” (coded 7), “100,000 to $150,000” (coded 8), and “$150,000 or more” (coded 9) (PIAL M = 4.77, SD = 2.38, N = 2,994; PPP M = 4.97, SD = 2.46, N = 2,241). Education was measured by asking participants, “what is the last grade or class that you completed in high school?” Response options included, “none or grade 1-8” (coded 1), “high School Incomplete” (coded 2), “high school graduate” (coded 3), “technical, trade or vocational school after high school” (coded 4), “some college or associate degree” (coded 5), “college graduate (4-year degree)” (coded 6), and “post-graduate training” (coded 7) (PIAL M = 4.36, SD = 1.66, N = 2,243; PPP M = 4.43, SD = 1.63, N = 2,994). Lastly, sex was recorded by the interviewer as either male (PIAL N = 1,103, PPP N = 1,430) or female (PIAL N = 1,156, PPP N = 1,576).

**News Attention.** Participants’ general interest in news was controlled in the PIAL study analyses. Participants were asked, “Some people like to follow the news all or most of the time. Others don’t follow it that often. How about you?” Response options included “hardly ever” (coded 1), “only now and then” (coded 2), “some of the time” (coded 3), and “all or most of the time” (coded 4). Participants who responded “never,” a response option not read, were coded 0 (N = 2,247, M = 3.30, SD = .03).
**Political Control Variables.** Political ideology and party affiliation are also important variables when investigating political news consumption. Those who are strong ideologues and have strong party allegiances are more likely to be polarized in their news readership (e.g., Iyengar & Hahn, 2009). Therefore, political ideology and party affiliation will be controlled in the survey analyses.

Both the PPP and PIAL surveys measure political ideology by asking participants, “Describe your political views as.” Response categories include “very conservative” (coded 1), “conservative” (coded 2), “moderate” (coded 3), “liberal” (coded 4), and “very liberal” (coded 5) (PIAL $M = 2.82$, $SD = 1.00$, PPP $M = 2.79$, $SD = .97$). Both the PPP and PIAL surveys measure political party affiliation by asking participants, “In politics today, do you consider yourself a Republican, Democrat, or Independent?” If the participant reported affiliation with the Republican Party, the control variable Republican was coded “1” (PIAL $N = 535$, PPP $N = 764$). If a participant reported affiliation with the Democratic Party, the control variable Democrat was coded 1 (PIAL $N = 709$, PPP $N = 991$).

**Analysis Plan**

The survey data is analyzed using a series of regression models to test H1, RQ1, H2, H3 and RQ2. Personalized news use is the independent variable in all models. Models are tested with dependent and control variables included. H1, RQ1, RQ2 and H3 utilize standard OLS regression models to determine the influence of personalized news reading on the dependent variables. RQ1 is tested with a series of OLS regression models for each offline media source. H2 utilizes ordinal probit regression due to the limited number of response categories. Unstandardized survey weights are utilized in all
analyses in order to best approximate a valid population estimate. Analyses were calculated using the SVY tools in STATA.

*Missing Data.* In all analyses, listwise deletion is utilized when data is missing from cases in the variables of interest. The control variables for income (PIAL = 19.26%, PPP = 15.97%) and political ideology (PIAL = 7.57%, PPP = 6.39%) contain over 5% missing cases in both the PIAL and PPP data. Hot-deck imputation is a good method to impute missing data in these circumstances (Roth, 1994). Hot-deck imputation randomly matches “donor” participants who match participants with missing data on a variety of other “deck” variables. The donor value is used to impute the missing values. Income was imputed using age, sex, race, education, employment status, marriage status and parental status as “deck” variables. Political ideology was imputed using political party affiliation, age, sex, race, education, employment status, marriage status and parental status as “deck” variables. Imputation was conducted using a hot-deck SPSS macro (for full details, see Myers, in press). After imputing these two variables, missing data fell to a level below 5% level for all variables in the analyses.

*Results*

Preliminary analyses of the bivariate correlation matrices of variables in the PIAL (Table 1) and PPP (Table 2) data sets show relationships between variables without controls. It is notable that without control variables, personalized news use has a significant positive relationship with number of online news sources and categories viewed as well as number of offline news types viewed. The PPP data shows a significant positive relationship between nearly every type of offline news viewing.
**Table 1. Bivariate zero-order correlations from PIAL data.**

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Note:* p < .05 level, two tailed, N = 1,449 unless otherwise noted.
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<td>9. Sex</td>
<td>-.049*</td>
<td>.047</td>
<td>-.030</td>
<td>.035</td>
<td>.034</td>
<td>.053</td>
<td>.063*</td>
<td>.016</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>10. Age</td>
<td>-.213*</td>
<td>.226*</td>
<td>.066*</td>
<td>.092*</td>
<td>.064*</td>
<td>.071*</td>
<td>.208*</td>
<td>.138*</td>
<td>.066*</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>11. Income</td>
<td>.088*</td>
<td>.012</td>
<td>.130*</td>
<td>-.029</td>
<td>.050</td>
<td>.025</td>
<td>-.049*</td>
<td>.148*</td>
<td>-.102*</td>
<td>-.026</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>12. Education</td>
<td>.130*</td>
<td>-.005</td>
<td>.042</td>
<td>-.092*</td>
<td>.054</td>
<td>.006</td>
<td>-.075*</td>
<td>.136*</td>
<td>-.003</td>
<td>-.044*</td>
<td>.475*</td>
<td>--</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13. Political</td>
<td>.045*</td>
<td>-.026</td>
<td>-.096*</td>
<td>-.323*</td>
<td>.112*</td>
<td>.060</td>
<td>-.079*</td>
<td>-.021</td>
<td>.045*</td>
<td>-.183*</td>
<td>-.048*</td>
<td>.035</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ideology</td>
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<td></td>
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<td></td>
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<tr>
<td>14. Democrat</td>
<td>-.001</td>
<td>.076*</td>
<td>-.070*</td>
<td>-.178*</td>
<td>.124*</td>
<td>.157*</td>
<td>.021</td>
<td>.007</td>
<td>.109*</td>
<td>.052*</td>
<td>-.113*</td>
<td>-.021</td>
<td>.257*</td>
<td>--</td>
<td></td>
<td></td>
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<td>15. Republican</td>
<td>-.027</td>
<td>-.041</td>
<td>.081*</td>
<td>.263*</td>
<td>-.110*</td>
<td>-.132*</td>
<td>.014</td>
<td>.032</td>
<td>-.001</td>
<td>.100*</td>
<td>.149*</td>
<td>.069*</td>
<td>-.354*</td>
<td>-.434*</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>16. Minority</td>
<td>.066*</td>
<td>.014</td>
<td>.015</td>
<td>.000</td>
<td>.113*</td>
<td>.073*</td>
<td>-.011</td>
<td>-.041</td>
<td>-.023</td>
<td>-.197*</td>
<td>.168*</td>
<td>-.062*</td>
<td>.131*</td>
<td>-.244*</td>
<td>-.229*</td>
<td>--</td>
</tr>
<tr>
<td>17. Internet User</td>
<td>.305*</td>
<td>-.044</td>
<td>.084*</td>
<td>-.043</td>
<td>-.024</td>
<td>.003</td>
<td>-.059*</td>
<td>.086*</td>
<td>-.049*</td>
<td>-.397*</td>
<td>.344*</td>
<td>.354*</td>
<td>.028</td>
<td>-.129*</td>
<td>.025</td>
<td>-.062*</td>
</tr>
</tbody>
</table>

Note * indicates a significant relationship at the \( p < .05 \) level, two tailed, \( N = 2,737 \) unless otherwise noted

Table 2. Bivariate zero-order correlations from PPP data.
Table 3. OLS regression model estimating level of being overwhelmed by the quantity of news from personalized news use and control variables.

The OLS model results in Table 3 shows the results of modeling personalized news use as a predictor of being overwhelmed by news. Coefficients and standard errors are unstandardized using population weights included in the PIAL data. H1 predicted personalized news use would result in being less overwhelmed by the total amount of news. While the results are in the predicted direction, there is no significant difference between personalized news users and non-users in describing the amount of news as
<table>
<thead>
<tr>
<th>Personalized News Use</th>
<th>Network News</th>
<th>Cable News</th>
<th>Local News</th>
<th>Newspapers</th>
<th>Fox News</th>
<th>CNN</th>
<th>MSNBC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>.436***</td>
<td>.339***</td>
<td>.227***</td>
<td>.146**</td>
<td>.151*</td>
<td>.254***</td>
<td>.136†</td>
</tr>
</tbody>
</table>

| Sex                   | .113        | -.007      | .111*      | .041       | .092     | .068  | .0103  |
|                       | (.072)      | (.069)     | (.045)     | (.051)     | (.069)   | (.069) | (.065) |

| Age                   | .017***     | .008***    | .013***    | .013***    | .004*    | .006*** | .007*** |
|                       | (.002)      | (.002)     | (.001)     | (.001)     | (.002)   | (.002) | (.002) |

| Income                | .017        | .050***    | -.008      | .042***    | .008     | .032†   | .025   |
|                       | (.017)      | (.015)     | (.012)     | (.012)     | (.014)   | (.017) | (.016) |

| Education             | -.022       | -.028      | -.051**    | .045*      | -.070**  | .022   | -.018  |
|                       | (.025)      | (.023)     | (.016)     | (.018)     | (.025)   | (.024) | (.024) |

| Political Ideology    | -.009       | -.060      | -.055*     | .010       | -3.02*** | .085*  | .021   |
|                       | (.045)      | (.043)     | (.028)     | (.031)     | (.038)   | (.039) | (.040) |

| Democrat              | .061        | -.112      | .019       | .039       | -.218*   | .126   | .208*  |
|                       | (.087)      | (.082)     | (.054)     | (.061)     | (.082)   | (.086) | (.083) |

| Republican            | -.129       | .074       | -.019      | .016       | .443***  | -.134  | -.208* |
|                       | (.095)      | (.088)     | (.055)     | (.065)     | (.091)   | (.087) | (.080) |

| Minority              | .108        | .174†      | .063       | .044       | .265**   | .277** | .134   |
|                       | (.088)      | (.084)     | (.059)     | (.064)     | (.089)   | (.095) | (.090) |

| Internet User         | .035        | .194       | .123†      | .311***    | -.067    | -.118  | .194   |
|                       | (.126)      | (.126)     | (.074)     | (.085)     | (.113)   | (.120) | (.113) |

| Constant              | .540*       | 1.52***    | 1.68***    | 5.18***    | 2.30***  | .662** | .482*  |
|                       | (.239)      | (.241)     | (.162)     | (.170)     | (.232)   | (.237) | (.231) |

| R²                    | .089        | .060       | .067       | .061       | .154     | .058   | .046   |

| N                     | 1365        | 1367       | 2745       | 2747       | 1382     | 1379   | 1377   |

Note † < .10 *p < .05 **p < .005 *** p < .001, two-tailed

Table 4. OLS regression models estimating frequency of offline news viewing from personalized news use and control variables.
<table>
<thead>
<tr>
<th></th>
<th>Number of Online News Sources</th>
<th>Number of Online News Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>Personalized News Use</td>
<td>.338*** (.053)</td>
<td>1.60*** (.169)</td>
</tr>
<tr>
<td>Sex</td>
<td>-.037 (.048)</td>
<td>-.089 (.165)</td>
</tr>
<tr>
<td>Age</td>
<td>-.014*** (.002)</td>
<td>-.046*** (.005)</td>
</tr>
<tr>
<td>Income</td>
<td>.112 (.013)</td>
<td>.093* (.040)</td>
</tr>
<tr>
<td>Education</td>
<td>.086*** (.019)</td>
<td>.548*** (.062)</td>
</tr>
<tr>
<td>Political Ideology</td>
<td>-.028 (.028)</td>
<td>.049 (.093)</td>
</tr>
<tr>
<td>Democrat</td>
<td>.016 (.063)</td>
<td>.468* (.218)</td>
</tr>
<tr>
<td>Republican</td>
<td>-.082 (.063)</td>
<td>.137 (.199)</td>
</tr>
<tr>
<td>News Attention</td>
<td>.241*** (.031)</td>
<td>.906*** (.097)</td>
</tr>
<tr>
<td>Minority</td>
<td>.002 (.070)</td>
<td>.018 (.219)</td>
</tr>
<tr>
<td>Constant</td>
<td>1.12*** (.165)</td>
<td>1.64*** (.570)</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>.185</td>
<td>.275</td>
</tr>
<tr>
<td>N</td>
<td>1477</td>
<td>1549</td>
</tr>
</tbody>
</table>

Note *p < .05 **p < .005 ***p < .001, one-tailed

Table 5. OLS regression model estimating frequency of online news viewing from personalized news use and control variables.
overwhelming, $\beta = -.058$, $t(1540) = -0.97$, $p = .17$, one-tailed. This hypothesis is not supported.

Table 4 shows a series of models comparing offline news use between personalized news users and non-users to test RQ1. Coefficients and standard errors in parenthesis are unstandardized using population weights included in the PPP data. In nearly all cases, personalized news users report significantly more usage of offline media types including network news, cable news, local news, and newspapers. Personalized news users also report viewing Fox News and CNN cable news channels more than non-users. An increase in MSNBC news viewing was marginally significant for personalized news users ($p = .06$). In sum, there is ample evidence that personalized news users are viewing more offline news than non-users.

Moving from offline to online news viewing, Table 5 shows models that confirm H2 and H3 predictions that personalized news users view more news sources online and news categories online compared with non-users. Coefficients and standard errors in parenthesis are unstandardized using population weights included in the PIAL data. As predicted, personalized news users report viewing significantly more sources of news online compared with non-users, $\beta = .338$, $t(1467) = 6.39$, $p < .001$. Analysis also reveals that personalized news users report viewing significantly more categories of news online compared with non-users, $\beta = 1.59$, $t(1539) = 9.42$, $p < .001$.

Lastly, the exploratory ordinal regression models testing RQ2 in table 6 reveal no differences between personalized news users and non-users in their preference for their news source perspectives. Coefficients and standard errors in parenthesis are
<table>
<thead>
<tr>
<th></th>
<th>Form 1(^1)</th>
<th>Form 2(^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Personalized News Use</td>
<td>-.032 (.114)</td>
<td>-.037 (.111)</td>
</tr>
<tr>
<td>Sex</td>
<td>-.119 (.093)</td>
<td>.075 (.092)</td>
</tr>
<tr>
<td>Age</td>
<td>-.002 (.003)</td>
<td>.000 (.003)</td>
</tr>
<tr>
<td>Income</td>
<td>-.041 (.008)</td>
<td>.010 (.023)</td>
</tr>
<tr>
<td>Education</td>
<td>-.009 (.032)</td>
<td>-.049 (.035)</td>
</tr>
<tr>
<td>Political Ideology</td>
<td>-.045 (.055)</td>
<td>-.057 (.056)</td>
</tr>
<tr>
<td>Democrat</td>
<td>.137 (.117)</td>
<td>.073 (.122)</td>
</tr>
<tr>
<td>Republican</td>
<td>.313* (.110)</td>
<td>.412** (.112)</td>
</tr>
<tr>
<td>News Attention</td>
<td>-.075 (.060)</td>
<td>.008 (.041)</td>
</tr>
<tr>
<td>Minority</td>
<td>.046 (.124)</td>
<td>.189 (.124)</td>
</tr>
<tr>
<td>Internet User</td>
<td>-.055 (.146)</td>
<td>-.140 (.163)</td>
</tr>
</tbody>
</table>

N 935 962

Note *p < .05 **p < .001, two-tailed
\(^1\) Final response option ”challenge your point of view”
\(^2\) Final response option ”differ from your point of view”

Table 6. Ordinal regression model estimating perspective-sharing preferences of news sources from personalized news use and control variables.
unstandardized using population weights included in the PIAL data. Participants were
given three different response options representing perspective sharing, no perspective,
and differing perspective in their preferred news sources. Form 1 and form 2 participants
were given slightly different question wording. The affirmative and no-perspective
response options were the same in both forms while the last response option used
“challenge your point of view” in form 1 and “differ from your point of view” in form 2.
Neither wording produced any significant difference in responses from personalized and
non-personalized users.

Chapter Summary

This chapter provided the details for a study investigating the relationship
between personalized portal use and news viewing behaviors and news attitudes. First,
the study methodology was detailed. Two nationally representative data sets provided
comparisons between personalized portal users’ and non-users’ news viewing attitudes
and behaviors. Next, empirical results showed a positive relationship between
personalized portal use and online and offline news exposure. No differences between
personalized and non-personalized users were found in attitudes about feeling
overwhelmed by news and preferences for perspective-sharing or perspective-challenging
news.
Chapter 4: Experimental Study

This chapter will discuss the details of an online mock-election experiment of Ohio adults recruited through an Internet panel. This experiment manipulates personalization system design details to examine differences in news information processing (H4-H12). After introducing the details of the methods of this experiment, results will be provided. Like the previous chapter, the results will be discussed beginning with a discussion of the bivariate relationship between the predictor and outcome variables, followed by more rigorous multivariate analyses.

Methods

The second study in this dissertation is an online news experiment designed to evaluate cognitive outcomes of differences in news portal designs (H3-H12). In order to test these hypotheses, the experiment manipulates explicit user customization and the amount of information in personalized news portals in different conditions along with a generic news portal control group (see Figure 1). A mock gubernatorial election was constructed to examine an online panel of Ohio adults gathered by Survey Sampling International (SSI). The source of the news stories was manipulated across conditions of the experiment, while the content of the election news was randomly distributed between the sources. Participants in the personalized conditions will receive recommendations for sources that align to their preferences. Participants in the customized conditions will explicitly choose their recommendations. Participants in the recommended-information
conditions will only have access to the news stories recommended to them. Participants in the generic portal will see all news sources with no personalized recommendations.

Participants

Data in this study was collected from a convenience sample of 491 Ohio adult Internet users who agreed to participate in the mock gubernatorial election. Participants were recruited from an online panel managed by 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 surveys, including this online experiment. All panel participants who completed the survey were entered into a quarterly drawing for $25,000. Participants from populations that typically have low response rates, such as those between 18-24 years of age, were also credited 100 “points” in their individual account with SSI. Once a participant has accumulated at least 1,000 points, the points may be redeemed for prizes or money.

In total, 27,450 invitations were e-mailed to SSI panel members. Of these, 939 participants clicked on the invitation link to start the online experiment. About 28 percent or 264 of these participants did not complete the experiment and their results were omitted. From the remaining 675 participants, 111 participants were screened out of the survey experiment because they either did not consent to participate or they were not Ohio residents. From the remaining 564 participants who completed the online experiment, 23 were removed from the analyses due to technical problems viewing the news articles, 14 participants were removed for lagging (total time to complete the survey over 1 hour), 28 participants were removed for speeding (total time to complete
experiment under 7.85 minutes), and 7 duplicate participants were removed leaving a 491 valid respondents.

A post-portal technology-check question asked participants, “Were you able to view new stories when you clicked on news headlines?” Participants who answered “no” and also answered “0” to the question “How many news stories did you read?” were removed from the analyses due to technical problems. There were no systematic problems identified based on web browser or operating system versions. Each of the participants removed for lagging spent considerable time to answer their vote-choice question. This indicates the participants did not pay close attention to the news portal, rather they likely stepped away from the computer during the 3.5-7 required minutes inside the portal and came back to finish the survey. In each of these cases, response set was observed for the key dependent variable, elaboration. Therefore, these participants were not providing high quality data. Speeding participants similarly displayed response set and were likely quickly moving through the survey to receive the rewards provided for completion. Lastly, the participants removed as duplicates responded from the same IP address with identical demographic responses indicating these participants were taking the survey under multiple participant identification numbers to receive added benefits. Participant identification numbers for the laggards, speeders, and duplicates were reported to SSI.

Procedure

Participants were recruited via e-mail through SSI’s online panel between July 6-11, 2011 (see recruitment e-mail in Appendix A). Participants who clicked on the study link were randomly sent to a website for one of five experimental conditions varying the
level of personalization and information displayed in a mock election news portal. Participants in all conditions were asked an identical series of pre-news portal questions. Immediately before viewing the election news portal, participants viewed an informational web site describing the election news portal and news sources. Participants viewed between 2 and 6 news stories in their election news portal. Participants spent between 3.5 and 7 minutes in the election news portal. After leaving the election news portal, participants in all conditions were given a series of identical post-portal questions. After answering these questions, users were thanked and provided with a link to SSI’s member portal where they received credit for their participation. The full procedure will be detailed more thoroughly below.

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 with no incumbent running in the election. Both candidates had previous political experience. The Democratic candidate, Tom Barrett, was the mayor of Milwaukee, the largest city in Wisconsin and the Republican candidate, Scott Walker, was the Milwaukee county executive. Similar to Ohio, 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 policy changes were
passed, 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.

Candidate’s names have been changed in the mock election to Democratic candidate “Walter Smith,” “Cleveland Mayor” and Republican candidate “George Williams,” “Cuyahoga County Executive.” Economic policies were the primary focus of the election coverage due to the state’s recession. 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. Real-world stories were selected and modified so carried professional journalistic qualities and are similar in length. A full list of possible stories is presented in Appendix B. News stories present unbiased, objective news. The Associated Press, a non-partisan wire service, originally created all four of the hard news stories. The same author, Scott Bauer, wrote each of the four original articles. 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 has been modified so they are all purportedly covering the second debate and an undated election.

The two blog articles were selected to feature a non-partisan editorial stance on the debates. One article argues the debate “was not a debate” because it did not cover
new ground and “most of the talking points I’d heard before.” In the end, the blog author writes, “The winner? Each side will claim victory, although the format precludes determining a clear winner.” The second blog post article argues that despite “genuine and substantial differences between the two candidates,” their campaigns are tarnished by negative and untruthful claims. Examples of untrue statements are presented for each candidate and the author concludes, “Whoever wins on Nov. 2 will have to contend with expectations he can't meet and promises he can't keep. And knowing that, at least on occasion, he reached the state's highest office by taking the lowest roads.”

**Source Effects.** The key personalization and information manipulations in this experiment will vary the sources of news available to participants. Scholars in the selective exposure debate have argued that an increase in polarization of news media affects the way news consumers approach information (e.g., Bennett & Iyengar, 2008; Iyengar & Hahn, 2009; Sunstein, 2007). That is, consumers process information differently based on both the source and content of news. Therefore, to avoid confounded information effects from source effects, this study will randomly assign the balanced hard news articles among the news sources presented to the participants in the online news portal. The two editorial blog post articles will also be distributed randomly between the two news blog sources.

The mock election consists of an information universe of 6 news sources. There are two hard 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. There were two newspaper source options available including 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 somewhat more liberal MSNBC service. Lastly, a liberal blog, the Daily Kos, and a conservative blog, RedState, were used.

*Pre-News Portal Questions*

Participants who clicked on the link in the invitation e-mail (see Appendix A) were taken to one of five experimental conditions hosted on The Ohio State University School of Communication branded Qualtrics web survey platform. Participants in all conditions were asked a series of pre-election news portal questions.

*Screening questions.* First, participants were asked to explicitly consent to participating in the study. Participants were presented with the text, “We are studying how online news shapes political decisions. As part of this process, we are interested in learning about your political attitudes after you read some online news stories about a fictional Ohio election for Governor. We will ask questions about your political attitudes, news viewing habits, and Internet use. Data will remain confidential. We will not collect any information to identify you, personally. The survey should take about 15 minutes to complete.” Participants were given the response options “Yes, I agree to participate” and “No, I do not agree to participate.” Participants were then asked a second screening question, “Are you an Ohio resident over the age of 18?” Participants answered yes or no.

Participants who did not answer “yes” to both screening question were taken to their SSI member portal page where they were provided with links to other award-qualifying studies. Participants who answered yes to both questions were taken to the next set of pre-portal questions.
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 implicitly personalized news portal conditions. Adapting question wording from the media use questions in the PPP survey in Study 1, each media use question will have the response options of regularly (coded 4), sometimes (coded 3), hardly ever (coded 2) or never (coded 1). The five media use questions were asked in a random order. For newspaper viewing habits, participants were asked, “How often do you read a daily newspaper NOT on the web?” Participants were also asked, “How often do you read newspaper stories on the web?” For cable news viewing, participants were asked, “How often do you watch cable news channels such as CNN, MSNBC, or the Fox News Channel?” Participants were also asked if they view the websites for cable news channels, “How often do you read news online from cable news channels such as CNN, MSNBC, or the Fox News Channel?” Participants were asked about their online blog viewing habits, “How often do you read blogs about news, current events, or politics?” See Table 7 for descriptive statistics.

Political party affiliation. Participants were then asked a series of questions about their personal political views. Participants were asked, “I consider myself a….“ Response options included, “Republican” (N = 114), “Democrat” (N = 190), “Independent” (N = 144), and “Other” (N = 40). Participants who affiliated themselves with the Republican Party or Democratic Party were coded “1” in dummy control variables Republican or Democrat in the analyses. If participants respond “Independent,” “Other,” or do not respond, they were be asked, “Do you lean more towards the….“ Response options were, “Republican Party” (N = 45), “Democratic Party” (N = 55) and “Neither Party” (N = 87).
<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Newspaper NOT online</td>
<td>2.77</td>
<td>1.04</td>
<td>490</td>
</tr>
<tr>
<td>Newspaper online</td>
<td>2.97</td>
<td>0.92</td>
<td>489</td>
</tr>
<tr>
<td>Cable News</td>
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<td>1.00</td>
<td>490</td>
</tr>
<tr>
<td>Cable News Website</td>
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<td>1.03</td>
<td>490</td>
</tr>
<tr>
<td>News Blog</td>
<td>2.46</td>
<td>1.03</td>
<td>489</td>
</tr>
</tbody>
</table>

Note: 1=Never, 4=Regularly

Table 7. Experimental media use descriptive statistics

**Political ideology.** Participants were then asked, “In general, would you describe your political views as…?” Response options included, “Very Conservative” (coded 1), “Conservative” (coded 2), “Moderate” (coded 3), “Liberal” (coded 4), and “Very Liberal” (coded 5) ($M = 2.98$, $SD = .93$). This variable is also included in the analyses as a control variable.

**Political News Interest.** Lastly, participants were asked if they agree with the following statement, “In general, I am very interested in political news.” Response options included “Strongly Agree” (coded 5), “Agree” (coded 4), “Neither Agree nor Disagree” (coded 3), “Disagree” (coded 2), “Strongly Disagree” (coded 1) ($M = 3.65$, $SD = 1.03$, $N = 490$). This item was included in the analyses as a control variable.

**Experimental Conditions**
Participants were randomly assigned to one of five conditions. The first condition is a generic news portal condition ($N = 102$). The four personalized news portal conditions were manipulated in terms of explicit user customization and level of visible information. The four personalized news portal conditions are as follows: 1) implicitly personalized recommendations using machine-based recommendations, full information ($N = 96$); 2) explicitly personalized using customized user recommendations, full information ($N = 90$); 3) implicitly personalized, recommended stories only ($N = 103$); and 4) explicitly personalized, recommended stories only ($N = 100$).

Control condition. First, participants randomly assigned to the non-personalized, generic news portal 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.

Customization. Participants randomly assigned in a personalized news portal were randomly assigned to either explicitly customized or non-customized conditions. Participants in the non-customized conditions had their news sources recommended from information based on their pre-portal question responses. Participants in the customized conditions explicitly chose their recommended news sources.

Machine-based recommendations. Participants in the implicitly personalized, machine-based recommendation conditions first received recommended news sources that shared their political ideology. That is, conservative participants (ideology $< 3$) were recommended stories from The Columbus Dispatch, Fox News, or RedState. The more liberal participants (ideology $> 3$) were recommended stories from The Cleveland Plain-Dealer, MSNBC, or Daily Kos. If participants did not select any ideological preferences
(ideology = 3 or no answer), sources were recommended based on party affiliation. 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 the daily newspaper were not recommended a newspaper source, while those who at least “sometimes” read the daily newspaper were be recommended a newspaper source. The first recommended news source(s) displayed was/were the type(s) that participants reported spending the most time and the last recommended news source(s) displayed will be from the type(s) that participants report spending the least time viewing. Participants who only reported 0 or 1 type of news as greater than “sometimes” were then also recommended the type(s) of news they reported they viewed “hardly ever.” Participants who selected a political ideology or party affiliation 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 do not report any ideological preference (ideology = 3 or no answer) and do not affiliate with either political party were recommended both sources of the news media they prefer. Each of the news sources for a given news media will be displayed for non-ideologues for all sources they view “regularly” or “sometimes” but not “hardly ever” or “never.” If these participants do not answer “regularly” or “sometimes” for any media, then those that are viewed “hardly ever” will be recommended. Lastly, if each of the news media types is selected as “never,” then both newspaper sources were recommended. Descriptive statistics for the number of recommendations are presented in Table 8.
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<th>Condition</th>
<th>Mean</th>
<th>SD</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Implicit Recommendations / All Stories</td>
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<td>1.11</td>
<td>96</td>
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<tr>
<td>Customized Recommendations / All Stories</td>
<td>2.24</td>
<td>.567</td>
<td>90</td>
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<tr>
<td>Implicit Recommendations / Recommended Stories Only</td>
<td>2.71</td>
<td>.775</td>
<td>103</td>
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<td>Customized Recommendations / Recommended Stories Only</td>
<td>2.27</td>
<td>.694</td>
<td>100</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>2.53</td>
<td>.857</td>
<td>389</td>
</tr>
</tbody>
</table>

Table 8. Number of recommendations by experimental condition

*Customized recommendations.* Participants randomly assigned to the customized conditions were able to select their recommended news sources from the list of news sources and news types before entering the news portal. 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 8.

*Information.* Participants assigned to the personalized news portals were randomly assigned to full information or recommended-only news portal conditions. Participants in the full information personalized news portals were displayed a list of all six sources of news. The sources of news recommended to them were placed towards the
top of the list with blue headlines and a star. Non-recommended stories appeared in black. Participants in the personalized-only condition 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-Portal Information*

Following the pre-portal questions, participants were taken to a website describing their election news portal. First, participants were told,

Please read this page carefully.

You are about to enter the election news portal. To view a news story, simply click on the headline of that story. Please spend time carefully browsing the news stories to inform you about the candidates in the election.

After a few minutes of reading, you will see a link appear on the bottom of your screen. When you click the link, you will be able to cast your vote. After 7 minutes in the news portal, you will automatically proceed to cast your vote. After you vote in the election, you will be asked to answer a few questions about the election.

Participants in the generic portal were then told,

Your news portal will contain 6 sources of news, coming from a variety of news companies with different political perspectives. Below is a list of the news sources available in the news portal.

Participants in the implicitly personalized, machined-based recommendation portals were told,
Your personalized news portal will contain (#) sources of news, coming from a variety of news companies with different political perspectives. Below is a list of the news sources available in the news portal.

Participants in the personalized, explicitly customized portals were asked to select their preferred sources,

Your customized news portal will contain a number of sources of news coming from a variety of news companies with different political perspectives. Below is a list of the news sources available in your news portal. Please select the check box to the left of each of the sources of news you would like to view in your news portal. Please select AT LEAST TWO news sources. You may check as many as you would like.

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.

*Election News Portal*

Participants were required to stay in the election news portal 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. After 7 minutes in the news portal, you will automatically proceed to make your vote.

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.

*Time reading article.* The time each participant spent viewing news articles was unobtrusively recorded in seconds ($M = 280.85$, $SD = 80.44$).

*Post-Test Variables*

*Vote choice.* After viewing the election news portal, participants were first asked to participate in the mock election by voting. They were asked, “Which candidate do you choose to vote for Ohio governor in this election?” Response options were: “(R) George Williams” ($N = 172$), “(D) Walter Smith” ($N = 236$), and “I would not vote” ($N = 82$). Respondents who select “I would not vote” were subsequently asked, “Which candidate
do you prefer as Ohio governor?” Response options were: “(R) George Williams” ($N = 29$) and “(D) Walter Smith” ($N = 50$). These measures are not used in the analyses.

*News elaboration.* Participants were asked to respond to two message elaboration scales. Both scales ask participants to respond to a series of questions about reading the news articles. Both scales are coded on an ordinal scale from “Strongly Disagree” (1) to “Strongly Agree” (5). First, a 12-item news 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.” An average of a balanced number of 6 positively coded and 6 reverse-coded items will be computed for an overall elaboration score where a low score represents low elaboration and a high score represents high elaboration ($M = 3.65, SD = .56, N = 491, \alpha = .87$).

The second elaboration scale is comprised of 5-items asking participants to respond to the prompt, “When reading the news items” (Perse, 1990). Items include, “I think about what should be done,” “I think about what this will mean to me and my family,” and “I think about how these stories relate to other things I know.” A mean of all the items was computed where a low score represents low elaboration and a high score represents high elaboration ($M = 3.87, SD = .588, N = 491, \alpha = .82$).

*News stories.* Participants were then asked, “How many news stories did you read?” Participants were asked to enter a numeric number ($M = 2.88, SD = 1.39, N = 491$).

*Time spent per article.* The variable measuring the amount of time spent reading an average article was calculated by dividing the total number of seconds reading articles
observed unobtrusively while users were in the news portal by the number of stories participants read ($M = 119.28$, $SD = 67.40$, $N = 491$).

*Manipulation checks.* Participants were asked a series of Likert-scale statements to verify that the manipulations were effective. Each of the manipulation checks had response options of “Strongly Agree” (coded 5) to “Strongly Disagree” (1). In order to test if participants were aware of personalization, participants responded to the statement, “The news sources I viewed were recommended for me, individually.” Respondents in the personalized conditions should be more likely to agree than those in the generic condition. In order to check explicit user customization, participants were asked to respond to the statement, “I had input into the news sources that were recommended to me.” Participants in the customized conditions should score higher than those in the other conditions. Participants were asked, “I only saw news stories from sources recommended for me, individually.” Participants in the recommended-only conditions should score higher than those in other conditions. 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.

*Internet skill.* Skill using Internet technology is an important predictor of online user behavior (e.g., DiMaggio, Hargittai, Celeste, Shafer, 2004; Hargittai & Walejko, 2008; Hargittai & Hinnant, 2008; Hargittai, 2010). A 10-item Internet skill measurement was measured as a control variable in the analyses (Hargittai & Hsieh, in press). Participants were asked about their familiarity with a variety of computer and Internet-related terms such as “PDF,” “Spyware,” and “Wiki” (for the full details of the 10-item measure, see Hargittai & Hsieh, in press). Participants were asked to respond on a scale
from 1-5 for each item where 1 represented “no understanding” and 5 represented “full understanding” \((M = 3.13, SD = 1.13, N = 490, \alpha = .94)\).

**Demographics.** A series of demographic questions will be used for both descriptive purposes and as control variables in analyses. Participants were asked to identify their biological sex with males coded 0 \((N = 233)\) and females coded 1 \((N = 256)\). Participants were asked to report their age, in years \((M = 45.65, SD = 14.84, N = 491)\). Next, participants were asked to indicate their race. Participants who are non-Hispanic whites were coded “0” for the variable minority \((N = 395)\), while others were

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<thead>
<tr>
<th>Variable</th>
<th>Experiment</th>
<th>Ohio</th>
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</thead>
<tbody>
<tr>
<td>Sex: Female(^1)</td>
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<td>Age(^2)</td>
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<td>Hispanic(^1)</td>
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<td>Race: White(^1)</td>
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<td>Race: African-American/Black(^1)</td>
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<td>Race: Asian American/Asian(^1)</td>
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<td>Race: Native American(^1)</td>
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<td>Race: Other(^1)</td>
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<tr>
<td>Income(^2)</td>
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</table>

Note: Ohio data based on 2010 Ohio Census Results.
\(^1\)Proportion
\(^2\)Median

Table 9. Experimental demographic and Ohio demographic summaries
coded 1 \((N = 88)\). Education level was measured by asking respondents to provide the last level of schooling completed. Response options included, “none” (coded 1), “grade 1-8” (coded 2), “high school incomplete” (coded 3), “high school graduate” (coded 4), “technical, trade or vocational school after high school” (coded 5), “some college” (coded 6), “associate degree” (coded 7), “4-year college graduate” (coded 8), and “post-graduate training” (coded 9) \((M = 6.21, SD = 1.73)\). Lastly, participants were asked to provide their income. Response options available were “less than $10,000” (coded 1), “10 to under $20,000” (coded 2), “20 to under $30,000” (coded 3), “30 to under $40,000” (coded 4), “40 to under $50,000” (coded 5), “50 to under $75,000” (coded 6), “75 to under $100,000” (coded 7), “100,000 to $150,000” (coded 8), and “$150,000 or more” \((M = 4.42, SD = 2.11, N = 485)\). Table 9 shows a comparison of the demographics of this sample compared with the population of Ohio.

**Analysis Plan**

This study utilizes a series of OLS regression models to test H4-H10. A dummy variable for personalized conditions \((personalized)\) is used as the independent variable in H4-H6. Personalized portal users are coded 1 while generic portal users are coded 0. A dummy variable for customized news portals \((customized)\) is used to test H7-H9. Customized portal users are coded 1 while others are coded 0. Lastly, a dummy variable for high and low information conditions \((recommended)\) is used to test H10-H12. Participants who only received recommended stories are coded 1, while participants who had access to all news sources were coded 0.
As mentioned above, the models will also test the indirect effect of personalized portal use through increased average time spent reading on elaboration (see Figure 1). This relationship is often called mediation. Mediation is often tested using a multi-step approach where the direct relationship between the predictor variable and outcome variable are modeled then compared with a model including the mediator variable (e.g. Baron & Kenny, 1986). Hayes (2009) argues this method is not optimal due to its lack of power and specificity. Indirect effects 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. Furthermore, significant indirect effects can coexist with a direct effect from the predictor variable on the outcome variable. Significant indirect effects can also be found when the mediator variable has no statistically significant direct relationship with the outcome variable. This approach will be used to test the proposed indirect effects in this study (H6, H9, H12). Hayes & Preacher (under review) have developed a macro for SPSS, MEDIATE, that quantifies indirect effects and provides confidence intervals using a bootstrap method. Using this method, random subsamples of the study sample are taken and the indirect effects are modeled each time. One benefit of this technique is it allows for non-normal distribution of the indirect effects. If the derived confidence intervals do not include 0, the null hypotheses that no indirect effects are present can be rejected. This macro will be used to test the proposed indirect effects.
**Results**

Preliminary analysis of the bivariate correlation matrix of the variables in the data set shows relationships between variables without controls in Table 10. It is notable that without statistical controls, none of the proposed predictor variables is significantly related to either elaboration measure. There is a relationship between using a customized web portal as well as a portal with recommended articles only with increased time spent per article as predicted, but the relationship is not significant for all the personalized portals. Lastly, there is a moderately strong relationship between the two elaboration scales.

**Manipulation Checks**

A series of independent groups *t*-tests were conducted to verify expected differences in the web portal user experience based on the experimental manipulations. As expected, participants in the personalized news portals (*M* = 3.16, *SD* = .99) were more likely than those in the generic portals (*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 portals (*M* = 3.17, *SD* = 1.07) were more likely than those in non-customized portals (*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 portals 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
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<td>2. Customized Portal</td>
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<td>6. Elaboration2</td>
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<td>7. Sex (F) <em>(N = 489)</em></td>
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<td>14. Minority <em>(N = 483)</em></td>
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<td>16. Internet Skill <em>(N = 490)</em></td>
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<td>.143*</td>
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<td>.113*</td>
<td>.022</td>
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<td>-.007</td>
<td>-.210*</td>
</tr>
</tbody>
</table>

Note * indicates a significant relationship at the $p < .05$ level, two tailed. $N = 491$ except where noted (lower value used).

Table 10. Bivariate zero-order correlations from experimental data.
recommended for me, individually,” $t(447) = -4.18$ (Welch-Satterthwaite), $p < .001$. These results confirm the expectations of the experimental manipulations.

**Analyses**

The hypotheses for this experiment followed a similar trend for each set (see Figure 1). Each manipulation, including personalized portals, explicit user customized portals and portals showing only recommended stories was expected to increase the amount of time a user spends per story (H4, H7, H10). Each of these portal manipulations was also expected to increase news elaboration (H5, H8, H11). Lastly, an indirect effect between the portal manipulations and news elaboration was expected through the increase time spent per story (H6, H9, H12).

The first column in Table 11 shows the OLS regression model predicting time spent per article from the portal conditions, using the control group as a reference group. Personalized portal use did not significantly increase the amount of time spent per article, $b = -.866$, $t(458) = -.960$, $p = .17$, one-tailed. Users in the customized web portals did spend significantly more time reading per article than compared with portal users in the non-customized conditions, as predicted, $b = 14.55$, $t(458) = 2.10$, $p < .05$, one-tailed. Lastly, users in the portals with only recommended articles also spent more time reading per article, as predicted, $b = 22.48$, $t(458) = 3.28$, $p < .001$. H7 and H10 are supported; H4 is not supported.

The second and third columns in Table 11 show the OLS regression models predicting the 11-item and 5-item elaboration scales, respectively. In both models there is no significant relationship between portal type and elaboration. H5, H8, and H11 are not supported. Also, in both models, there is no significant indirect effect between portal type
<table>
<thead>
<tr>
<th></th>
<th>Predicting Time Spent Per Article</th>
<th>Predicting Elaboration (12-item measure)</th>
<th>Predicting Elaboration (5-item measure)</th>
</tr>
</thead>
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<tr>
<td>Time Spent Per Article</td>
<td>--</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td>Personalized News Portal¹</td>
<td>-8.66</td>
<td>.036</td>
<td>-.052</td>
</tr>
<tr>
<td></td>
<td>(9.02)</td>
<td>(.069)</td>
<td>(.075)</td>
</tr>
<tr>
<td>Personalized Indirect Effect²</td>
<td>--</td>
<td>-.004</td>
<td>.004</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(.007)</td>
<td></td>
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<tr>
<td>Customized News Portal¹</td>
<td>14.55*</td>
<td>-.018</td>
<td>-.009</td>
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<tr>
<td></td>
<td>(6.93)</td>
<td>(.053)</td>
<td>(.058)</td>
</tr>
<tr>
<td>Customized Indirect Effect²</td>
<td>--</td>
<td>.007</td>
<td>-.006</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(.007)</td>
<td></td>
</tr>
<tr>
<td>Recommended News Portal¹</td>
<td>22.48***</td>
<td>.054</td>
<td>-.008</td>
</tr>
<tr>
<td></td>
<td>(6.90)</td>
<td>(-0.023)</td>
<td>(.058)</td>
</tr>
<tr>
<td>Recommended Indirect Effect²</td>
<td>--</td>
<td>.011</td>
<td>-.010</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(.010)</td>
<td></td>
</tr>
<tr>
<td>Sex (F)</td>
<td>1.76</td>
<td>.160***</td>
<td>.196***</td>
</tr>
<tr>
<td></td>
<td>(6.29)</td>
<td>(.048)</td>
<td>(.052)</td>
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<tr>
<td>Age</td>
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<td>.004*</td>
<td>-.001</td>
</tr>
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<td></td>
<td>(.224)</td>
<td>(.002)</td>
<td>(.002)</td>
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<tr>
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<td>-.021</td>
</tr>
<tr>
<td></td>
<td>(1.54)</td>
<td>(.012)</td>
<td>(.013)</td>
</tr>
<tr>
<td>Education</td>
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<td>.050***</td>
<td>.006</td>
</tr>
<tr>
<td></td>
<td>(1.95)</td>
<td>(.015)</td>
<td>(.016)</td>
</tr>
<tr>
<td>Minority</td>
<td>15.14*</td>
<td>-.158**</td>
<td>-.035</td>
</tr>
<tr>
<td></td>
<td>(8.27)</td>
<td>(.064)</td>
<td>(.069)</td>
</tr>
<tr>
<td>Political Ideology (Liberal)</td>
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<td>.000</td>
<td>-.011</td>
</tr>
<tr>
<td></td>
<td>(3.74)</td>
<td>(.029)</td>
<td>(.031)</td>
</tr>
<tr>
<td>Democrat</td>
<td>-2.44</td>
<td>.035</td>
<td>.041</td>
</tr>
<tr>
<td></td>
<td>(7.32)</td>
<td>(.056)</td>
<td>(.061)</td>
</tr>
<tr>
<td>Republican</td>
<td>16.02*</td>
<td>.036</td>
<td>.125*</td>
</tr>
<tr>
<td></td>
<td>(8.69)</td>
<td>(.067)</td>
<td>(.073)</td>
</tr>
<tr>
<td>Political News Interest</td>
<td>3.61</td>
<td>-.169***</td>
<td>-.193***</td>
</tr>
<tr>
<td></td>
<td>(3.28)</td>
<td>(.025)</td>
<td>(.027)</td>
</tr>
<tr>
<td>Internet Skill</td>
<td>-5.99*</td>
<td>.074***</td>
<td>.069**</td>
</tr>
<tr>
<td></td>
<td>(2.92)</td>
<td>(.022)</td>
<td>(.024)</td>
</tr>
<tr>
<td>Constant</td>
<td>118.92***</td>
<td>3.14***</td>
<td>4.016***</td>
</tr>
<tr>
<td></td>
<td>(27.67)</td>
<td>(.216)</td>
<td>(.235)</td>
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R² = .285, N = 472

Note *p < .05 **p < .005 *** p < .001, one-tailed. Unstandardized coefficients with standard error in parentheses
¹Control group used as reference, ²Indirect effect predicted through time spent per article

Table 11. Experimental OLS regression models
and elaboration (see Table 12). Indirect and total effects were calculated using the MEDIATE macro by Hayes & Preacher (under review). In each of the portal manipulations, the bias-corrected confidence intervals for the indirect effect through time spent per article contained 0, meaning there is no way to distinguish the indirect effects from chance. H6, H9, and H12 are not supported.

Post-Hoc Analyses. An alternative model was tested to see if there was a conditional relationship between the portal manipulation variables and the time spent reading per article. Here, interaction variables were placed into the OLS model to test for conditional effects. The results, found in Table 13, show a significant interaction between users of customized news portals and time spent per article for both the 12-item elaboration measure, \( b = .002, t(454) = 1.98, p < .05 \), one-tailed, and the 5-item elaboration measure, \( b = .002, t(454) = 1.77, p < .05 \), one-tailed. That is, for every second spent reading the article, a .002 increase in elaboration is expected (see Figure 2). The MODPROBE macro was used to calculate the regions of significance using the Johnson-Neyman technique (see Hayes & Matthes, 2009). The results of this analysis
<table>
<thead>
<tr>
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<th>Elaboration (12-item measure)</th>
<th>Elaboration (5-item measure)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time Spent Per Article¹</td>
<td>.000 (0.001)</td>
<td>-.001 (0.000)</td>
</tr>
<tr>
<td>Personalized News Portal²</td>
<td>.037 (0.070)</td>
<td>.043 (0.076)</td>
</tr>
<tr>
<td>Personalized X Time Spent¹</td>
<td>-.001 (0.001)</td>
<td>.000 (0.001)</td>
</tr>
<tr>
<td>Customized News Portal²</td>
<td>-.029 (0.054)</td>
<td>-.020 (0.058)</td>
</tr>
<tr>
<td>Customized X Time Spent¹</td>
<td>.002* (0.001)</td>
<td>.002* (0.001)</td>
</tr>
<tr>
<td>Recommended News Portal²</td>
<td>-.035 (0.054)</td>
<td>-.020 (0.059)</td>
</tr>
<tr>
<td>Recommended X Time Spent¹</td>
<td>.001 (0.001)</td>
<td>.000 (0.001)</td>
</tr>
<tr>
<td>Sex (F)</td>
<td>.159 (0.048)</td>
<td>.196*** (0.052)</td>
</tr>
<tr>
<td>Age</td>
<td>.004*** (0.002)</td>
<td>-.001 (0.002)</td>
</tr>
<tr>
<td>Income</td>
<td>-.020* (0.012)</td>
<td>-.022* (0.013)</td>
</tr>
<tr>
<td>Education</td>
<td>.054*** (0.015)</td>
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<tr>
<td>Minority</td>
<td>-.174** (0.064)</td>
<td>-.051 (0.070)</td>
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<tr>
<td>Political Ideology (Liberal)</td>
<td>.004 (0.029)</td>
<td>-.006 (0.031)</td>
</tr>
<tr>
<td>Democrat</td>
<td>.041 (0.056)</td>
<td>.044 (0.061)</td>
</tr>
<tr>
<td>Republican</td>
<td>.044 (0.068)</td>
<td>.138* (0.074)</td>
</tr>
<tr>
<td>Political News Interest</td>
<td>-.170*** (0.025)</td>
<td>-.195*** (0.027)</td>
</tr>
<tr>
<td>Internet Skill</td>
<td>.078*** (0.023)</td>
<td>.073** (0.025)</td>
</tr>
<tr>
<td>Constant</td>
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<td>3.92 (0.232)</td>
</tr>
<tr>
<td>R²</td>
<td>.218</td>
<td>.176</td>
</tr>
<tr>
<td>N</td>
<td>472</td>
<td>472</td>
</tr>
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</table>

Note † < .10 *p < .05 **p < .005 *** p < .001, two-tailed. Unstandardized coefficients with standard error in parentheses
¹Time spent per article mean centered, ²Time spent per article control group used as reference.

Table 13. Post-Hoc analyses probing for portal interactions with time spent per article.
show that users of customized portals who spend 253.98 seconds or more per article are predicted to report significantly higher elaboration in the 12-item elaboration scale than users reading for the same amount of time in non-customized conditions. Again, from the model predicting the 12-item elaboration scale, users reading 65.38 seconds and below are predicted to elaborate less. The conditional effect is weaker for the model predicting the 5-item measure of elaboration. In the model predicting the 5-item elaboration scale, users of customized portal who spend 328.17 seconds or more per article are predicted to
report just marginally significantly higher elaboration than users spending the same time in non-customized portals. Users who spend only 11.54 seconds or lower per article report marginally significantly lower elaboration using the 5-item scale. A significant interaction was not found for time spent reading the article and users of personalized web portals or portals with only the recommended stories.

Chapter Summary

This chapter provided the methodological detail and results for an experiment investigating the relationship between personalized portal use and news viewing behaviors and news information processing. The study used an Ohio adult sample of volunteer online panel members in an online election experiment to compare personalized portal design differences on election news exposure and news elaboration. Results showed a positive relationship between specific personalized portal designs and time spent with news stories. While the expected relationship between personalized portal usage and news elaboration was not found, a post-hoc analysis revealed a conditional effect for customized news use and increased time spent with news stories on increased news elaboration. The next section will discuss these findings, along with the findings from the survey study, in more detail.
Chapter 5: Discussion

This chapter will summarize the empirical results of both studies and discuss the theoretical and practical implications of each set of results. This chapter begins with an overview of the results from the two studies. Strengths and limitations of both studies will be discussed, along with suggestions for future research on these topics. The contributions of this research to the emerging body of social science research focused on the democratic and behavioral implications of interactive Internet technologies will be suggested. Lastly, suggestions for follow-up studies to continue in this line of research will be discussed.

Summary of Findings

Personalized messages and information systems are proliferating throughout the communication industries. The goal of this dissertation is to contribute to understanding how personalized portal usage impacts news reading behaviors, attitudes, and information processing. In the first study, using survey data from random national samples, a series of hypotheses predicted a positive relationship between personalized portal use and online news acquisition. Personalized news users reported viewing both more sources of news and more categories of news online compared with others. Similar results were found when comparing personalized portal users’ offline news viewing behavior with non-users. In nearly every type of media and media channel, personalized portal users reported increased news viewing. Contrary to the prediction that personalized portal users
would perceive the amount of news as less overwhelming compared with non-users, no differences were found. Personalized portal users also reported no differences in their preferences for perspective-sharing or perspective-challenging news.

The second study used an online mock election experiment to investigate causal differences in news reading behaviors between users of different types of news portals. As expected, customized portals providing news recommendations based on explicit user preferences resulted in an increase in time spent per article in the portal. Portals that only provided users with their recommended stories also resulted in increased time spent per article, as expected. Contrary to expectations, there was no difference in time spent per article between users of personalized news portals that provided machined-based recommendations based on profile information compared with generic news portal users. Furthermore, no differences in news elaboration were found between portal conditions either through direct effects or indirect effects through the added time spent with the news portal. A post-hoc analysis revealed a conditional effect for increased news elaboration. An interaction was found between viewing customized news portals and time spent per article. That is, a significant increase in news elaboration was found for users who viewed the customized portal and spent increased reading time per article. The following discussion will discuss explanations for each of these findings, along with a discussion of the limitations of these studies and the directions for future research.

**Explanation of Findings**

First, it was expected that accessing personalized portals would result in users feeling less overwhelmed by the amount of news. This hypothesis was not supported, as there was no difference found between personalized portal users and non-users. It was
expected that the increased personal relevance of personalized news would allow for users to more easily engage in the news. The relationship between increased news exposure and personalized portals could mean personalized portal users are more aware of the utter vastness of the information available in the news world through increased news engagement. As mentioned earlier, there is so much news available through the various media outlets on and offline that no one can attend to all the accessible news of the day. The feeling of being overwhelmed by the news doesn’t seem to be reduced when using technology to help organize news information.

The next set of analyses focused on news exposure both offline and online. In all models, the quantity of news acquisition was positively related to personalized portal use. Despite scholarly worry that more narrow types of news would be viewed when using personalized filters (e.g., Sunstein, 2009), an increase in news sources, channels, and categories was found for personalized Internet portal users. Therefore, we can conclude that personalized portal users are not narrowing the sources of news (e.g., just Fox News) or categories of news (e.g., only sports news) they view. As expected, these findings support previous empirical research demonstrating news users with access to technology that fosters selectivity actually increases news exposure (e.g., Garrett, 2009b). Avoiding the time-consuming step of searching for compelling news stories to view, personalized portals offer users personally relevant headlines immediately. These results contribute to a growing body of selective exposure and public opinion research findings indicating Internet access may foster positive democratic outcomes through increased news engagement.
Much of the selective exposure debate by public opinion scholars is centered on people’s behaviors as a result of their decreased exposure to diverse perspectives. The findings above demonstrate an increase in news category and source exposure, yet it is possible that all of those sources share users’ perspective providing them with a skewed perception of the public sphere. This increased polarization is a primary concern for public opinion scholars. Results indicate users of personalized portals report no difference in their personal preferences for news sources sharing or challenging their personal perspectives compared with non-users. The average news viewer seems to favor news that doesn’t have a particular biased perspective. That is, news users seem to prefer objective news sources that provide both perspective-sharing and perspective-challenging news. This result also indicates personalized portal use made possible by the Internet may foster positive democratic outcomes through increased news engagement. Taken together, these results indicate an increase in news exposure and no increase in preference for perspective-sharing news sources.

The experimental study specifically focused on news behavior and information processing differences between news portal users. Participants were randomly assigned to a generic or personalized news portal. Four personalized news portals manipulated design choices for recommendation systems including providing users with either machine-based news source recommendations based on their profile or allowing users to explicitly customize their news source recommendations, and either showing users all news stories, both recommended and not recommended or showing users only their recommended stories.
As predicted, the amount of time spent reading news per article increased in the portals with explicit user customization and when users were only displayed their recommended stories. Contrary to expectations, the machine-recommended portals did not result in increased time reading news per article. These findings indicate that the increased personal relevance of sources provided through personalized portals increases news story attention. The results also indicate that increased agency or control caused by explicit user interaction or removing the non-recommended stories is better for designing news portals when increased time spent reading articles is an ideal outcome. These findings confirm previous research that shows customized portals increase perceived personal relevance, involvement, and interactivity compared with non-customized portals (Kalyanarman & Sundar, 2006). These findings also indicate that the machine-based recommendations don’t have as strong of an effect with engagement with news articles compared to the other personalized settings. One explanation for this could be the machine-recommendation algorithm based on user political preferences and media-viewing habits was not ideal for increasing news engagement, despite being designed to increase personal relevance.

Contrary to expectations, there was no significant difference in the direct or indirect effect through increased time spent per article of news portal type on news elaboration. However, an interaction between customized news portals and increased time spent per article on increased news elaboration shows that the expected finding is conditional. That is, when a user engages in increased time spent reading per article in the customized news portal they reported higher elaboration than other non-customized news portal users. This interaction confirms the expected increase in elaboration guided by
dual-process theories of information (e.g., Chaiken & Trope, 1999; Petty & Cacioppo, 1986). The personalized portal conditions were each expected to increase motivation and ability through personal relevance and a reduction in cognitive load from surveillance. This experiment utilized a relatively small information universe: only a maximum of 6 news stories were displayed to users in the mock election. A possible explanation for the lack of findings in the other portal conditions is the lack of cognitive load in such a small information universe. That is, the interactive result indicates that with an increase in overall time required to wade through news information to make a decision, customization may have a more pronounced increase in news elaboration.

**Strengths and Limitations**

The goal of the first study in this dissertation was to understand how portal users in the real world differ from non-users. The empirical results in this study provide information about which Americans use personalized web portals and how they use them. While survey methods lack the control of an experiment, understanding how real people use technologies and who those people are is very important for understanding how technology is actually employed.

Results from the first study come from secondary representative national cross-sectional survey data. While these results have high external validity, providing a good baseline profile of personalized portal users, causal effects cannot be established. Based on these data, there is no way to establish if personalized portal users are engaging in more online and offline news as a result of increased personal relevance or if users who are engaged in more online and offline news acquisition are more likely to turn to personalized portals. Prior (2007) shows a subset of the population who are interested in
the news are likely to engage in increased news attention in a media landscape where news is more easily accessible while others, less interested in news, are likely to tune out. On the other hand, Kalyanaraman and Sundar (2006) show increased personalization leads to increased personal relevance and involvement with information provided by portals. Both of these empirical examples could provide explanations for the order effects in relationship between personalized portal use and news information acquisition. A possible reciprocal relationship between news acquisition and portal use could also be present.

Next, the survey results showed a significant increase in personalized portal users’ online news category exposure, online news source exposure, as well as offline news media type and source exposure. No differences between personalized portal users and non-users were reported in their preferences for news source perspective-sharing and perspective-challenging. These findings are notable because they indicate personalized portal use is related to increased news acquisition without an increase in perspective-sharing news sources. However, research shows that news viewer’s reported preferences and actual behavior can diverge (e.g., Tewksbury, 2003).

The second study was an experiment conducted with a sample of Ohio adult online panel members viewing different news portals. Volunteer respondents broadly matched the demographic diversity of Ohio adults, rather than being undergraduate laboratory subjects often used in social science research. While the study lacked the strict control found in a traditional laboratory experiment, it did confront real people with experimental stimuli in a natural environment. Therefore, while not meeting the formal
requirements to be representative of the population, the results here offer a number of benefits compared with traditional laboratory experiments.

The experimental study did not find the proposed mediated relationship between personalized portal use and news elaboration through time spent per article. An interaction between customized portal use and time spent per article was observed as a conditional effect on increased news elaboration. This study examined a rather short news period in an artificial mock gubernatorial election. This evidence indicates a relationship between some personalized designs and increased elaboration should be further explored. The theoretical mechanisms proposed rely 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. Therefore, one might expect that more pronounced effects would exist in a real-world personalized election news portal.

Furthermore, 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. However, the experiment was not designed to test the impact of personalized news portals on selecting news stories relevant to public opinion decisions in a news environment comprised of news less relevant to the public sphere.

The experiment was conducted with a sample of opt-in Internet panel users. This panel is not representative; therefore these findings cannot be generalized to the population. However, participants were randomly assigned to their portal conditions and this study does indicate evidence for the proposed mechanism of increased news elaboration through more highly personalized web portals.
Future Research

Taken together, this dissertation indicates a need for more research on the highly debated impact of personalized information systems. Scholars in the public opinion and selective exposure literature have argued that polarization may be fostered by personalization technologies. The results in these studies show that these fears might be overstated. Future studies should continue to focus on answering the questions raised in this debate. Specifically, this dissertation has demonstrated personalization is related to an increase in news acquisition and news elaboration. Using a social psychological theoretical framework, this dissertation was able to speak to polarization concerns about the impact of personalized information.

Future studies should continue this work by focusing on establishing a causal relationship between personalized portal usage and increased news category and source acquisition in real-world news environments. Furthermore, more conclusive results could be found in an over-time research study that investigates if patterns of changing behavior come after becoming used to personalized news environments. Previous research shows that privacy concerns moderate the attitudes and behaviors of personalized news users (Sundar & Marathe, 2010). Research also shows that increased time spent with a technology product can increase a user’s ability to manage privacy settings (boyd & Hargittai, 2010). Therefore, it may be through increased over-time use of personalized information systems that privacy concerns diminish and attitude and behavioral effects become more pronounced.

Future research should also focus on content exposure differences between personalized portal users and non-users. The inadvertency thesis (Brundridge, 2010b)
indicates increased exposure through filtering technology could lead to increased inadvertent exposure to cross-cutting perspectives. On the other hand, selective avoidance may show that filtering technologies may lead to a decrease in exposure to perspective-challenging news. This research would be valuable in helping answer questions about overall diversity of content exposure when using filtering technologies. That is, what is the relationship between personalized portal usage and both the category exposure of pro- and counter-attitudinal ideas and the quantity of pro- and counter-attitudinal ideas (see McDonald & Dimmick, 2003).

Additional variables further illuminating the relationship between personalized portal use and increased cognitive processing could also provide convincing additional evidence to support the proposed mechanisms described in this dissertation. For example, future studies could investigate a relationship between personalized portal usage and attitude accessibility or content knowledge to test if filtering technologies work on both pro- and counter-attitudinal information.

Evidence provided in this dissertation indicates future studies should focus on specific design choices when discussing personalized systems (see also Kalyanaraman and Sundar, 2008). 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 technologies that meet company goals as well as promote a positive user experience and positive democratic outcomes.
Follow-Up Studies

A follow-up study could use survey data to focus specifically on political news diversity and news portal usage. That is, a survey with data providing data with election news usage information and personalized portal usage could provide insight into partisan perspective-sharing and perspective-challenging news attitudes and opinions specifically in the political domain.

The personalized portal software developed for the experiment presented in this dissertation should be useful for future research. For example, in a future real-world election, real news stories could be piped in to the various portal conditions to test differences in portal use over-time with participants. Modifying the recommendation algorithm in this portal to promote specific outcomes could further test implicit machine-recommended stories. 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).

Lastly, an expansion of this research program 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 all integrate social network contacts as recommenders of news alongside machine-based or user-based 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

Empirical evidence in this dissertation shows filtering technology provides an avenue for citizens to engage with news more easily without negatively impacting decision-making conditions. Many possibilities for expanding on this research are ripe for future studies. This research focus needs to be expanded because the diffusion of personalized communication technologies is pervasive and unstoppable.
References


Hastie, R., & Park, B. (1986). The relationship between memory and judgement depends on whether the judgement task is memory-based or on-line. Psychological Review. 93, 258-268.


Dear Participant,

We are studying how online news shapes political decisions. As part of this process, we are interested in learning about your political attitudes after you read some online news stories about a fictional election for Governor of Ohio. We will ask questions about your political attitudes, news viewing habits, and how you use the Internet. The research is being conducted by Dr. Gerald Kosicki and Michael Beam, M.A. from the School of Communication at The Ohio State University.

We would very much appreciate it if you could take about 15 minutes to complete our online survey. Your participation in the study is voluntary, and there are no known risks to participating in the study. Further, your data is confidential and the researchers at Ohio State will never be able to connect your survey to your name.

When you signed up for a membership at Survey Sampling International’s SurveySpot you agreed to a set of standard incentives for participation in online surveys. Your participation in this project will result in your account receiving credit for survey participation.

By clicking the link to access the survey, you acknowledge being aware of the above information and agree to participate in this study. If you have any questions, please contact one of the researchers listed below.

For questions about your rights as a participant in this study or to discuss other study-related concerns or complaints with someone who is not part of the research team, you may contact Ms. Sandra Meadows in the Office of Responsible Research Practices at The Ohio State University at 1-800-678-6251.

[LINK]

Thank you for your help with this project.

Cordially,

Gerald M. Kosicki, Ph.D.  Michael A. Beam, M.A.
Associate Professor  Doctoral Student
614-292-9237  614-915-5532
kosicki.1@osu.edu  beam.33@osu.edu
Appendix B: Experiment News Articles


**Governor candidates George Williams, Walter Smith spar over jobs, stem-cell research**

COLUMBUS — If Republican George Williams is elected governor and follows through on his pledge to cut taxes amid a massive budget shortfall, essential state programs will be "ripped apart," Democrat Walter Smith said Friday during a debate.

Williams said he would protect essential services at the same time he would cut taxes on small businesses and others as part of a plan to increase jobs in the state. He accused Smith of attacking him in the debate, much like he did in the first one two weeks ago, because polls show he is behind.

Both candidates said the gubernatorial election comes down to who voters trust more.

Ohio's governor's office is open for the first time in 28 years since unpopular incumbent Democratic Gov. John Downs decided against seeking a third term. A Democrat has never been in the office for more than eight years in state history.

Friday's wide-ranging, 60-minute debate was broadcast statewide from Columbus and included questions asked by citizens in five other cities.

Economic issues dominated the discussion, but one of the most spirited interchanges came over their positions on stem cell research.

Smith supports abortion rights and embryonic stem cell research, which was pioneered at The Ohio State University. In response to a question, Williams said as governor he would direct state funding to research on types of stem cell research other than embryonic.

"We don't need to get caught up in the political controversy of this," Williams said.

Smith challenged Williams, noting that he had told anti-abortion rights group Pro-Life Ohio that he was in favor of banning embryonic stem cell research.
"Politicians should not be telling world-renowned scientists what they should do," Smith said.

On the economy, Williams attempted to tie Smith to Downs, who is leaving office instead of seeking a third term. Williams said Smith supports the same policies Downs championed that contributed to the current recession.

Smith, the mayor of Cleveland, argued that Williams, the Cuyahoga County executive, hasn't followed through on promises he made before taking office eight years ago and his pledges to cut state taxes are unrealistic.

The third and final debate will be held in Cincinnati.


Gubernatorial candidates Walter Smith, George Williams debate position on jobs, economy

COLUMBUS — Republican George Williams promised in Friday’s debate that as governor he would immediately cut taxes for small businesses and eliminate a tax on health savings accounts, saying he could pay for it by reducing government waste.

In response, his Democratic challenger Walter Smith said Williams has an abysmal record as Cuyahoga County executive in creating jobs and would be no better as governor.

"He's continuing his pattern of saying anything to anyone to get elected," Smith, the Cleveland mayor, said in a debate on Friday.

Smith cited Williams's elimination of a county economic development office last year as evidence of a poor record on jobs creation. Williams has defended that, saying he moved functions of the closed office elsewhere. Williams last week announced the hiring of a new county economic development director.

Williams has promised to create 250,000 jobs as governor. Smith has said he would aim to replace the 180,000 jobs lost during the recession.

Williams, in a phone interview Monday, said he would call a special legislative session on his first day in office and push his job creation plan.

Williams, a former state representative, said he believes whichever party is in control of the legislature after the election would want to work with him on helping Ohio's economy.
"Obviously it's easier if there's a Republican majority, no doubt about it," Williams said. "But I think in times of crisis, people demand leadership, they crave leadership."

Williams didn't have a price estimate for the biggest proposal he announced Monday — to cut taxes as much as 20 percent for businesses that employ 50 people or fewer. His other idea, eliminating the tax on Health Savings Accounts, would cost about $34 million over the next two years based on estimates done for a bill introduced last year to do it.

Williams said he would find the money to pay for his tax cuts, in part, through a reduction in government waste and abuse. He wants to create a commission to find $300 million in savings.

"We can't afford not to do it," Williams said of his tax cut proposals.

Williams has largely built his campaign around promises to cut taxes, including $1.8 billion in increases passed last year that primarily target large multistate corporations and couples earning more than $300,000 a year.

Smith called Williams's tax cut promises irresponsible given that Ohio faces a projected $2.7 billion budget shortfall. He said Williams has proposed spending the $300 million he promised to find in government waste "every which way but Sunday."


COLUMBUS — Republican George Williams promised in a debate Friday to immediately cut taxes to jumpstart Ohio’s economy if elected governor, while his Democratic opponent Walter Smith said the plans would put the state into a spiral of debt that would bring deep cuts to schools and other services.

The gubernatorial candidates’ debate got testy at times as they highlighted their differences. The hour-long event was the first of three debates planned before the election.

He also challenged Williams on his attempts to tie Smith to the unpopular incumbent Democratic Gov. John Downs, whose approval ratings are at all-time lows.

“I believe the governor we have right now in Columbus has taken the state down the wrong course,” Williams said in his opening comments.

“Scott, Gov. Downs’s not running,” Smith said to Williams later in the debate.

Smith told Williams, who ran for governor in 2006 but dropped out in the Republican primary, that he should have stayed in that race if he wanted to take on Downs.
Williams said there is no difference between Smith and Downs because they both supported the same tax increases passed in 2009 that Williams wants to repeal.

Smith said he’s against that approach, because it would nearly double the state’s budget shortfall and because those taxes were aimed at large, multistate businesses and wealthy people earning more than $300,000 a year. Smith said he would focus tax cuts on companies that create jobs in the state.

“We’ve got to be straight to the people of this state,” he said. “You can’t promise everyone tax cuts.”

Williams said his plan to cut taxes on small businesses would help put the economy on track and lead to the creation of 250,000 jobs over four years.

Smith said his plans would lead to replacing the 180,000 jobs Ohio has lost during the recession.

On other topics, Smith defended his support of constructing a high-speed train line between Cincinnati and Cleveland with $810 million in federal stimulus money because it would create 5,500 construction jobs. Williams opposes the train line because he said the cost isn’t worth the small number of permanent jobs that will be created. He also doesn’t want the state to be on the hook for the ongoing operation costs, estimated to be about $7.5 million a year.

On education, Smith said he couldn’t promise K-12 schools they would get as much money next year as they are getting now. Williams said he wasn’t looking to cut school aid, but he would work with schools to make better use of the money they do get.

Smith touted his support for embryonic stem cell research, something Williams opposes. Smith is Cleveland’s mayor and Williams is Cuyahoga County executive.

Smith, Williams spar over tax plans

COLUMBUS — Republican George Williams said in Friday’s governor’s race debate that voters were “sick and tired” of attacks being made against him in the campaign, while his Democratic opponent Walter Smith said Williams wasn’t being honest about his plans for cutting taxes.

The lively one-hour debate was the second of three debates before the gubernatorial election.

Smith accused Williams of not being forthright with voters about his plans to cut billions of dollars in taxes, including those benefiting couples earning over $300,000 a year and large, multistate businesses. Smith said implementing those tax cuts, and also doing away
with the corporate income tax, would be an “outright assault on education, health care, and property taxes.”

Smith said in the face of a $2.7 billion budget shortfall it would be irresponsible to cut taxes and he hasn’t promised to do that.

Williams focused on other tax cuts he’s touted targeting small businesses and companies that relocate to Ohio. Cutting those taxes, he said, would spur growth and help lead to the creation of 250,000 jobs over four years.

Smith, the Cleveland mayor, challenged Williams’s record as Cuyahoga County executive the past eight years, saying he’s done nothing to help create jobs within the city. Williams has run an ad in the campaign attacking Smith’s leadership as mayor given Cleveland’s high poverty rate.

Williams said Smith was only offering attacks against him and not real solutions.

“I think the voters are sick and tired of that,” he said.

Williams and Smith will find out how voters feel on Tuesday. The winner will replace retiring Gov. John Downs, a Democrat who decided not to seek a third term and is suffering under his worst approval ratings of his tenure. The seat is open for the first time in 28 years.

The White House has shown keen interest as Ohio is traditionally a swing state and will be important in the 2012 presidential race. President Barack Obama has already hosted a fundraiser for Smith as well as a rally on The Ohio State University campus where Smith introduced him to more than 26,000 students and others.

A number of Republican governors have come to Ohio to campaign for Williams.


**Walter Smith and George Williams are lying!**

Everyone knows the American public has a low opinion of politicians. What's sometimes overlooked is why. And the biggest reason is the politicians themselves — not what they do, necessarily, but what they say about each other. During the second of three scheduled debates both candidates took shots at each other, Smith more than Williams, while making lofty claims about themselves.

Make no mistake: There are genuine and substantial differences between the two candidates. Smith is pro-choice; Williams is "100% pro-life" and even opposes a law that requires the state's public schools to teach contraception. Williams opposes federal funding for embryonic stem-cell research; Smith supports it, warning of lost jobs in Ohio if his opponent imposes new controls. But these distinctions in policy are all but lost in
the din of the campaign and especially the ads run by the candidates and their supporters. Here the differences are more stark — not between this way or that, but between good and evil, right and wrong.

*Lies about each other*

The will to distort runs deep in both campaigns. Take Williams's accusation that Smith voted for "the largest tax increase in history." In fact, the 1993 federal tax hike Smith voted for as a member of Congress was actually the ninth highest, well behind the hike passed in 1982 under President Ronald Reagan. It's only the largest in terms of raw dollars, unadjusted for inflation, which hardly seems fair. Moreover, as a *We the People* fact check noted, this tax hike mostly increased the tax burden on the very wealthy, while reducing the burden for low-income families.

Smith, in turn, claims Williams saddled Cuyahoga County taxpayers with $400 million in pension-fund debt, which Smith contrasts to his own much more competent handling of the city of Cleveland’s pension fund shortfall. But, as *We the People* noted, Smith's claim to have filled the city's gap with "smart cuts" overlooks that he also raised the tax levy by 4%. And while Cuyahoga County under Williams did issue $400 million in pension obligation bonds, this money will be reinvested and hopefully yield a higher return. It's risky, but if the economy improves it could prove to be smart.

Whoever wins the election will have to contend with expectations he can't meet and promises he can't keep. And knowing that, at least on occasion, he reached the state's highest office by taking the lowest roads.


The second “debate” for Ohio governor between George Williams and Walter Smith was held Friday night. Here are my impressions:

First of all, it was not a debate. Opening statements were made by both candidates and then a panel of three took turns asking questions. There was little room or time for rebuttal. The debate ended with closing statements by both candidates.

Both seemed well-prepared. I didn’t notice any slip-ups although I’m sure some one will find some.

Nor did I hear any new ground. Most of the talking points I’d heard before. The themes for Williams were tax cuts and getting government to work for people again. Smith’s themes were that Ohio needs adult leadership and we have serious problems that need serious answers.

Smith was more often on the attack. Williams was content, for the most part, to present his program, although he attacked as well.
The winner? Each side will claim victory, although the format precludes determining a clear winner.