Introduction to Data Donation

Workshop TU Ilmenau 2026

Session 4️⃣: Bias in Digital Trace Data & Outro

👉 Part of the SPP DFG Project Integrating Data Donations in Survey Infrastructure

UNIVERSITÄT KLAGENFURT

Agenda

1. **Bias in Data Donation Studies**
2. **What's Next for Data Donation?**
3. **Summary & Evaluation**

Image by Hope House Press via Unsplash

1) Bias in Data Donation Studies

Source: Image by Markus Winkler via Unsplash

What is bias?

Definition 💡 : *the systematic difference between a true value of a quantity for a population and how a study observe its*

(Hase et al., in press)

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

What is bias?

In CSS, the **bias-variance tradeoff** plays an important role: Often, we can *either* improve reduce variance or bias for models.

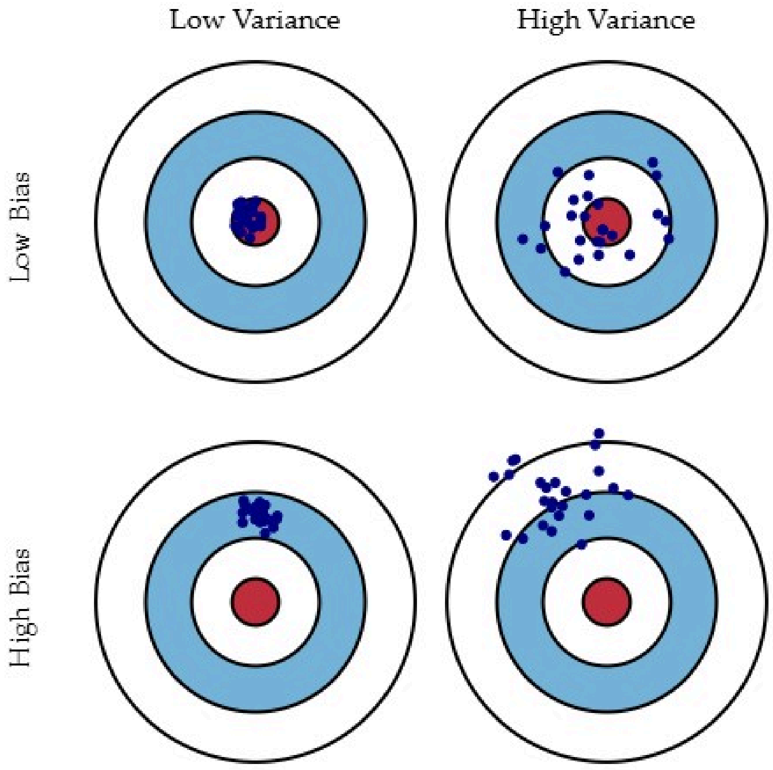

Fig. 1 Graphical illustration of bias and variance.

Bias-variance tradeoff

Source: Scott Fortmann-Roe (2012)

What is bias?

In CSS, the **bias-variance tradeoff** plays an important role: Often, we can *either* improve reduce variance or bias for models.

- Complex models often make better predictions (*less bias*), but with less inferential precision (*more variance*)
- Less complex models are less likely to overfit on the training data (*less variance*) but may make less accurate predictions (*more bias*)

Bias in CSS

Bias is an underestimated problem in CSS (Hase et al., 2025; Kathirgamalingam, Kulichkina, et al., 2025)

- Distorts scientific findings **and** has real-world consequences, such as unfairness through socio-technical systems
- Examples: AI in health resource allocation, hiring, or content moderation may induce gender bias (Lambrecht & Tucker, 2019; Siemon, 2025; Stoll et al., 2025) and racism (Kathirgamalingam, Lind, et al., 2025; Sap et al., 2019).

Police

West Midlands police chief apologises after AI error used to justify Maccabi Tel Aviv ban

Craig Guildford says he gave incorrect evidence to MPs and mistake arose from 'use of Microsoft Copilot'

Neha Gohil

Wed 14 Jan 2026 10.47 CET

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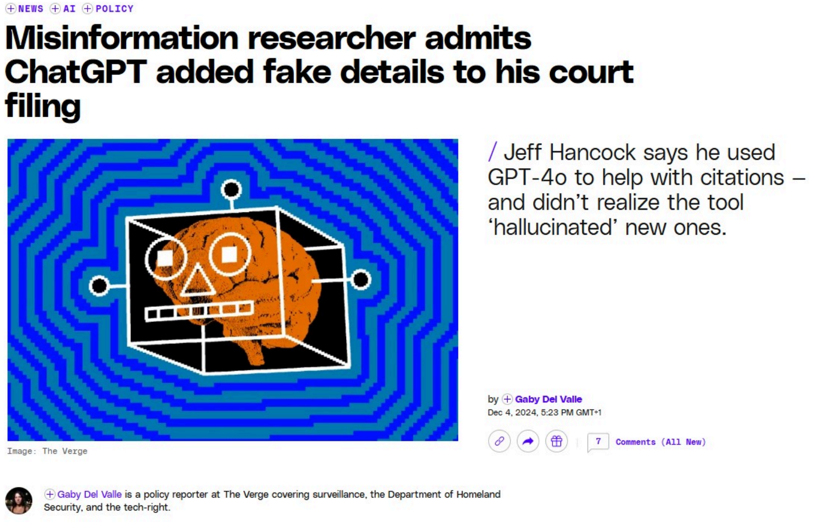
Craig Guildford, the chief constable of West Midlands police. Photograph: Ben Whitley/PA



NEWS AI POLICY

Misinformation researcher admits ChatGPT added fake details to his court filing

/ Jeff Hancock says he used GPT-4o to help with citations – and didn't realize the tool 'hallucinated' new ones.

by Gaby Del Valle

Dec 4, 2024, 5:23 PM GMT+1

7 Comments (All New)

Image: The Verge

Gaby Del Valle is a policy reporter at The Verge covering surveillance, the Department of Homeland Security, and the tech-right.

Source: The Verge, 2024

Source: The Guardian, 2024

Bias in CSS

Bias is an underestimated problem in CSS (Hase et al., 2025; Kathirgamalingam, Kulichkina, et al., 2025)

- Distorts scientific findings **and** has real-world consequences, such as unfairness through socio-technical systems
- We lack clear definitions, methods for quantifying bias, and solutions for adressing it

COMMUNICATION METHODS AND MEASURES
2025, VOL. 19, NO. 4, 281–293
https://doi.org/10.1080/19312458.2025.2575468

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Critical, but constructive: defining, detecting, and addressing bias in Computational Social Science

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ABSTRACT
Computational Social Science (CSS) increasingly engages in critical discussions about bias in and through computational methods. Two developments drive this shift: first, the recognition of bias as a societal problem, as flawed CSS methods in socio-technical systems can perpetuate structural inequalities; and second, the field's growing methodological resources, which create not only the opportunity but also the responsibility to confront bias. In this editorial to our Special Issue on CSS and bias, we introduce the contributions and outline a research agenda. In defining bias, we emphasize the importance of embracing epistemological pluralism while balancing the need for standardization with methodological diversity. Detecting bias requires stronger integration of bias detection into validation procedures and the establishment of shared metrics and thresholds across studies. Finally, addressing bias involves adapting established and emerging error-correction strategies from social science traditions to CSS, as well as leveraging bias as an analytical resource for revealing structural inequalities in society. Moving forward, progress in defining, detecting, and addressing bias will require both bottom-up engagement by researchers and top-down institutional support. This Special Issue positions bias as a central theme in CSS – one that the field now has both the tools and the obligation to address.

Special Issue in Communication Methods and Measures

Bias in Data Donation Studies

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

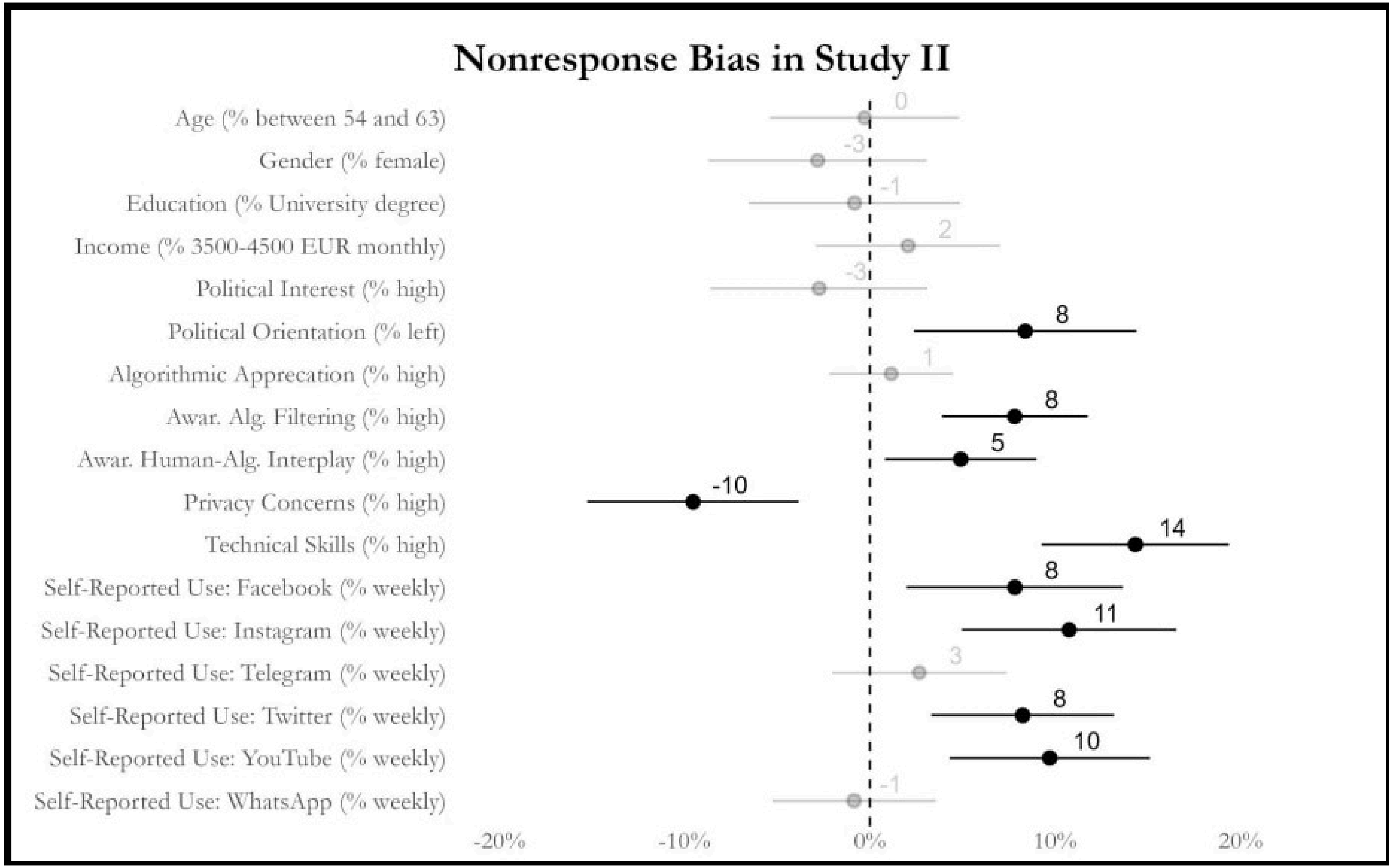
Errors in representation

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?

Errors in representation

Example study by Hase & Haim (2024):



Source: Figure from Hase & Haim (2024)

Errors in representation

Literature review by Xiong et al. (2025) and own experiences

Research design

- Sensitivity of the requested data
- Autonomy and control over the process
- Burden/Complexity of the study

Participant characteristics

- Privacy concerns
- Digital savviness/skills
- Mixed findings on sociodemographics
- Mixed findings on prosocial motivation

Errors in representation: Quantification

Methods for bias detection often draw from validation strategies, though this may not be enough (Hase et al., 2025)

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

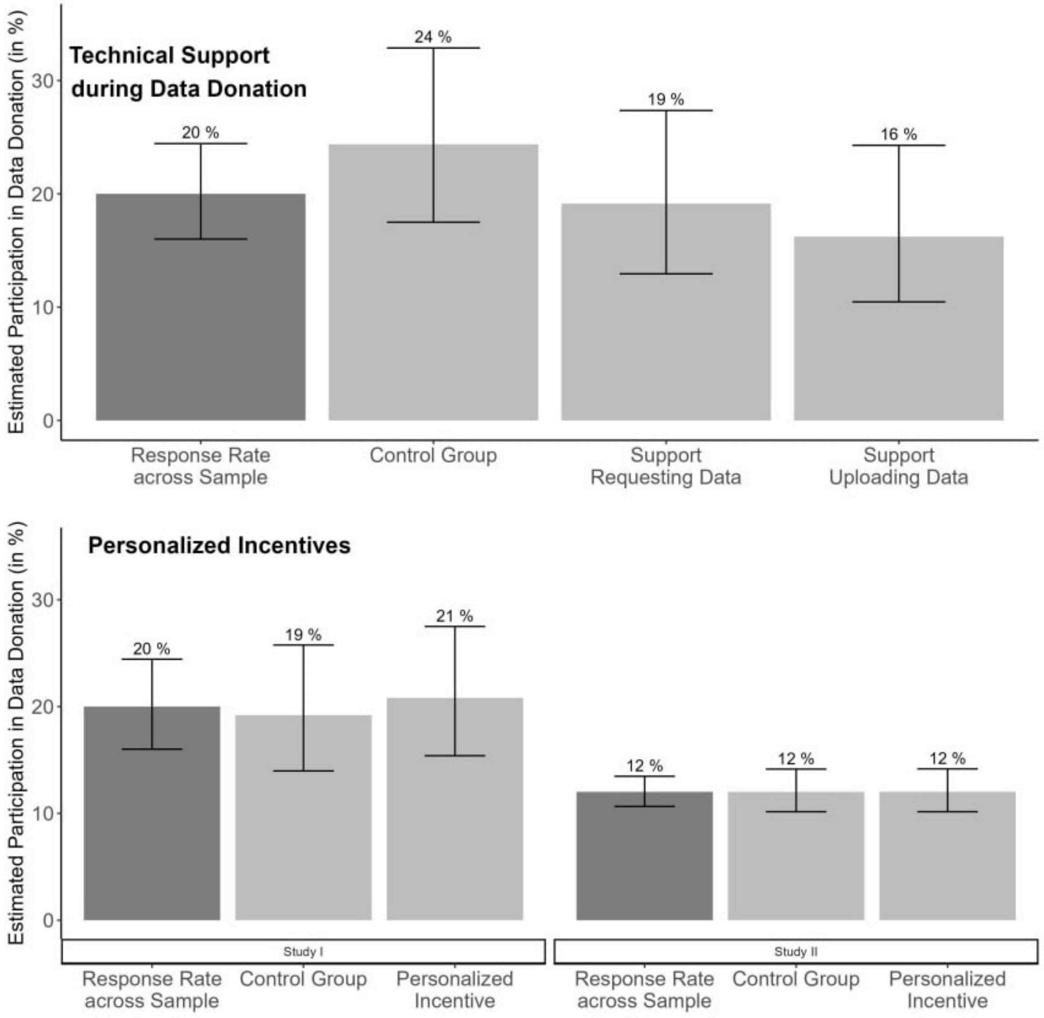
👉 "*a more pragmatic vision of bias detection: one that abandons the pursuit of perfect benchmarks in favor of comparative assessments of biases across CSS and non-CSS methods.*" (Hase et al., 2025, p. 5)

Errors in representation: Solutions

- **A posteriori strategies**:
  - Infrastructure: Integration in probability-based panels
  - Learning from survey design strategies (e.g., incentives, study framing) (Hase & Haim, 2024)
  - DDT design (e.g. UX-perspective)
- **Post hoc strategies**:
  - Statistical modeling like weighting (Pak et al., 2022)

Errors in representation: Solutions

For now: limited studies, limited success



Source: Figure from Hase & Haim (2024)

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

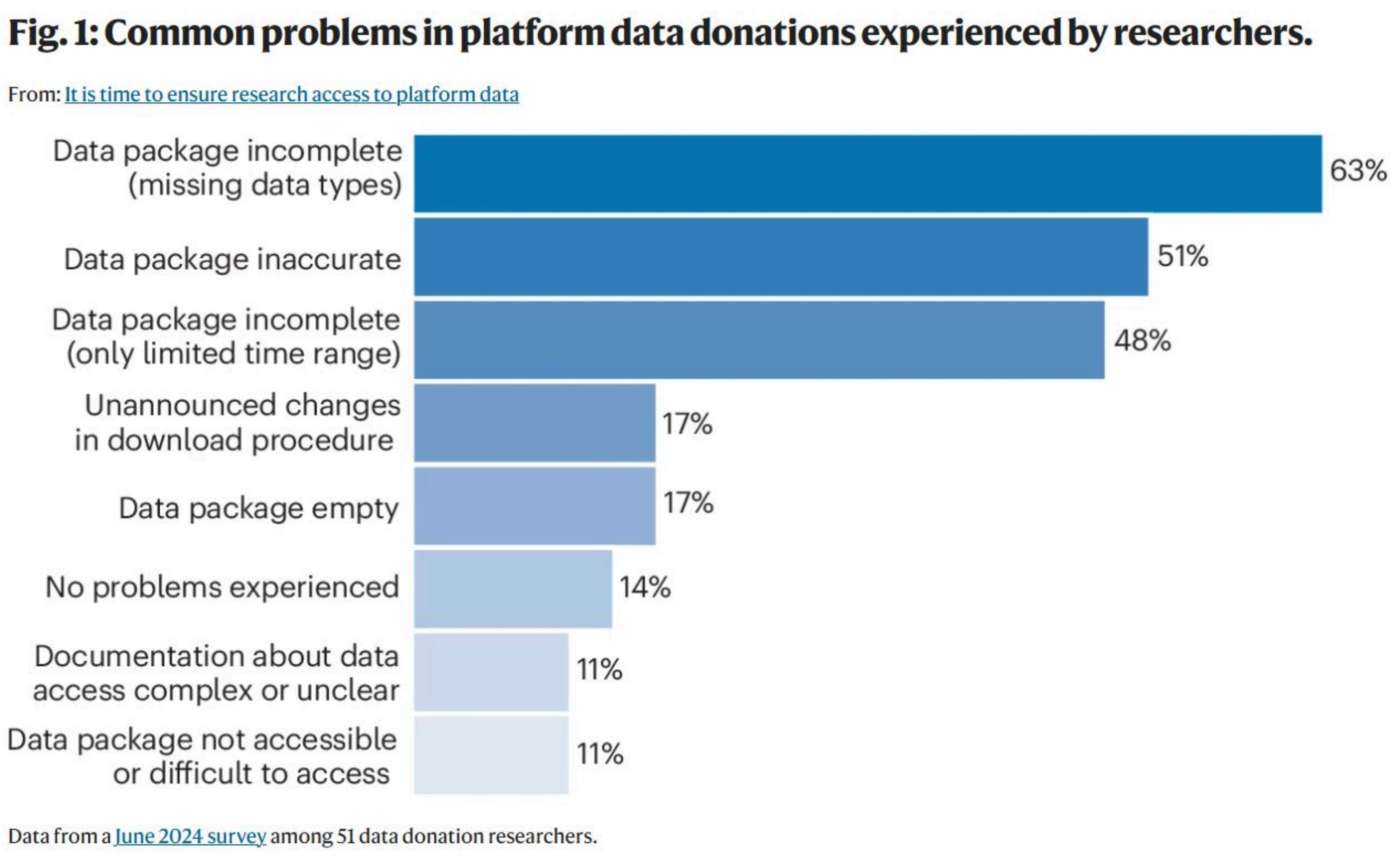
Errors in measurement

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):



Source: Figure from Valkenburg et al. (2024)

Errors in measurement: Quantification

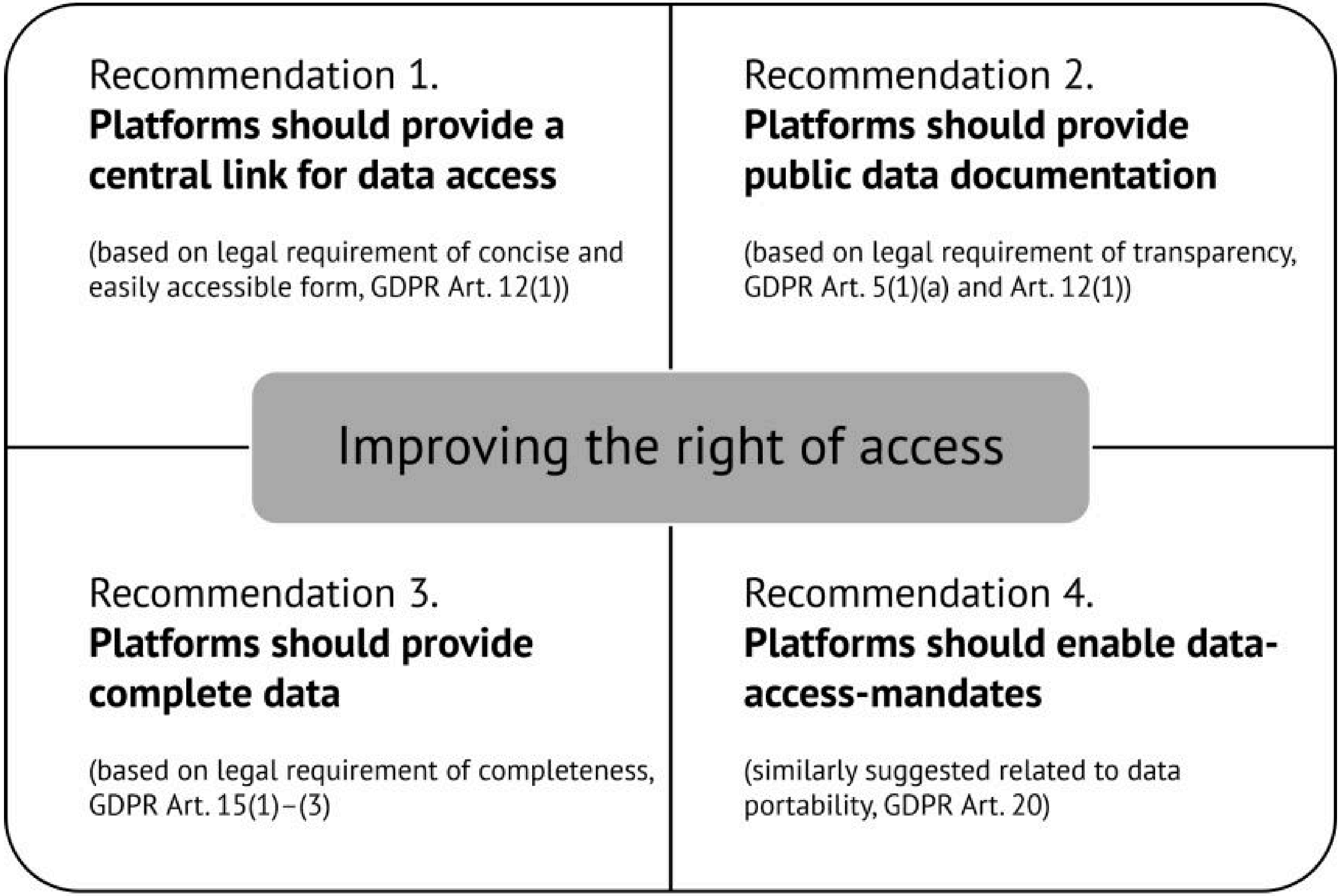
- Para data (e.g., failed uploads)
- Correlation between self-reported and observed behavior
- Multi Trait Multi Method (MTMM) approaches (Cernat et al., 2024)
- Estimation of misclassification effects (TeBlunthuis et al., 2024)

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 (Gebru et al., 2021)

Errors in representation: Solutions

In a recent policy paper, around 20 scholars from different CSS labs argued (Hase et al., 2024):



Source: Figure from Hase et al. 2024

A final remark on data donations for research

Despite my lengthy rant about bias, this is **not** a statement against data donations.

Just be sure to:

- Carefully consider whether data donations make sense for your theoretical puzzle
- This relates to populations you can(not) study and latent phenomena you can(not) operationalize
- Often, the goal may not be highly representative panels - but targeting specific populations

Questions?

2) What's next for data donation studies?

Source: Image by Markus Winkler via Unsplash

The road ahead I: Open Science

Preregistration:

- Many researcher degree of freedom
- Few existing studies (e.g., for power calculations)
- Almost no templates (Langener et al., 2024)

👉 Our recent preregistration includes 70 pages 😭 and we fully simulated results to understand potential decision trees

The road ahead I: Open Science

Preregistration:

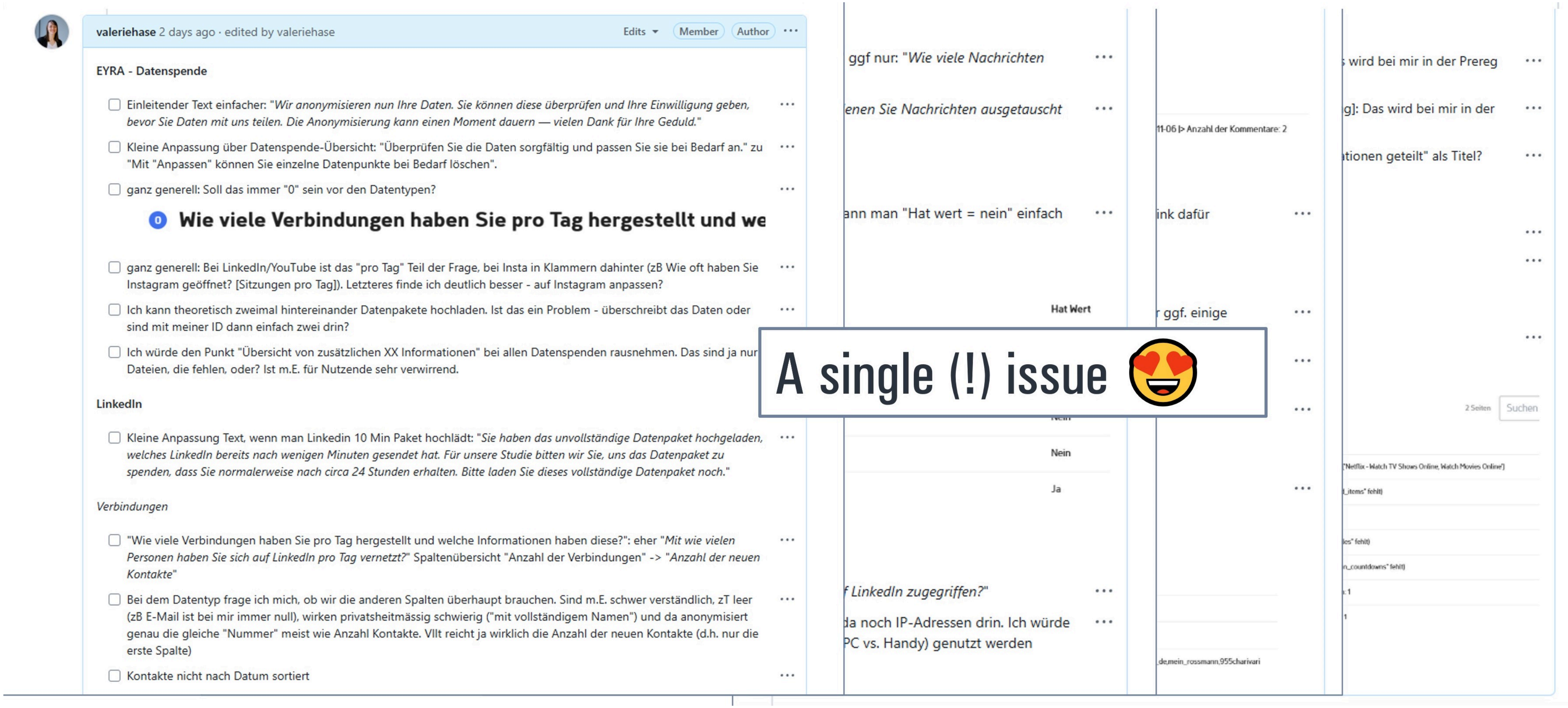


Figure. Github issues - Testing the tool

The road ahead I: Open Science

Open Data:

- Some useful primers (Munzert et al., 2023)
- Still, strategies (e.g., aggregation, synthetic data, differential privacy) remain debated

Open Materials:

- Big data of data donation: tools are almost exclusively open source!

The road ahead II: Advancing the method

- Multimodal & cross-platform data 📸 (Wedel et al., 2025)
- Less standardized data (e.g., chatbot or message logs)
- In-tool, local classification (e.g., local SML/LLMs?)
- Workflow/UX-perspective

Source: Image by DariuszSankowski via Pixabay

The road ahead III: Data in a world of political turmoil

The road ahead III: Data in a world of political turmoil

- Platforms do (willingly?) not provide data according to the GDPR/DSA (Hase et al., 2024)
- The EU may sanction platforms like X/TikTok, but exact sanctions remain unclear (see DSA Observatory)
- DSA subject to larger geo-political debates (Seiling et al., 2025), where some politicians falsely claim "censorship" as the reason behind regulations
- Recent GDPR Omnibus amendment would make data donation unfeasible (see our open letter to the European Commission)

Source: Image by WilliamCho via Pixabay

Questions? 

3) Outro

Source: Image by Markus Winkler via Unsplash

I would ❤️ your feedback! 🙃

👉 Please fill out this 3-minute feedback form: https://forms.gle/xaRy2Ldr9mU9jGc3A

Thanks for joining the workshop 🙌

References

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. https://doi.org/10.1080/19312458.2024.2393165

Cernat, A., Keusch, F., Bach, R. L., & Pankowska, P. K. (2024). Estimating Measurement Quality in Digital Trace Data and Surveys Using the MultiTrait MultiMethod Model. *Social Science Computer Review*, 08944393241254464. https://doi.org/10.1177/08944393241254464

Gebru, T., Morgenstern, J., Vecchione, B., Vaughan, J. W., Wallach, H., Iii, H. D., & Crawford, K. (2021). Datasheets for datasets. *Communications of the ACM*, *64*(12), 86–92. https://doi.org/10.1145/3458723

Hase, V., Ausloos, J., Boeschoten, L., Pfiffner, N., Janssen, H., Araujo, T., Carrière, T., De Vreese, C., Haßler, J., Loecherbach, F., Kmetty, Z., Möller, J., Ohme, J., Schmidbauer, E., Struminskaya, B., Trilling, D., Welbers, K., & Haim, M. (2024). Fulfilling Data Access Obligations: How Could (and Should) Platforms Facilitate Data Donation Studies? *Internet Policy Review*, *13*(3). https://doi.org/10.14763/2024.3.1793

Hase, V., Bachl, M., & TeBlunthuis, N. (2025). Critical, but constructive: Defining, detecting, and addressing bias in Computational Social Science. *Communication Methods and Measures*, *19*(4), 281–293. https://doi.org/10.1080/19312458.2025.2575468

Hase, V., Bachl, M., TeBlunthuis, N., & Widder, D. G. (in press). Bias in Computational Social Science. In M. Haim & E. Domahidi (Eds.), *ICA Handbook of Computational Communication Research*.

Hase, V., & Haim, M. (2024). Can We Get Rid of Bias? Mitigating Systematic Error in Data Donation Studies through Survey Design Strategies. *Computational Communication Research*, *6*(2), 1. https://doi.org/10.5117/CCR2024.2.2.HASE

Kathirgamalingam, A., Kulichkina, A., Bernhard-Harrer, J., & Hase, V. (2025). *Reflecting on Social Bias: Challenges and Opportunities for Computational Social Science*. SocArXiv. https://doi.org/10.31235/osf.io/xr45y_v1

Kathirgamalingam, A., Lind, F., & Boomgaarden, H. G. (2025). Measuring racism and related concepts using computational text-as-data approaches: A systematic literature review. *Annals of the International Communication Association*, *49*(3), 241–256. https://doi.org/g9353n

Lambrecht, A., & Tucker, C. (2019). Algorithmic Bias? An Empirical Study of Apparent Gender-Based Discrimination in the Display of STEM Career Ads. *Management Science*, *65*(7), 2966–2981. https://doi.org/10.1287/mnsc.2018.3093

Langener, A. M., Siepe, B. S., Elsherif, M., Niemeijer, K., Andresen, P. K., Akre, S., Bringmann, L. F., Cohen, Z. D., Choukas, N. R., Drexl, K., Fassi, L., Green, J., Hoffmann, T., Jagesar, R. R., Kas, M. J. H., Kurten, S., Schoedel, R., Stulp, G., Turner, G., & Jacobson, N. C. (2024). A template and tutorial for preregistering studies using passive smartphone measures. *Behavior Research Methods*, *56*(8), 8289–8307. https://doi.org/10.3758/s13428-024-02474-5

Munzert, S., Ramirez-Ruiz, S., Watteler, O., Breuer, J., Batzdorfer, V., Eder, C., Wiltshire, D. A., Barberá, P., Guess, A. M., & Yang, J. (2023). *Publishing combined web tracking and survey data*. Center for Open Science. https://doi.org/10.31219/osf.io/y4v8z

Pak, C., Cotter, K., & Thorson, K. (2022). Correcting Sample Selection Bias of Historical Digital Trace Data: Inverse Probability Weighting (IPW) and Type II Tobit Model. *Communication Methods and Measures*, *16*(2), 134–155.

https://doi.org/10.1080/19312458.2022.2037537
Sap, M., Card, D., Gabriel, S., Choi, Y., & Smith, N. A. (2019). The Risk of Racial Bias in Hate Speech Detection. *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 1668–1678. https://doi.org/gf9wr8
Seiling, L., Ohme, J., & De Vreese, C. (2025). Wird Europa den DSA in Verhandlungen mit Trump opfern? *Tagesspiegel*. https://background.tagesspiegel.de/digitalisierung-und-ki/briefing/wird-europa-den-dsa-in-verhandlungen-mit-trump-opfern
Siemon, M. (2025). Beyond the binary? Automated gender classification of social media profiles. *Communication Methods and Measures*, 1–19. https://doi.org/g95x5s
Stoll, A., Yu, J., Andrich, A., & Domahidi, E. (2025). Classification bias of LLMs in detecting incivility towards female and male politicians in German social media discourse. *Communication Methods and Measures*, 1–19. https://doi.org/g94g68
TeBlunthuis, N., Hase, V., & Chan, C.-H. (2024). Misclassification in Automated Content Analysis Causes Bias in Regression. Can We Fix It? Yes We Can! *Communication Methods and Measures*, *18*(3), 278–299. https://doi.org/10.1080/19312458.2023.2293713
Valkenburg, P. M., Van Der Wal, A., Siebers, T., Beyens, I., Boeschoten, L., & Araujo, T. (2024). It is time to ensure research access to platform data. *Nature Human Behaviour*, *9*(1), 1–2. https://doi.org/10.1038/s41562-024-02066-5
Wedel, L., Ohme, J., & Araujo, T. (2025). Augmenting Data Download Packages – Integrating Data Donations, Video Metadata, and the Multimodal Nature of Audio-visual Content. *Methods, Data, Analyses*, *19*(2), 11–45. https://doi.org/10.12758/mda.2024.08