# Day 7 - Looking Ahead

UMN CSS Workshop 2025

Instructor: Alvin Zhou

# Group

- Group 1
  - Gretchen Corcoran
  - Jikai Sun
  - Shreepriya Dogra
  - Jialu Fan
- Group 2
  - Jiacheng Huang
  - Paulina Vergara Buitrago
  - Jong Won Lee
  - Eun Sun Kyoung
- Group 3
  - Sijin Chen
  - Michael Ofori
  - Jinny Zhang
  - Dongwook Kim
- Group 4
  - Raj Wahlquist
  - Nicole Marie Klevanskaya
  - Wenhui Cheng
  - Rita Rongwei Tang

- Mixed background and coding skills
- Group members who are confident in their coding skills, please help other members during the afternoon coding labs

# Learning Goals

- Is CSS a paradigm? What does that mean?
- Watts (2017): Solution-Oriented Social Science
- Wallach (2018): CSS ≠ CS + Social Data
- Methodological Triangulation and Mixed Methods
- Social Good and the Politics of Knowledge
- What’s Next? Large Language Models, Ethics, and Scale

# What Is a Paradigm?

- Thomas Kuhn (1962): Paradigms are frameworks that guide scientific inquiry: what questions are asked, how they're answered, and what counts as "progress."
- CSS is more than a toolkit—it's a shift in:
  - Objects of study (e.g., behavior, interaction, policy outcomes)
  - Evidence (e.g., digital exhaust, embedded sensors)
  - Methods (e.g., machine learning, agent-based models)
  - Epistemology (e.g., hybrid of prediction and explanation)

# Watts (2017): A Call for Reorientation

- “Should social science be more solution-oriented?”
- Traditional social science overemphasizes explanatory depth at the expense of solving real-world problems.
  - **Incentive distortion:** We value elegant theory more than actionable insight.
  - **Model complexity ≠ accuracy:** Simple models can work surprisingly well.
  - **“Explain first” bias:** We delay solving problems, waiting for perfect understanding.
- CSS Potential:
  - Combines prediction + experimentation + scalability
  - Enables policy simulation, rapid prototyping of interventions
  - Redefines “contribution” in terms of impact, not just theory

# Wallach (2018): CSS ≠ CS + Social Data

- You can't just throw social data into computer science models and call it CSS.
- Key tensions:
  - **Epistemological mismatch:** CS prioritizes performance; social science prioritizes inference and interpretation.
  - **Context collapse:** Scraping social media strips away the social context embedded in communication.
  - **Data ≠ Truth:** What's observable online isn't the same as what's meaningful offline.
- CSS requires **bridging**—not blurring—disciplinary logics.

# What do you think?

- Is computational social science changing the *how* and *why* we do social research—or just the *what* we research in social science?

# Looking Ahead

- If the discussion of CSS philosophy is too high-level, what can we do in practice when conducting our studies?
- Some Directions I Think That Are Valuable
  - Computational Storytelling:
    - Molding data, questions, and methods simultaneously
    - One Story, Deeply Told
  - DEMM Framework (Description → Experimentation → Mediator/Moderator identification)
  - Methodological Triangulation
  - Social Good and Ethical Imperatives

# Molding data, questions, and methods

- Good CSS doesn't just apply a method to a dataset—it reshapes data, questions, and methods simultaneously.
- I will swiftly introduce three studies of mine to illustrate the point.

# Study 1

- Zhou, A., Yang, T., & González-Bailón, S. (2025). The puzzle of misinformation: Exposure to unreliable content in the United States is higher among the better informed. *New Media & Society*, *27*(3), 1526–1543. https://doi.org/10.1177/14614448231196863

# RQs and Findings

- RQs
  - Citizens who maintain healthy news diets need to:
    - **1. Limit misinformation exposure**
    - **2. Seek news from ideologically diverse sources**
  - But what’s the relationship between the two?
- Findings
  - Three things that we want:
    - Read more news
    - Read more diverse news
    - Don’t read misinformation

# RQs and Findings

- RQs
  - Citizens who maintain healthy news diets need to:
    - **1. Limit misinformation exposure**
    - **2. Seek news from ideologically diverse sources**
  - But what’s the relationship between the two?
- Findings
  - Three things that we want:
    - ✓ Read more news
    - ✓ Read more diverse news
    - ✗ Don’t read misinformation
  - But we cannot get all three things together, at least now based on observed data

# Data and Methods

Web Browsing Tracking Panel Data

- N ~ 140,000 unique users in the US
- January to December of 2018
- Nielsen
- Representative of the US population with weights
- URL-level granularity
- What they visit, as well as how long (in seconds) they spent visiting those pages
- Demographic attributes: gender, age, education, race, ethnicity, and income
- Repeated observations for the same individuals

# Data and Methods

Measure 1: Misinfo Exposure

- Lists of misinformation website: Grinberg et al. (2019) and NewsGuard
  - Grinberg et al. (2019): N = 510 domains from journalistic outlets and prior research (Allcott & Gentzkow, 2017; Guess et al., 2018)
  - NewsGuard: Web domains trust score from 0-100; Lower than 60 means unreliable

Measure 2: (Reliable) News Exposure

- Lists of news website: five previous published studies (Bakshy et al., 2015; Budak et al., 2016; Grinberg et al., 2019; Peterson et al., 2021; Yang et al., 2020)
- N = 813 domains, but only N = 707 (87%) was visited at least once by our panelists

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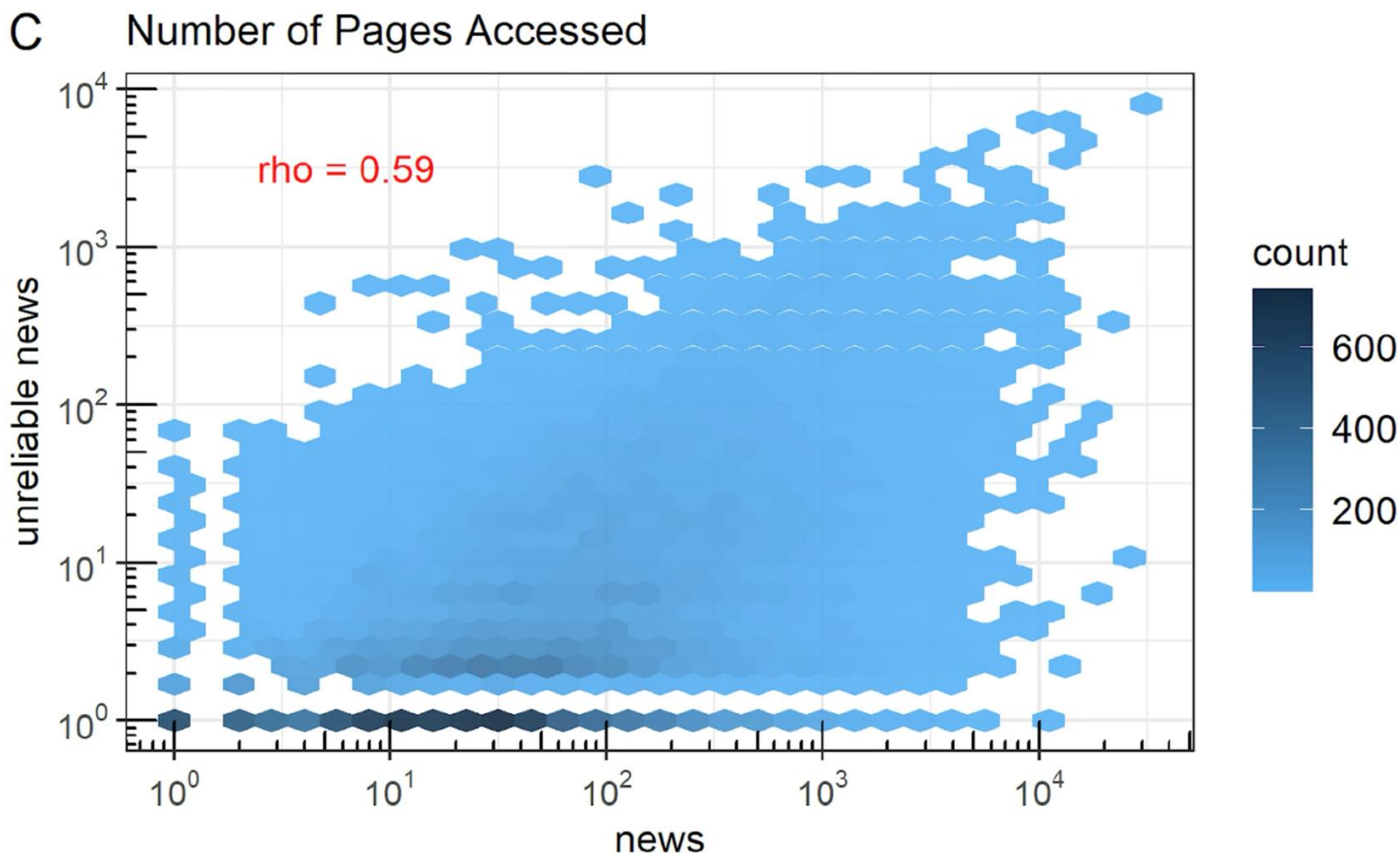
# More reliable news -> More misinformation exposure

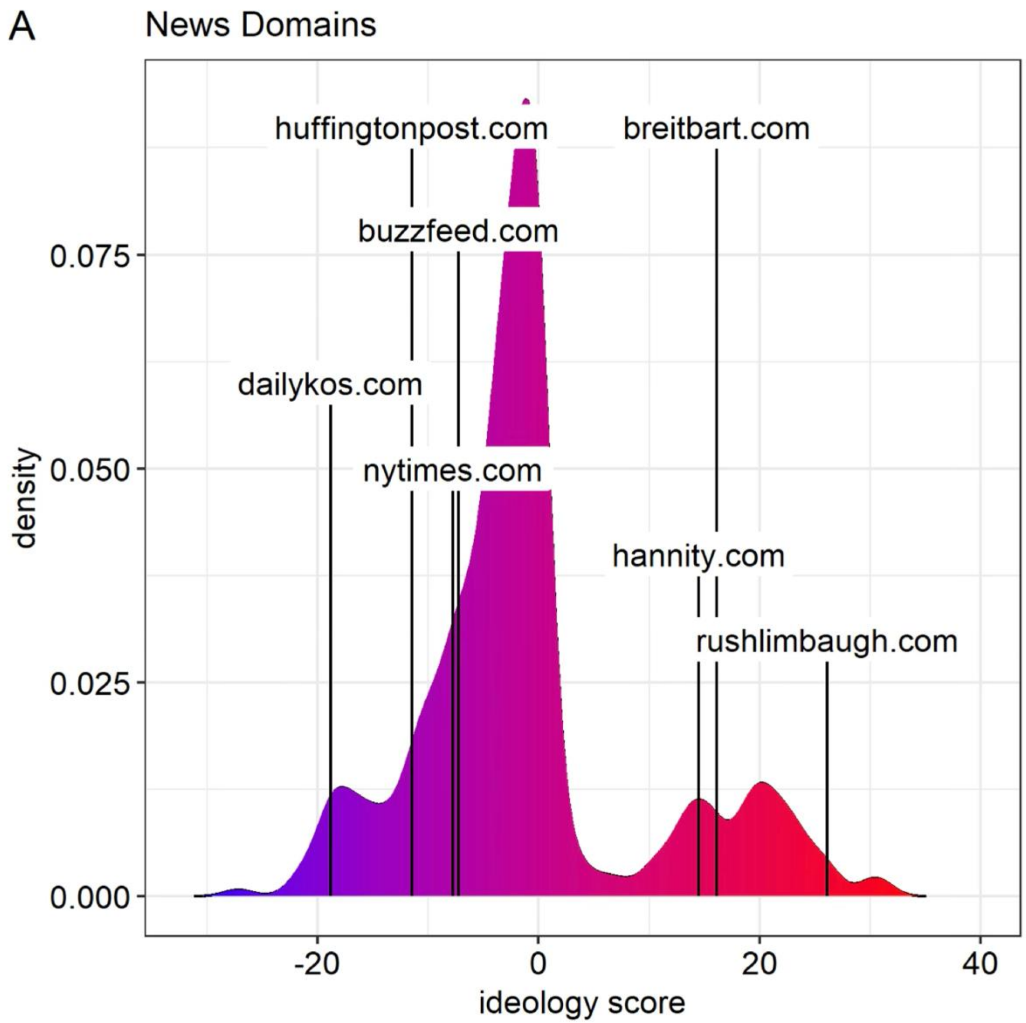


# Data and Methods

Measure 3: Ideological Scores of News Domains

- Ad Fontes (e.g., Aslett et al., 2022)
  - Samples articles on news domains' websites and employs an ideologically balanced panel of experts to rate news article's ideological slant
  - Ranges from -38.5 (most extreme liberal bias) to +38.5 (most extreme conservative bias)
- Audience-based measure of news domain bias (e.g., Tyler et al., 2021; Yang et al., 2020)

# Ideological Scores of News Domains

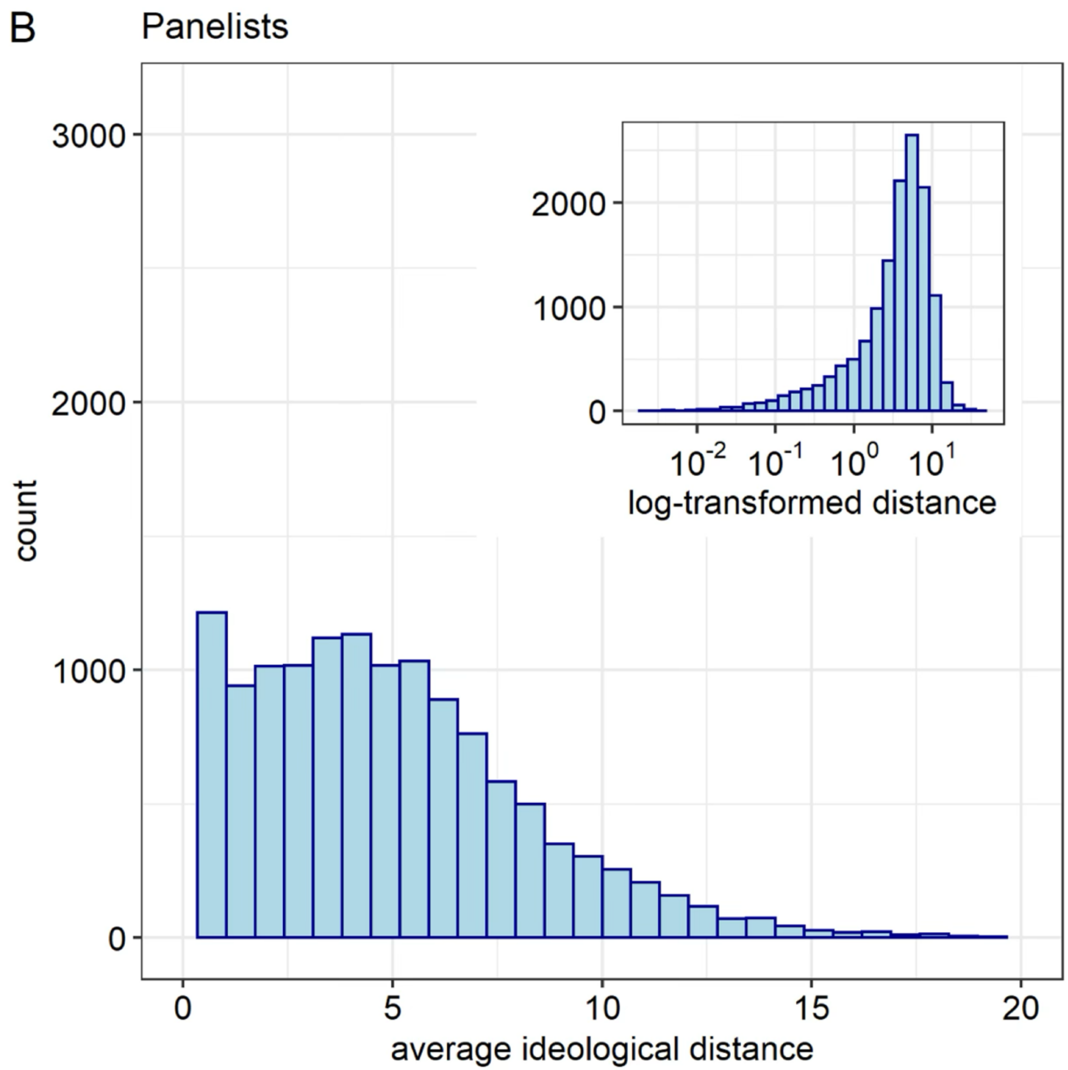


# Data and Methods

## Measure 4: Diversity of News Diets

- Pairwise ideological distance for news pages visited by the panelists by month
  - If panelist *i* accessed three pages in month *m* from the Activist Post, BuzzFeed, and the New York Times, we first calculate the ideological distance between each pair of these outlets, and then average the pairwise distances to a summary statistic for panelist *i* in month *m*
  - Smaller when accessing ideologically similar domains
  - Larger when accessing ideologically diverse domains

# Diversity of News Diets (Ideological Distance)



# Data and Methods

Measure 5: Demographic Variables

- Gender, age, education, employment status, race, ethnicity, and income
- Panelists' partisan leaning:
  - Instead of self-disclosed party affiliation, we extrapolate the partisan leaning of our panelists by averaging ideological scores of the news pages they visited each month
- More flexible and granular:
  - It can change from month to month (if news diets change)
  - Differentiate individuals that would otherwise look identical in their party affiliation based on self-reports

# So, what variables we have now?

Variable 1 (DV): Misinformation Exposure

1. Number of unreliable pages accessed
2. Time spent on those pages

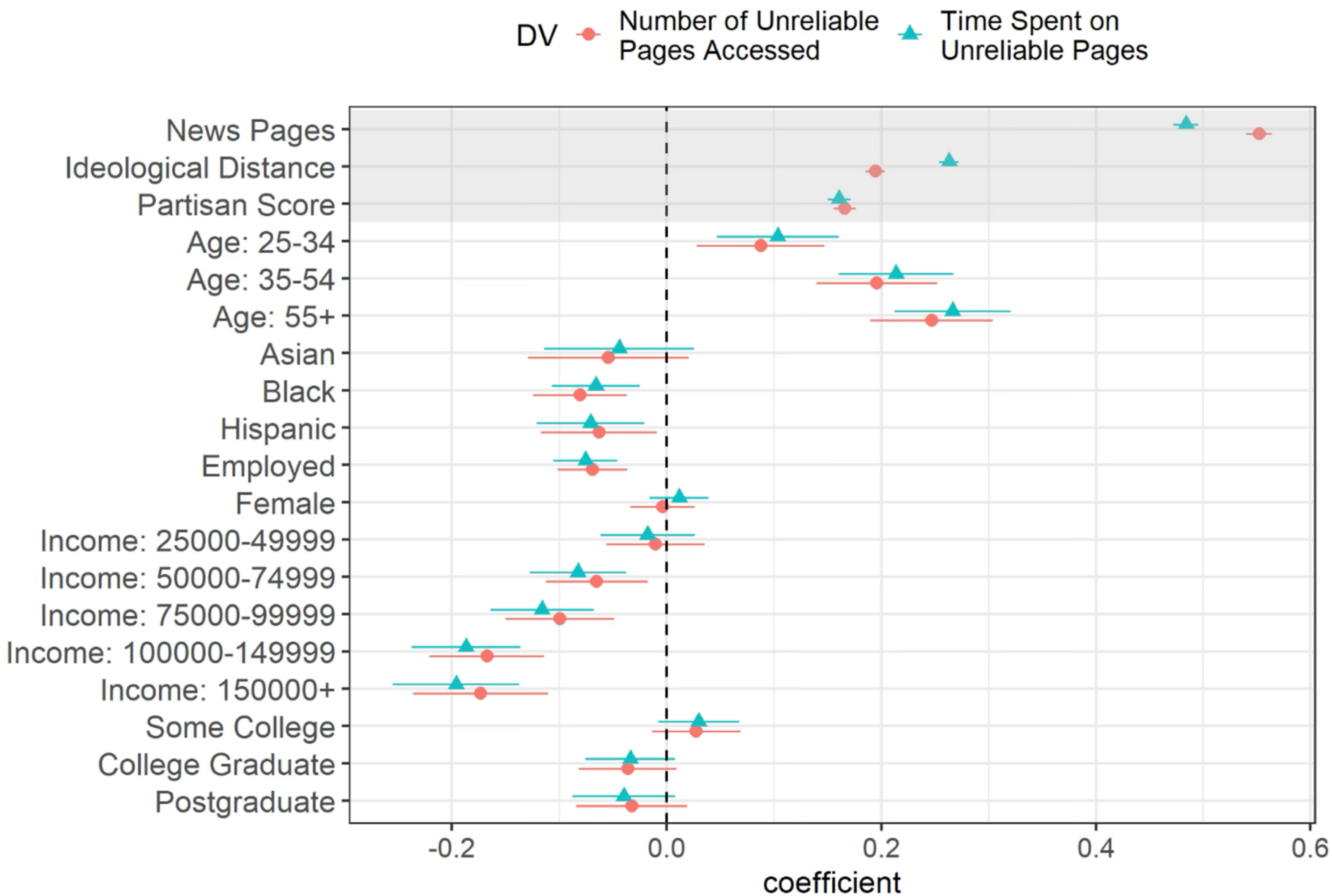
Variable 2 (IV): Number of news pages accessed

Variable 3 (IV): Ideological Distance (among visited pages)

Variables 4: Demographic Variables (including partisan leaning)

Linear mixed effects model, with panelist ID and month as random effects. All variables were scaled and log-transformed where appropriate.

# More diverse news diets -> More misinformation exposure



# How about within-person effects?

**Table A2. Fixed-Effects Regression Models**

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Number of Unreliable Pages | | | Time on Unreliable Pages | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| News Pages | 0.208*** | | 0.120*** | 0.543*** | | 0.386*** |
| | (0.009) | | (0.005) | (0.022) | | (0.013) |
| Ideological Distance | 0.108*** | 0.130*** | | 0.433*** | 0.488*** | |
| | (0.005) | (0.006) | | (0.017) | (0.019) | |
| Observations | 208,078 | 208,078 | 695,664 | 208,078 | 208,078 | 695,664 |
| $R^2$ | 0.781 | 0.768 | 0.750 | 0.697 | 0.686 | 0.665 |
| Adjusted $R^2$ | 0.695 | 0.677 | 0.689 | 0.579 | 0.563 | 0.583 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 | | |

# Guess where we start from?

# Guess where we start from?

- Starting from Data
- Harmony Labs is a nonprofit media research lab, that regularly posts CFPs for dataset access
- Access to their Nielsen Web panel data (~ 140,000 unique users in the United States; what they visit at the URL level for the year 2018 & their demographic and weight)

- From data to question (Tian and I): “the paradox between cross-cutting news consumption and misinformation exposure”
- From question to method (Sandra): average clustering coefficient Lydon-Staley et al. (2021) or pairwise ideological distance

**Acknowledgments**

We are grateful to Harmony Labs for facilitating access to the data and for crucial research support.

# Study 2

- Zhou, A., Capizzo, L. W., Page, T. G., & Toth, E. L. (2023). Exploring public relations research topics and inter-cluster dynamics through computational modeling (2010-2020): A study based on two SSCI journals. *Journal of Public Relations Research*, *35*(3), 135–161. https://doi.org/10.1080/1062726X.2023.2180373

# Case: Zhou et al. (2023)

- Exploring PR research topics via topic modeling
- Use STM to identify topics and clusters
- Compare topic distributions across journals and time
- Network simulation to test inter-cluster dynamics

# RQ & Findings

- What topics do public relations scholars study?
- What clusters/themes emerge?
- Do these clusters/themes intersect with each other?

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- What clusters/themes emerge?
- Do these clusters/themes intersect with each other?

- Identify 65 topics
- These 65 topics cluster into 9 subfields
- These subfields do not talk to each other

# Data and Methods

- Web Scraping Data
  - Time: from 2010 to 2020
  - Journals:
    - Public Relations Review (PRR)
    - Journal of Public Relations Research (JPRR)
  - 1093 papers from PRR and 200 from JPRR
  - 7,400,685 words

# Data and Methods

- Method 1: Structural Topic Modeling
  - We identified 65 topics, such as
    - “Twitter” “Facebook”
    - “Relationship management” “Nonprofit Management”
    - “Image Repair” “Situational Crisis Communication Theory”

# Data and Methods

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  - We identified 65 topics, such as
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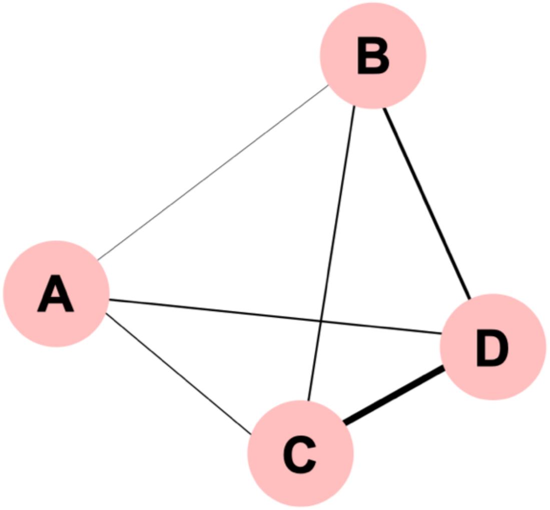
    - “Relationship management” “Nonprofit Management” --- “Strategic Management”
    - “Image Repair” “Situational Crisis Communication Theory” --- “Crisis Comm”
  - <Like, comment, and share on Facebook: How each behavior differs from the other> is detected to have:
    - Digital Media (73.7%)
    - Strategic Management (18.7%)
    - Public Relations Professionalism (0.1%), Crisis Communication (2.3%), Internal Communication (0.8%), Global Public Relations (0.0%), Rhetoric and Philosophy (0.1%), Media Relations (0.2%), Critical Studies (0.0%)

# Data and Methods

- Method 2: Inter-Cluster Network Analysis

| | Cluster A | Cluster B | Cluster C | Cluster D |
|---|---|---|---|---|
| Article 1 | 0.1 | 0.2 | 0.3 | 0.4 |

| Article 1's Contribution to the Tie Strength in the Inter-Cluster Network | | | | |
|---|---|---|---|---|
| | Cluster A | Cluster B | Cluster C | Cluster D |
| Cluster A | - | 0.1*0.2 | 0.1*0.3 | 0.1*0.4 |
| Cluster B | - | - | 0.2*0.3 | 0.2*0.4 |
| Cluster C | - | - | - | 0.3*0.4 |
| Cluster D | - | - | - | - |



# Data and Methods

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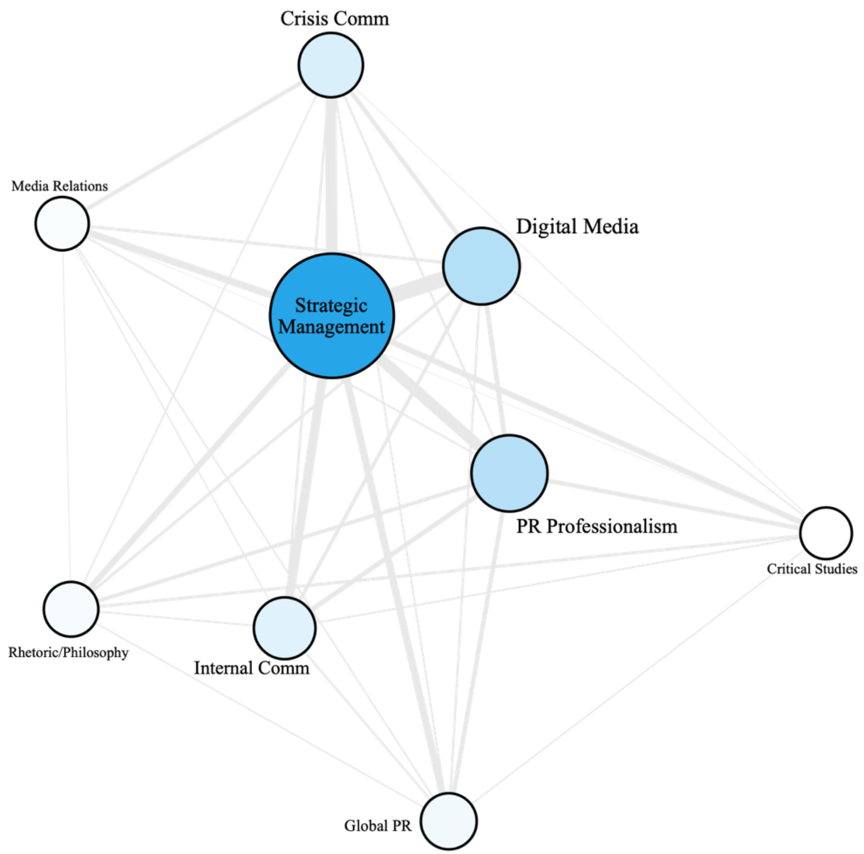

# Data and Methods

- Method 3: Network Simulation

| Article | Crisis | Digital | Global | … | Management | Critical | Media |
|---|---|---|---|---|---|---|---|
| 1 | 0.000 | 0.003 | 0.001 | … | 0.749 | 0.001 | 0.000 |
| 2 | 0.006 | 0.002 | 0.070 | … | 0.420 | 0.005 | 0.003 |
| 3 | 0.204 | 0.010 | 0.004 | … | 0.226 | 0.025 | 0.370 |
| 4 | 0.167 | 0.028 | 0.031 | … | 0.124 | 0.000 | 0.012 |
| … | … | … | … | … | … | … | … |
| 1291 | 0.008 | 0.061 | 0.012 | … | 0.076 | 0.063 | 0.007 |
| 1292 | 0.786 | 0.001 | 0.002 | … | 0.102 | 0.001 | 0.001 |
| 1293 | 0.003 | 0.233 | 0.001 | … | 0.142 | 0.082 | 0.006 |

# Data and Methods

- Method 3: Network Simulation
  - For each article, cluster proportions add up to 100%
  - For each cluster, its proportion across all articles remains the same

| | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 | … | Cluster 7 | Cluster 8 | Cluster 9 |
|---|---|---|---|---|---|---|---|---|
| Paper 1 | | | | | | | | |
| Paper 2 | | | | | | | | |
| Paper 3 | | | | | | | | |
| … | | | | | | | | |
| Paper 1292 | | | | | | | | |
| Paper 1293 | | | | | | | | |

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| … | | | | | | | | |
| Paper 1292 | | | | | | | | |
| Paper 1293 | | | | | | | | |

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| | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 | … | Cluster 7 | Cluster 8 | Cluster 9 |
|---|---|---|---|---|---|---|---|---|
| **Paper 1** | | | | | | | | |
| **Paper 2** | | | | | | | | |
| **Paper 3** | | | $[i_1, j_1]$ | | | $[i_1, j_2]$ | | |
| … | | | | | | | | |
| **Paper 1292** | | | $[i_2, j_1]$ | | | $[i_2, j_2]$ | | |
| **Paper 1293** | | | | | | | | |

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|---|---|---|---|---|---|---|---|---|
| **Paper 1** | | | | | | | | |
| **Paper 2** | | | | | | | | |
| **Paper 3** | | | $[i_1, j_1] - \Delta$ | | | $[i_1, j_2] + \Delta$ | | |
| **…** | | | | | | | | |
| **Paper 1292** | | | $[i_2, j_1] + \Delta$ | | | $[i_2, j_2] - \Delta$ | | |
| **Paper 1293** | | | | | | | | |

# Data and Methods

- Method 3: Network Simulation
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  - For each cluster, its proportion across all articles remains the same

- 1000 Simulated Networks / Alternative Universes/Timelines
- 95%/5% upper/lower bound as the confidence interval for tie strengths
- We simulated “what the field’s interconnection could have been”.

# Data and Methods

- Method 3: Network Simulation

| | Public Relations Professionalism | Digital Media | Crisis Communication | Internal Communication | Global Public Relations | Rhetoric and Philosophy | Media Relations | Critical Studies |
|---|---|---|---|---|---|---|---|---|
| Strategic Management | *20.549 [26.535, 26.615]* | **28.031 [25.162, 25.240]** | *20.493 [23.409, 23.483]* | *16.518 [18.079, 18.139]* | *12.960 [14.895, 14.946]* | *11.071 [14.593, 14.644]* | *12.801 [14.059, 14.110]* | *10.528 [13.308, 13.355]* |
| Public Relations Professionalism | | *8.494 [13.193, 13.244]* | *4.114 [12.235, 12.286]* | *8.630 [9.337, 9.377]* | **7.934 [7.661, 7.696]** | *6.890 [7.490, 7.523]* | *3.735 [7.185, 7.218]* | **7.889 [6.823, 6.855]** |
| Digital Media | | | *7.872 [11.559, 11.607]* | *6.484 [8.755, 8.793]* | *4.181 [7.168, 7.200]* | *5.363 [7.036, 7.068]* | *5.337 [6.742, 6.774]* | *2.900 [6.377, 6.406]* |
| Crisis Communication | | | | *4.440 [8.144, 8.180]* | *3.236 [6.648, 6.680]* | *3.048 [6.521, 6.552]* | **7.374 [6.293, 6.323]** | *1.411 [5.910, 5.938]* |
| Internal Communication | | | | | *4.044 [4.997, 5.022]* | *3.107 [4.890, 4.915]* | *2.110 [4.698, 4.723]* | *3.210 [4.441, 4.464]* |
| Global Public Relations | | | | | | *2.664 [3.981, 4.002]* | *3.071 [3.832, 3.853]* | *2.714 [3.612, 3.632]* |
| Rhetoric and Philosophy | | | | | | | *1.579 [3.751, 3.772]* | **5.239 [3.558, 3.579]** |
| Media Relations | | | | | | | | *1.035 [3.402, 3.421]* |

# Guess where we start from?

# Guess where we start from?

- Starting from Question
- An interview study by Tyler G. Page (Connecticut) and Luke W. Capizzo (Michigan State)
- Interviewees lamented/suspected that many single-topic/cluster review studies omitted signals of inter-topic/cluster development, and there were silos within: PR scholars do not know / work with other PR scholars.
- Zoom call with me: “any way we can identify interactions of subfields?”

ELSEVIER

Public Relations Review

Volume 47, Issue 5, December 2021, 102115

Full Length Article

From “an open field” to established “waves”: Public relations scholarship through the lens of *Public Relations Review*

Tyler G. Page [a], Luke W. Capizzo [b]

# Guess where we start from?

- Starting from Question
- From question to method 1: “decompose articles into topics” -> STM
- From question to method 2: “intersecting topic/cluster” -> Network
- From question to method 3: “silos within” -> Simulation
- From method to data: web scraping (or contact journals) and *CrossRef*

ELSEVIER

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Full Length Article

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# Study 3

- Wang, S., Huang, S., Zhou, A., & Metaxa, D. (2024). Lower quantity, higher quality: Auditing news content and user perceptions on Twitter/X algorithmic versus chronological timelines. *Proceedings of the ACM on Human-Computer Interaction*, *8*(CSCW2), 1–25. https://doi.org/10.1145/3687046

# RQs and Findings

- RQs
  - Two common rankings for social media feeds:
    - Algorithmic vs.
    - Chronological
  - Algorithm Audit: How do they affect content?
  - User Audit: How do they affect users?
- Findings
  - Tracking Twitter/X users' algorithmic vs chronological feeds
  - Manipulating feed selection and fielding periodical surveys
  - Algorithmic feed provides less, but better (lower congruence, lower extremity, higher reliability) news URLs.
  - Changing feeds did not significantly impact user perceptions.

# Data and Methods

Intervenr Infrastructure

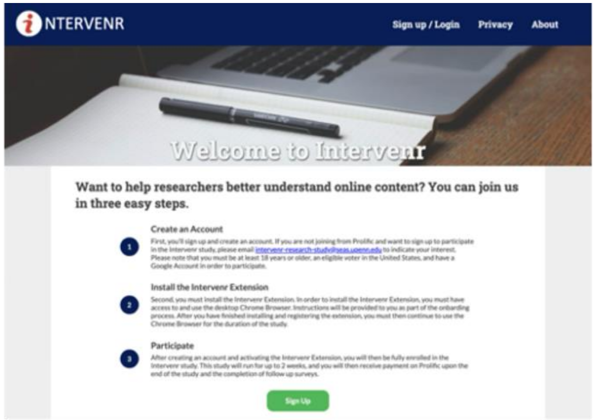
- Web App: Web interface for participant consent / onboarding / survey
- Chrome Browser Extension: Collect URLs/engagement and assign conditions
- Analysis Pipeline: AWS instance rehydrating t.co to original URLs daily

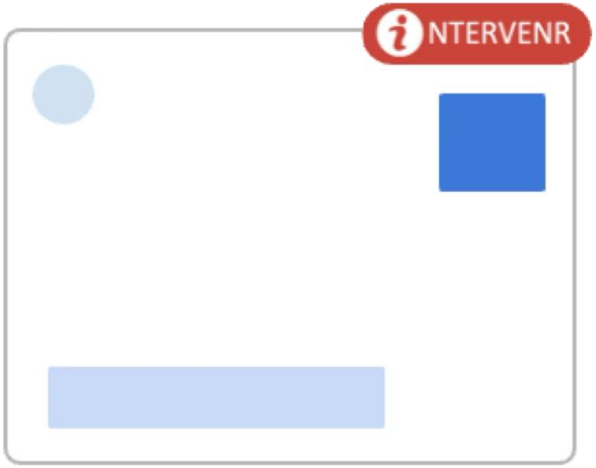
# Data and Methods

Participant UI

Experiment UI

Survey UI




URL Collection

Engagement

Intervention

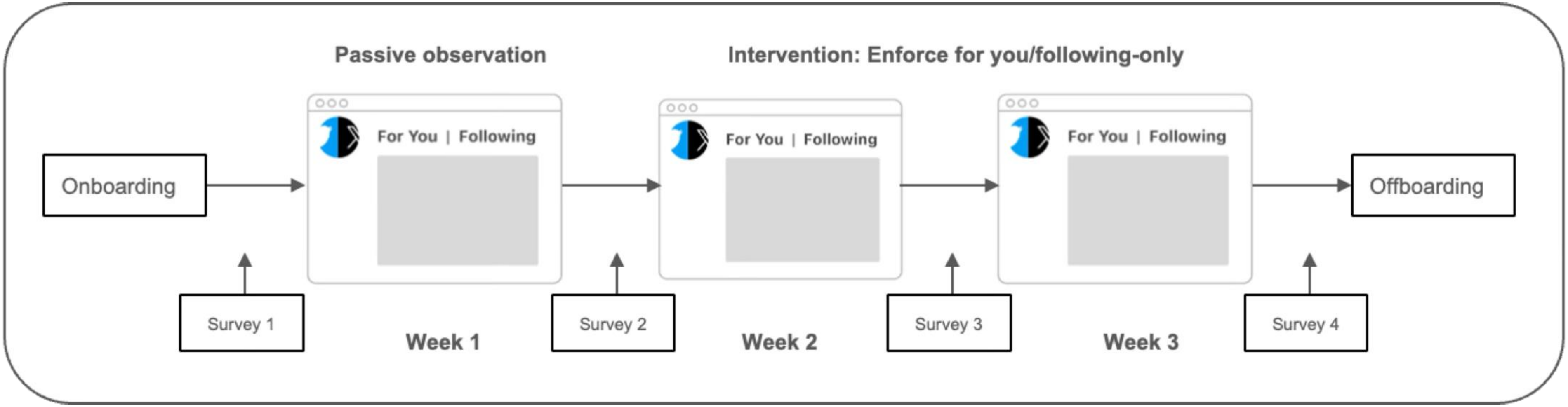
t.co to Original

URL Classification

# Data and Methods

Study Procedure

- Week 1: Survey 1 -> Observation
- Week 2: Survey 2 -> either “For You” or “Chronological” -> Survey 3
- Week 3: either “Chronological” or “For You” -> Survey 4



# Data and Methods

Participant Management

- Prolific:
  - Live in the United States; At least 18 years old; Use Google Chrome as a main web browser; Use Twitter/X; Access Twitter/X from their main web browser at least a few times per week
  - 822 onboard with background survey
  - 243 completed at least two weeks
  - 218 completed the whole 3-week study
- $0.25 for screening survey
- $5 for each survey; $20 maximum

# Data and Methods

Measurement System

- Onboarding Survey:
  - Ideology (-3~+3), Age, Education, etc.
- URL Annotation:
  - Media Bias: Ad Fontes (most liberal -42 to most conservative +42)
  - News Credibility: Ad Fontes (least credible 0 to most credible 64)
- Between-Week Survey:
  - Perceived echo chambers
  - Media satisfaction
  - Perceived news credibility and media trust
  - Perception of the platform

# Data and Methods

Dataset

- 846,494 Tweets
  - 313,517 during observation (first week)
  - 253,471 during first intervention (second week)
  - 279,506 during second intervention (third week)
- Users engaged (liked, commented, retweeted) 1.89% (16,014) of them
- 1.75% (14,817) tweets contained external news URLs

- All analyses are conducted at the user level with userID as random effects
- i.e., compare one participant’s natural vs. chronological vs. algorithmic

# Observation Week

News Density

- 1.6% of tweets in the algorithmic timeline contained a news URL
- 7.5% in the chronological timeline contained a news URL

In the chronological/algorithmic timeline

- Right-leaning users saw a moderate amount (13.5/11.8% of all news links) of news links from left-leaning news domains
- Left-leaning users saw very little (1.5/2.7% of all news links) news links from right-leaning news domains

# Algorithm Audit

Ideological Congruence

- Weighted Congruence Score: (-3 user)*(-8.13 NYTimes) = 24.39
- More congruent in chronological > algorithmic ($p$ = .031)

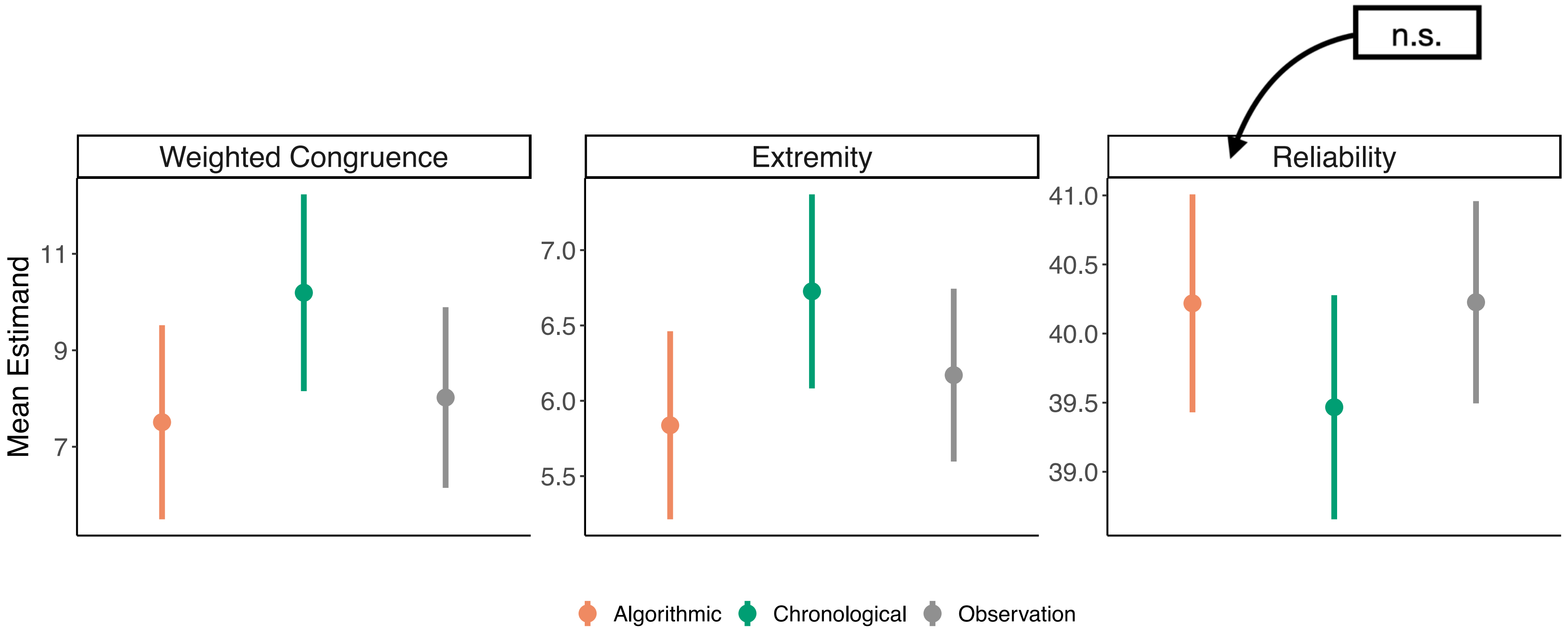
News Extremity

- Mean Absolute Bias: |-8.13 NYTimes| = 8.13
- More extreme in chronological > algorithmic ($p$ = .003)

News Reliability

- ? More reliable in algorithmic > chronological ($p$ > .05)

# Algorithm Audit



# User Audit

## User Exposure

- More news URLs in chronological > algorithmic ($p$ = .002)

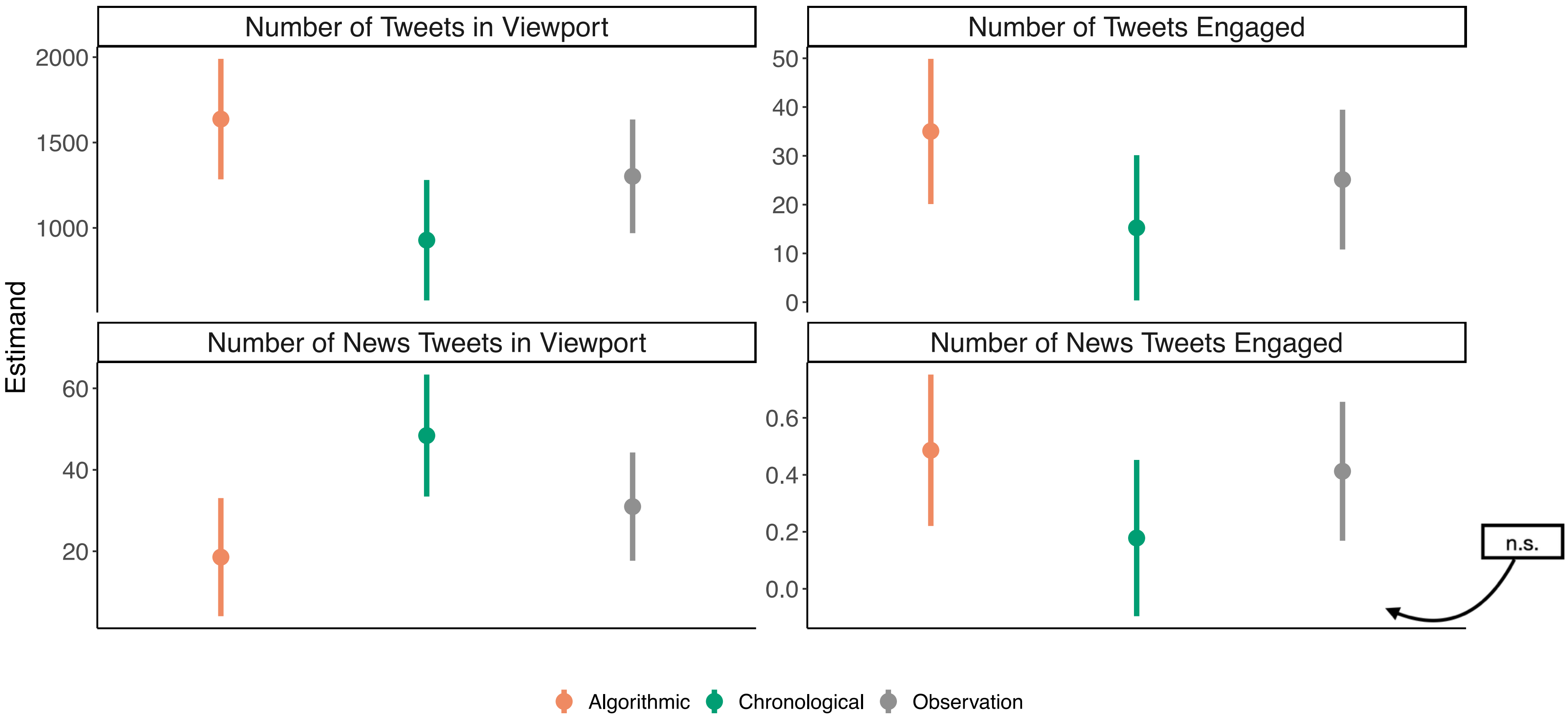
## User Engagement

- More tweets and engagement ($p$ < .001) in algorithmic > chronological
- ? More engagement with tweets with news URLs ($p$ > .05)

## User Satisfaction

- Users hated us enforcing timeline sorting (from 3.38 to 3.23/3.21)

# User Audit


Number of Tweets in Viewport
Number of Tweets Engaged
Number of News Tweets in Viewport
Number of News Tweets Engaged
Estimand
2000
1500
1000
50
40
30
20
10
0
60
40
20
0.6
0.4
0.2
0.0
n.s.
Algorithmic
Chronological
Observation

# User Audit

## User Perceptions of Bias

- Perceptions of bias associated with their actual news bias ($p$ < 0.001)
- Their exposure to news bias did not change their perceptions of:
  - The average bias of all news links available on Twitter
  - Whether the Twitter/X algorithm favors conservatives or liberals

## User Perception of Credibility

- Exposure to news of higher credibility leads to less perceived credibility ($p$ = .012) and lower media trust ($p$ = .002)

## User Perception of Other Users

- "A typical Republican's timeline is less conservative than I thought."
- "A typical Democrat's timeline is more liberal than I thought."

# Guess where we start from?

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- Starting from Method
- Danaë (HCI, Computer Science) developed the Intervenr infrastructure
- With their secondary appointment in communication, let's audit/intervenr news?
    - What platform to audit?
    - What changes to make for extension/Prolific/surveys?
    - What news consumption topics should we investigate?


ELSEVIER

Public Relations Review
Volume 47, Issue 5, December 2021, 102115

Full Length Article

From "an open field" to established "waves": Public relations scholarship through the lens of *Public Relations Review*

Tyler G. Page [a], Luke W. Capizzo [b]

# Guess where we start from?

- Starting from Method
- From method to question: Algorithmic vs. Chronological
- From method to data: Participants' Twitter timelines across 3 weeks
- From method to data: Acquiring Ad Fonte, NewsGuard, and comScore

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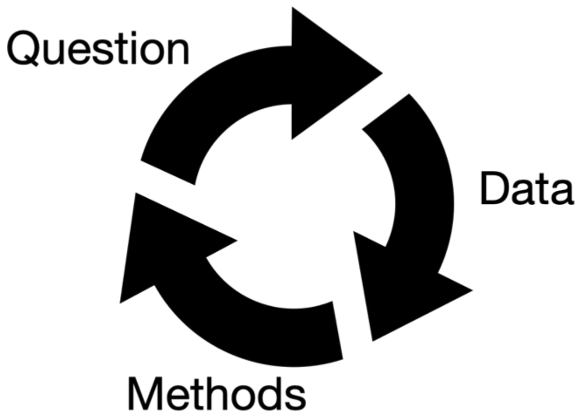
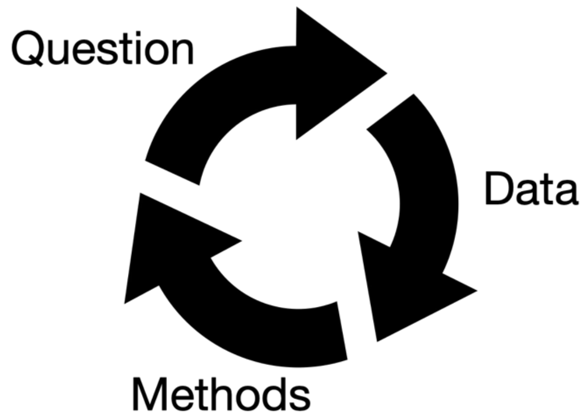



Instead of blindly applying computational methods to social data, computational social scientists should forge synergy between question, data, and method — starting with an interesting research question, or some invaluable data, or an innovative methodological framework — to create a research design that tells a compelling social science story.




- Computational social science > computational methods / social media / big data
- Research design (i.e., the "so what") is more important than the data
- CSS studies tell stories, and ask yourself if your story is compelling
- If you are starting from scratch, (maybe) start from the question.

# Looking Ahead

- If the discussion of CSS philosophy is too high-level, what can we do in practice when conducting our studies?
- Some Directions I Think That Are Valuable
  - Computational Storytelling:
    - Molding data, questions, and methods simultaneously
    - One Story, Deeply Told
  - DEMM Framework (Description → Experimentation → Mediator/Moderator identification)
  - Methodological Triangulation
  - Social Good and Ethical Imperatives
- In the end, we will touch upon LLM

# One Story, Deeply Told

- Barari, S. (2024). Political speech from corporate America: Sparse, mostly for Democrats, and somewhat representative. *Journal of Quantitative Description: Digital Media, 4*. https://doi.org/10.51685/jqd.2024.icwsm.5

- High-resolution coding of sparse, noisy behavior
- How careful annotation, domain understanding, and scale can come together
- In CSS, “big” doesn’t have to mean “messy” or “shallow”

- Sometimes the best computational study is a narrow, well-told story.

# DEMM Framework

- Description → Experimentation → Mediator/Moderator identification

- Describe the social phenomenon you are addressing
  - Collect observational data
  - Computational tools
  - Large-scale, multiple contexts
  - Simple descriptive analyses, visualizations, and correlations
- Experiment on the mechanism you are interested in
  - Field or digital interventions that test mechanism
- Mediator/Moderator
  - Unpack *how* and *for whom* effects operate

- CSS often begins with a description, but must not stop there.

# Presentation: Lee (2021)

# Methodological Triangulation


- Nelson, L. K. (2020). Computational grounded theory: A methodological framework. *Sociological Methods & Research, 49*(1), 3–42. https://doi.org/10.1177/0049124117729703
- Ophir, Y., Walter, D., & Marchant, E. R. (2020). A collaborative way of knowing: Bridging computational communication research and grounded theory ethnography. *Journal of Communication, 70*(3), 447–472. https://doi.org/10.1093/joc/jqaa013
- Than, N., Fan, L., Law, T., Nelson, L. K., & McCall, L. (2025). Updating "the future of coding": Qualitative coding with generative large language models. *Sociological Methods & Research*. https://doi.org/10.1177/00491241251339188

# Social Good and Ethical Imperatives

# Presentation: Yang et al. (2021)

# Presentation: Wang et al. (2022)

# Generative AI: A New Frontier

- LLM
  - Text synthesis and augmentation
  - Multilingual content coding
  - Simulated social agents and interactions (e.g., Park et al. 2023: Generative Agents)
- New dilemmas
  - What counts as authorship?
  - Can LLMs reinforce biases or ideologies?
  - What LLM means for social theories?

# Lab Preview

- LLM coding (Jiacheng Huang guest lecture)