

# Follow the User?!

## Data Donation Studies for Collecting Digital Trace Data

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Session : Bias & Outro

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👉 Part of the SPP DFG Project [Integrating Data Donations in Survey Infrastructure](#)

# Agenda

1. Bias in Data Donation Studies
2. What's Next for Data Donation?
3. Outro



Image by Hope House Press via Unsplash

# 1) Bias in Data Donation Studies (Valerie)



Source: Image by Markus Winkler via Unsplash

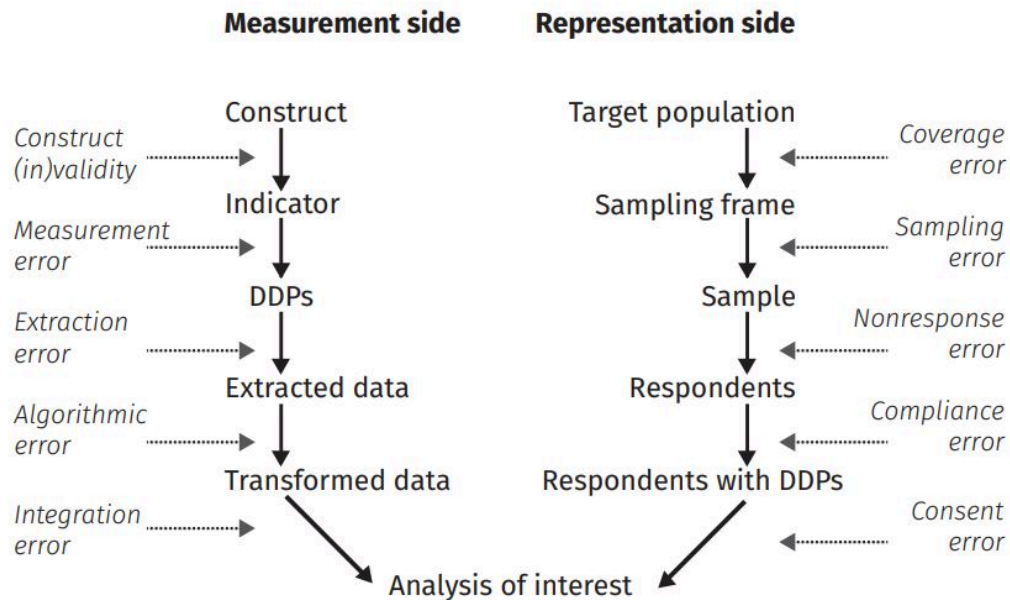
# What is bias?

**Definition** 💡 : *Deviations from the true value of a theoretical concept introduced by its measurement* (Peytchev, 2013)

- Non-systematic errors: random deviations influence variance of estimates
  - Systematic errors (or: **bias**): depend on omitted variables
- 👉 Bias can influence descriptive results but also attenuate/inflate inferential conclusions.

# What is bias?

- Errors in representation: *Who participates in data donation studies?*
- Errors in measurement: *Which latent concepts can we measure with data donation studies?*



**Figure 2.** "Total error framework" for social-scientific data collection with DDPs. Each step in the data collection process is shown, together with the errors resulting from this step. Subsequent processing, modeling, and inference steps (Amaya et al., 2020) are omitted.

Source: Image from Boeschoten et al., 2022, p. 396

# Errors in representation

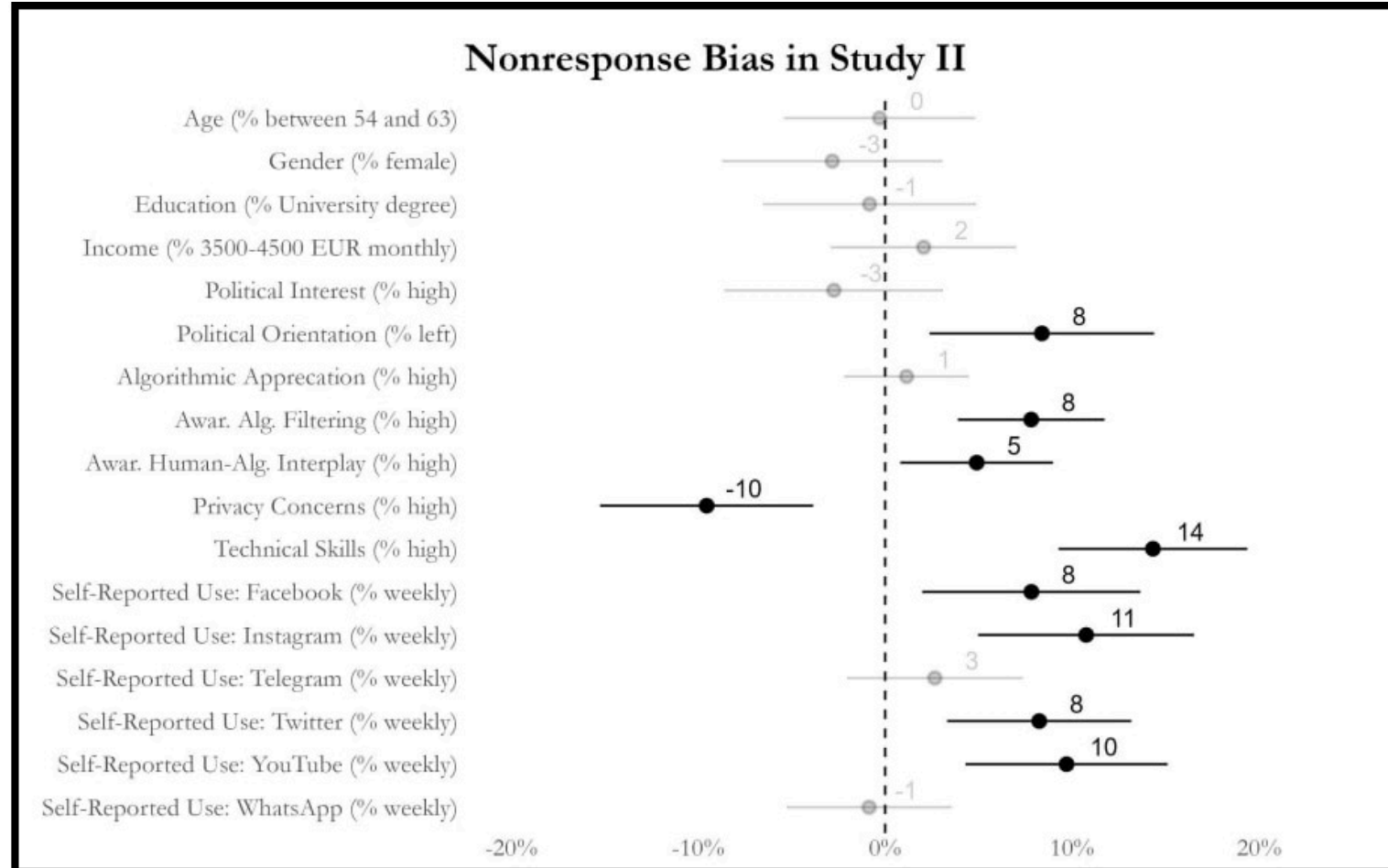
For example ...

- **Coverage error:** Who is (not) represented in the sampling frame? (e.g., social media users vs. YouTube users)
- **Sampling error:** Who is (not) represented in the sample? (e.g., non-probability samples)
- **Non-response error:** Who does (not) want to participate in the data donation?
- **Compliance error:** Who is (not) able to participate in the data donation?

*What do you think: Which participant characteristics may correlate with non-response or non-compliance?* 🤔

# Errors in representation

Example study by Hase & Haim (2024):



Source: Figure from Hase & Haim (2024)



*Any ideas (from your discipline): How can we quantify/address errors in representation?* 🤔

# Errors in representation: Quantification

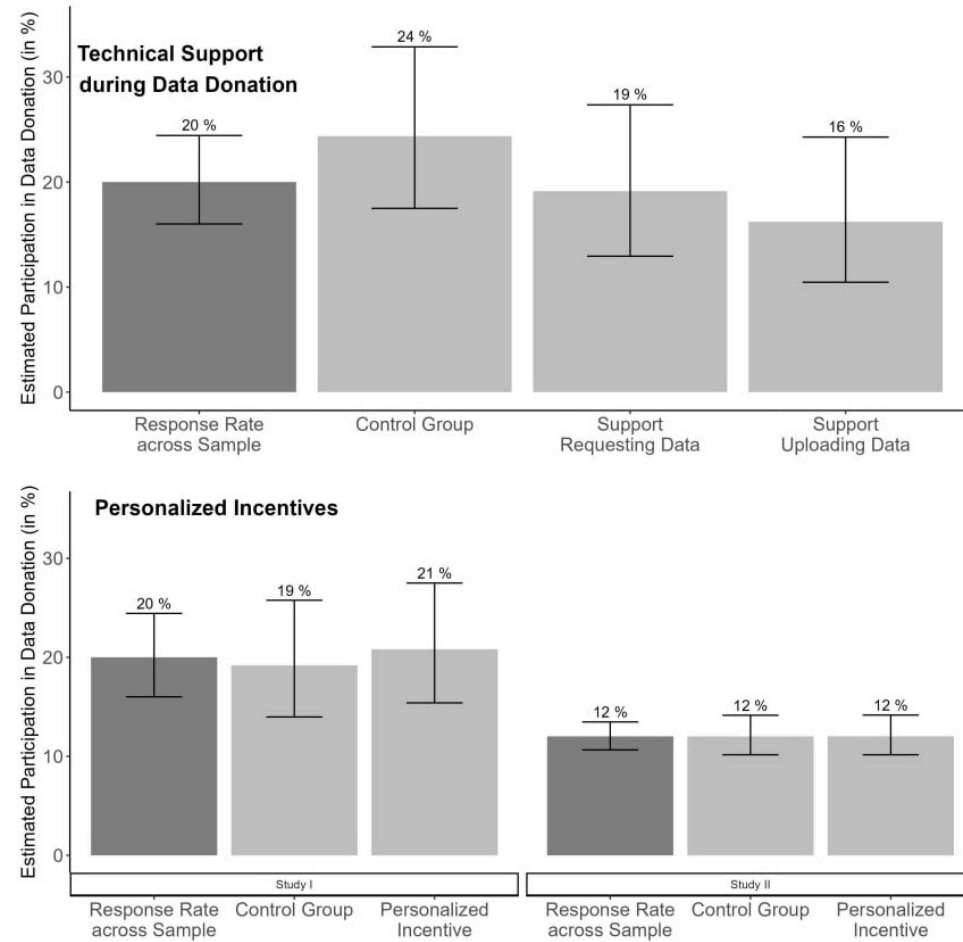
- Response rates across study stages
- Para data as quality indicators (e.g., speeding)
- Non-response bias (e.g. traits of survey vs. donation participants)

# Errors in representation: Solutions

- A posteriori strategies:
  - Infrastructure: Integration in probability-based panels
  - Survey design strategies (e.g., incentives, study framing)
  - DDT design (e.g. UX-perspective)
- Post hoc strategies:
  - Statistical modeling (e.g., weighting, see [Pak et al., 2022](#))

# Errors in representation: Solutions

For now: limited studies, limited success of existing solutions



Source: Figure from Hase & Haim (2024)

*What do you think: How could errors in measurements sneak into data donation studies?* 🤔

# Errors in measurement

For example ...

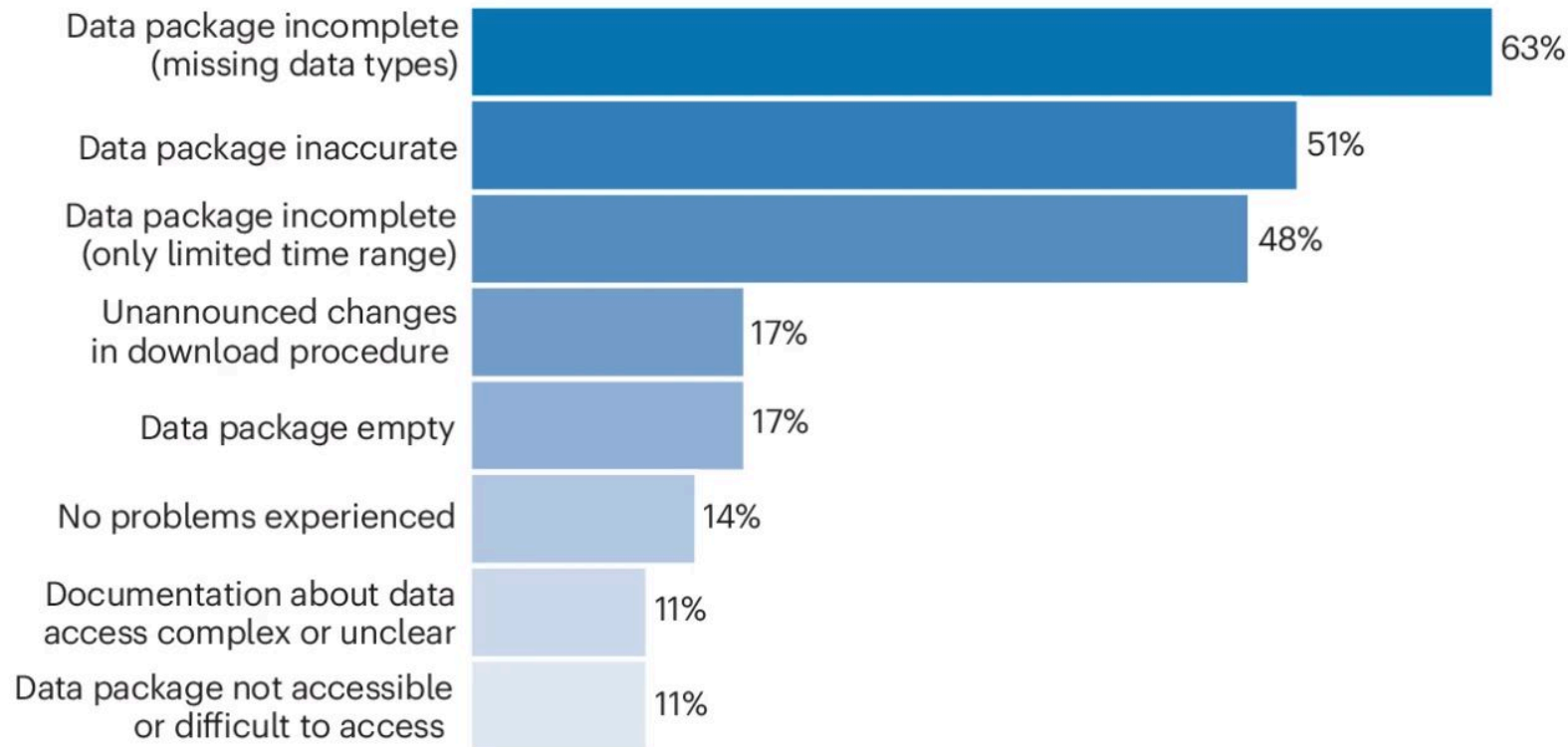
- **Construct (in-)validity:** How do DDP variables relate to latent measurements? (e.g., likes vs. political participation)
- **Measurement error:** How correct is data in our DDP? (e.g., missing data)
- **Extraction error:** Did we extract all relevant files and variables?

# Errors in measurements

Example study by Valkenburg et al. (2024):

**Fig. 1: Common problems in platform data donations experienced by researchers.**

From: [It is time to ensure research access to platform data](#)



Data from a [June 2024 survey](#) among 51 data donation researchers.

Source: Figure from Valkenburg et al. (2024)

*Any ideas (from your discipline): How can we quantify/address errors in measurements?* 🤔



# Errors in measurement: Quantification

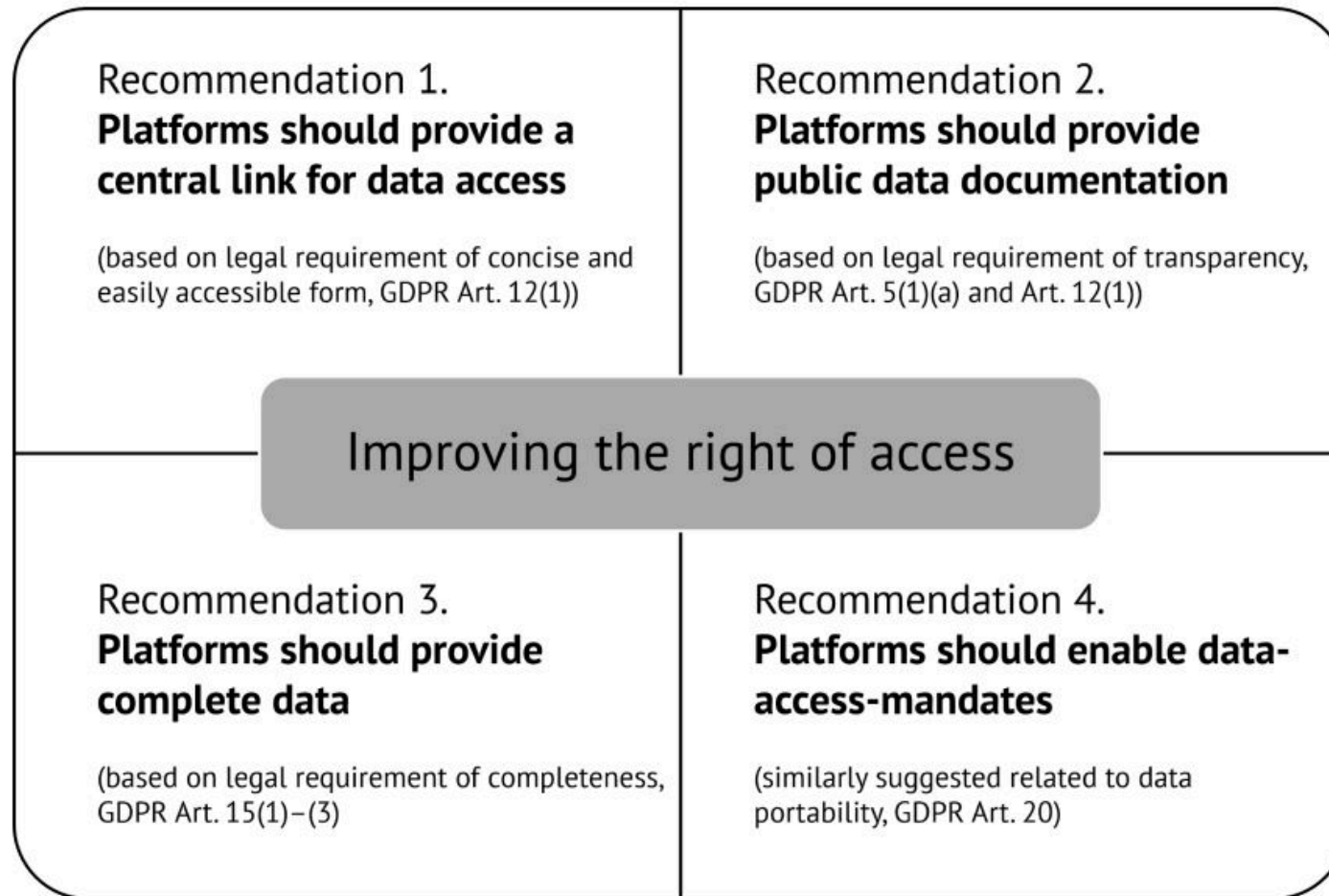
- Para data (e.g., failed uploads)
- Correlation between self-reported and observed behavior
- Multi Trait Multi Method (MTMM) approaches ([Cernat et al., 2024](#))
- Estimation of misclassification effects ([TeBlunthuis et al., 2024](#))

# Errors in representation: Solutions

- A posteriori strategies:
  - Talk to everyone (e.g., IRB, Data Strward)
  - Repeated testing & DDP download
  - Simulate downstream errors ([Bosch et al., 2024](#))
- Post hoc strategies:
  - Multiverse approaches
  - Statistical error correction ([TeBlunthuis et al., 2024](#))
  - Error documentation ([Gebu et al., 2021](#))

# Errors in representation: Solutions

Example study by Hase et al. (2024):



Source: Figure from Hase et al. 2024

# Questions?

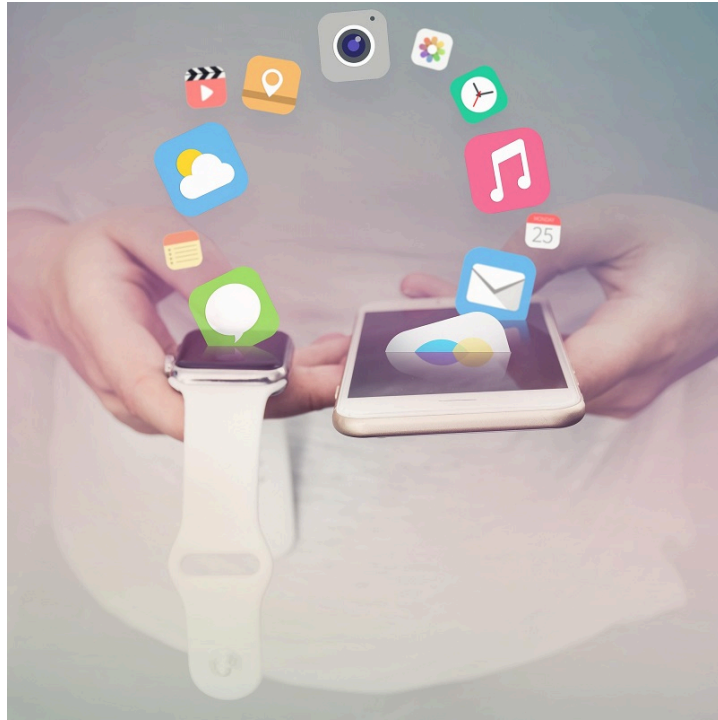
## 2) What's next for data donation studies? (Frieder)



Source: Image by Markus Winkler via Unsplash

# The road ahead I: Advancing the method

- Multimodal & cross-platform data 📷 (Wedel et al., 2024)
- In-tool, local classification (e.g., local SML/LLMs?)
- Workflow/UX-perspective



Source: Image by DariuszSankowski via Pixabay

# The road ahead II: Data as a political tool

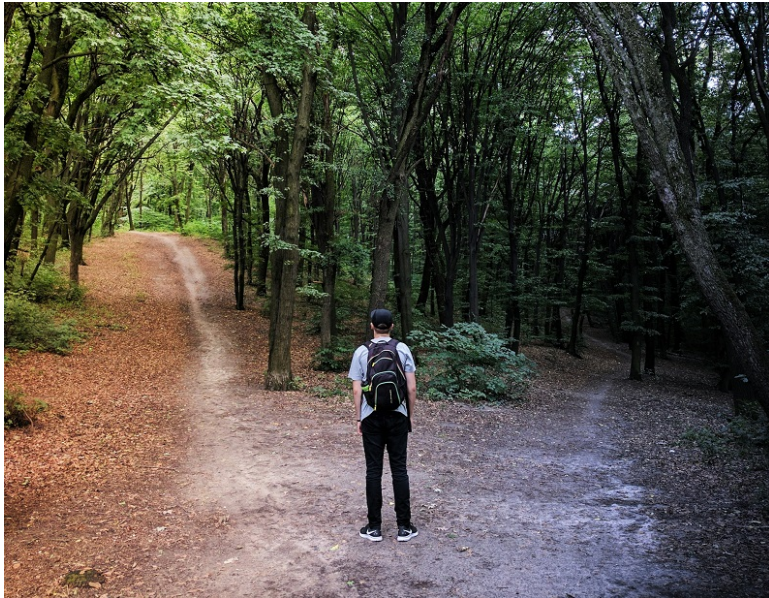
- Platforms do (willingly?) not provide data according to the GDPR/DSA ([Hase et al., 2024](#))
- The EU has started to sanction platforms like X/TikTok
- DSA may become the subject of larger geo-political debates with the USA ([Seiling et al., 2025](#))



Source: Image by WilliamCho via Pixabay

# The road ahead III: Can we improve & apply the method?

- Can the method actually be applied for empirical research? (few examples, like [Thorson et al., 2021](#); [Wojcieszak et al., 2024](#))
- Requires interdisciplinary perspectives (e.g., addressing bias, integration in probability-based panels)



Source: Image by Vladislav Babienko via Pixabay



# Questions?

### 3) Outro (Frieder)



Source: Image by Markus Winkler via Unsplash

# We want your feedback! 🙄

👉 Please fill out this 3-minute feedback form: <https://forms.gle/KLMweywhW7odGyfk8>



QR code for survey

Thanks for joining the  
workshop 🙌

# Quellen

Bosch, O. J., Sturgis, P., Kuha, J., & Revilla, M. (2024). Uncovering Digital Trace Data Biases: Tracking Undercoverage in Web Tracking Data. *Communication Methods and Measures*, 1–21.

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