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Systematic review of the use of Google Street View in health research: Major themes, strengths, weaknesses and possibilities for future research☆

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ABSTRACT

We systematically reviewed the current use of Google Street View (GSV) in health research and characterized major themes, strengths and weaknesses in order to highlight possibilities for future research. Of 54 qualifying studies, we found that most used GSV to assess the neighborhood built environment, followed by health policy compliance, study site selection, and disaster preparedness. Most studies were conducted in urban areas of North America, Europe, or New Zealand, with few studies from South America or Asia and none from Africa or rural areas. Health behaviors and outcomes of interest in these studies included injury, alcohol and tobacco use, physical activity and mental health. Major strengths of using GSV imagery included low cost, ease of use, and time saved. Identified weaknesses were image resolution and spatial and temporal availability, largely in developing regions of the world. Despite important limitations, GSV is a promising tool for automated environmental assessment for health research. Currently untapped areas of health research using GSV include identification of sources of air, soil or water pollution, park design and usage, amenity design and longitudinal research on neighborhood conditions.

1. Introduction

Since its development and official launch in the United States in 2007, Google Street View (GSV, a component of Google Maps) has become a source of 'big data' characterized by high spatial resolution, freely available images that provide panoramic views of homes, streets, businesses and neighborhoods at eye-level (Charreire et al., 2014). Currently, GSV is available for a number of cities globally, including almost complete coverage of the cities in many developed countries. Less-developed and rural areas or footpaths are also being added to the GSV database (Google, 2018). On the other hand, public backlash driven by privacy norms in many European countries (e.g., Germany) has restricted the amount and detail of GSV coverage available (Miller and O'Brien, 2013).

The image data for GSV is typically collected from cars equipped with special cameras capturing overlapping images that are reconstructed into a 360° view linked to GPS data identifying the location of the image. Neighborhood image data are then updated by Google at a frequency that is dependent upon population density and weather conditions (Google, 2018). The older images, dating back to 2007, are retained and are now viewable through a timeline feature released in 2014 (Shet, 2014).

GSV is an emerging source of data for health researchers. Research uses may include auditing the built environment of neighborhoods via the development of outcome- or exposure-specific tools, which rely on GSV data in lieu of the costly, time-consuming and/or impractical in-person auditing (Charreire et al., 2014; Fleischhacker et al., 2013). Assessment of exposures in the built environment is an established area of health research, for both mental and physical health outcomes (Li et al., 2015a). For example, maintained and visible urban green spaces have been associated with a multitude of positive health outcomes for nearby residents, including the facilitation of physical activity and the promotion of positive mental well-being (Barton and Pretty, 2010). Conversely, areas characterized by disorder (e.g., broken windows, graffiti) have been associated with negative social and health outcomes such as fear of crime (Bader et al., 2015). GSV offers an opportunity to assess the built environments of many places for relatively little time or financial cost. In addition to exposure assessment, emerging research

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Table 1
Summary of health studies included in this systematic review. Studies are organized based on purpose for using GSV and then alphabetically.

Study	Study location	Reason for using GSV	Health outcome/behavior of interest	GSV image data used (quantity)
Built environment assessment				
Adu-Brimpong et al. (2017)	Washington, D.C., USA	Neighborhood walkability	Physical activity	Active Neighborhood Checklist and Walk Score items (12 street segments for each of 82 homes)
Bader et al. (2015)	Unidentified metropolitan locations, USA	Neighborhood walkability and disorder	Mental health	CANVAS items (300 census tracts)
Bader et al. (2016)	New York City, New York, San Jose, California, Philadelphia, Pennsylvania Detroit, Michigan, USA	Neighborhood disorder	Mental health	CANVAS items (1826 street segments)
Badland et al. (2010)	Auckland, New Zealand	Neighborhood walkability	Physical activity	NZ-SPACES items (48 street segments)
Ben-Joseph et al. (2013)	Boston, Massachusetts, USA	Obesogenic features	Physical activity	Brownson et al. 2004 items (84 street segments)
Bethlehem et al. (2014)	Randstad megalopolis, Netherlands	Obesogenic features	Physical activity	SPOTLIGHT items (128 street segments)
Brookfield and Tilley (2016)	Edinburgh, United Kingdom (UK)	Neighborhood walkability	Physical activity	FASTVIEW items (19 walking routes)
Chudyk et al. (2014)	Vancouver, British Columbia, Canada	Neighborhood walkability	Physical activity	Walk Score items (48 street segments)
Clarke et al. (2010)	Chicago, Illinois, USA	Neighborhood features	Mental health	CCAHS items (224 street segments)
Clews et al. (2016)	Wellington, New Zealand	Alcohol-related data	Alcohol-related health	Alcohol signage (12 street segments)
Compernolle et al. (2016)	Five European urban regions	Obesogenic features	Physical activity	SPOTLIGHT items (4486 street segments)
Curtis et al. (2013)	Five regions in United States recently subjected to natural disaster	Imagery date changes in study site	Generalized health	Street segments (281,591.66 total meters)
Evans-Cowley and Akar (2014)	Columbus, Ohio, USA	Bikeability	Injury prevention for bicyclists	Bike route (59)
Feuillet et al. (2016)	Five European urban regions	Obesogenic features	Physical activity	SPOTLIGHT items (4486 street segments)
Griew et al. (2013)	Wigan, UK	Neighborhood walkability	Physical activity	FASTVIEW items (54 street segments)
Gullón et al. (2015)	Madrid, Spain	Neighborhood walkability	Physical activity	M-SPACES items (500 street segments)
Hanson et al. (2013)	New Jersey, USA	Audit of crash site	Pedestrian death	2351 crash sites
Hyam (2017)	Edinburgh, UK	Perceived naturalness	Mental health	Random panoramic images (768)
Johnson and Gabler (2015)	Michigan, USA	Audit of guard rails	Traffic injury	Crash sites (1,001)
Kelly et al. (2013)	St. Louis, Missouri and Indianapolis, Indiana, USA	Obesogenic features	Physical activity	Active Neighborhood Checklist items (288 street segments)
Kelly et al. (2014)	St. Louis, Missouri and Indianapolis, Indiana, USA	Obesogenic features	Physical activity	Active Neighborhood Checklist items (400 street segments)
Kepper et al. (2016)	Louisiana, USA	Neighborhood "incivilities"	Physical activity	Checklist items (84 homes and street segments)
Kepper et al. (2017)	Southeast Louisiana, USA	Neighborhood disorder (perceived safety)	Mental health	Street segments (54)
Lafontaine et al. (2017)	Ottawa, Ontario, Canada	Environment aesthetics	Mental health	Residential blocks (150)
Li et al. (2015a)	New York City, New York, USA	Street greenery	Mental health	Green space pixels (300 sites)
Li et al. (2015a)	Hartford, Connecticut, USA	Street greenery	Mental health	Green space pixels (3000 sites)
Li et al. (2015b)	Boston, Massachusetts and New York City, New York, USA; Linz, Salzburg, Austria	Neighborhood disorder (perceived safety)	Mental health	GSV images (4126)
Li et al. (2016)	Hartford, Connecticut, USA	Street greenery	Mental health	Green space pixels (18 images)
Marco et al. (2017)	Valencia, Spain	Neighborhood disorder	Mental health	Itemized checklist of disorder criteria (92 census block groups)
Mertens et al. (2017)	Five European urban regions	Bikeability	Physical activity	SPOTLIGHT items (4486 street segments)
Mooney et al. (2014)	New York City, New York, San Jose, California, Philadelphia, Pennsylvania Detroit, Michigan, USA	Neighborhood disorder	Mental health	CANVAS items (1826 block faces)
Mooney et al. (2016)	New York City, New York, USA	Audit of intersections	Pedestrian injury	Walk Score items (532 intersections)
Mygind et al. (2016)	Victoria, Australia	Quality, public open spaces	Physical activity	POSDAT items (171 open spaces)
Naik et al. (2014)	Boston, Massachusetts and New York City, New York, USA; Linz, Salzburg, Austria	Neighborhood disorder (perceived safety)	Mental health	Streetscore items (4109 GSV images)
Odgers et al. (2012)	England and Wales, UK	Neighborhood disorder	Mental health	SSO i-Tour items (2024 children's streets)
Pliakas et al. (2017)	England and Scotland, UK	Walkability/transportation	Geriatric health	OPECR tool (1396 street segments)
Porzi and Bul (2015)	Boston, Massachusetts and New York City, New York, USA; Linz, Salzburg, Austria	Neighborhood disorder (perceived safety)	Mental health	Automatic scene recognition in GSV images (4136)
Quinn et al. (2016)	New York City, New York, USA	Neighborhood disorder	Mental health	CANVAS items (532 block faces)
Roda et al. (2016)	Five European urban regions	Obesogenic features	Physical activity	SPOTLIGHT items (60 neighborhoods)
Rundle et al. (2011)	New York City, New York, USA	Neighborhood disorder	Mental health	Block faces (37)
Silva et al. (2015)	Sao Paulo, Brazil	Obesogenic features	Physical activity	Objective Evaluation of Environment items (29 street segments)

(*continued on next page*)

Table 1 (*continued*)

Study	Study location	Reason for using GSV	Health outcome/behavior of interest	GSV image data used (quantity)
Vanwolleghem et al. (2014)	Flanders, Belgium	Bikeability	Physical activity	EGA-Cycling items (50 cycling routes)
Vanwolleghem et al. (2016)	Belgium	Obesogenic features	Physical activity	MAPS Global items (68 routes)
Wilson et al. (2012)	St. Louis, Missouri and Indianapolis, Indiana USA	Obesogenic features	Physical activity	Active Neighborhood Checklist items (369 street segments)
Wu et al. (2014)	Cambridgeshire, UK	Environment aesthetics	Mental health	REAT items (24 streets)
Yin and Wang (2016)	Buffalo, New York, USA	Walkability (visual enclosure)	Physical activity	Visible sky (3592 images)
Health policy compliance				
Ahmetovic et al. (2015)	San Francisco, California, USA	Locations of zebra crosswalks	Injury prevention for the blind	Zebra crosswalks (137)
Ahmetovic et al. (2017)	San Francisco, California and Manhattan, New York, USA; Milan, Italy	Locations of zebra crosswalks	Injury prevention for the blind	Zebra crosswalks (1292)
Hammond et al. (2014)	Five communities in USA	Handicap accessibility	Injury/recovery	Civic centers in 5 communities
Wilson and Thomson (2015)	New Zealand	Smokefree signage	Smoking-related health	Public hospitals (30)
Wilson et al. (2015)	New Zealand	Smokefree signage	Smoking-related health	Primary and secondary schools (50)
Study site selection				
Burgoine and Harrison (2013)	Cambridgeshire, UK	Food outlet classification	Classifying food outlets related to obesogenicity	GSV images to corroborate classification of outlets
Less et al. (2015)	Oakland, California and Minneapolis and St. Paul, Minnesota, USA	Study site comparability	Alcohol-related health	Liquor stores (20) and corresponding neighborhoods
Disaster preparedness				
Mitsuhara et al. (2017)	Japan	Disaster preparedness	Injury	Virtual representation of study site (campus)

suggests that GSV may be useful for other facets of the health research process, such as designing a sampling scheme or identifying study sites (Less et al., 2015; Pliakas et al., 2017). Still other research has identified uses of GSV data for smoking-related policy compliance (Wilson et al., 2015). However, a systematic review of the current health research uses of GSV has yet to be conducted. Such a review could usefully highlight future research opportunities to make use of this emerging and continually enhancing source of big data.

Other studies have reviewed the use of GSV imagery for health research. Still, all reviews to date are limited to specific health outcomes or were not systematically conducted. One review examined the use of free geospatial services to assess the built environment, specifically for dietary and physical activity features (Charreire et al., 2010). Others examined the utility of GSV to study tobacco-related issues (Wilson et al., 2017). A systematic review by Charreire et al. (2014) examined the use of GSV and other technologies to assess features of the built environment, but only those related to diet and physical activity. The authors found GSV to be a reliable tool in all 13 studies included in the review. Another review, although not systematic, examined a wide overview of emerging geospatial technologies such as GSV, drones, and other omnidirectional imagery (Schootman et al., 2016). Last, another review that focused on secondary food source data only included GSV as a source of data (Fleischhacker et al., 2013). Therefore, there has been no systematic review to date, of the use of GSV for broadly examining health research. Thus, we aimed to systematically review the existing literature on the use of GSV in health research in order to categorize major themes, understand strengths, weaknesses, and subsequently discuss research gaps and potential opportunities for future research.

2. Methods

This review adheres to the PRISMA guidelines for systematic reviews, where applicable (Moher et al., 2009). Studies were eligible for review if they were published in peer-reviewed publications, in English, and utilized GSV as a component of health research. Studies were considered health research if they pertained to health outcomes, health policy compliance, environmental audits, accident/injury assessment, prediction or prevention and disaster recovery. Studies evaluating aesthetics without explicitly tying methods or findings to health were excluded. We also excluded studies that were only peripherally related to health including those concerned with privacy, current or potential building damage, heat efficiency, learning support, and land use. Studies that utilized non-image, non-spatial GSV data, specifically methane sensors installed on the GSV car (von Fischer et al., 2017), were also excluded. Last, studies that discussed only theoretical applications or implications via GSV (e.g., (Wolthers, 2016)) were excluded. There were no restrictions on year of publication due to the relatively recent launch of GSV in 2007.

Various search terms were used in PubMed to develop a comprehensive understanding of the depth of the health literature utilizing GSV. Due to the relatively small number of studies using GSV, it was determined that all studies pertaining to GSV would be collected and then assessed manually for relationships to health so as to not unintentionally exclude less conventional approaches that may have otherwise not been identified by a health-related search term. The search term "GSV" was removed from the search query as it returned results for the "great saphenous vein" rather than Google Street View-related studies. Then, a search of existing literature was performed by the first author, using the terms: [("Google Street View") OR ("Google Streetview") OR (virtual "street audit")] on PubMed and Web of Science. This search was performed on 23 May 2017. After articles were selected for inclusion, the second investigator then examined citations for additional qualifying articles.

The lead author was responsible for the compilation of the database search results (n = 231). Then, two reviewers independently performed

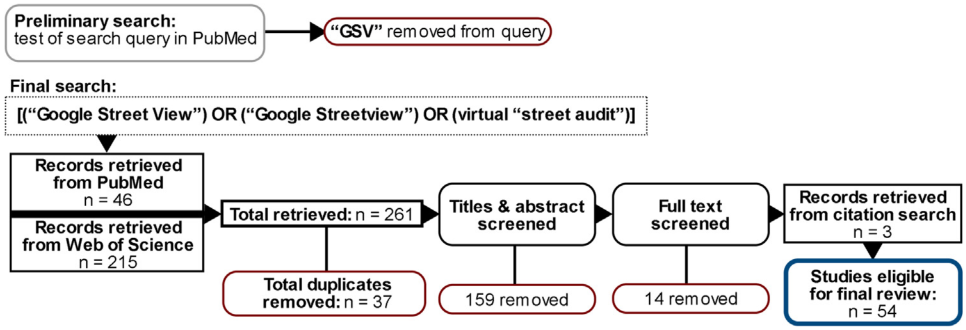

Fig. 1. Diagram of the search process and results at each stage.

title and abstract screening using the website Covidence (Covidence, 2017). Differences between reviewer evaluations were identified by Covidence and subsequently discussed and resolved in person (n = 65). Criteria for the items considered to be health-related (see above) were refined in this stage. Then, both reviewers conducted full-text screening and documentation of study characteristics (Table 1). All included studies were approved by both reviewers (Fig. 1). Significant discrepancies were resolved through discussion, but these were rare (n = 3). After qualifying studies were selected, the second investigator examined the citations for additional qualifying studies (n = 3). Included studies were heterogeneous in their aims, scope and methodology. Thus, results were synthesized, described and compared to other included works. Additional details such as study site, unit of analysis and relationship to health were also extracted. Because this review was focused on the methodology (usage of GSV), we determined that a meta-analysis of the reported quantitative results or risk of bias assessment would not be appropriate. From the tabular data for all studies included in the final review, future research opportunities were then identified for discussion.

3. Results

The first search returned 46 results from PubMed and 215 from Web of Science, with 37 duplicates as determined by Covidence, yielding a total of 224 studies assessed for eligibility. Next, 159 studies were removed after screening the abstract, due to lack of meeting the criteria of health research, not utilizing GSV, or being purely theoretical in content. A further 14 studies were disqualified upon full screening of content. This left a total of 51 studies qualified for the full review, with three additional studies identified via citations, yielding a final total of 54 studies (Fig. 1). Below, we highlight the major themes identified in the studies included in our review, followed by identified strengths and weaknesses of the use of GSV in health research.

3.1. Major themes

Of these included studies, research themes emerged including study site locales, health behaviors and outcomes related to neighborhood environments, and purposes of using of GSV in health research. In terms of study site locales, most study sites (57%) were in North America and/or Europe (37%), followed by four studies based in New Zealand (7%) and one (2%) each from Australia, Japan, and Brazil. We did not identify any studies from any other countries in South America or Asia; none from Africa were identified. Most studies occurred in urban, metropolitan areas including New York City, USA, Madrid, Spain, and Auckland, New Zealand. No studies were conducted in rural areas. Health behaviors and outcomes studied using GSV data (in Table 1) included physical activity (walking or biking), mental health, health-related behaviors (smoking, consuming alcohol) and injury (traffic crashes, disasters). Still, we identified little research in the areas of exposures to sources of pollution or amenity design (such as park or playground equipment).

The usage of GSV in the health studies in our review can be characterized, in order of prevalence, as pertaining to: 1) assessment of the neighborhood built environment (n = 46); 2) health policy compliance and prevention (n = 5); and 3) selection of study sites or other purposes (n = 3).

Most studies included in our review used GSV to audit multiple aspects of the built environment. Neighborhood audits typically involved assessing the presence of items in GSV images via a checklist. Such checklists were either designed to quantify multiple aspects of the built environment or to target specific features. For example, the European-designed and employed 40-item SPOTLIGHT (S-VAT) tool was used to assess obesogenic features, including the presence (or lack) of sidewalks, public transport and physical activity facilities in five studies included in our review (see Table 1). Similarly, the American CANVAS tool is a computer-assisted checklist of 187 items pertaining to walkability and physical disorder of neighborhoods and was used by four studies included in the review (Table 1). Most audits were focused on obesogenic built features and street features that promote walkability or bikeability (Evans-Cowley and Akar, 2014; Mertens et al., 2017; Vanwolleghem et al., 2014). Other audits identified the presence of sub-populations of interest such as elderly persons who may respond differently to the built environment than other adults (Pliakas et al., 2017). Still other itemized checklists were used in mental health research (see Table 1 for list) to capture features of neighborhood disorder which affect fear of crime, stress, and also physical activity. In such studies using GSV to score items on a checklist, the authors typically reported that the use of GSV was easy to use, cheaper, and safer than in-person street audits, with one exception (Clews et al., 2016). Another study by Curtis et al. (2013) assessed the spatio-temporal variability in GSV images, for the purposes of auditing. In addition to itemized checklists, built environment audits also included quantification of green space (Li et al., 2015a), open sky (Yin et al., 2015), or the perceived comparative safety of city images (Naik et al., 2014) using GSV imagery. Notable advantages of using GSV in these assessments included the ability to automate image processing using the Google Maps API. The purpose of auditing the built environment was primarily to quantify neighborhood exposures, including signs of neighborhood disorder, walkability/bikeability, presence of health-related amenities and food outlets (see Table 1).

Next, five studies (10%) used GSV to examine compliance and implementation of public health policies. Specifically, two studies used GSV to identify the location of 'zebra crosswalks' to aid blind pedestrians and prevent crashes (Ahmetovic et al., 2015, 2017). GSV was also used to identify the presence of required smoke-free signage on the grounds of hospitals and schools in New Zealand (Wilson and Thomson, 2015; Wilson et al., 2015). In five communities throughout the United States, civic centers were assessed for their handicap accessibility compliance using GSV (Hammond et al., 2014).

Last, we identified only two studies which used GSV as a sampling tool or to supplement other sampling methods. In one study, GSV was used to confirm the homogeneity of multiple study sites, in terms of availability of liquor stores (Less et al., 2015). This GSV-facilitated sampling method was determined to be useful but limited by caveats found in several GSV studies, discussed in the next section. Burgoine and Harrison (2013) tested the usefulness of GSV for food outlet classification, with the ultimate goal to create a sample frame of food outlets by type for further research in Cambridgeshire, UK. Lastly, we identified only one study which used GSV imagery for a disaster evacuation simulation (Mitsuhara et al., 2017). This study, from Japan, created a virtual reality ‘game’ to teach participants how to respond to natural disasters. GSV imagery was added to the simulation so that participants could experience the evacuation in a realistic setting, with the ability to change routes and repeat the exercise.

3.2. Strengths and weaknesses

Strengths of using GSV in health research include cost-effectiveness, time effectiveness, and it being an easily accessible source of big data. The breadth of health behaviors and outcomes utilizing GSV in research suggests that GSV is a useful source for original data collection, particularly in relation to the construction and implementation of auditing instruments designed to investigate the relationship between the built environment and human health. Still, a meta-analysis of the relative cost-effectiveness of using GSV compared to in-person assessment or field observations has yet to be completed. One study concluded that a single researcher was able to audit more street segments in almost half as many days using GSV, compared to four researchers conducting foot-based audits (Pliakas et al., 2017).

The particular strength of GSV for exposure and outcome assessment studies continues to be the ability to remotely (and thus, time- and cost-effectively) assess neighborhoods in a wide range of global contexts, as has been identified in previous systematic reviews (Charreire et al., 2010, 2014). Another strength of GSV is its facilitation of automated methods. For example, Hyam (2017) used a bank of images rated for perceived naturalness (as it relates to mental health and cognition) and the Google Vision API which uses GSV images. In this work, the Calculated Semantic Naturalness metric was automatically generated. Automated methods were also used to successfully assess street greenery by modifying a green view index (Li et al., 2015a, 2015b, 2016; Li et al., 2015a, 2015b, 2016) and to quantity visible sky (Yin and Wang, 2016). These novel automated methods, which are largely unexplored in comparison to audit-based methods, require more intricate technical development but are advantageous in their ability to quickly and effectively assess large quantities of image data.

Weaknesses of using GSV imagery pertain to geographic availability of imagery, image quality, frequency of image capture, the size or spatial-fixedness of the feature of interest, and the potential for the images to be blocked or blurred. In the Clews et al. (2016) study, GSV was found to be an inadequate tool in comparison to in-person observations, as only 50% of alcohol outlets and 52% of associated marketing data collected in-person were also identified using GSV images due to poor image quality. It is unclear whether this will be an ongoing issue with GSV or whether image quality is likely to keep improving over time. In September 2017, in an online media report, Google stated that cameras will be upgraded to be higher definition, with the goal of being able to read fine print on buildings. While the camera specifications are not provided (Google, 2018; Weston, 2017), the Google API services report a maximum resolution of 2048 × 2048 available to their Premium Plan customers (Google, 2018). Thus, it is difficult to assess the extent of this weakness, as high definition imagery may already be available in some areas and not others. Still, inconsistencies in image date and resolution quality may result in the misclassification or erroneous inclusion/exclusion of, for example, built environment exposures.

Also related to data availability, Curtis et al. (2013) assessed the effectiveness of evaluating change over time of street segments. Both image quality and infrequent image capture affected the ability to audit environments, with issues related to the construction of a building not yet captured by GSV imagery (Curtis et al., 2013). At the time of writing, frequency of image capture remains a caveat of GSV. For example, some neighborhoods in Lansing, MI have had imagery updated annually for the period 2018–2015, while many neighborhoods in Detroit, MI have not been updated since 2013. Additionally, GSV imagery is currently unavailable in many lower-income regions of the globe including countries in Africa, South America and Southeast Asia. Currently, low and middle income countries, apart from Brazil, are unrepresented in this review, largely due to unavailability of data. In many of these settings, footpaths (rather than streets equipped to carry cars) may be important places for image capture, and are currently available on a limited basis. Likewise, studies in our review were carried out only in urban and suburban communities. It is unclear whether this relates to poorer availability of GSV data in rural areas.

Small (e.g., discarded cigarette ends) or intermittent features (e.g., litter) were found to be difficult to identify in images (Wilson et al., 2017). The power of GSV as a sampling tool is largely dependent on the visibility (size) and permanence of the targeted features as well as uniform data availability and resolution. Last, similar to in-person observations, some assessments were more subjective than others, leading to low inter-rater reliability (e.g., severity of graffiti) (Charreire et al., 2014).

4. Discussion

4.1. Strengths and limitations of our review

A strength of this review is that it is the first, full systematic review of the use of GSV for a broad range of health research. Such a review has allowed for the categorization of themes in health research utilizing GSV. However, it is limited by the lack of coverage of non-peer reviewed grey literature, including reports published on official websites. The review also does not include studies making use of other freely available geospatial data, such as Bing Maps or Google Earth. While this review encompasses a wide range of approaches to health research using GSV imagery, the scope may still be limited by our conceptualization of ‘health’. For example, we did not include studies focused on building heat efficiency, which could have downstream health effects (via fuel poverty and via climate change). This review also purposely excludes direct observation of human behavior via GSV, an important component of the social environment, and ultimately linked to a variety of health outcomes.

4.2. Opportunities for future research using GSV

The themes identified in this review suggest that there are a number of opportunities for health research using GSV. For example, at the time of this review, no studies were identified that utilized GSV to study: parks, playground design, or street trees for health research purposes including promotion of physical activity, injury reduction, sun safety, or reduction in noise or air pollution. Other potential areas of GSV health research could include the identification of sources of air, soil or water pollution and amenity design. As data become increasingly available, health research could make use of “footpath view” to understand the retail environment and health-related signage away from roads. Additionally, the recently released archival feature of GSV provides historical image data for the same location and has been mentioned as a potentially important tool for research (Schootman et al., 2016). Yet, these historical data have been otherwise unexplored in health studies, to date. Future longitudinal research on neighborhood conditions may usefully employ these data.

To conclude, this review suggests that Google Street View has thus far proven to be a generally useful tool for observing features for a wide range of health-related studies. With the geographic and off-road expansion, repeated image capture over time, and improved image resolution, GSV is likely to become a growing source of data in health research. This review demonstrates how advances in technology, public availability of imagery and neighborhood-health research are becoming integrated in ways that expand our ability to approach geospatial health research.

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