ROYAL SOCIETY
OPEN SCIENCE

rsos.royalsocietypublishing.org

Research

Check for updates

Article submitted to journal

**Subject Areas:**

subject 1, subject 2, subject 3

**Keywords:**

one, two, optional, optional, optional

**Author for correspondence:**

C.Cabrera-Arnau

e-mail: C.Cabrera-Arnau@liverpool.ac.uk

# An approach to quantifying the extent of bias in aggregated human population data extracted from digital platforms

Carmen Cabrera-Arnau[1], Francisco Rowe[1]

[1]Geographic Data Science Lab, Department of Geography and Planning, University of Liverpool, Liverpool, United Kingdom.

The abstract text goes here. The abstract text goes here. The abstract text goes here. The abstract text goes here. The abstract text goes here. The abstract text goes here. The abstract text goes here. The abstract text goes here.

THE ROYAL SOCIETY
PUBLISHING

The main document should include:

Title (no more than 150 characters)

Author names and affiliations, and ORCID iDs where available

Abstract (no more than 200 words). (This will be used in reviewer invitation emails so please think about how to describe your work to make it easy for a potential reviewer to determine whether they would be suitable.)

All main manuscript text. Ensure that all figures, tables and any relevant supplementary materials are mentioned within the text References

Acknowledgements and funding statement (ensure that you have included grant numbers and the names of any funding providers)

Tables with captions Figure captions with credits where relevant

## 1. Introduction (FR)

Technological advances in computational power, storage and digital network platforms have unleashed a data revolution producing large trails of digital trace data containing location information. These data have revolutionised research and business activities offering novel opportunities to understand human behaviour and processes [1]. Digital trace data offer high spatial granularity, geographic coverage, high temporal frequency and instant information to capture and understand human activities at unprecedentedly high resolution and scale, and produce actionable intelligence in real time to support rapid decision making. Digital trace data have been used for a range of applications, such monitoring footfall changes [REF], inferring mobility signatures [REF], sensing land use patterns [REF], predicting socioeconomic levels [REF], defining urban extents [REF] and estimating population displacement [REF].

However, the use of digital trace data present major epistemological, methodological and ethical challenges [1]. A key unresolved challenge is the potential presence of biases in digital trace data to compromise their statistical representativeness and perpetuate social injustice [REF]. Biases reflect societal digital and socioeconomic inequalities. Biases emerge from differences in the access and use of the particular digital technology used to collect data, such as mobile phone applications [2]. Only a fraction of the population in an area owns a mobile phone, and even an smaller share actively use a specific mobile phone app. In the UK, for example, 98% of the adult population have a mobile phone and 92% of this population use a smartphone [3], but a smaller percentage actively use Facebook (70%) or Twitter (23%) [4]. Additionally, biases emerge from differences in the access and use of digital technology across population subgroups according to their socioeconomic and demographic profile. For instance, wealthy and urban populations tend to be over-represented in mobile phone data [REF] and of digital social platforms, such as Facebook [REF] and Twitter/X [REF].

The use of biased digital trace data can thus have major practical and societal implications.

As a result, population statistics derived from digital trace data cannot provide population-level representation. They can only offer rough signals about the spatial distribution of (e.g. spatial concentration), trends (e.g. increasing) and changes (e.g. low to high) in populations [5].

and amplify socioeconomic disparities

Gaps:

Aim: We propose an approach to measure biases -

Research questions:

Contribution:

Structure:

Efforts have been made to correct these biases through two general approaches. A first general approach consists in adjusting DF-derived population counts from social media by developing correction factors (e.g. [6], [7]). Correction factors are often estimated as the ratio of active social media users to census population counts by demographic attributes (e.g. age). The principles are similar to survey post-stratification methods i.e. to make DF-derived population counts representative of the census populations. However, a key data requirement of this approach is on having data on population by attribute, but such data are generally unavailable from DFs. Only information on location, time and total active users is recorded. As such, this approach cannot be generalised to different DFD sources and geographical contexts, and when applied on total population counts, biases associated with demographic and socioeconomic user attributes are not corrected (e.g. [8], [9], [10]). A second approach uses a regression modelling approach. Intuitively this approach produces representative population counts by explicitly measuring and removing the sources of biases in the data [11]. This approach has primarily been used in Ecology to obtain representative population distributions of animal species [12], but it has not been used in the context of DFD. In recent work, the PI adopted a similar approach to correct multiple sources of biases in census data to produce bias-adjusted migration estimates [13]. DEBIAS builds on this work to develop a general framework and software package aiming to correct biases in origin-destination mobility counts derived from DFs in the absence of demographic and socioeconomic information on users of digital platforms.

# 2. Data and methods

## (a) Data (CCA)

### (i) Facebook

We use anonymised aggregate location data from Facebook app users who have the location services setting turned on on their smartphone for the UK, covering March 2021, the month when the 2021 UK Census was carried out. We use the Facebook Population dataset created by Meta and accessed through their Data for Good Initiative (https://dataforgood.facebook.com). Prior to releasing the datasets, Meta ensures privacy and anonymity by removing personal information and applying privacy-preserving techniques [@Maas19]. Small-count dropping is one of these techniques. A data entry is removed if the population or movement count for an area is lower than 10. The removal of small counts may mean that population counts in small sparsely populated areas are not captured. A second technique consists in adding a small undisclosed amount of random noise to ensure that it is not possible to ascertain precise, true counts for sparsely populated locations. Third, spatial smoothing using inverse distance-weighted averaging is also applied is applied to produce a smooth population count surface.

The Facebook Population dataset offers information on the number of active Facebook users in a spatial unit at a given point in time. The data is temporally aggregated into three daily 8-hour time windows (i.e. 00:00-08:00, 08:00-16:00 and 16:00- 00:00). In this work, we are interested in capturing resident population, so we consider only data corresponding to the time window corresponding to the night-time hours (00:00-08:00).

The Facebook Population dataset is spatially aggregated according to the Bing Maps Tile System developed by Microsoft (Microsoft). The Tile System is a geospatial indexing system that partitions the world into tile cells in a hierarchical way, comprising 23 different levels of detail (Microsoft). At the lowest level of detail (Level 1), the world is divided into four tiles with a coarse spatial resolution. At each successive level, the resolution increases by a factor of two. The data that we used are spatially aggregated into Bing tile levels 13. That is about 4.9 x 4.9km at the Equator [@Maas19]. In the next steps, we compare the Facebook Population data with UK census data. To facilitate this comparison, we aggregate the data into administrative units, specifically UK Local Authority Districts (LADs).

### (ii) Twitter

We use an anonymised, openly available, analysis-ready dataset of active Twitter users in the UK. The data is derived from X (previously Twitter) in the form of monthly active user counts residing across the UK geography. The dataset is based on tweets from UK users [14] collected via the Twitter Academic API. These tweets are either geolocated at the time of posting or manually geocoded using a bounding box provided by the Twitter Academic API, based on the IP address of the posting device. The full dataset includes 161 million tweets from February 2019 to December 2021; however, we focus on data from March 2021 to align with the 2021 UK Census. Users' Local Authority District (LAD) of residence is identified using a frequency-based home-location algorithm. Further details on the dataset's methodology can be found in [14] .

While the X Academic API is no longer available to download data, but existing and future projects offer an opportunity for research based on X data. Global repositories of historical geolocated tweet data are accessed through the Internet Archive (1996) and Harvard Geotweet Archive (https://gis.harvard.edu/data). Despite these limitations, we consider X data as it remains a key source of historical digital trace data.

### (iii) Multi-app GPS data

The data used in this study were sourced by a data analytics company that collects GPS location data from around 26% of smartphones in the UK. The raw data is collected for individual anonymised devices, from numerous smartphone applications where the users have explicitly granted location-sharing permissions. The full dataset covers 7 days corresponding to the first week of April for the UK, including X GPS records and X unique devices. While the dates covered by dataset do not exactly coincide with the 2021 UK Census dates, the alignment is very close.

We process the data to estimate users' place of residence by assuming that the residence of a device owner corresponds to the location with the highest number of GPS records during night hours (11 PM – 7 AM). For a location to be classified as a residence, it must account for more than 50% of recorded nighttime locations and be visited at least twice. To ensure consistency in our analysis when comparing with other data sources, we aggregate these residence locations at the Local Authority District (LAD) level.

## (b) Methods

In this section, we outline our proposed methodology, which consists of two interconnected stages aimed at quantifying two types of biases: coverage biases and representational biases. Coverage biases relate to the sample size of the dataset and refer to the proportion of the population covered in the dataset. Representational biases, arise from the demographic and socioeconomic characteristics of the users who generate the digital trace data through specific technologies.

In the first stage of our methodology, we focus on quantifying coverage biases by examining the variations in coverage across different spatial units. We leverage the spatial granularity of digital trace data to analyse coverage biases at more localised spatial scales. This allows us to identify the extent to which different regions are represented within the datasets, revealing any potential underrepresentation or overrepresentation in specific locations.

In the second stage, we focus on quantifying representational biases. To do this, we leverage the spatial heterogeneity of coverage biases and model this variation in terms of demographic and socioeconomic variables that characterise local populations. This analysis allows us to identify which specific demogrpahic and socioeconomic population attributes, such as average income, education level or age composition, are more likely to be associated with higher values of coverage bias, thus highlighting which population groups tend to be underrepresented in different sources of digital trace data.

### (i) Measuring coverage bias (CCA)

We define a metric to quantify the magnitude of coverage bias in each subnational area. This metric is based on the population coverage of the dataset, which we compute as the ratio of the population captured (sample size) by dataset $D$, denoted as $P_i^D$, to the total local population of an area, $P_i$. Formally, the coverage $c_i$ is given by:

$$c_i = \frac{P_i^D}{P_i} \times 100, \tag{2.1}$$

where $D$ identifies a given dataset, and $i$ denotes each subnational area. The resulting ratio $c_i$ is assumed to take values between $0$ and $100$, with $100$ representing full population coverage. If users have multiple accounts, the ratio can exceed $100$, since the total sample size could be greater than the local population of area $i$.

We then define the size of bias $e_i$ as:

$$e_i = 100 - c_i \tag{2.2}$$

In this case, a value of $e_i = 0$ indicates a lack of coverage bias, which corresponds to full population coverage ($c_i = 100$). We use this bias indicator to analysis the magnitude and spatial distribution of coverage bias across multiple sources of digital trace data.

### (ii) Assessing the driving factors of bias (FR)

We seek to understand the association between the size of bias and area-level demographic and socioeconomic attributes. To what extent different demographic and socioeconomic groups are represented in DFD? And how do these vary geographically and across digital platform? We will assess these questions by measuring the area-level association between our coverage indicator and key demographic and socioeconomic attributes. We will use a random forest to model our coverage indicator as a function of demographic and socioeconomic attributes. The outcomes will identify the most important area-level demographic and socioeconomic features to predict the coverage bias of a given digital technology. We will use this information to inform our models in WP-II.

eXtreme Gradient Boosting (XGBoost) is an efficient and scalable implementation of gradient boosting framework by [**? ?** ].

# 3. Results

## (a) Varying extent of bias across data sources

As digital trace data becomes increasingly accessible, it opens up new avenues for studying human behaviours with remarkable temporal and spatial precision, extensive geographic coverage, and near real-time access. However, the potential presence of biases can undermine the validity of the data to deliver statistically representative evidence.

In this section, we focus on quantifying the biases in multiple sources of digital trace data that arise due to the extent of population coverage, i.e. the proportion of the total population captured in the dataset. In Figure , we contextualise these findings by comparing them with various traditional datasets, particularly key UK surveys available through the UK Data Service [15]. On the $x$-axis, we represent two variables: at the top, the sample size of the dataset, expressed as the number of respondents or subjects per 1,000 people, which reflects the population coverage of the dataset; and at the bottom, a measure of bias in terms of this coverage, as defined in equation 2.2. The figure highlights the remarkable ability of digital trace data to capture a larger share of the total population compared to traditional surveys, thanks to the automated, passive nature of data collection on digital platforms. This contrasts with the manual recruitment and data collection processes required for surveys. As a result, the size of bias is generally lower for digital trace data, highlighting its potential to inform comprehensive empirical analyses.

While the findings in Figure 1 demonstrate the potential of digital trace data compared to traditional data sources, high population coverage alone does not ensure the data is representative of different population groups.

In surveys, specific strategies are usually implemented during the data generation process to improve the statistical representativeness of the sample. For example, sampling techniques such as stratified sampling or cluster sampling can be applied so that the sample reflects the broader population of interest. After sampling, if certain groups remain under-represented, responses can be adjusted using post-stratification techniques. However, even when these strategies are applied, there is no guarantee that the survey will be fully representative of the broader population of interest [16]. This is because representativeness can only be achieved with respect to a finite set of attributes (e.g. age, gender, income levels, location, etc.). Ensuring perfect representativeness would only be possible either by surveying the whole population.

With digital trace data, achieving statistical representativeness is even more challenging. Unlike survey data, which is actively collected using structured sampling methods, digital trace data is generated passively as a byproduct of online interactions, transactions, or device usage, without any control over who is included in the dataset. Furthermore, by the time this data reaches researchers or analysts, it is often anonymised, and does not contain demographic identifiers. As a result, it is not possible to apply the standard post-stratification

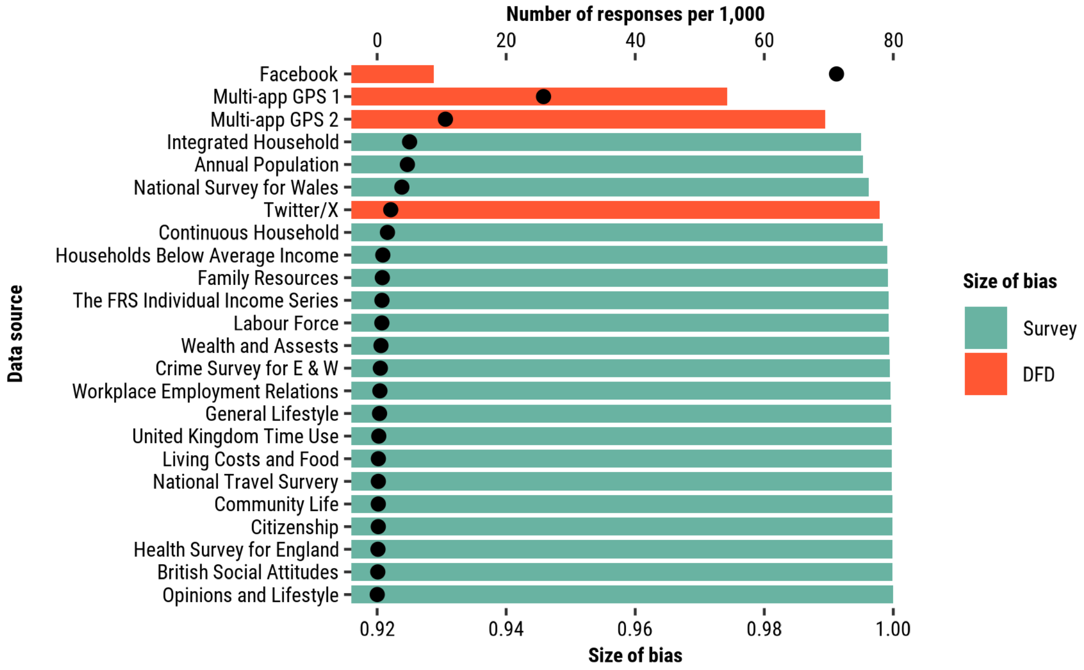


**Figure 1.** Size of bias and population coverage (per 1,000 population) by data source.

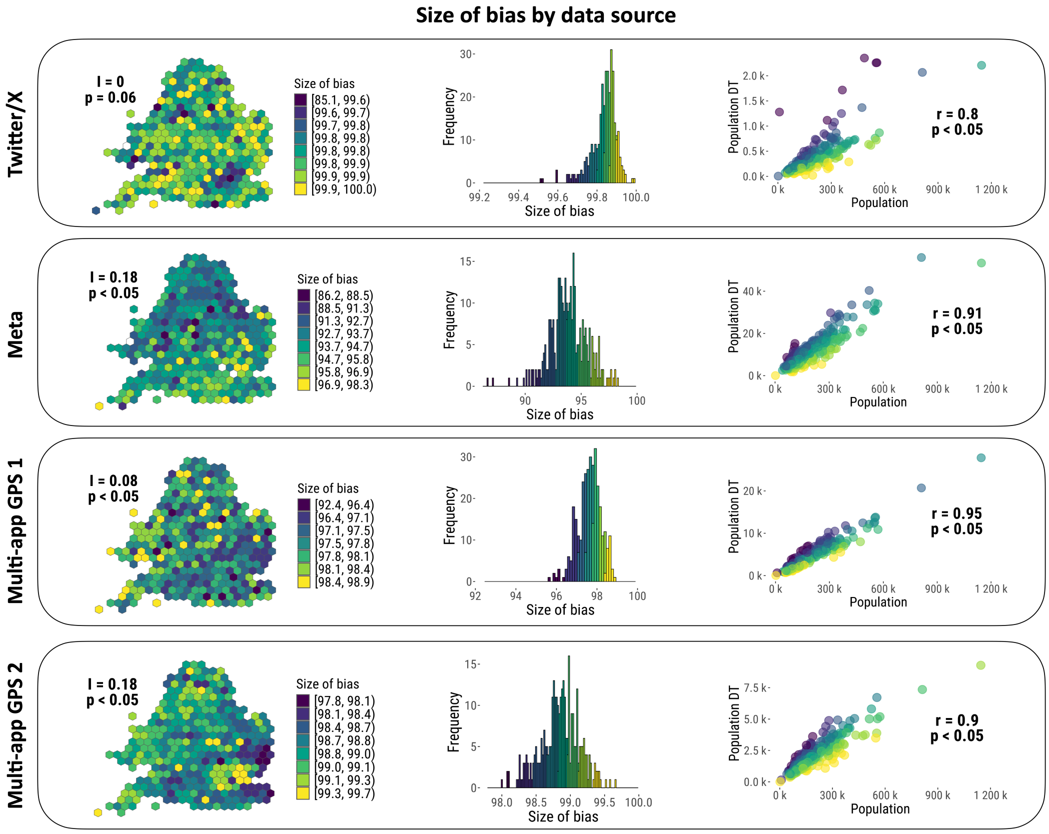
weighting techniques that are typically used to adjust survey or census data for improved representativeness.

We argue that, even though we do not always have specific demographic information of the individuals captured through digital trace data, we can infer some of these characteristics by leveraging the spatio-temporal granularity of digital trace data. We argue that this is a necessary first step to understand which population groups might be under or over-represented in different sources of digital trace data. This information is necessary to later adjust the data so that it is more representative of the population of interest.

## (b) The spatial distribution of biases (CCA)

Next, we take advantage of the detailed geographic information in the digital trace data to analyse bias at smaller, more localised spatial levels. This helps us understand how well different geographic areas are represented in the datasets. Since local populations vary in their socioeconomic characteristics, we can use the degree of bias at these smaller scales in the next step of our analysis, to determine which population attributes are most associated with underrepresentation in the data.

Figure **??** shows the geographic variation of the size of bias at the Local Authority District (LAD) level. Each row in the figure corresponds to each of the digital trace datasets analysed here. Within each row, we include: i) an hexagonal cartogram for the size of bias in each LAD, representing the LADs as hexagons of equal size to simplify the visualisation while maintaining relative positions; with this cartogram, we report Moran's I as a measure of spatial autocorrelation and its associated p-value, ii) a histogram of the size of bias, showing the distribution of values across LADs, iii) a scatter plot of the population covered by the digital trace data vs. the actual population of each LAD; with the scatter plot, we include the Pearson correlation coefficient and its associated p-value.



Examining the spatial variation in bias size, we observe distinct patterns across the DT datasets considered. These varied spatial patterns likely stem from differences in the demographic composition of users for each technology. Factors such as age, socioeconomic status, digital literacy, and regional preferences for certain platforms or devices may contribute to these variations. Bias tends to display stronger spatial patterns for Meta data and the second source of multi-app GPS data, with lower bias in the North of England and Wales. In contrast, Twitter/X data and the first souce of multi-app GPS data follow more mixed patterns, as demonstrated by the values of Moran's I closer to zero. Twitter/X data generally exhibits high bias, except in London, the South East, and a few isolated areas. Similarly, bias in first source of multi-app data tends to be lower in the South and South East.

Turning to the histograms, we observe that bias size is highest for Twitter/X data, with all values exceeding 99.5 except for a single outlier, the City of London. This outlier likely arises due to the unique demographic and occupational characteristics of the area. While relatively few people reside in the City of London, it hosts a large number of workers, including temporary professionals, who may be staying in hotels. The home-detection algorithm in [14] used to generate the Twitter/X data used here might classify the workplace or temporary accommodations of City of London workers as their primary residences, leading to an anomalously low bias measurement. Following Twitter/X, the second source of multi-app GPS data exhibits the next highest bias values. In contrast, the first source of multi-app data shows lower bias, while Meta data has the lowest overall bias. Notably, Meta data also displays the widest distribution of bias values, indicating greater variability across different locations.

The scatter plots show a high linear correlation between the population covered by the digital trace data and the actual population of each LAD, as demonstrated by the Pearson coefficient, all above 0.8. This suggests that, on average, the actual population in the LADs is not an indicator of the size of bias in DT data, as the population coverage $c_i$ remains the consistent regardless of $P_i$ . This could be a result of the fact that the biases in the data are not driven by the number of people, but rather by other their demographic characteristics such as age, income or educational level. In the next section, we explore the variability of demographic attributes of local populations as possible determinants of the size of bias.

### (c) Explaining biases (FR)

## 4. Discussion (FR)

## 5. Conclusion (CCA)

Ethics. Please provide details on the ethics.

Data Accessibility. Please provide details on the data availability.

Authors' Contributions. Please provide details of author contributions here.

Competing Interests. Please declare any conflict of interest here.

Funding. Please provide details on funding

Disclaimer. Please provide disclaimer text here.

Acknowledgements. Please include your acknowledgments here, set in a single paragraph. Please do not include any acknowledgments in the Supporting Information, or anywhere else in the manuscript.

## References

1. Rowe F. 2023 pp. 42 – 47. In *9.: Big data*, pp. 42 – 47. Cheltenham, UK: Edward Elgar Publishing.
2. Wesolowski A, Eagle N, Noor AM, Snow RW, Buckee CO. 2013 The impact of biases in mobile phone ownership on estimates of human mobility. *Journal of The Royal Society Interface* **10**, 20120986.
3. Ofcom. 2023 Communications Market Report 2023. Accessed: Nov 2023.
4. Statista. 2024 Social Media & User-Generated Content - Market Overview. Accessed: 2024-11-14.
5. Rowe F, Neville R, González-Leonardo M. 2022 Sensing Population Displacement from Ukraine Using Facebook Data: Potential Impacts and Settlement Areas. *OSF Preprints*. Submitted.
6. Yildiz D, Holland JA, Vitali A, Munson J, Tinati R. 2017 Using Twitter data for demographic research. *Demographic Research* **37**, 1477–1514.
7. Hsiao Y, Fiorio L, Wakefield J, Zagheni E. 2024 Modeling the Bias of Digital Data: An Approach to Combining Digital With Official Statistics to Estimate and Predict Migration Trends. *Sociological Methods & Research* **53**, 1905–1943.
8. Rodriguez-Carrion A, Garcia-Rubio C, Campo C. 2018 Detecting and Reducing Biases in Cellular-Based Mobility Data Sets. *Entropy* **20**.
9. Schlosser F, Sekara V, Brockmann D, Garcia-Herranz M. 2021 Biases in human mobility data impact epidemic modeling. .
10. Chankyung Pak KC, 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**, 134–155.
11. Kramer-Schadt S, Niedballa J, Pilgrim JD, Schröder B, Lindenborn J, Reinfelder V, Stillfried M, Heckmann I, Scharf AK, Augeri DM, Cheyne SM, Hearn AJ, Ross J, Macdonald DW, Mathai J, Eaton J, Marshall AJ, Semiadi G, Rustam R, Bernard H, Alfred R, Samejima H, Duckworth JW, Breitenmoser-Wuersten C, Belant JL, Hofer H, Wilting A. 2013 The importance of correcting for sampling bias in MaxEnt species distribution models. *Diversity and Distributions* **19**, 1366–1379.
12. Zizka A, Antonelli A, Silvestro D. 2021 sampbias, a method for quantifying geographic sampling biases in species distribution data. *Ecography* **44**, 25–32.

13. Aparicio Castro A, Winiowski A, Rowe F. 2023 A Bayesian approach to estimate annual bilateral migration flows for South America using census data. *Journal of the Royal Statistical Society Series A: Statistics in Society* **187**, 410–435.
14. Wang Y, Zhong C, Gao Q, Cabrera-Arnau C. 2022 Understanding internal migration in the UK before and during the COVID-19 pandemic using twitter data. *Urban Informatics* **1**.
15. UK Data Service UK surveys - UK Data Service. https://ukdataservice.ac.uk/help/data-types/uk-surveys/. [Accessed 17-02-2025].
16. Cochran W. 1977 *Sampling Techniques*. Wiley Series in Probability and Statistics. Wiley.