



## Assessing the Quality of Digital Behavioral Data for Measuring Smartphone Use

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# Measuring digital technology use

- ▶ Inequalities in smartphone use and skills in general population (*second-level digital divide*; Hargittai, 2002) has implications for social inequalities (Helsper, 2021)
- ▶ Most previous digital divide research has relied on surveys for measuring digital technology use and skills
  - ▶ But self-reports of behaviors are prone to measurement error
- ▶ Digital behavioral data (DBD) are an alternative method for collecting data about digital technology use (Keusch & Kreuter, 2022)
  - ▶ Advantages compared to surveys: behaviors can be measured unobtrusively, in a more detailed way, and over a longer period of time

# Research questions

1. To what extent do DBD-based measures of smartphone use align with survey-based measures?
  - ▶ Usage dimensions: *amount, variety, activities of use* (Blank & Groselj, 2014)
2. How does the alignment vary by sociodemographic characteristics?
3. To what extent do smartphone usage types identified from latent class analysis align between DBD and survey data?

# Data and Methods

## Sample

### Political Identities and News Consumption in Election Times (PINCET; Bach et al., 2023)

- ▶ Online panel members in Germany invited to web surveys in Aug-Dec 2021
  - ▶ Aged 18+, resident in Germany, eligible to vote in 2021 German federal election
  - ▶ Quotas for gender, age, and state
- ▶  $N=1,204$  smartphone users completed the wave 1 survey and had downloaded the research app on their smartphone
  - ▶ Information about app use (name + date, time, duration of use) and website visits (URL, domain + date, time, duration of visit)
- ▶ For each participant, we use the app data collected prior to their wave 1 interview
  - ▶ Median duration: 47 days (min: 1 day, max: 55 days)

# Data and Methods

## Survey-based measures

- ▶ *Amount of use*: time spent using the smartphone on ordinary day (hours, mins)
- ▶ *Activities of use*: each coded as yes vs. no
  - (1) Making and receiving phone calls, (2) Using messenger services, (3) Visiting websites, (4) Sending and/or reading emails, (5) Taking photos, (6) Using social media, (7) Shopping, (8) Online banking, (9) Using location-based apps, (10) Playing games, (11) Listening to music or watching videos, (12) Health and/or fitness tracking, (13) Reading, listening, or watching the news
- ▶ *Variety of use*: number of different activities summed up (min: 1, max: 13)

# Data and Methods

## DBD-based measures

- ▶ *Amount of use*: time spent on all apps during the data collection period, divided by the number of days for which smartphone was tracked
- ▶ *Activities of use*: each coded as yes vs. no
  - ▶ Classification of apps into activities:
    - (1) App store categories were used as the starting point
    - (2) Categories were refined through manual coding
- ▶ *Variety of use*: number of different activities summed up (min: 0, max: 13)

# Data and Methods

Alignment measures (Araujo et al., 2017)

## Absolute error

- ▶ Continuous: absolute difference between DBD and survey
- ▶ Categorical: 1 if different, 0 if not different

## Underreporting: behavior observed in DBD, not in survey

- ▶ Continuous: difference between DBD and survey if underreported
- ▶ Categorical: 1 if underreported, 0 if not underreported

## Overreporting: behavior observed in survey, not in DBD

- ▶ Continuous: difference between DBD and survey if overreported
- ▶ Categorical: 1 if overreported, 0 if not overreported

# Results

1. To what extent do DBD-based measures of smartphone use align with survey-based measures?

	Absolute error	Underreporting	Overreporting
<i>Amount of use</i>	min	min	min
Mean	157	20	137
<i>Variety of use</i>	#	#	#
Mean	3	1	2



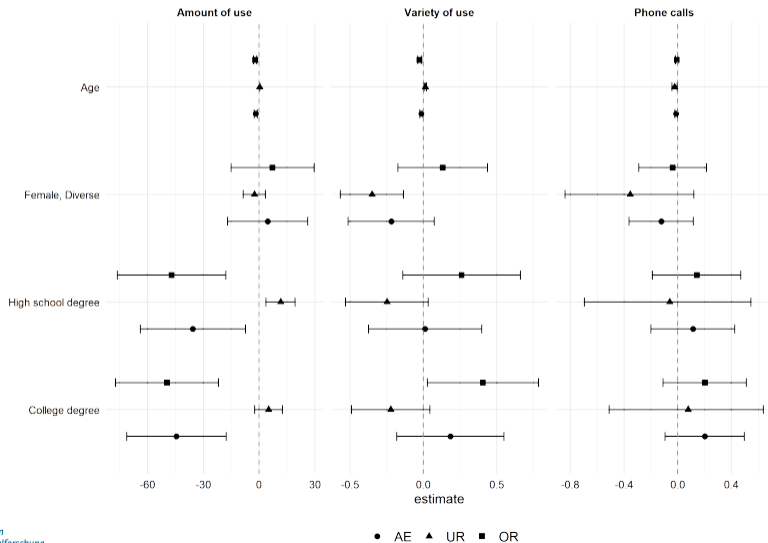
# Results

## 1. To what extent do DBD-based measures of smartphone use align with survey-based measures?

	Absolute error	Underreporting	Overreporting
<i>Activities of use</i>	%	%	%
Browsing websites	68	2	66
News	60	1	60
Health or fitness	47	36	11
Shopping	40	32	8
GPS	40	18	22
Music or videos	39	32	8
Photos	35	11	24
Phone calls	35	6	29
Online banking	32	16	16
Games	29	17	12
Emails	23	11	13
Social media	22	14	9
Messenger services	14	8	6

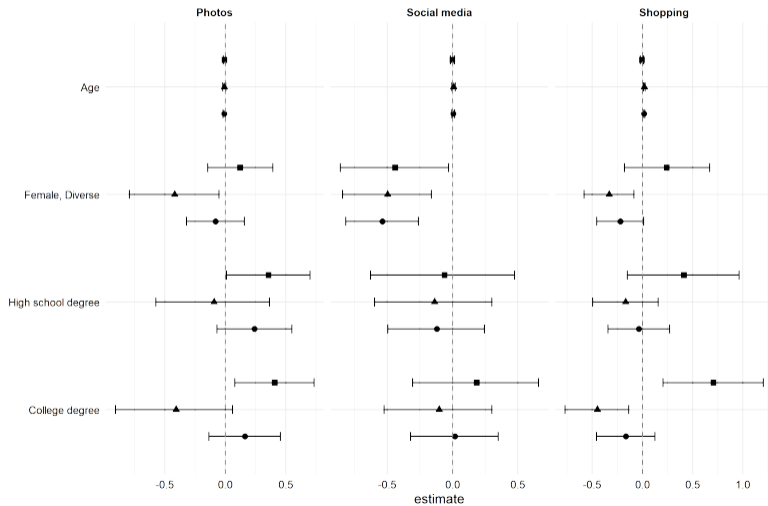
# Results

## 2. How does the alignment vary by sociodemographic characteristics?



# Results

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# Results

## 3. To what extent do smartphone usage types align between DBD and survey data?

Survey	Advanced users	Intermediate users	Basic users
%	53	34	13
<i>Amount of use</i>	Large	Medium	Small
<i>Variety of use</i>	Large	Small	Small
<i>Activities of use</i>	Most	Several	News, phone calls, messenger, photos

DBD	Advanced users	Social media users	Phone call users	Basic users
%	56	16	16	12
<i>Amount of use</i>	Large	Medium	Medium	Small
<i>Variety of use</i>	Large	Small	Small	Small
<i>Activities of use</i>	Most	Messenger, social media, shopping + others	Messenger, phone calls, photos + others	Messenger, emails

# Results

## 3. To what extent do smartphone usage types align between DBD and survey data?

% DBD	Survey		
	Advanced users	Intermediate users	Basic users
Advanced users	32	19	5
Social media users	11	4	1
Phone call users	5	7	4
Basic users	5	5	2

## Key takeaways

1. To what extent do DBD-based measures align with survey-based measures?
  - ▶ *Amount of use*: considerable overreporting in the survey
  - ▶ *Variety of use*: close alignment
  - ▶ *Activities of use*: alignment differs by type of activity
2. How does the alignment vary by sociodemographic characteristics?
  - ▶ Alignment is systematically related to age, gender, and educational attainment
3. To what extent do smartphone usage types align between DBD and survey data?
  - ▶ Similar typologies, but more nuanced in the DBD
  - ▶ Classes have similar size, but small overlap on individual level

# Discussion

- ▶ Findings in line with previous research
  - ▶ Correlations between self-reported and tracked measures are generally small to moderate (e.g., Parry et al., 2021)
- ▶ DBD and survey data might better measure different aspects of smartphone use
  - ▶ DBD better at measuring *amount of use*
  - ▶ DBD and survey data equally suitable for measuring *variety of use*
  - ▶ Survey data better for *activities* carried out across multiple apps (e.g., news consumption, watching videos)
  - ▶ DBD better for *activities* carried out within distinct apps (e.g., calls, taking photos)

Any questions?



# Appendix

Alignment measures (Araujo et al., 2017)

Absolute error

- ▶ *Amount and variety of use* =  $|\text{Survey} - \text{DBD}|$
- ▶ *Activities of use* =  $\begin{cases} 1 & \text{if different} \\ 0 & \text{if not different} \end{cases}$

# Appendix

Alignment measures (Araujo et al., 2017)

Underreporting: behavior observed in DBD, not in survey

$$\blacktriangleright \textit{Amount and variety of use} = \begin{cases} \text{DBD} - \text{Survey} & \text{if underreported} \\ 0 & \text{if not different or overreported} \end{cases}$$

$$\blacktriangleright \textit{Activities of use} = \begin{cases} 1 & \text{if underreported} \\ 0 & \text{if not different or overreported} \end{cases}$$

# Appendix

Alignment measures (Araujo et al., 2017)

Overreporting: behavior observed in survey, not in DBD

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# Appendix

## Latent class analysis (LCA)

- ▶ To create typologies of smartphone use, LCAs were conducted separately for the DBD and survey data
- ▶ Participants assigned to classes based on their similarity in the indicator variables
  - ▶ *Amount* and *Variety* of use: coded as below median vs. equal or above median
  - ▶ *Variety of use*: 13 activities coded as yes vs. no
- ▶ Number of classes were varied from 2 to 10
- ▶ Best-fitting model selected based on LL, AIC, BIC