Encouraging Reading of Diverse Political Viewpoints with a Browser Widget

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Paul Resnick
50% of adults watched one of three broadcasts in 1970.

by 2007, this had dropped to just 10%

Prior 2007, Bennett & Iyengar 2008
The Filter Bubble

What is the Internet hiding from you?

Eli Pariser

republic.com
casssunstein
Perils of choice

• People prefer to see agreeable opinions. (Selective Exposure)

• Technology makes it easier for people to act on those preferences, and, in some cases, provides content after assuming those preferences.
Perils of choice

• People prefer to see **agreeable opinions**. (Selective Exposure)

• Technology makes it easier for people to **act on those preferences**, and, in some cases, provides content after assuming those preferences.

• When people predominantly access agreeable opinions:
  - consensus.
  - understanding & empathy.
  - learning.
Mixed evidence, lots of hand-wringing

• People say they seek diversity (Stromer-Galley 2003)
• People seem to agree with the norm of diverse news exposure (Garrett & Resnick 2012)
• Ideological segregation segregation online is not as bad as some fear. (Gentzkow & Shapiro 2010)
• People seek agreeable information but are indifferent to challenging information (Garrett 2009)
• Some people are challenge averse and some are diversity seeking (Munson & Resnick 2010)
• … but is worse online than other media (Gentzkow & Shapiro 2010)
Efforts to nudge

Highlighting & ordering based on agreeability.

Didn’t work.

(Munson & Resnick 2010)
Efforts to nudge

Highlighting ordering based on agreeability didn’t work.
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Recommendations of different facets on a topic.
Success in the lab.
(Park et al. 2009)
Efforts to nudge

Highlighting and ordering based on agreeability on a topic. Didn’t work. (Munson & Resnick 2010)

Recommendations of different facets on a topic. Success in the lab. (Park et al. 2009)

Memorandum Colors. Colored links by expected bias. No evaluation. (Baio)
Efforts to nudge

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Memorandum colors.
Colored links by expected bias. No evaluation.
(Baio)

Anonymous search. Effort to avoid Filter Bubble, shows there is interest.
Research objectives

Can we design interfaces that help people read more balanced news in an environment of choice?
Research objectives

Existing behavior
• To what extent do people read ideologically agreeable or disagreeable news?
• Can we predict this based on personality or demographic traits?

Changing behavior
• Can we design interfaces that help people read more balanced news in an environment of choice?
• Are there personality or demographic traits that predict persuadability?
Study Design

Measuring Behavior • Changing Behavior
Study Design

Measuring Behavior • Changing Behavior
Apparatus

• Chrome extension recording visits to all sites matching a whitelist of news sites ($n=10,570$), including up to 30 days of pre-installation history.

• Subset ($n=7,618$) of sites classified according to political lean.

Available at balancestudy.org
Classifying visits

Classified at top-level domain by:

• Averaging lean from several sources, including:
  – Memeorandum Colors (link-similarity based; Baio)
  – Left and right audience share (Gentzkow & Shapiro 2010)
  – Votes from classified Digg users and links from blogs (Munson et al. 2009)

• Classifying some columnists separately (e.g., David Brooks on New York Times)

• Manual corrections during testing (the Ann Coulter effect)

Sites & classification at balancestudy.org/whitelist-classifiable.html
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Measuring Behavior • Changing Behavior
Our widget

**Personal informatics approach:** designed to reveal users’ actual lean in reading behavior
When do people consider diverse views?

• When their **curiosity** has been piqued. (e.g., Newscube)

• When they have been reminded of **norms of fairness and balance.**

• When they are **less confident** in their own knowledge.
Our widget

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**Personal informatics approach:** designed to reveal users’ actual lean in reading behavior

**Normative message,** added to encourage a user to be balanced.
Field Deployment: Procedure

1 Subject accesses website & reviews materials

Balancer
Reveal the balance of your newsreading.

Install Chrome extension now

Balancer analyses your web browsing to show you the political slant of your reading history. If you get way out of balance, we may even give you reading suggestions.

You should know
This is a research project. Balancer transmits a portion of your browsing history — sites matching a list of known news sites — to us. We do not ask for any personally identifiable information and cannot link your history back to you, only to your extension.

After you install the extension, you’ll be asked to complete a brief (4 minute) survey. This helps us with our research.

You may stop participation at any time by uninstalling the extension.

If you have questions, you can email us at balanceteam@umich.edu.

How it works
Balancer classifies pages based on their address: does this source tend to get linked to by mostly liberals or conservatives? Is it regularly visited by liberals, conservatives, or a mix? This is imperfect, but in aggregate, it’s pretty good.

Sean Munson & Paul Resnick • School of Information, University of Michigan • Department of Human Centered Design & Engineering, University of Washington • supported by National Science Foundation award #118-0916099
Field Deployment: Procedure

1. Subject accesses website & reviews materials
2. Subject installs browser extension
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3. Subject prompted to complete survey
   (political lean, Big 5 personality, demographics)
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2. Subject installs browser extension
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4. Randomized to treatment or control. Up to 30 days of prior history captured.
Field Deployment: Procedure

1. Subject accesses website & reviews materials

2. Subject installs browser extension

3. Subject prompted to complete survey
   (political lean, Big 5 personality, demographics)

4. Randomized to treatment or control.
   Up to 30 days of prior history captured.

5. Control:
   28-day waiting period

5. Treatment:
   Immediate & ongoing feedback
Field Deployment: Subjects

- Recruited by word of mouth (email, social network sites), Google extension directory, & the media
- 15 September – 18 November 2012
- 1,145 installs with transmitted data
- 990 subjects completed the survey
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736 men, 181 women (80% male)

mean age: 36.7 years (stdev: 13.8)

political lean: 2.89 (stdev: 1.37)
  (1 = strongly liberal; 7 = strongly conservative)

partisanship: 2.93 (stdev: 1.48)
  (1 = strongly Democrat; 7 = strongly Republican)
Results

Measuring Behavior • Changing Behavior
Results

Measuring Behavior • Changing Behavior
S: A user’s Balance score

\[ S = \text{Average left-right score of all news page visits.} \]

Normalized to \([1,11]\) (because we had 11 pictures)

\[ R_A: \text{Agreeable news-reading measure} \]

\[ R_A = \begin{cases} 
S - 6 & \text{if } u \text{ is liberal} \\
6 - S & \text{if } u \text{ is conservative}
\end{cases} \]
$R_A$: pre-install
Individual differences as predictors of $R_A$?

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Coefficient</th>
<th>Std Err</th>
<th>$p$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.567</td>
<td>0.335</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Ideology (1-7)</td>
<td>-0.335</td>
<td>0.025</td>
<td>&lt; 0.0001</td>
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<tr>
<td>Age (years)</td>
<td>0.002</td>
<td>0.002</td>
<td>ns</td>
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<tr>
<td>Female</td>
<td>0.040</td>
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<td>Extraversion</td>
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<td>Agreeableness</td>
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<td>ns</td>
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<td>Conscientiousness</td>
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<td>0.042</td>
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<td>Intellect</td>
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<td>0.064</td>
<td>ns</td>
</tr>
<tr>
<td>Neuroticism</td>
<td>0.077</td>
<td>0.049</td>
<td>0.0597</td>
</tr>
</tbody>
</table>

OLS model for $R_A$, prior to installation, $F=26.09$ on 8 and 74 degrees of freedom, $p<0.0001$, adjusted $R^2=0.21$. 
Results

Measuring Behavior • Changing Behavior
$S_{\text{Post}} - S_{\text{Pre}}$

**Need red**
- Control: $\Delta = -0.15$
- Treat: $\Delta = -0.28$

$t = 2.446, n = 601$
$p = 0.015$

**Balanced**
- Control: $\Delta = -0.16$
- Treat: $\Delta = -0.02$

$t = 1.24, df = 104$
$p = 0.218$

**Need blue**
- Control: $\Delta = 0.83$
- Treat: $\Delta = 0.99$

$t = -0.425, n = 41$
$p = 0.67$
For median liberal-reading user (187 visits per 28 days), the difference in change between control and treatment is equivalent to:

- 4 new monthly visits to a right-leaning site or
- 20 new monthly visits to a neutral site
Individual differences as predictors of $S_{Post} - S_{Pre}$?

No.

Age, gender, ideological extremity, and Big 5 not predictors.

Not enough power and likely selection limit ability to evaluate effects of left-right ideology.
Encouraging Reading of Diverse Political Viewpoints with a Browser Widget

First study to use personal informatics to increase the diversity of news reading in the wild.

Persistent reminder of norm.

Persistent feedback.

Recommendations.

Goal setting.

Personalized recommendations.

Sharing or reputation elements.

...
Encouraging Reading of Diverse Political Viewpoints with a Browser Widget

• First study to use personal informatics to increase the diversity of news reading in the wild.

• Age, gender, and Big Five were not good predictors of bias in news reading or persuadability.

• Large design space of interventions to explore and test. Lots of work to do.
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Funders
NSF awards IIS-0916099 & IIS-0812042
Intel PhD Fellowship
Yahoo! Key Technical Challenge Grant