Going beyond conventional web surveys: New measurement opportunities to enhance or extend web survey data

UB seminar series

6 June 2024

Melanie Revilla | IBEI

Acknowledgments:
This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No. 849165). I want to thank Oriol Bosch, Patricia Iglesias, and Carlos Ochoa for all their helpful feedback and inputs.

Which new opportunities?

Growing use of (mobile) Internet

web data opp

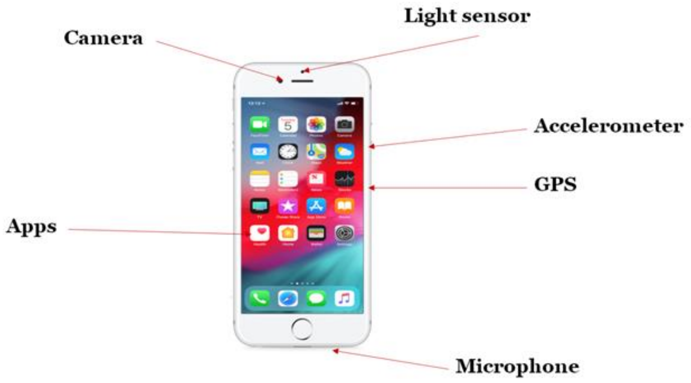
More and more of people's life happens **online**

+30m Average daily time[1] spent online by each internet user from 2016 to 2021

More and more of the online activity is done through **smartphones**

83% of the world population have smartphones[2]

Smartphones have sensors + apps
→ possible to collect many different types of new data



[1] https://datareportal.com/reports/digital-2022-global-overview-report; [2] https://www.bankmycell.com/blog/how-many-phones-are-in-the-world

WHICH NEW OPPORTUNITIES

New data types considered

web data opp

VISUAL DATA

Screenshots
Photos/videos taken during the survey
Visual files saved on (or accessible from) the device

VOICE DATA

Dictation
Voice recording

Most of those data can also be collected for PCs

METERED DATA

Obtained through a tracking application ("meter") installed by the participants on their devices to register at least the URLs of the webpages visited. Usually collected in metered panels.

GEOLOCATION DATA

Obtained through a tracking application installed on participants' mobile devices to register at least the GPS coordinates

IN-THE-MOMENT SURVEYS triggered by such data

How could they help?

Main expected benefits (Revilla, 2022)

Researchers

- Reduce some of the issues related to measurement errors
- Massive amount of data
- Granular / detailed data
- Real time / continuous (passive data)
- Provide data for new concepts (not measured so far)
- Answer new research questions

Participants

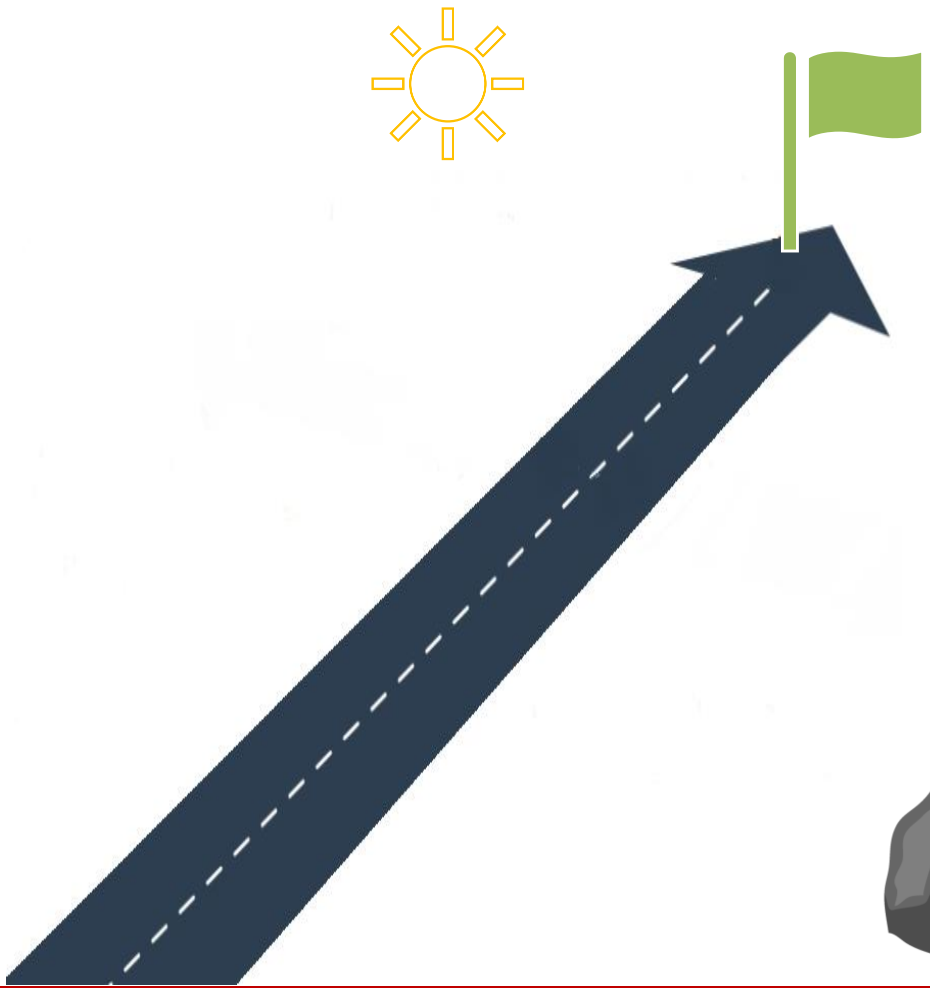
- Reduce time dedicated to provide information
- Reduce efforts
- More enjoyable

But this is not that easy…

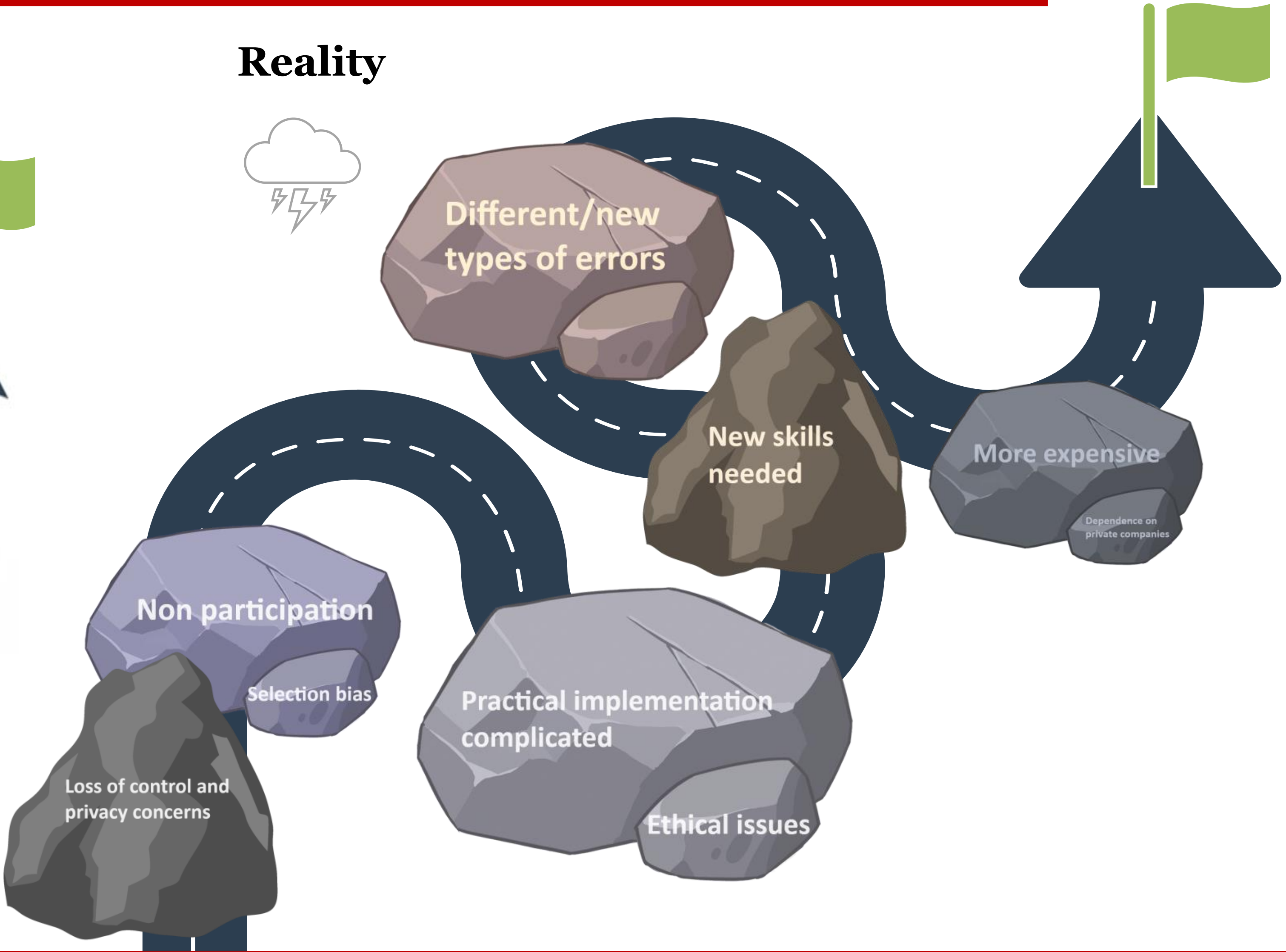
web data opp

Our goal = get more knowledge that will help better use such data

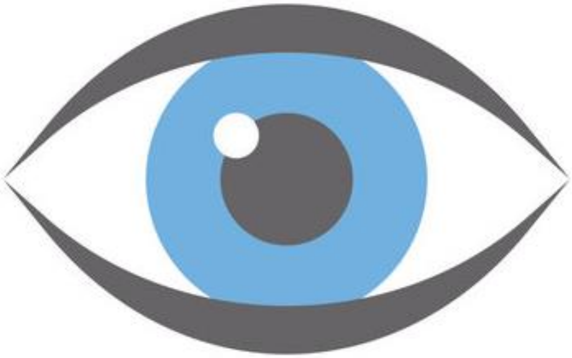
What most people think



Reality



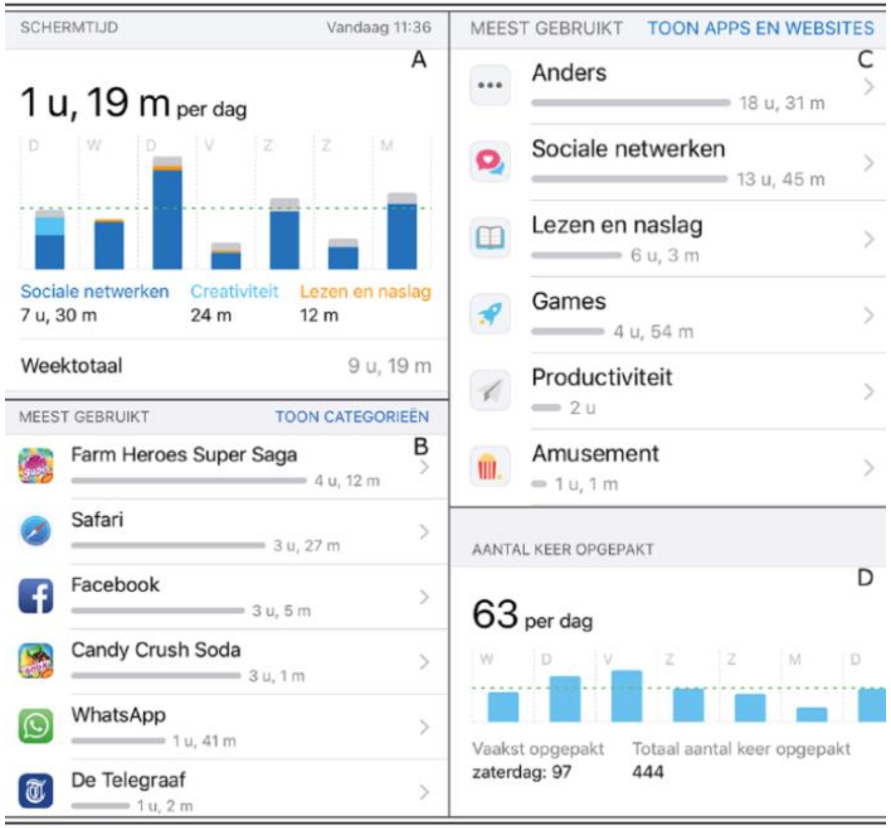
Example 1: visual data



EXAMPLE 1: VISUAL DATA

Visual data have been used to study different topics

Screen-time

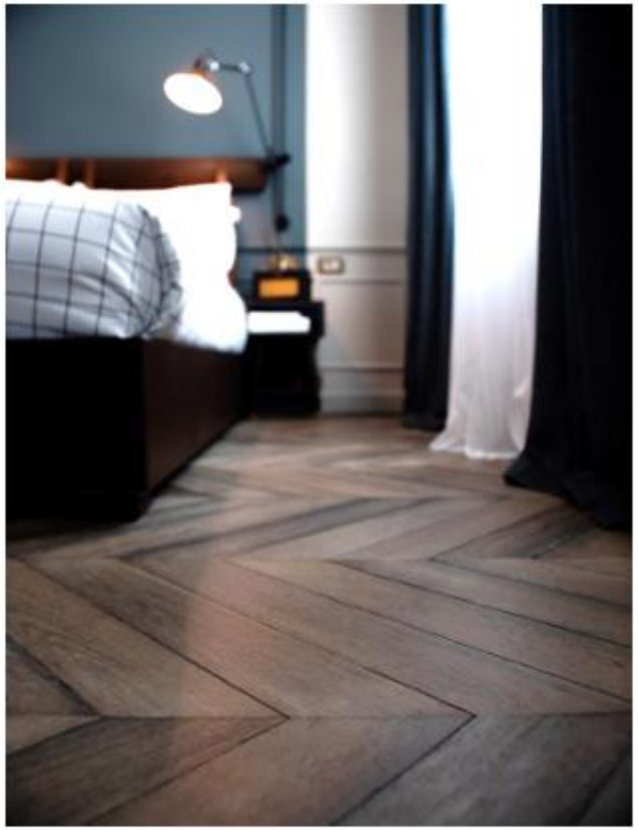


Ohme et al. (2021)

Heating system

Ilic et al. (2022)

Bedroom flooring



Slavec (2024)

EXAMPLE 1: VISUAL DATA

But lot of different challenges

How can the information be extracted from the images?

Will participants share the images?

How can the images be stored safely?

Which tool can be used to collect the photos?

EXAMPLE 1: VISUAL DATA

Understanding non-participation

Quality & Quantity (2024) 58:1071–1092
https://doi.org/10.1007/s11135-023-01670-3

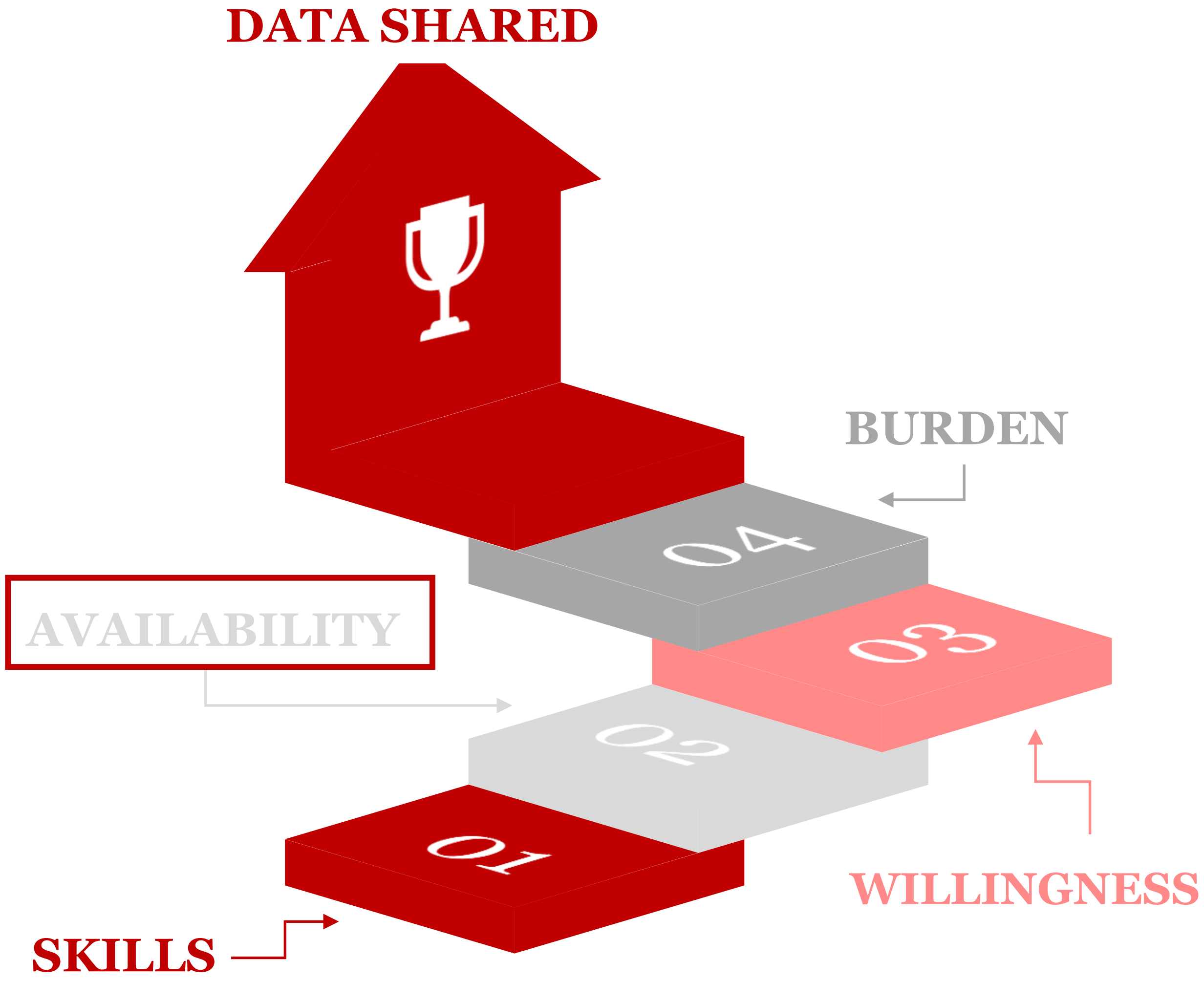
Check for updates

Skills, availability, willingness, expected participation and burden of sharing visual data within the frame of web surveys

Patricia A. Iglesias[1] · Melanie Revilla[1]

Accepted: 12 April 2023 / Published online: 22 May 2023

Abstract
Although there is literature on the willingness to share visual data in the frame of web surveys and the actual participation when asked to do so, no research has investigated the skills of the participants to create and share visual data and the availability of such data, along with the willingness to share them. Furthermore, information on the burden associated with answering conventional questions and performing visual data-related tasks is also scarce. Our paper aims to fill those gaps, considering images and videos, smartphones and PCs, and visual data created before and during the survey. Results from a survey conducted among internet users in Spain (N = 857) show that most respondents know how to perform the studied tasks on their smartphone, while a lower proportion knows how to do them on their PC. Also, respondents mainly store images of landscapes and activities on their smartphone, and their availability to create visual data during the survey is high when answering from home. Furthermore, more than half of the participants are willing to share visual data. When analyzing the three dimensions together, the highest expected participation is observed for visual data created during the survey with the smartphone, which also results in a lower perception of burden. Moreover, older and lower educated respondents are less likely to capture and share visual data. Overall, asking for visual data seems feasible especially when collected during the survey with the smartphone. However, researchers should reflect on whether the expected benefits outweigh the expected drawbacks on a case-by-case basis.



EXAMPLE 1: VISUAL DATA

Collecting and processing images

ELSEVIER

Social Sciences & Humanities Open

journal homepage: www.sciencedirect.com/journal/social-sciences-and-humanities-open

Regular Article

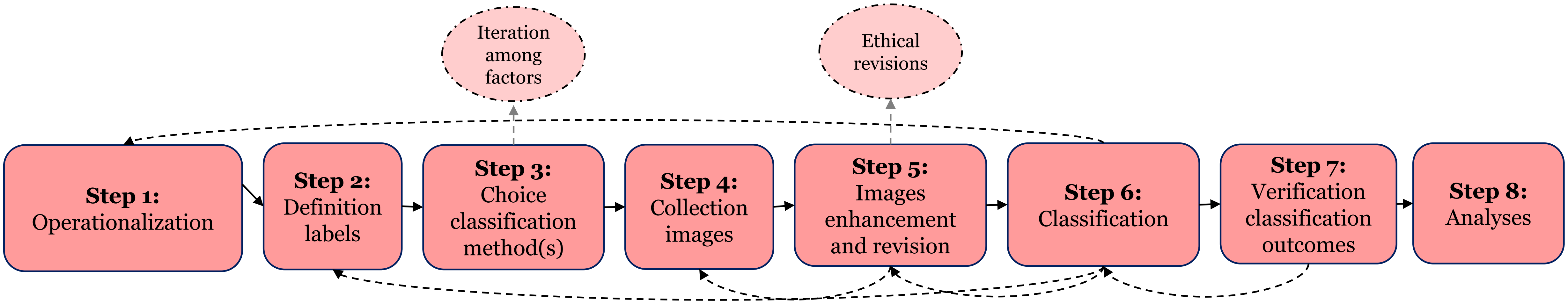
A practical guide to (successfully) collect and process images through online surveys

Patricia A. Iglesias [a,*], Carlos Ochoa [a], Melanie Revilla [b]

[a] *Research and Expertise Centre for Survey Methodology (RECSM), Department of Political and Social Sciences, Universitat Pompeu Fabra, Barcelona, Ramon Trias Fargas, 25-27, 08005, Barcelona, Spain*
[b] *Institut Barcelona d'Estudis Internacionals (IBEI), C/ de Ramon Trias Fargas, 25-27, 08005, Barcelona, Spain*

A B S T R A C T

Asking online survey respondents to share images is a practice that has gained notoriety recently. Although this collecting strategy may offer many advantages, it requires researchers to know how to operationalize, collect, process, and analyze this type of data, which is not yet an extended expertise among survey practitioners. This paper aims to guide researchers inexperienced in image analysis by presenting the main steps involved in the process of using images as a new data source: 1) operationalization, 2) definition of the labels, 3) choice of the most suitable classification method(s), 4) collection, 5) enhancement, and 6) classification of the images, 7) verification of the classification outcomes, and 8) data analysis. Following this eight-step process can help practitioners assess whether image collection is appropriate for their research problem and, if so, plan their image-based research, by providing them with the key considerations and decisions to address throughout their implementation.

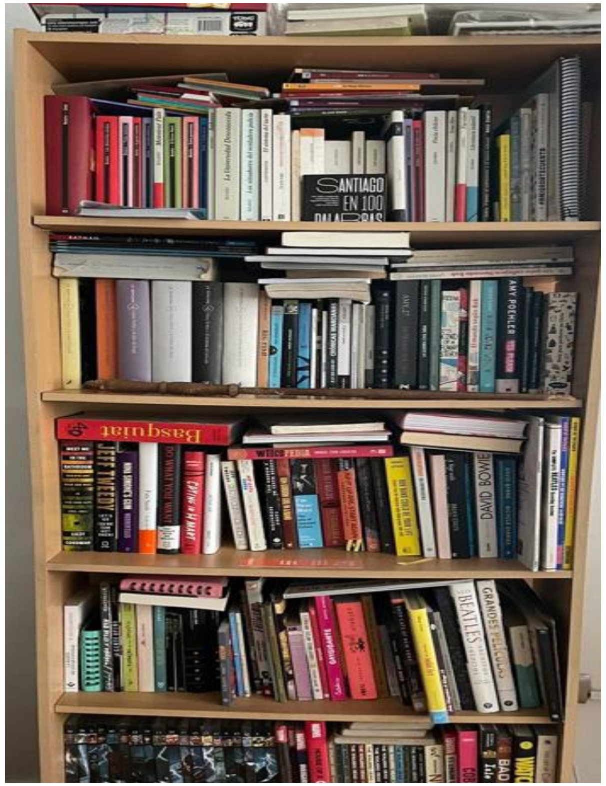


EXAMPLE 1: VISUAL DATA

Collecting photos of the books people have at home (Iglesias et al., 2023)

- Number of books often used as indicator of cultural or economic capital
  - But people do not know how many books they have
  - Social desirability bias expected → over-reporting
  - Kind of books also matter (cooking vs history books)
- Asking for photos of the books has the potential to provide:
  - More accurate information about the number of books
  - Extra information (kind of books, language, storage, etc.)
- Still working on the analyses/papers → everything more complicated than expected…

A *picture* is worth a **thousand** words



Example 2: metered data

Metered data have been used to study different topics

web data opp

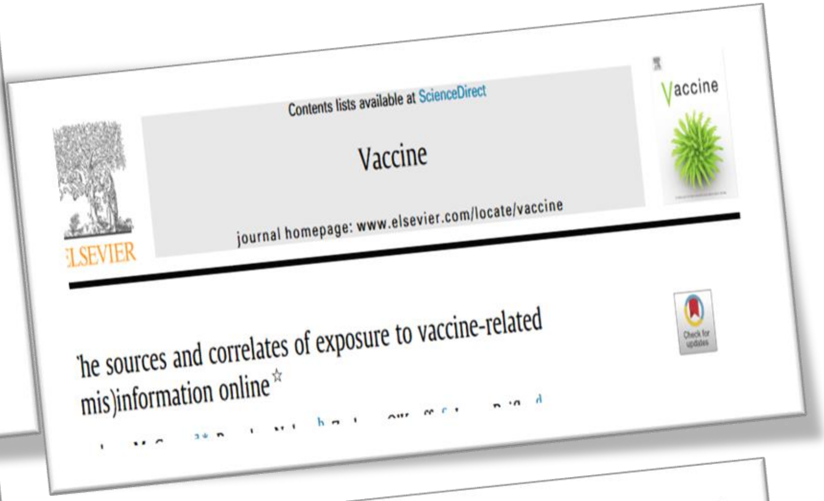
More than **80 papers** published using metered data


AMERICAN JOURNAL of POLITICAL SCIENCE

ARTICLE

(Almost) Everything in Moderation: New Evidence on American Online Media Diets

Andrew M. Guess


Contents lists available at ScienceDirect

Vaccine

journal homepage: www.elsevier.com/locate/vaccine

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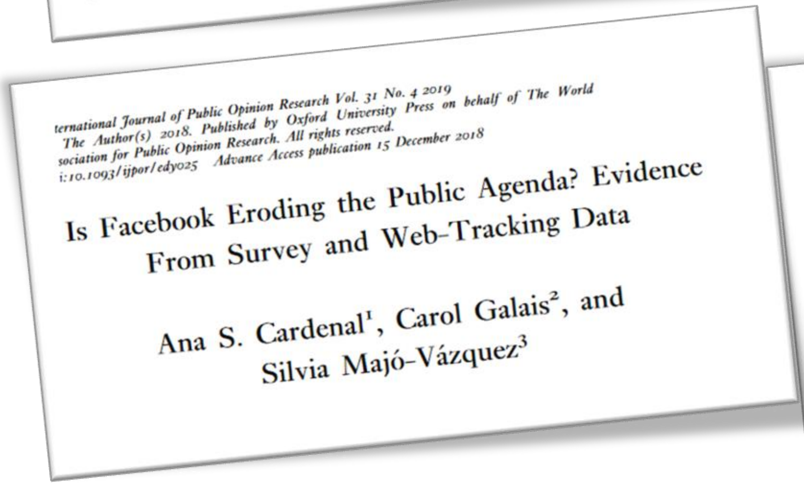
'he sources and correlates of exposure to vaccine-related mis)information online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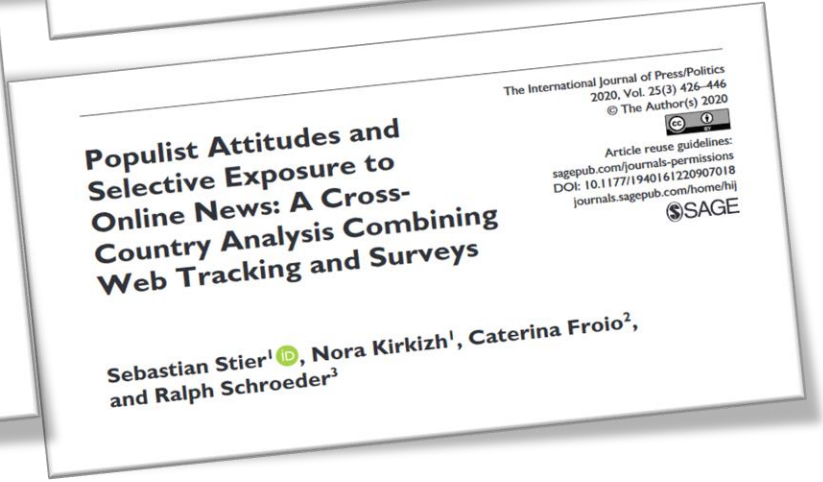
i:10.1093/ijpor/edy025 Advance Access publication 15 December 2018

Is Facebook Eroding the Public Agenda? Evidence From Survey and Web-Tracking Data

Ana S. Cardenal[1], Carol Galais[2], and Silvia Majó-Vázquez[3]


The International Journal of Press/Politics
2020, Vol. 25(3) 426–446
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Populist Attitudes and Selective Exposure to Online News: A Cross-Country Analysis Combining Web Tracking and Surveys

Sebastian Stier[1], Nora Kirkizh[1], Caterina Froio[2], and Ralph Schroeder[3]

They usually do not consider that metered data have **errors**

But can we assume this?

EXAMPLE2: METERED DATA

Many potential errors

JOURNAL ARTICLE

When Survey Science Met Web Tracking: Presenting an Error Framework for Metered Data

Oriol J. Bosch, Melanie Revilla Author Notes

Journal of the Royal Statistical Society Series A: Statistics in Society, Volume 185, Issue Supplement_2, December 2022, Pages S408–S436, https://doi.org/10.1111/rssa.12956

Total Error framework for digital traces collected with **Meters** (TEM)

Overview of possible errors & their causes

Error components	Specific error causes
Specification error	– Measuring concepts from which not enough data is available – Inferring attitudes – Defining valid information
Measurement error	– Non-trackable target – Meter not installed – Uninstalling the meter – New non-tracked device – Technology limitations – Technology errors – Hidden behaviours – Shared device – Social desirability – Extraction error
Processing error	– Coding error – Aggregation at the domain level – Data anonymization
Coverage error	– Non-trackable individuals
Sampling error	– Same error causes than for surveys
Missing data error	– Noncontact – Non-consent – Non-trackable target – Meter not installed – Uninstalling the meter – New non-tracked device – Technology limitations – Technology error – Hidden behaviour – Social desirability – Extraction error

Meter not installed

Shared devices

Technology limitations

EXAMPLE2: METERED DATA

Important problem of undercoverage

UNCOVERING DIGITAL TRACE DATA BIASES: TRACKING UNDERCOVERAGE IN WEB TRACKING DATA

Oriol J. Bosch, Patrick Sturgis, Jouni Kuha, and Melanie Revilla

Abstract

In the digital age, understanding people's online behaviours is vital. Digital trace data has emerged as a popular alternative to surveys, many times hailed as the gold standard. This study critically assesses the use of web tracking data to study online media exposure. Specifically, we focus on a critical error source of this type of data, tracking undercoverage: researchers' failure to capture data from all the devices and browsers that individuals utilize to go online. Using data from Spain, Portugal, and Italy, we explore undercoverage in commercial online panels and simulate biases in online media exposure estimates. The paper shows that tracking undercoverage is highly prevalent when using commercial panels, with more than 70% of participants affected. In addition, the primary determinant of undercoverage is the type and number of devices employed for internet access, rather than individual characteristics and attitudes. Additionally, through a simulation study, it demonstrates that web tracking estimates, both univariate and multivariate, are often substantially biased due to tracking undercoverage. This represent the first empirical evidence demonstrating that web tracking data is, effectively, biased. Methodologically, the paper showcases how survey questions can be used as auxiliary information to identify and simulate web tracking errors.

TRI-POL data (Torcal et al., 2023)

Netquest panels in Spain, Portugal and Italy

N = 2,653

Only **26%** of participants are fully covered

Simulations suggest that some bias occurs due to this undercoverage

EXAMPLE2: METERED DATA

Potential problems in validity and reliability

web data opp

VALIDITY AND RELIABILITY OF DIGITAL TRACE DATA IN MEDIA EXPOSURE MEASURES: A MULTIVERSE OF MEASUREMENTS ANALYSIS

Oriol J. Bosch

Abstract

Understanding online media exposure is critical, especially in contemporary politics. Given the doubts about survey self-reports, research on media exposure has turned to web tracking data, sometimes considered the gold standard. However, studies revealed that web tracking data is also biased. To improve the understanding of the quality of web tracking measures of media exposure, this paper estimates their predictive validity and true-score reliability. It additionally identifies design choices that optimize their validity and reliability. Using data from a three-wave survey in Spain, Portugal, and Italy, combined with web tracking, this paper conducts a multiverse analysis to assess the validity and reliability of +2,500 web tracking measures of media exposure. Results show an overall high, but imperfect, reliability (0.86). However, in terms of predictive validity, the association between media exposure measures and political knowledge appears weak. This raises questions not only about the predictive validity of web tracking measures but also about the overemphasis on similar critiques regarding survey-based measures. Additionally, results suggest that the design decisions made by researchers can have a substantial impact on the quality of the web tracking data. Methodologically, the paper presents the multiverse of measurements approach, allowing researchers to embrace uncertainty, and improve the transparency of web tracking research.

+2,500 measures of media exposure

Predictive validity	Reliability
Association between media exposure & political knowledge (TRI-POL)	Is the measure consistent across multiple observations? (Quasi simplex model)
↓	↓
Media exposure is a bad predictor of political knowledge	Average is **.86**, but large fluctuations
↓	↓
Low validity?	Quite similar to survey questions

Alternative to study validity and reliability: the MTMM approach

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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Jouni Kuha| Department of Methodology, LSE

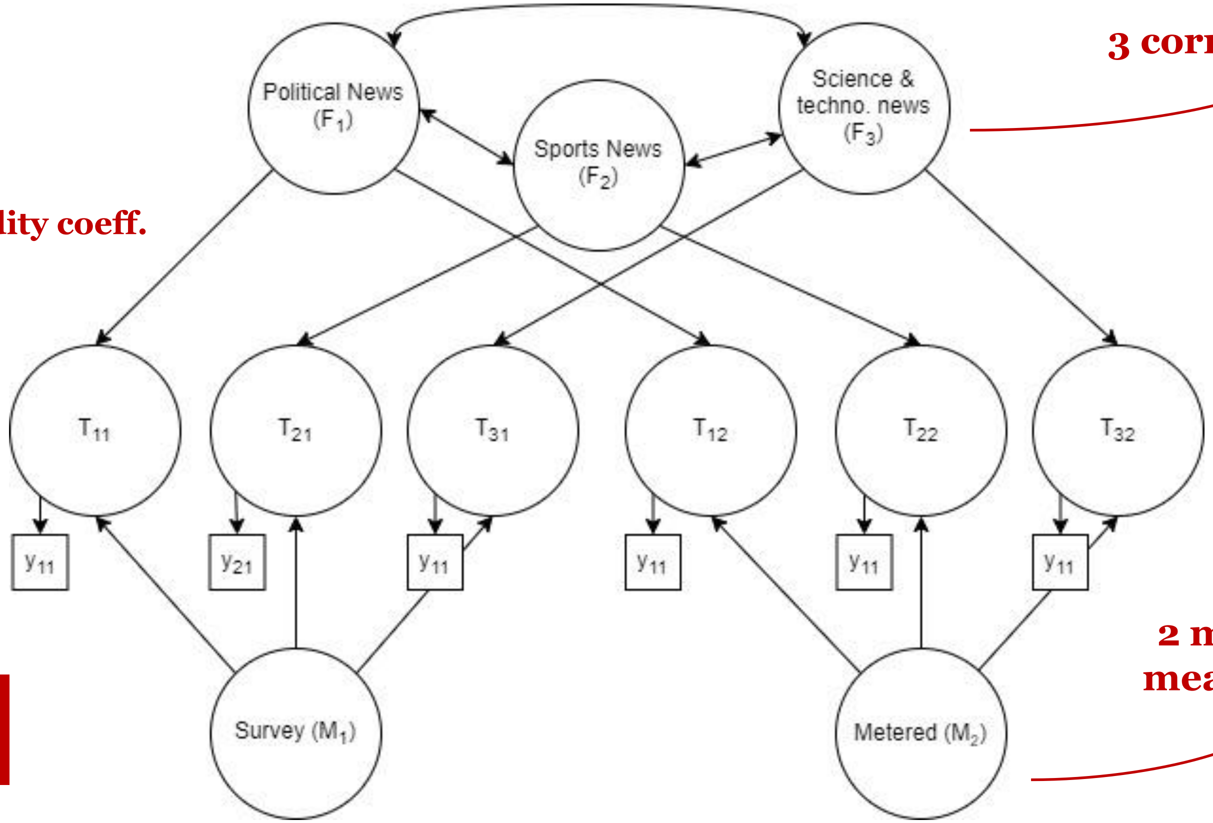
ESRA 2023 Conference, Milan

Validity coeff.

Reliability coeff.

3 correlated traits

2 methods to measure them



Measurement quality = validity x reliability

EXAMPLE2: METERED DATA

Alternative to study validity and reliability: the MTMM approach

Netquest metered panel in Spain

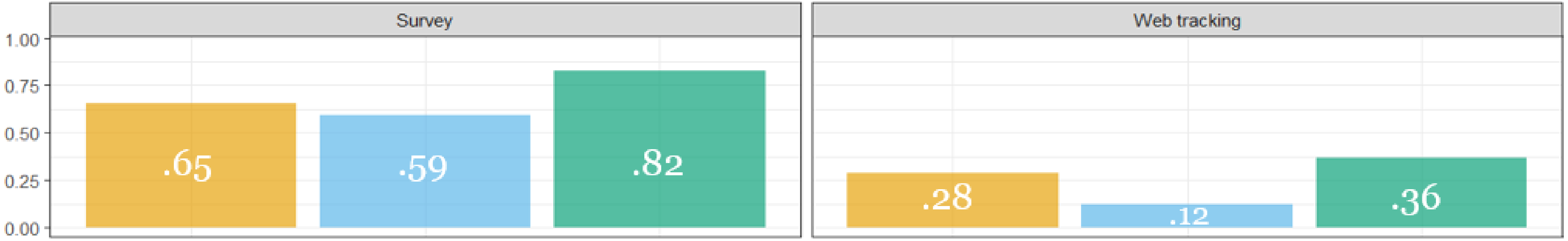
N = 1,200

May/June 2023

Tracking mobile and PCs

Measurement quality of metered data often (much) lower than the one of survey

First experiment: News



Second experiment: Communication

Third experiment: Entertainment

Alternative to study validity and reliability: the MTMM approach

Netquest metered panel in Spain

N = 1,200

May/June 2023

Tracking mobile and PCs

Measurement quality of metered data often (much) lower than the one of survey

Conclusions

Starting is difficult,
finishing is way **harder**

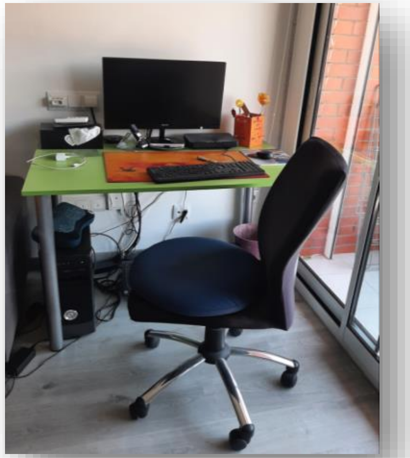
CONCLUSIONS

Increasing interest in new data types

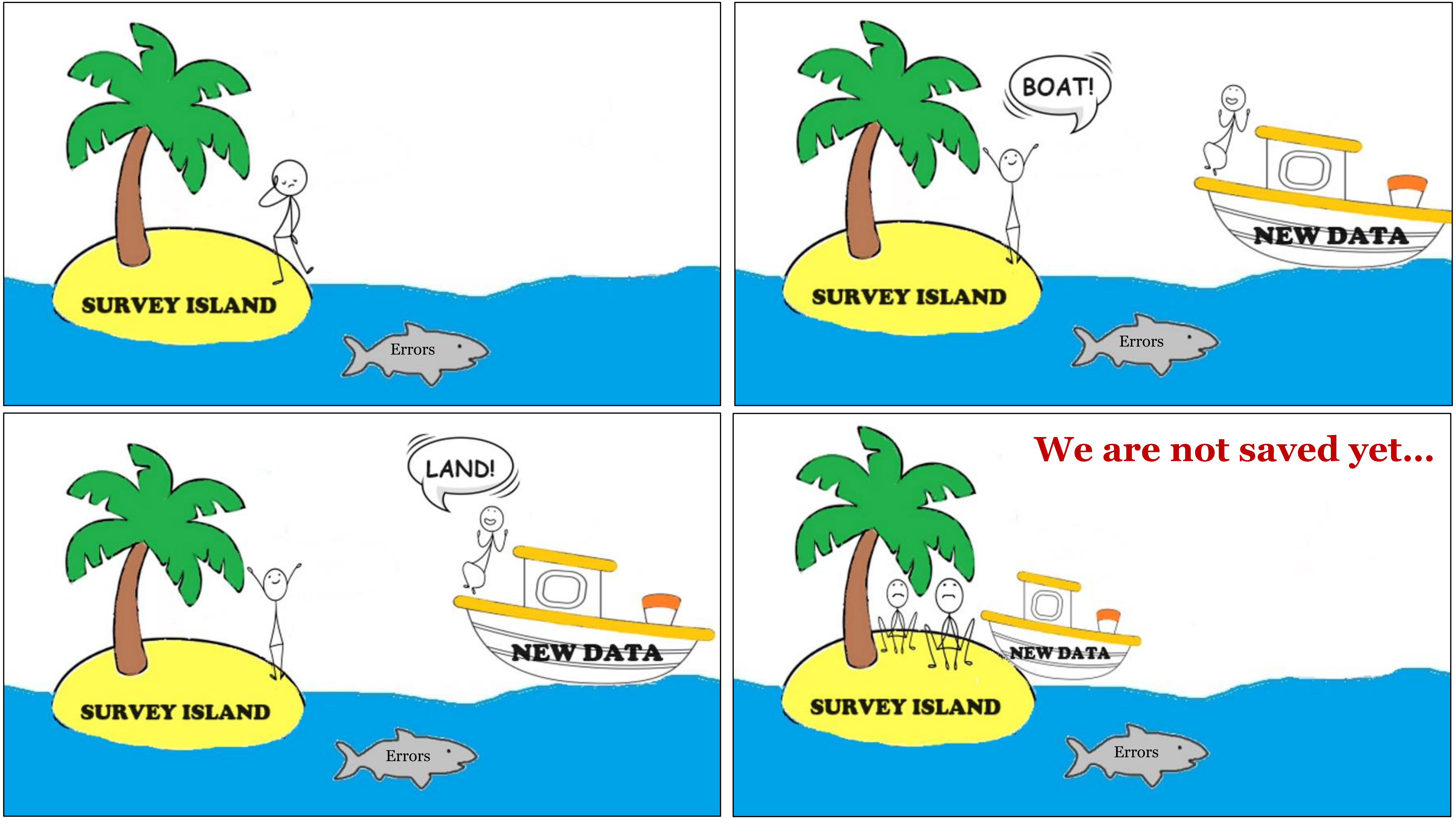
- Issues in conventional surveys push researchers to consider **new data types**
  - Could reduce some types of errors + provide new/more detailed data

- Potentially **broad applications** and new insights





- But lot of **challenges** as well


SURVEY ISLAND
Errors
BOAT!
SURVEY ISLAND
NEW DATA
Errors
LAND!
SURVEY ISLAND
NEW DATA
Errors
We are not saved yet…
SURVEY ISLAND
NEW DATA
Errors

CONCLUSIONS

Much more research needed

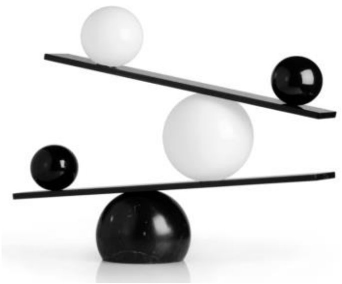
1 Learn more about the **errors** of these data in different contexts

Types of errors | Size of errors | Effects on the results

2 Understand better **when** it is worth using new data types

Need to better understand the mechanisms

Need to identify when benefits > problems (researchers & participants)



Much more research needed

3 Understand better **how** to use these data

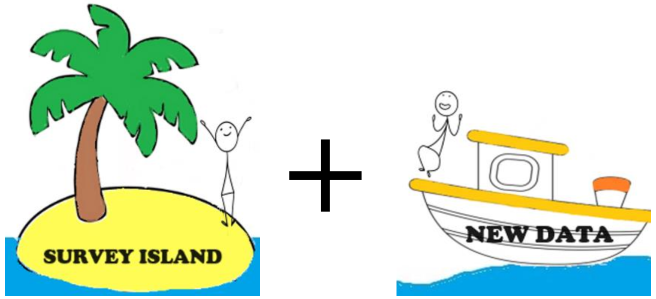
Replace conventional data?

Errors will always be present

Crucial to **identify** them and think about their **consequences**

Combine with conventional surveys?

Provide **different** but **complementary information**



Thanks!

Questions?

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https://www.upf.edu/web/webdataopp

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