

# Surveys or digital trace data, which one should we use?

Using MultiTrait-MultiMethod models to simultaneously estimate the measurement quality of surveys and digital trace data.

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# The importance of measuring what people do online

- Increased importance of understanding the extent and the type of media/content people are exposed to
- As well as its **effect** on how people **think**, **feel**, and **behave**





 Journal of Family and Economic Issues
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 Cite this article

 2475
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 Metrics

#### Abstract

This study examines the effect of contraceptive knowledge on fertility during the period when Taiwan's family planning programs were in effect. This study contributes to previous studies by directly measuring individual's contraceptive knowledge and fertility, as well as applying an instrumental variable approach to gauge the effect of contraceptive knowledge on fertility. The results indicate that mass media and social networks play important roles in disseminating contraceptive knowledge. This study finds that women transform their knowledge into behavior—that is, contraceptive knowledge reduces fertility, no matter which fertility metric is measured (life-time fertility or probability of giving birth).





### Digital trace data to understand online behaviours

• Survey self-reports are still the **most common approach** 

The Immensely Inflated News Audience: Assessing Bias in Self-Reported News Exposure Get access > Markus Prior ⊠

Public Opinion Quarterly, Volume 73, Issue 1, Spring 2009, Pages 130–143, https://doi.org /10.1093/poq/nfp002 Published: 18 March 2009

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#### Abstract

Many studies of media effects use self-reported news exposure as their key independent variable without establishing its validity. Motivated by anecdotal evidence that people's reports of their own media use can differ considerably from independent assessments, this study examines systematically the accuracy of survey-based self-reports of news exposure. I compare survey estimates to Nielsen estimates, which do not rely on self-reports. Results show severe overreporting of news exposure. Survey estimates of network news exposure follow trends in Nielsen ratings relatively well, but exaggerate



# Digital trace data to understand online behaviours

- Survey self-reports are still the **most common approach**
- More and more availability of **digital traces to directly observe media exposure**



# Individual-level approach: web trackers

Direct observations of online behaviours using tracking solutions, or *meters*.

Group of tracking technologies (plug-ins, apps, proxies, etc)

Installed on participants devices

**Collect traces** left by participants when **interacting with their devices online: URLs, apps visited, cookies...** 

Great, we will get unbiased measures!





### Is web tracking data actually unbiased?

# Little but growing evidence that **web tracking data is affected by errors**





#### ORIGINAL ARTICLE 🖞 Open Access 💿 🗿

#### When survey science met web tracking: Presenting an error framework for metered data

#### Oriol J. Bosch 🔀 Melanie Revilla

#### First published: 06 November 2022 | https://doi.org/10.1111/rssa.12956

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#### Abstract

Metered data, also called web-tracking data, are generally collected from a sample of participants who willingly install or configure, onto their devices, technologies that track digital traces left when people go online (e.g., URLs visited). Since metered data allow for the observation of online behaviours unobtrusively, it has been proposed as a useful tool to understand what people do online and what impacts this might have on online and offline phenomena. It is crucial, nevertheless, to understand its limitations. Although some research have explored the potential errors of metered data, a systematic categorisation and conceptualisation of these errors are missing. Inspired by the Total Survey Error, we present a Total Error framework for digital traces collected with Meters (TEM). The TEM framework (1) describes the data generation and the analysis process for metered data and (2) documents the sources of bias and variance that may arise in each step of this process. Using a case study we also show how the TEM can be applied in real life to identify, quantify and reduce metered data errors. Results suggest that metered data might indeed be affected by the error sources identified in our framework and, to some extent, biased. This framework can help improve the quality of both stand-alone metered data research projects, as well as foster the understanding of how and when survey and metered data can be combined.

Is web tracking data actually unbiased?

web data *opp* 

Little but growing evidence that **web tracking data is affected by errors** 

We know that these errors can introduce measurement errors of a considerable size



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But still not near what we know about surveys!



![](_page_7_Picture_6.jpeg)

# Is web tracking data actually unbiased?

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But still not near what we know about surveys!

**My pitch**: adapt decades of knowledge in psychometrics and survey methodology to improve how we use digital trace data

![](_page_8_Figure_6.jpeg)

![](_page_8_Picture_7.jpeg)

Simultaneously estimating the measurement quality of digital trace data and surveys using MultiTrait-MultiMethod (MTMM) models

![](_page_10_Picture_1.jpeg)

### Measurement quality

Quality = part of variance explained by the latent concept of interest

→ complement of measurement errors

e = random error 11 point scale

![](_page_10_Figure_5.jpeg)

Quality = strength of the relationship between the latent concept of interest and the observed answers

![](_page_11_Picture_1.jpeg)

![](_page_11_Figure_2.jpeg)

![](_page_12_Figure_1.jpeg)

![](_page_13_Figure_1.jpeg)

![](_page_14_Figure_1.jpeg)

![](_page_15_Figure_1.jpeg)

This study

THIS STUDY

### Research questions

![](_page_17_Picture_2.jpeg)

![](_page_18_Picture_1.jpeg)

What is the overall validity, reliability, method effect and measurement quality of several measurements computed with digital trace data? (**RQ.1**)

And how do these compare with the quality estimates from equivalent survey questions? (RQ.2)

THIS STUDY

### Data

![](_page_19_Picture_2.jpeg)

- Netquest metered panel in Spain
  - **Cross-quotas:** gender, age, and education
  - Sample size: 1,200
  - Fieldwork: Late May Early June 2023
- Tracking technologies installed in both **mobile and desktop devices**
- Part of the ERC project **WEB DATA OPP**

![](_page_19_Picture_9.jpeg)

### Three differ groups of traits of interest

### 1. News exposure traits

- Exposure to news about politics
- Exposure to news about sports
- Exposure to news about science and technology

### 2. Communication traits:

- Use of social media
- Use of instant messaging
- Use of e-mails

### 3. Entertainment traits:

- Use of video platforms (YouTube, Vimeo, Twitch)
- Use of audio streaming (Spotify, Audible, Apple podcast)
- Use of TV/Movie streaming (Netflix, BBC online)

![](_page_20_Picture_14.jpeg)

![](_page_21_Picture_1.jpeg)

### 1. Survey questions

More specifically, on average, how much time per day do you spend on the Internet reading news and articles...

- MC4\_1. ... about politics and current affairs?
- MC4\_1\_HH. Hours: [SMALL NUMERIC OPEN BOX] MC4\_1\_MM. Minutes: [SMALL NUMERIC OPEN]

![](_page_22_Picture_1.jpeg)

### 1. Survey questions

### 2. Web tracking data

Characteristics	My choices			
Metric	Minutes			
List of traces				
List of media	Tranco			
Top media	All			
Information	Those identified as specific concept			
Exposure				
Time threshold	1 second			
Devices	All devices (with or without app)			
Tracking period	31 days			

### The measurements

1. Survey questions

I use the log of these measures

2. Web tracking data

![](_page_23_Picture_5.jpeg)

# Results

Web tracking:	Politics	Sports	Science	Social Media	Messages	Emails	Videos	Audio	TV
Survey:									
Politics	.17								
Sports		•33							
Science			.07						
Social Media				.41					
Messages					.14				
Emails						.11			
Video							.17		
Audio								.29	
TV									•34

![](_page_25_Picture_1.jpeg)

![](_page_25_Picture_2.jpeg)

![](_page_26_Picture_1.jpeg)

# #1 News: quality estimates

![](_page_26_Figure_3.jpeg)

![](_page_27_Picture_1.jpeg)

### #1 News: quality estimates

![](_page_27_Figure_3.jpeg)

![](_page_28_Picture_1.jpeg)

### #2 Communication: quality estimates

![](_page_28_Figure_3.jpeg)

![](_page_29_Picture_1.jpeg)

### #3 Entertainment: quality estimates

![](_page_29_Figure_3.jpeg)

![](_page_30_Picture_1.jpeg)

### #3 Entertainment: quality estimates

![](_page_30_Figure_3.jpeg)

# CONCLUSIONS

![](_page_32_Picture_1.jpeg)

- Results **put into question** the measurement quality of web tracking measurements
  - Some concepts are measures very accurately: **communication and video streaming**

Variance explained by trait: +/- 80%

• While others are extremely off: **news media exposure and some entertainment** 

Variance explained by trait: 12-39% !!!

![](_page_33_Picture_1.jpeg)

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Surveys, on the other hand, perform acceptably well. They also struggle more with news, but their quality is never below .50 and generally around .70 (agrees w/ Alwin)

• While other

![](_page_34_Picture_1.jpeg)

- Results **put into question** the measurement quality of web tracking measurements
  - Some concepts are measures very accurately: **communication and video streaming**

Even if surprising, some of these results make logical sense when we think about the theory of the potential error causes of web tracking data!

entertainment

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#### CONCLUSIONS

### The limits of this approach

![](_page_35_Picture_2.jpeg)

- VERY preliminary results...take with a pinch of salt
- We need to think much more about the MTMM models used, how to fine tune them, and their limitations
  - 1. Is it biased towards surveys?
  - 2. Is it of any value if surveys and web tracking do not measure the same to start with?
  - 3. True score model??
  - 4. Differential measurement errors!

# **Thanks!**

# *Questions?*

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![](_page_36_Picture_3.jpeg)

orioljbosch

![](_page_36_Picture_5.jpeg)

https://orioljbosch.com/

![](_page_36_Picture_7.jpeg)

![](_page_36_Picture_8.jpeg)

![](_page_36_Picture_9.jpeg)