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Big data in modelling geographical accessibility to healthcare: a scoping review protocol

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ABSTRACT

Introduction Research on modelling geographical accessibility to healthcare services has witnessed rapid methodological advancement and refinement. One of the contributing factors is the increasing availability of big data detailing the link between the population in need of care and the health facility such as infrastructure, travel modes and speeds, traffic congestion and the quality of road network. This has allowed more granular computation of geographic access metrics, particularly in low-and-middle income countries where data are scarce. However, there are no reviews providing a comprehensive overview of the availability and use of big data for assessing geographical accessibility to healthcare. This protocol aims to describe a methodological approach that will be used to review the existing literature on the application of big data (past or potential) in evaluating geographical accessibility to healthcare.

Methods and analysis To characterise the big data that can be used to model geographical accessibility to healthcare, a scoping review will be undertaken and reported according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extensions for Scoping Reviews guidelines. We will search seven scientific databases (PubMed, Scopus, Web of Science, EBSCOhost-CINAHL, Cochrane, Embase and MEDLINE via Ovid), grey literature, reference lists of identified publications and conference proceedings. Search engines will be used to identify relevant big data services not yet used in published academic literature. All literature published in English or French will be included, regardless of publication type, geographical location or year of publication provided it describes or mentions big data that may be useful for evaluating geographical accessibility to healthcare. Study selection and data extraction will be performed independently by two researchers with a third resolving any discrepancies. Analysis will be conducted to summarise big data providers, their characteristics and their usefulness in terms of types of spatial accessibility metrics that can be derived.

Ethics and dissemination Formal ethical approval is not required, as primary data will not be collected in this review. Findings will be disseminated through peer-reviewed publication in a journal, conference presentation and condensed summaries for stakeholders through professional networks and social media summaries.

STRENGTHS AND LIMITATIONS OF THIS STUDY

⇒ The review is the first to provide a comprehensive catalogue of available big data for evaluating and modelling healthcare geographical healthcare accessibility.
⇒ The review will include any big data useful for evaluating geographical accessibility of healthcare, including those that have not yet been applied to model spatial accessibility.
⇒ Given their rapidly evolving nature, some big data might be different at the time of the publication compared with their characteristics as presented in the review, or may no longer be publicly available.
⇒ The review will be limited to results in English and French, excluding big data that might be only available in other languages.

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INTRODUCTION

Geographical accessibility to healthcare

Geographical accessibility—the ease of geographically accessing healthcare services from a location of need[1–3]—is a key dimension of healthcare access. Suboptimal geographical accessibility is associated with poor health outcomes such as maternal and neonatal mortality or low immunisation coverage.[4–7] This emphasises the importance of robustly and comprehensively measuring geographical accessibility to inform policies, healthcare planning and health service delivery.[8 9]

Various indicators have been used to evaluate geographical accessibility to healthcare facilities; also referred to as spatial health metrics.[1–3] These include travel time to a facility, which is measured either as a self-reported, modelled metric or the percentage of the population living within a predefined threshold (eg, 2 hours catchment area).[2] Other indicators include physical distance from a patient's location to a facility and the

number of facilities accessible within a given travel time window or distance.[2 10] These indicators are the foundation for various methods of computing geographical accessibility such as least-cost algorithms, network analysis and gravity models.[2 3 11]

While many of these methods of computing access are well known and widely documented in the literature, they have several limitations.[8 12] They fail to account for prevailing travel conditions and on-ground experiences, for example, of traffic congestion, time of the day and day of the week when the journey was made, referral between facilities, region (informal settlements, periurban), security and conflict, flooding, heat waves and the role of gender in health seeking and travel.[9 10 13] Additionally, estimating travel time to the nearest facility does not account for bypassing behaviour due to factors such as cost, perceived quality of care or trust.[14–16] The reliance on oversimplified spatial access metrics, often due to lack of observational data, does not fully reflect real-world conditions and risk misinforming policies.[10] This underscores the need for robust methodologies to improve accuracy in estimates of geographic accessibility.[8 9 11]

While the methods for modelling spatial accessibility are well known, innovations related to all three key input parameters are occurring: modelling of the population in need of care; mapping the locations of health facilities and improving the understanding of how infrastructure, travel modes, prevailing travel conditions influence the accessibility between the dynamic population and the static health facility.[8] Progress has been made in mapping high-resolution estimates of population[17 18] and assembling geocoded health facility databases.[19–23] However, studies assessing approaches to improve the way we capture the link between the facilities and population (eg, travel speeds, quality of road network, traffic congestion) are few. This is often seen as the weakest link in deriving realistic travel time estimates.[10 12] To bridge this gap, the use of big data in computing realistic estimates of geographical access to healthcare is progressively being recognised.[6 9]

Big data

Big data is defined in several ways, but in general, it is characterised by high volume, variety, velocity (the speed at which data is generated) and value, which also includes high veracity (accuracy, quality), variability and completeness.[24–27] That is, large amounts of continuously collected and collated data from diverse sources at a high rate, characterised by a wide range of formats requiring both technologies and analytical methods to transform the data into value.[25–27] In the context of geographic accessibility and this review, we define big data as large datasets from various sources with a spatial dimension, which facilitates the computation of spatial access indicators, such as distance and travel time. Big data may include real-time user-generated travel data, satellite data, Global Positioning System (GPS) data, geolocated mobile phone data, public transport data (eg, smart card usage), navigation data from web-based platforms such as OpenStreetMap, Google Maps, Bing Maps and social network data.[28–30] These big datasets can provide information on travel speeds, travel times, the quantity and quality of road segments, congestion or inaccessibility due to events such as flooding and the frequency of use of road segments as input parameters in modelling spatial accessibility indicators more realistically reflecting lived reality. Accessing big data often requires a 'big data service' that we define as a platform, system or tool that provides access to, management of and analytical capabilities for large, complex datasets (such as transportation networks or population movement data) enabling the computation of spatial access metrics.

Big data in improving geographical access metrics

Existing evidence suggests that the use of big data in geographic accessibility to services, including healthcare services, can be a transformative tool relative to traditional methods.[10 12 30–33] It has large potential to improve estimates to reflect more on ground reality for the link between the population in need and the location of services. For example, big data integrates real time and historical data to bridge the gap between theoretical models and lived experiences of healthcare seekers.[10 12 31–33] Despite its potential, the role of big data in modelling geographical accessibility to healthcare is still nascent and not well described.[2] Previous reviews on the use of big data in healthcare[34] have not primarily examined its role in enhancing the understanding of geographical accessibility to healthcare. Instead, some have focused on the use of big data in clinical applications, such as disease surveillance, diagnosis and treatment,[35 36] while others have explored aspects such as the role of big data in multimodal transportation and temporal changes in spatial accessibility.[37] Notably, reviews specifically assessing the application of big data in healthcare are yet to explore its potential in evaluating spatial accessibility to healthcare services.[38–40] To date, no studies have synthesised the use of big data, its potential and limitations in the context of geographic accessibility to healthcare. This gap limits the use of big data in evaluating realistic spatial accessibility metrics. This is because closer-to-reality estimates of spatial accessibility can be derived through the application of big data, as shown by studies in Nigeria, Kenya and Colombia.[10 12 30–33] However, without a clear understanding of the range and nature of available big datasets, their potential remains underutilised. The estimation of accessibility to points of interest is inherently multidimensional, requiring inputs such as patient location, modes of transport, prevailing travel conditions, travel speed, land cover/use and road networks. Big data sources that capture these dimensions—individually or in combination—offer significant opportunities to improve the precision and robustness of spatial access metrics.

Scoping review objectives

The research objectives were guided by the following research questions:

1. What are the existing big data (big data itself, its providers, platforms and any associated services) and their characteristics relevant to modelling geographic accessibility to healthcare?
2. How has big data (identified in 1) been used to assess geographic access to healthcare services including the type of spatial access metric that can be derived?

This scoping review aims to catalogue big data services including their corresponding software, infrastructure and platforms that are useful for computing geographical accessibility to various services including healthcare, even if they have not been used in the context of healthcare. The findings will provide a comprehensive knowledge base to guide researchers and policymakers in leveraging big data to improve healthcare accessibility, while advancing equitable and timely delivery of services such as healthcare.

METHODS AND ANALYSIS

Informed by Preferred Reporting Items for Systematic Reviews and Meta-Analyses extensions for Scoping Reviews reporting guidelines,[41] this protocol describes our planned approaches to catalogue and assess big data services relevant to modelling geographical accessibility to healthcare services. This protocol has been developed a priori and registered on The Open Science Framework: https://doi.org/10.17605/OSF.IO/S496F.

Types of studies

To identify eligible studies for review, we shall apply the eligibility criteria outlined in table 1.

Table 1 Inclusion and exclusion criteria for article selection

Inclusion criteria	Exclusion criteria
1. Studies describing a big data than can be (or has been) used for the assessment of geographical accessibility to any services such as healthcare, education, restaurants among others. 2. Research articles mentioning big data services for accessibility, without a clear description of a specific big data service (eg, general commentaries). 3. Websites, companies or applications providing big data services or elements for assessment of geographical accessibility alongside documentation of their characteristics 4. Studies using big data with a spatial component (eg, distances, travel time, speed) that can be applied in assessing geographic accessibility, eg, distance, travel time, speed, etc. 5. Studies in English or French	1. Studies that describe big data which cannot be used to model geographical accessibility to healthcare 2. Big data services offered by any provider (company, website, etc.) that do not focus or are not applicable to geographical accessibility to any service

Search methods

Databases

We will search academic databases: PubMed, Scopus, Web of Science, EBSCOhost-CINAHL, Cochrane, Embase and MEDLINE via Ovid to find peer-reviewed articles relevant to the research questions. Additional literature will be identified by screening the reference list of identified eligible studies. We shall also search repositories of international conference proceedings and their corresponding reference lists. A parallel search for grey literature will also be conducted, by using main web search engines such as Google to find big data services that have not been mentioned or referenced in peer-reviewed articles. This will include relevant websites and manuals of big datasets. Furthermore, for all big data sources identified in peer-reviewed publications, we will consult their respective websites to obtain any additional details not reported in the published literature, thereby supplementing the information extracted from peer-reviewed source.

Search strategy

We have developed a search strategy in PubMed (online supplemental appendix) to retrieve relevant literature. This search strategy will be adapted in searching other databases. There will be no restriction on the period nor on study locations. We shall only consider publications in English and French.

Study/service selection

Search results from running the search terms will be exported to EndNote and deduplicated by LL and AN. The deduplicated library will be imported to Covidence systematic review software (Veritas Health Innovation, Melbourne, Australia), a web-based collaboration software platform that streamlines the production of systematic and other literature reviews.

Level 1 screening

Two reviewers (LL and AN) will screen the titles and abstracts based on the inclusion criteria. Conflicts arising from disagreements in the inspection process will be resolved by a third reviewer (PMM) to reach a consensus. Level 1 screening will be guided by the following questions.

1. Is the title/abstract in English or French? (yes: neutral, no: exclude)
2. Does the title/abstract mention big data or a related term (eg, crowd-sourced data)? (yes: neutral, no: exclude)
3. Does the title/abstract reference a big data service relevant to assessing geographical accessibility to a service? (yes: neutral, no: exclude)

Table 2 Variables to be extracted from each article and/or website

Bibliography	► Author details ► Journal ► DOI or URL ► Year of publication
Study characteristics	► Title ► Main objective ► Type (eg, a research paper, website, conference proceedings) ► Study design (eg, cross-sectional, longitudinal) ► Main objective
Study area	► Geographical location of study (country(ies), world region(s)) ► Urbanicity (whether, urban, rural or both) ► Population for which access metric was computed (eg, children) ► Unit of analysis such as district, census tract
Big data characteristics (multiple per study or website possible)	► Name of the big data provider, for example Google ► Big data source for example crowdsourced, GPS probes, satellite imagery ► Big data warehousers (if any) ► Data elements (eg, speeds, travel time, GPS locations, geolocated tweets, and other quantitative characteristics that can be used to compute accessibility) ► Data type: for example, tables, JSON, XML, text, images, video ► Geographical coverage ► Resolution (temporal and spatial) ► Date and location of collection ► Update frequency (eg, real time, static or delayed) ► Method of access (eg, downloading, API, web service, etc) ► Methods of collection (eg, smartphones or crowd sourcing, remote sensing) ► Cost (if applicable) of the data ► Licensing/terms of use: restrictions on commercial or derivative use ► Quality indicators (eg, % missing data) ► Last update
Big data services (multiple per study or website possible)	► Service name ► Provider/owner: organisation or company offering the service. ► Domain/scope: the area of data it covers (eg, geospatial, social media). ► Documentation availability ► Authentication/authorisation (API keys, OAuth, open access.) ► Rate limits (requests per second/day, throttling policies) ► Data access models (from free/open-access to freemium to paid/subscription) ► Cost if applicable (in case of paid/subscription models) ► Latency: average response time ► Language support (such as Python, R, Java, etc.)
Methods (if applicable) multiple possible	► Transportation mode considered such as walking ► Service to which access was computed, for example, education, healthcare ► Accessibility metrics derived such as travel time, distance ► Methods or approaches used to compute the accessibility metric with the big data retrieved ► Software, tools or programmes used to process the retrieved big data to get accessibility metric
Final summary (if applicable) free text form	► Limitations mentioned in the paper/website linked to the big data or big data services ► Recommendations to address the limitations by the authors

API, application programme interface; GPS, Global Positioning System.

4. Does the study focus on big data in the context of geographical accessibility, even if it does not mention a specific big data service? (yes: include, no: exclude unless criterion 2 is met)

Level 2 screening

The two reviewers (LL and AN for English and EMA and FMG for French literature) will read the text of the paper or inspect the website to gather key information on the big data mentioned and decide whether to include the resource in the review or mark it as irrelevant. Conflicts arising from differing opinions between the two reviewers will be arbitrated by a third reviewer (PMM for English and OAB for French) to reach a consensus.

Data extraction

We will create a customised data extraction form in Microsoft Excel (Microsoft 365) that will be used to extract relevant data from all included studies. We shall first pilot the form on a variety of a few studies. Key data elements outlined in table 2 will be extracted by LL, AN, EMA and FMG based on the pretested form. In case of any differences, we shall resolve these through discussion with PMM and OAB for English and French literature, respectively.

DATA SYNTHESIS

Data synthesis

The variables outlined in table 2 will be used to provide a summary of the findings. We expect that the various big data sources will be heterogeneous in terms of their characteristics; therefore, we shall adopt a thematic narrative approach in characterisation of big data for geographical healthcare accessibility.

Subgroup analysis, interpretation and presentation

We shall perform subgroup analysis for both big data and big data services. We shall create subgroups of the big data services based on key attributes (data elements) such as access models (open or closed proprietary), usage cost, update frequency and real-time capabilities. Similarly, the big dataset subgroups will be based on whether they have a big data service associated such as application programme interface, their geographic scope or coverage, range of applications (use cases, eg, healthcare and non-healthcare) and limitations (advantages and drawbacks). We shall also conduct subgroup analyses of various big datasets stratified by spatial access metrics (eg, travel time estimation using GPS probes on vehicles, Twitter usage data or mobility data from Meta). The final results will be presented as a detailed overview of the state of the art on the characteristics, pros, cons and applications of big data for evaluating geographical healthcare accessibility. We shall disseminate the findings through a peer-reviewed publication in a journal, conference presentation and condensed summaries for stakeholders through professional networks and social media summaries.

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