Algorithmically shaped news flows: The role of feedback loops

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Afdeling Communicatiewetenschap
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Today

Feedback loops in communication science

Why aren't we doomed?

Algorithmically shaped feedback loops

Moving forward

How I got interested in feedback loops: *a lot* of talk about bubbles and echochamers, but *despite* (seemingly) plausible mechanism, little real-world evidence.

That's fascinating!

ERC-Project NEWSFLOWS

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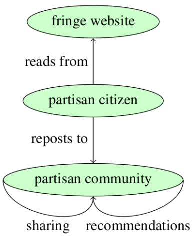


Figure 1: Example of a news flow in an echo-chamber (sharing) and/or filter bubble (algorithmic recommendations) scenario

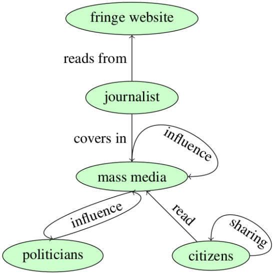
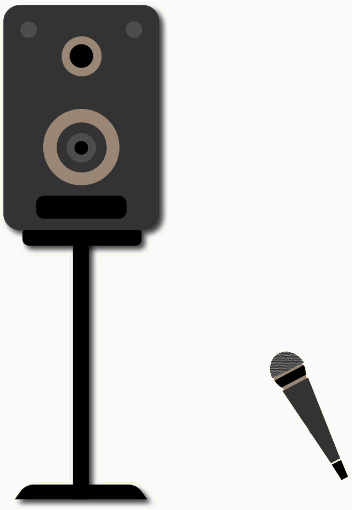


Figure 2: Example of a news flow in a complex scenario with multiple feedback loops

Feedback loops



What are feedback loops?

"parts joined so that each affects the other"
(Ashby, 1956, p. 54).

- cybernetics (e.g., Ashby, 1956)
- complexity science today (e.g., Meyers, 2009)
- system theory (e.g., Littlejohn & Foss, 2009)

The "feedback loop" notion in communication science i

Dynamic-transactional approach (Früh & Schönbach, 1982, 2005)

Feedback loops to model audience–producer relationships:

- overcome stimulus-response *and* uses-and-gratifications
- proposes "that it takes two to generate media effects, and that the relationship between the two actors may change during an effects process" (Schönbach, 2017, p. 8)

The "feedback loop" notion in communication science ii

Gatekeeping (Shoemaker & Vos, 2009; Westley & MacLean, 1957)

- Over time, journalists adopt their selection processes based on feedback they received from their audience
- Online more direct: "the dotted line [in Westley and MacLean's model] representing a weak audience feedback loop in mass communication models can now be made solid" (Shoemaker & Vos, 2009, p. 7)

The “feedback loop” notion in communication science iii

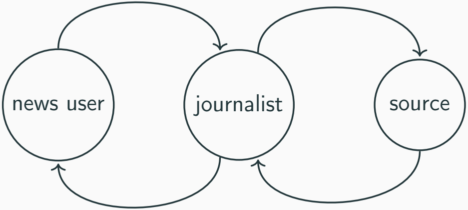


Figure 1: A system of two simple feedback loops in which the product that a journalist delivers is shaped by audience feedback on that product, but also by the feedback that sources (like interview partners) receive from the journalists.

The "feedback loop" notion in communication science iv

Reinforcing spirals (Slater, 2007)

"Mutually reinforcing processes, as opposed to self-regulating processes, might be expected to spin out of control or move to some extreme value—*a positive feedback loop*"

- two directions
- every cross-lagged models a feedback loop

The "feedback loop" notion in communication science v

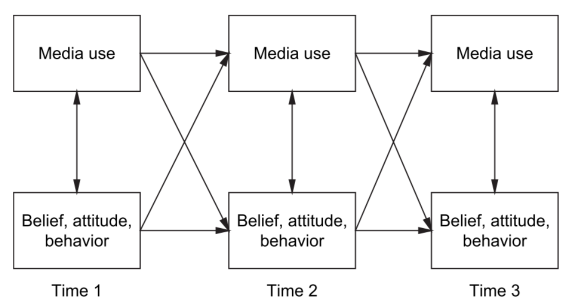


Figure 2: "Unrolling" a feedback loop and plotting it over multiple slices in time (figure by Slater, 2007)

Feedback loops

Why aren't we doomed?

Why aren't we doomed? i

Slater talks about *positive* feedback loops as "reinforcing processes" that "spin out of control".

But:

1. Also *negative*, self-regulating, feedback loops: "thermostat"
    - If recommendations become too tailored, or if the journalist is only driven by audience metrics, the result gets *boring* – users will turn away, changing the metrics
2. Nonlinearity: Over time, media effects will level off
3. "competing social, psychological, and environmental influences" ensure that the system is not fully "closed" (Slater, 2007, p. 288)

Why aren't we doomed? ii

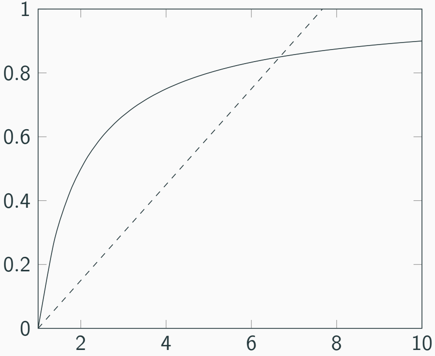


Figure 3: The linear function $y = 0.15 \times (x - 1)$ (dashed) and the non-linear function $y = 1 - \frac{1}{x}$ (solid).

While the notion of "feedback loops" seems to resemble filter bubble and echo chamber arguments, at least three arguments exist that show why feedback loops are compatible with a view that finds little evidence for the existence of filter bubbles or echo chambers (Bruns, 2019; Dahlgren, 2021; Flaxman et al., 2016; Haim et al., 2018; Zuiderveen Borgesius et al., 2016): negative feedback loops, non-linearity, and competing forces.

Algorithmically shaped feedback loops

Algorithms in journalism

Production side

- Google, social media recommendation/ranking, as research tool for journalists
- Trying to "beat" engagement metrics

Consumption side

- Google, social media recommendation/ranking
- News aggregators
- News recommendation on own platform

And more?

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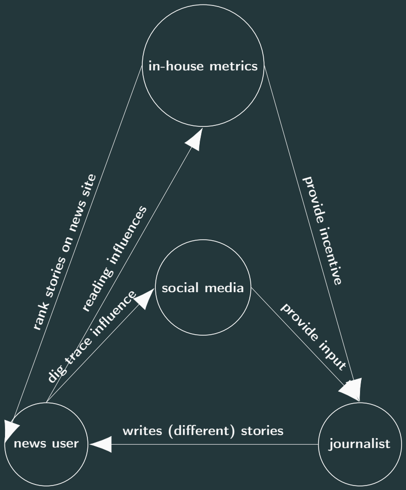
in-house metrics
social media
news user
journalist
rank stories on news site
reading influences
dig trace influence
provide incentive
provide input
writes (different) stories

What does that mean for our research?

- Increasingly difficult to say: $X \rightarrow Y$
- Tension between "static" research methods to study a dynamic system
- Hard to say who/what is to "blame" and to what extend
- Need new research designs

A move towards innovative methods

How do people *interact* with recommendation systems?

Online field experiments

But first some background:

A move towards innovative methods

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But first some background:

Three (four) types of recommender systems

General popularity Recommend what everyone reads

Semantic filtering Recommends what is most similar to current item

Collaborative filtering Recommends what similar users have read

(**Serendipity** Recommend something random)

(e.g., Bozdag, 2013)

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- only popularity → little to win, is read anyway
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Three (four) types of recommender systems

Modern systems use a *combination* of these!

- **popularity** makes sure you don't get only niche content
- **semantic filtering** makes sure you can continue reading on the topic
- **collaborative filtering** picks up signals that are not in the text (semantic)
- ***serendipity** makes sure readers can adjust (!!!) the system*

Three (four) types of recommender systems

If recommender systems worked as often assumed...

- you'd get nothing else after having read 10 aricles about sports
- get frustrated and stop using the system

How it works in realty

- after 10 articles about sports you get a *bit* more articles about sport
- (but you don't like sports; your partner used your pc)
- because the system also recommends other stuff (popularity, serendipity), and you choose those, it learns that you don't like sports that much after all and adapts

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Loecherbach and Trilling, 2019; Loecherbach et al., 2021: Do recommender systems reduce diversity?

Field experiment: we made a newssite with real (!) real-time (!) news and different recommendation algorithms.

The study

- 247 participants
- 23,000 choices (selections)
- two-week period
- point-based reward system ("gamification") to stimulate realistic usage pattern (incentivizing regular but not excessive use)
- Multiple conditions: random, implicit control (different rec sys), explicit control

Some results

1. No correlation between actual diversity and perceived diversity *(explanation: not linear, people just evaluate "good enough" (?))*
2. More control $\rightarrow$ less diversity (but also more variance, i.e. differnece between users)
3. For some topics (sports, economy), preferences override positioning effects and predictions based on past behaviour *(explanation: hate it or love it)*
4. Saturation effect: If a topic has been chosen a lot already, it won't be chosen again.
5. Really strong positioning effecs ($\approx$ 30% first option, $\approx$ 50% on mobile)

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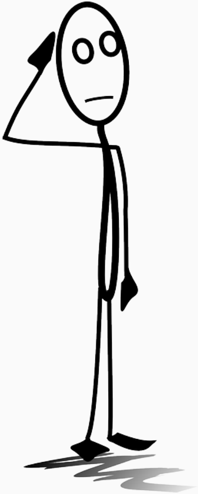
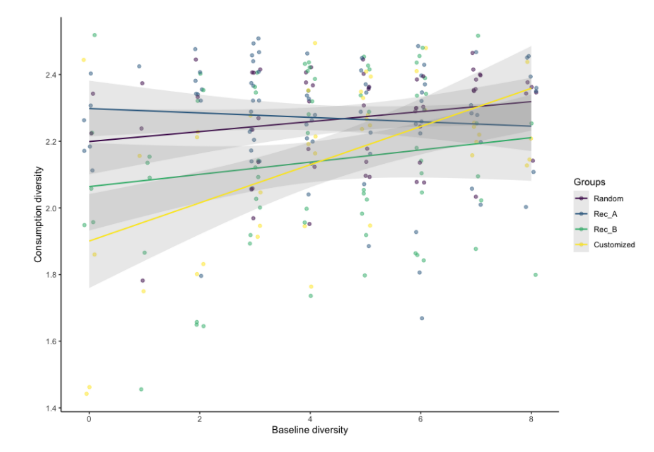


But is it the case that those who have less diverse interests to begin with indeed get less diverse news over time in such a system?

No.

Only for *explicit, self-selected* personalization (yellow), the diversity of someone's interest influences the over-time exposure diversity



Taken together, that's some evidence for more complex relationships: There are feedback loops within news sites, but the system does not *determine* people's selections, and other forces may be more relevant.

Moving forward

Three key take-aways

1. Communication has always been shaped by feedback loops
2. In today's media system, these are more visible, and potentially more influential, then before
3. Humans and algorithms *interact* in shaping feedback loops

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Three key challenges

1. counter-acting forces
2. non-linearity
3. data availability and measurement problems

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1. better theory (accounting for points above)
2. better operationalizations for testing them
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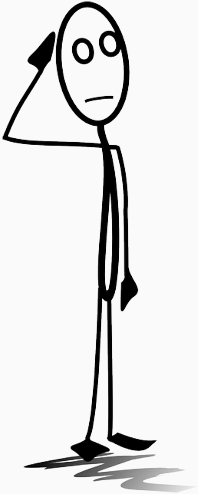

Any questions?

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