

# Sources of Active Travel Data

Subjects: [Green & Sustainable Science & Technology](#)

Contributor: Mohammad Alattar

Active travel (AT), namely journeys that have been undertaken either entirely or partially using human-powered transportation modes such as walking, cycling, or using a wheelchair, has been the focus of much attention due to its potential for remedying negative impacts of urbanization. Among other benefits, AT helps to meet required physical activity guidelines and reduces traffic congestion and pollution. Furthermore, AT induces the uptake of emerging micromobility, a term that describes the use of electrically assessed lightweight vehicles such as e-bikes, e-scooters, e-skateboards, and hoverboards.

active travel

emerging data sources

crowdsourced data

cycling

Strava

public participation geographic information system (PPGIS)

## 1. Introduction

Among other benefits, AT helps to meet required physical activity guidelines and reduces traffic congestion and pollution <sup>[1][2]</sup>. Furthermore, AT induces the uptake of emerging micromobility, a term that describes the use of electrically assessed lightweight vehicles such as e-bikes, e-scooters, e-skateboards, and hoverboards. Micromobility transport modes are less physically taxing with a shorter travel duration, reducing the reliance on conventional vehicles, particularly for short journeys <sup>[3][4]</sup>. However, the emphasis of transport planning in most cities is still car-dominant, with policies such as minimum car parking requirements and gas subsidies aiming to reduce car delays across many urban transport networks <sup>[5]</sup>.

In many cases AT can substitute for a large portion of journeys undertaken by motorized transport. Thus, to change this car-dominant transport paradigm, fostering AT requires well-informed policies and interventions, which have often been stalled by inadequate data available from traditional data sources. Manual data collection methods (e.g., using clickers to obtain AT user volumes) are laborious <sup>[6]</sup>, with much data underreported <sup>[7]</sup>. Nevertheless, traditional data is useful for the validation of emerging data sources.

The advent and ubiquity of information and communication technology, including smartphones and wearable devices, has allowed for emerging AT data (hereinafter emerging data) ventures. : volume (very large), variety (highly complex) and velocity (high growth rate), making them unmanageable through traditional methods <sup>[8]</sup>. Compared to traditional AT data, emerging data is much more voluminous, less obstructive, and relatively cheaper to collect. For example, Strava ((<https://www.strava.com/> accessed on 11 June 2021), a social fitness network (SFN) where users can track, share and monitor their physical activities such as cycling and running; more about

this type of data source is provided in Section 3.1) ridership datasets have a fine spatiotemporal resolution whereas traditional counts are limited both spatially and temporally [9]; and traditional safety incident reports (e.g., police and insurance) are underreported compared to BikeMaps ((<https://bikemaps.org/> accessed on 11 June 2021), an online platform where users can voluntarily report concerns about cycling safety, including incidents such as collisions, near misses and hazards; more about this type of data source is provided in Section 3.3)

In an attempt to review the emerging data and address their potential and limitations, this work surveys the current emerging AT data ecosystem, and builds and expands on previous reviews [10][11] to include additional AT modes and new data sources. This literature review was conducted employing Google Scholar using the following terms: active travel, active transportation, cycling, cycle, bicycle, pedestrian, bike sharing systems (BSSs), big data, data collection, Strava, crowdsourced, emerging data, and traditional data. This paper aims to assess the state of knowledge on emerging data. Section 2 introduces potential outcomes of AT, while Section 3.1 provides a brief review of traditional AT data sources and Section 3.2 focuses on emerging data.

## **2. Active Travel Outcomes**

Urbanization has transformed cities to obesogenic environments, a term that has been coined to describe environments that induce obesity through promoting a sedentary lifestyle and encouraging an excess calorie intake [12]. This has resulted in the first generation to have a shorter life expectancy than their parents [13].

Flint et al. [14] found that in the UK, AT users had a significantly lower body mass index compared to users of motorized travel modes, suggesting that they are less likely to be obese or suffer from related health conditions. [15] concluded that the duration of walking to work is positively associated with the reduction of hypertension. In Bogota, Colombia, cycling to school has been linked to an improved physical fitness profile compared to motorized transportation [16].

During the COVID-19 pandemic, AT provided transportation that adhered to the social distancing guidelines implemented to reduce the spread of the outbreak. Similarly, in Scotland BSSs were demonstrated as an alternative to public transportation [17]. Sydney exhibited a surge in the willingness to cycle due to hygiene reasons and recreational exposure [18]. In addition, delivery services increased their reliance on cycling during this period [19].

The physical activity gained from AT has been reported to improve mental wellbeing. Physically active individuals in the UK reported less anxiety-related symptoms or emotional distress [20]. Similarly, in Alameda County, California, Camacho et al. [21] demonstrated that inactive individuals are more likely to develop clinical depression.

However, Gelb and Apparicio [22] observed that in Paris, France, close proximity to traffic can impose wellbeing threats to AT users via noise and air pollution. In addition to more serious threats resulting from traffic injuries [23], Stelling-Konczak et al. [24] explored the impacts of cyclists' auditory perception (mobile conversation, music and electric cars' quietness) on their safety. The compensatory behavior (i.e., reducing speed, looking around more

frequently) of cyclists was found to counterbalance the risk arising from losing auditory cues such as tire and engine noises.

On a global scale, motorized vehicles are the second largest source of carbon emissions <sup>[25]</sup>. They also contribute to heat emission, ultimately magnifying the urban heat island effect. Since AT modes do not require fuel and produce substantially less heat, shifting from motorized transportation to AT will reduce climate change severity and the urban heat island effect <sup>[26][27]</sup>. Moreover, cities are designed to accommodate motorized transportation through highways, parking and tunnels.

Motorized transportation is associated with numerous overhead costs, such as fuel, insurance, and maintenance, whereas AT is much cheaper (or even free) <sup>[28]</sup>. Rauterkus & Miller <sup>[29]</sup> demonstrated a significant correlation between property values and walk scores when measuring walkability using sample properties from Jefferson County, Alabama, USA. Li & Joh <sup>[30]</sup> determined that bike scores exhibited a positive correlation with transit accessibility and property values in Austin, Texas, USA. These results collectively suggest that AT infrastructure investment can yield higher property values.

The New York City Department of Transportation <sup>[31]</sup> reported that retail sales increased by 49% when protected bicycle lanes were installed on 8th and 9th Avenues, compared to a 3% increase borough-wide, in Manhattan, New York. The Oakland Department of Transportation <sup>[32]</sup> also reported economic growth of 9% in retail sales after improvement via the Telegraph Avenue project in Oakland, California between 20th and 29th Streets. In particular, the project introduced eight high-visibility pedestrian crosswalks and bike lanes that stretched for nine blocks with parking protection to prevent vehicles from parking. This finding has been confirmed elsewhere, where sales and footfalls are proportional to AT users, for example in Toronto, Canada <sup>[33]</sup> and Auckland, New Zealand <sup>[34]</sup>.

Additionally, enabling adequate societal participation, known as social inclusion, can be promoted through AT as it provides equitable accessibility and availability (transport equity). horizontal equity, where fairness is established between individuals who are in the same class of wealth and ability; and (ii) vertical equity, where fairness is established between different income and social classes <sup>[35]</sup>. Another desirable societal outcome is social interaction, where people engage in mutual leisure activities such as walking or cycling <sup>[36]</sup>. This in turn can enhance community livability and add a sense of social cohesion <sup>[37]</sup>.

Indirectly, the social benefit of cycling and walking in the European Union has been estimated as €0.18 and €0.37 per kilometer using these modes, respectively. For automobiles, however, a social cost of €0.11 per kilometer has been estimated. This cost-benefit analysis includes numerous parameters such as environmental impact (cost of climate change impact; air, water and ground pollution; noise and space required for infrastructure), travel time and vehicle operation (cost of ownership and operation of a particular transport mode; travel time; roadway congestion imposed on other users), and other factors such as healthcare system savings, perceived safety and discomfort, and quality of life <sup>[38]</sup>.

### 3. Active Travel Data Sources

Traditional methods to collect AT data comprise manual and automated approaches. Manual methods require a low level of technology sophistication and are labor intensive, meaning more user input is required [39]. The primary advantage of such methods is that they can collect additional information on AT users, such as helmet usage, gender, travel direction, and mobile phone usage, and can differentiate between AT user types (e.g., cyclists, pedestrians, and skaters). These methods can also be used as ground truth counts to validate other methods [40].

Automated methods involve more advanced technology compared to manual methods. These methods replace human data collectors, and therefore require less or no user input and can be implemented for lengthier periods of time, irrespective of inclement weather conditions [41]. However, unlike manual methods, automatic methods cannot provide additional information on AT users. **Table 1** provides a summary of traditional methods.

**Table 1.** Summary of traditional methods for generating traditional AT data.

Method	Description
Manual Methods	
Video recording	A standard video camera mounted and directed (temporarily or permanently) in the path of AT users (sidewalks or multi-use trails). The footage is manually examined by the data collector using paper sheets, a handheld counter, or computer software [42].
Travel survey	Travel surveys ask subjects to describe their travel activities or any further information. Data collection methods are based on a range of instruments, such as GPS devices, interviews, and conventional web-based questionnaires [41].
Handheld counter	The use of handheld counters (also known as clickers or tally counters) to count AT users. The data collector can count up to 4,000 AT users per hour [43].
Ride-along observations	The observant collects data from participants during their trips. For instance, the data collector cycles with a study subject to perform a survey or an interview [44].
Automated Methods	
Pneumatic tubes	Two rubber tubes are stretched across roadways or pathways, perpendicularly attached to the pavement surface. When a bicycle or wheelchair passes over the tubes, a pulse of air is generated, triggering an electrical conduct that registers a count. The distance between the two tubes is programmed to determine the speed. This sensor is highly consumable, with a lifetime ranging from days to months [40][45].
Infrared sensors	Sensors utilize invisible light to detect AT users. There are two main types of sensors: active and passive. Active infrared instruments count AT users when the beam between the transmitter and the receiver is broken. Passive infrared sensors identify temperature variations as AT users move through the detection zone of the sensor. Note that surface temperatures can affect the accuracy of the sensor [40][45].
Magnetometers	Magnetometers detect changes in magnetic fields within the approximation of the sensor created by ferrous metal objects; thus, this sensor is not suitable for non-ferrous metal objects (e.g., carbon-fiber bicycles, pedestrians). The sensor is battery-powered and can be installed below the cycle path. Data are collected through radio communication [46].

Method	Description
Manual Methods	
Pressure and acoustic pads	A pressure pad sensor detects changes in weight that occur when AT users step on the detection zone. The sensor is capable of distinguishing between the pressure of cyclists and pedestrians. The acoustic pad sensor is limited to pedestrian counting as it uses ground energy waves caused by feet to detect changes. Both sensors are battery-powered and installed within the ground, making them less prone to vandalism <sup>[42][47]</sup> .
CCTV	CCTV positioned on streets aided by artificial intelligence (AI) is able to generate data counts for pedestrians and cyclists. Cameras take pictures at predefined time intervals, then process those images to count pedestrians and cyclists <sup>[48]</sup> .

Although the aforementioned limitations confine the applications of such data, they are typically used to validate, calibrate and in some cases complement emerging data sources. However, traditional data (specifically counts, which are considered to be reliable) often fail to accurately capture the number of AT users. Bunn <sup>[49]</sup> reported an outlier in Strava bike counter data, resulting from cycling in non-bicycle lanes.

Emerging methods of AT data collection feature high spatial and temporal coverage due to advances in smart devices <sup>[50]</sup>. Data obtained from emerging methods differ from traditional approaches, which are often spatially and temporally restricted, labor-intensive, time consuming, and cumbersome <sup>[9]</sup>. Emerging data can originate from various sources, most of which are considered to be crowdsourced, where a series of users provide data addressing the same topic. the emerging data sources adopted to generate AT data.

Willberg et al. <sup>[44]</sup> surveyed the relevant research to evaluate traditional methods (counters and observations), BSSs, GPS tracking, SFNs, surveys and interviews, Public Participation Geographic Information Systems (PPGIS), and other sources in terms of their spatial and temporal patterns, demographics, trip purpose, determinants, and barriers.

3.1. Social Fitness Networks

The phrase “social fitness” has its origins in physical exercise, weight loss regimes, and means of motivating individuals to achieve their fitness goals. Likewise, SFNs allow users to track and share their various physical activity (e.g., walking, cycling, swimming, handcycling, skiing, etc.) data with online communities <sup>[51]</sup>. (https://www.mapmyfitness.comaccessed on 11 June 2021), and Fitbit (https://www.fitbit.comaccessed on 11 June 2021), which in turn distribute the data commercially <sup>[41]</sup>.

These data sources can at times overrepresent certain demographic segments such as male, younger, and tech-savvy users <sup>[52]</sup>. In addition, Strava is associated with several privacy issues, such as unintentionally revealing military outpost locations <sup>[53]</sup>. Recent changes in Strava data specifications to maintain user anonymity have consequently resulted in information loss <sup>[54]</sup> and the data are also restricted by high data acquisition costs due to the high fees <sup>[55]</sup>. Strelnikova <sup>[56]</sup> compared Strava and Endomondo (a SFN that has been retired) in terms of spatial and temporal resolution in South Florida, concluding that although Strava provides more detailed information, Endomondo contains data on small road segments and off-road tracks.

### 3.2. In-house developed apps

In-house developed apps, also known as regional bicycling tracking apps, offer region-wide cycling data through GPS-oriented travel diaries that provide GPS traces, trip purpose and demographic information. These apps are generally developed by or for public agencies and aim to record cycling travel patterns for app users in order to improve cycling within the community <sup>[41]</sup>. However, the success led a number of agencies and municipalities (e.g., Austin, Texas; Seattle, Washington; and Salt Lake City, Utah) to adopt the app. Other cities have rebranded the app, including Lane County, Oregon (LaneTracks); Atlanta, Georgia (Cycle Atlanta); and Philadelphia, Pennsylvania (CyclePhilly) <sup>[57]</sup>. Although more nuances are provided by in-house developed apps (i.e., disaggregated data at the track level) compared to SFNs (i.e., aggregated data at the street level), participant recruitment is considered the main challenge for deploying in-house developed apps, due to the time-consuming and effort-intensive properties <sup>[10]</sup>.

### 3.3. Participatory mapping

Spatial knowledge from ordinary/non-expert users form datasets that can be collected through Volunteered Geographic Information (VGI), a Public Participation Geographic Information System (PPGIS). SafeLanes (<https://safelanes.org/> accessed on 11 June 2021) promote user engagement in the form of voluntary reporting of various issues that can implicate transportation planning <sup>[41]</sup>. PPGIS platforms (i.e., Maptionnaire (<https://maptionnaire.com/> accessed on 11 June 2021) and KoBo Toolbox (<https://www.kobotoolbox.org/> accessed on 11 June 2021)) are map-based surveys that solicit spatial and nonspatial information input by inviting respondents <sup>[58]</sup>. These platforms are usually operated by researchers or practitioners. The varied mapping skills and familiarity of study areas among users may result in data inconsistencies for such data sources <sup>[58]</sup>. In addition, participatory mapping platforms are subject to vandalism through false data entries <sup>[59]</sup>.

### 3.4. Imagery

High spatiotemporal resolution imagery obtained at low or no cost from satellites (e.g., Google Maps and Bing Maps), street view sources (e.g., Google Street View), or drones can be integrated into supervised or unsupervised methods to extract stationary (e.g., infrastructure) and non-stationary (e.g., ridership) data. Additionally, based on satellite imagery, volunteers can digitize identifiable features including roads and building footprints via the collaborative mapping project OpenStreetMap (OSM). Accordingly, many studies use OSM to extract street networks, a key factor in AT studies.

### 3.5. Bike sharing systems

BSSs allow for short-term bike rental with pickup and return locations (docks) across areas denoted as docked BSSs (known as third generation systems). In contrast, dockless BSSs (known as fourth generation systems) allow users to unlock and leave rental bikes within a geofence site <sup>[60]</sup>. BSS-conducted trips are generally less than 30 min <sup>[61]</sup> and the systems play a key role in increasing the connectivity between public transport and origin or destination locations (first mile/last mile) <sup>[62]</sup>. The spatial and temporal bike rebalancing issue is one of the main

challenges of BSSs, where certain locations at certain times (e.g., rush hours) suffer from bike shortages causing user dissatisfaction and reducing service reliability [63]. This issue may increase overheads, as operators have to instruct vehicles to reestablish the balance. In order to optimize the way BSSs operate, the provided data have been utilized to further investigate and mitigate this challenge. [64] propose financial incentives for users to pick up or drop off bikes in alternate locations. The vast majority of BSS dataset records are provided in origin–destination journeys rather than routes. Buning and Lulla's [65] work has, however, incorporated GPS data that reveals information about the used routes rather than just origin and destination. Furthermore, BSS datasets may be detailed enough to infer many useful attributes about the user such as subscription type (annual or casual), gender, year of birth, trip timestamp, and home zip code.

### 3.6. Social media

Social media platforms have great potential as reliable, cost-effective, and timely information sources [66]. Through mining techniques, researchers can extract user perceptions on certain topics, whereby user locations can be inferred from geotags [67]. These data have long been acquired from surveys, which require effort in recruiting the sample and may be hindered by low response rates [68]. Thus, transport policies can harvest information from social media to monitor traffic in real time, model travel behavior and demand, and qualitatively analyze facilities' service qualities [69]. Despite their benefits, social media data are subject to age group bias and inconsistencies in the data collection [68].

### 3.7. Other

Using GPS tracking apps (e.g., Gaia GPS (<https://www.gaiagps.com/> accessed on 21 June 2021)), subjects can record their trips and donate them to researchers. Heesch and Langdon [70] evaluated the usefulness of this type of app in detecting changes resulting from infrastructure improvement on cycling behavior. The work identified a failure in triangulating GPS data due to insufficient traffic-monitoring devices, which may lead to problematic results. In order to overcome this, the authors suggested complementing GPS data with other data sources.

Data service companies (e.g., StreetLight (<https://www.streetlightdata.com/> accessed on 21 June 2021)) can aggregate data from different sources to provide a user-friendly analytic platform. Turner [71] determined a high correlation between StreetLight data and ground-truth cyclist counts.

Several self-developed apps and web-based services aim to facilitate crowdsourced data. BikeCitizens (<https://www.bikecitizens.net> accessed on 21 June 2021) employs user-recorded trips and experiences after they are anonymized to improve cycling in cities. The Bike Data Project (<https://www.bikedataproject.org> accessed on 21 June 2021) aims to gather data from multiple platforms to improve cycling safety through the donation of user trips.

In response to the COVID-19 pandemic, Apple Mobility Data (<https://covid19.apple.com/mobility> accessed on 21 June 2021) reports direction requests (walking, driving, and transit) from the Apple Maps app and compares them to a baseline volume from 13 January 2020. The spatial resolution is confined to a country/region, sub-region, or



city, with a daily temporal resolution. Using these data, Oguzoglu [72] was able to infer walking trends in Istanbul during the lockdown.

## 4. Open Challenges and Research Directions

Numerous policies that operate at different scales (society, city, neighborhood, and individual) cater to AT. **Table 2** presents an overview of policy types that aim to increase AT. [5] determined that more adequate data collection and methodologies are required to optimally implement these policies. The authors explicitly state the need for data improvement and conducted large-scale studies to evaluate these policies. Given the fine spatiotemporal resolution of crowdsourced data, researchers and practitioners can prioritize locations that require policies and interventions and can also justify their investments by quantifying the policy impact.

**Table 2.** Policies to promote AT.

Policy Level	Description
Society	Policies to reduce the appeal of motorized vehicles through speed limit reductions and car parking limits, and to promote public transport to incorporate AT.
City	Policies to configure urban design through initiatives such as incorporating mixed land use within walking distance to residential areas, the application of car-free centers, reducing block size, and increasing street connectivity.
Neighborhood	Policies on AT infrastructure investments to make AT more convenient, comfortable and safe, by adopting separated paths, cycle tracks and end-of-trip facilities (e.g., bicycle parking, showers, lockers).
Individual	Policies targeting behavior change, for example through mass media and other campaigns or by providing financial incentives.

Reprinted with permission from ref. [5]. Copyright 2017 Springer International Publishing AG.

The ongoing need for evidence-based policies and investment make such a practice an open challenge for future research. For example, AT trends have changed as a result of COVID-19 lockdowns worldwide, requirements to meet recommended physical activity levels, and policies to ensure safe commuting [73]. Furthermore, most streets do not maintain the recommended distance between people (2 m). These exceptional circumstances, including the lockdown, travel restrictions, and curfews, demand appropriate policies and interventions to accommodate AT during such conditions, and the embedding of these practices in future transport planning activities.

High-definition imagery can potentially be incorporated into AT studies. The employment of free and commercial images allows researchers to obtain data on features known to improve the AT experience, namely green spaces and water bodies [74][75]. These two features can be delineated using multispectral imagery through spectral indices such as the normalized difference vegetation index (NDVI) and normalized difference water index (NDWI),



respectively. Researchers and practitioners can adopt the cloud service Google Earth Engine to manage, store and process the large amount of data [\[76\]](#).

Studies on cycling and micromobility (refer to [\[77\]](#)[\[78\]](#)[\[79\]](#) for micromobility studies in Austria, San Francisco, California, and Austin, Texas respectively) In contrast, products used to track non-cycling modes are limited. [\[19\]](#) indicated that emerging micromobility and conventional non-motored vehicles (i.e., skateboards, scooters, and rollerblades) share common challenges and interests with conventional bikes. The gap in the literature on non-cycling modes, including mobility aids for those with less mobility, creates an opportunity for future researchers to conduct more studies on these modes.

Previous research has indicated the biases of emerging data, which in turn threaten the outcome legitimacy of these data. BSSs provide data on all their users, eliminating the potential of social desirability and self-selection biases. Although BSSs tend to be more reflective of casual cyclists and visitors, the data are subject to spatial anonymity as the origin (or destination) represents the check-in (or -out) location of the bicycle [\[44\]](#). Combining multiple data sources, also known as data fusion techniques, has great potential in overcoming the data uncertainties and biases.

The increasing number of studies focusing on BSSs illustrates the merits of open data, whereby the data are openly accessible to the public. Such a practice facilitates replicability and prompts more researchers to attempt to answer questions using these data. Open data may also provide an opportunity for VGI platforms to engage researchers with their platforms as data collection instruments and increase their visibility among used platforms to achieve representative sample sizes.

Since SFN data ownership belongs to third parties, the data are subject to specification changes and acquisition fees that might problematize interpretation, replicability and acquisition, respectively. Additionally, the acquisition fees are regulated by area size and time span. Thus, to avoid these constraints, open source apps may to some extent substitute this data source. These challenges should be acknowledged by transport agencies prior to adopting this emerging data source.

---

## References

1. Norwood, P.; Eberth, B.; Farrar, S.; Anable, J.; Ludbrook, A. Active travel intervention and physical activity behaviour: An evaluation. *Soc. Sci. Med.* 2014, 113, 50–58.
2. Rissel, C.E. Active travel: A climate change mitigation strategy with co-benefits for health. *New South Wales Public Health Bull.* 2009, 20, 10–13.
3. Cherry, C.; Cervero, R. Use characteristics and mode choice behavior of electric bike users in China. *Transp. Policy* 2007, 14, 247–257.

4. O'Hern, S.; Estgfaeller, N. A scientometric review of powered micromobility. *Sustainability* 2020, 12, 9505.
5. Winters, M.; Buehler, R.; Götschi, T. Policies to promote active travel: Evidence from reviews of the literature. *Curr. Environ. Health Rep.* 2017, 4, 278–285.
6. Day, C.M.; Premachandra, H.; Bullock, D.M. Rate of pedestrian signal phase actuation as a proxy measurement of pedestrian demand. *Transp. Res. Rec.* 2016.
7. Winters, M.; Branion-Calles, M. Cycling safety: Quantifying the under reporting of cycling incidents in Vancouver, British Columbia. *J. Transp. Health* 2017, 7, 48–53.
8. Griffin, G.P.; Mulhall, M.; Simek, C.; Riggs, W.W. Mitigating bias in big data for transportation. *J. Big Data Anal. Transp.* 2020, 2, 1–11.
9. Alattar, M.A.; Cottrill, C.; Beecroft, M. Modelling cyclists' route choice using Strava and OSMnx: A case study of the city of Glasgow. *Transp. Res. Interdiscip. Perspect.* 2021, 9.
10. Nelson, T.; Ferster, C.; Laberee, K.; Fuller, D.; Winters, M. Crowdsourced data for bicycling research and practice. *Transp. Rev.* 2021, 41, 97–114.
11. Lee, K.; Sener, I.N. Emerging data for pedestrian and bicycle monitoring: Sources and applications. *Transp. Res. Interdiscip. Perspect.* 2020, 4.
12. Swinburn, B.; Egger, G.; Raza, F. Dissecting obesogenic environments: The development and application of a framework for identifying and prioritizing environmental interventions for obesity. *Prev. Med.* 1999, 29, 563–570.
13. Dallacker, M.; Hertwig, R.; Mata, J. The frequency of family meals and nutritional health in children: A meta-analysis. *Obes. Rev.* 2018, 19, 638–653.
14. Flint, E.; Cummins, S.; Sacker, A. Associations between active commuting, body fat, and body mass index: Population based, cross sectional study in the United Kingdom. *BMJ* 2014, 349, g4887.
15. Hayashi, T.; Tsumura, K.; Suematsu, C.; Okada, K.; Fujii, S.; Endo, G. Walking to work and the risk for hypertension in men: The Osaka Health Survey. *Ann. Intern. Med.* 1999, 131, 21–26.
16. Ramírez-Vélez, R.; García-Hermoso, A.; Agostinis-Sobrinho, C.; Mota, J.; Santos, R.; Correa-Bautista, J.E.; Amaya-Tambo, D.C.; Villa-González, E. Cycling to school and body composition, physical fitness, and metabolic syndrome in children and adolescents. *J. Pediatr.* 2017, 188, 57–63.
17. CoMoUK Scotland Bike Share Users Survey. Available online: (accessed on 12 June 2021).
18. Lock, O. Cycling Behaviour Changes as a Result of COVID-19: A Survey of Users in Sydney. *Transp. Find.* 2020.

19. Oliveira, F.; Nery, D.; Costa, D.G.; Silva, I.; Lima, L. A survey of technologies and recent developments for sustainable smart cycling. *Sustainability* 2021, 13, 3422.
20. Taylor, A.H. Physical activity, anxiety, and stress. In *Physical Activity and Psychological Well-Being*; Routledge: London, UK, 2003; pp. 22–52.
21. Camacho, T.C.; Roberts, R.E.; Lazarus, N.B.; Kaplan, G.A.; Cohen, R.D. Physical activity and depression: Evidence from the Alameda County Study. *Am. J. Epidemiol.* 1991, 134, 220–231.
22. Gelb, J.; Apparicio, P. Modelling cyclists' multi-exposure to air and noise pollution with low-cost sensors—The case of paris. *Atmosphere* 2020, 11, 422.
23. Stipdonk, H.; Reurings, M. The effect on road safety of a modal shift from car to bicycle. *Traffic Inj. Prev.* 2012, 13, 412–421.
24. Stelling-Konczak, A.; van Wee, G.P.; Commandeur, J.J.F.; Hagenzieker, M. Mobile phone conversations, listening to music and quiet (electric) cars: Are traffic sounds important for safe cycling? *Accid. Anal. Prev.* 2017, 106, 10–22.
25. Lingli, J. Smart City, Smart Transportation: Recommendations of the Logistics Platform Construction. In *Proceedings of the 2015 International Conference on Intelligent Transportation, Big Data and Smart City, Halong Bay, Vietnam, 19–20 December 2015*; IEEE. pp. 729–732.
26. Giles-Corti, B.; Foster, S.; Shilton, T.; Falconer, R. The co-benefits for health of investing in active transportation. *N. S. W. Public Health Bull.* 2010, 21, 122–127.
27. Wong, L.P.; Alias, H.; Aghamohammadi, N.; Aghazadeh, S.; Nik Sulaiman, N.M. Urban heat island experience, control measures and health impact: A survey among working community in the city of Kuala Lumpur. *Sustain. Cities Soc.* 2017, 35, 660–668.
28. Foley, L.; Dumuid, D.; Atkin, A.J.; Olds, T.; Ogilvie, D. Patterns of health behaviour associated with active travel: A compositional data analysis. *Int. J. Behav. Nutr. Phys. Act.* 2018, 15, 1–12.
29. Rauterkus, S.Y.; Miller, N. Residential land values and walkability. *J. Sustain. Real Estate* 2011, 3, 23–43.
30. Li, W.; Joh, K. Exploring the synergistic economic benefit of enhancing neighbourhood bikeability and public transit accessibility based on real estate sale transactions. *Urban Stud.* 2017, 54, 3480–3499.
31. New York City Department of Transportation. *Measuring the Street: New Metrics for 21st Century Streets*; New York City Department of Transportation: 2012. Available online: (accessed on 11 June 2021).
32. Oakland Department of Transportation Telegraph Avenue Progress Report. Available online: (accessed on 12 June 2021).

33. Tolley, R. Good for Busine \$\$: The Benefits of Making Streets more Walking and Cycling Friendly; Heart Foundation South Australia: 2011. Available online: (accessed on 11 June 2021).
34. Wooller, L.A. What are the Economic and Travel Implications of Pedestrianising a Roadway in Takapuna's Shopping Precinct. Master Thesis, Auckland University of Technology, Auckland, New Zealand, 2010. Available online: (accessed on 11 June 2021).
35. Litman, T. Social Inclusion as a Transport Planning Issue in Canada; 2003. Available online: (accessed on 11 June 2021).
36. Hartig, T.; Mitchell, R.; De Vries, S.; Frumkin, H. Nature and health. *Annu. Rev. Public Health* 2014, 35, 207–228.
37. Babb, C.; Curtis, C. Evaluating the built environment for children's active travel to school. In Proceedings of the Australasian Transport Research Forum (ATRF), 36th, Brisbane, Queensland, Australia, 2–4 October 2013.
38. Gössling, S.; Choi, A.; Dekker, K.; Metzler, D. The social cost of automobility, cycling and walking in the European Union. *Ecol. Econ.* 2019, 158, 65–74.
39. AMEC E&I Inc.; Sprinkle Consulting Inc. Pedestrian and Bicycle Data Collection. Available online: (accessed on 12 June 2021).
40. Minge, E.; Falero, C.; Lindsey, G.; Petesch, M.; Vorvick, T. Bicycle and Pedestrian Data Collection Manual; MnDOT Research Services & Library: Minneapolis, Minnesota, 2017.
41. Lee, K.; Sener, I.N. Emerging Data Mining for Pedestrian and Bicyclist Monitoring: A Literature Review Report. 2017. Available online: (accessed on 11 June 2021).
42. Ryus, P.; Ferguson, E.; Laustsen, K.M.; Prouix, F.R.; Schneider, R.J.; Hull, T.; Miranda-Moreno, L. Methods and Technologies for Pedestrian and Bicycle Volume Data Collection; The National Academies Press: Washington, DC, USA, 2014.
43. Schweizer, T. Methods for counting pedestrians. In Proceedings of the The 6th International Conference on Walking in the 21st Century, Zurich, Switzerland, 22–23 September 2005.
44. Willberg, E.S.; Tenkanen, H.; Poom, A.; Salonen, M.; Toivonen, T. Comparing Spatial Data Sources for Cycling Studies—A Review. In *Transport in Human Scale Cities*; Edwar Elgar: Cheltenham, UK, 2021; Available online: (accessed on 11 June 2021).
45. Miami-Dade Transportation Planning Organization. Miami-Dade Bicycle & Pedestrian Data Collection; Miami-Dade Transportation Planning Organization, Miami-Dade County, Florida: 2018. Available online: (accessed on 11 June 2021).
46. Figliozi, M.; Monsere, C.; Nordback, K.; Johnson, P.; Blanc, B.P. Design and Implementation of Pedestrian and Bicycle-Specific Data Collection Methods in Oregon; Portland State University, Portland, Oregon. 2014. Available online: (accessed on 11 June 2021).

47. Nordback, K.; Kothuri, S.; Petritsch, T.; McLeod, P.; Rose, E.; Twaddell, H. Exploring pedestrian counting procedures: A review and compilation of existing procedures, good practices, and recommendations. Report FHWA-HPL-16-026 produced for the Office of Highway Policy Information, Federal Highway Administration. 2016. Available online: (accessed on 11 June 2021).
48. Urban Big Data Centre; Glasgow City Council. Using Spare CCTV Capacity to Monitor Activity Levels during the COVID-19 Pandemic; Urban Big Data Centre: Glasgow, Scotland, 2020.
49. Bunn, H. The Power of Multiple Datasets and the Insights Hiding in Them. Available online: (accessed on 12 June 2021).
50. Adler, J.; Horner, J.; Dyer, J.; Toppen, A.; Burgess, L.; Hatcher, G. Estimate Benefits of Crowdsourced Data from Social Media; Noblis: Washington, DC, USA, 2014; Available online: (accessed on 11 June 2021).
51. Lupton, D. Lively Data, Social Fitness and Biovalue: The Intersections of Health Self-Tracking and Social Media; Sage: London, UK, 2017; Available online: (accessed on 11 June 2021).
52. Garber, M.D.; Watkins, K.E.; Kramer, M.R. Comparing bicyclists who use smartphone apps to record rides with those who do not: Implications for representativeness and selection bias. *J. Transp. Health* 2019, 15, 100661.
53. Nguyen, K.A.; Akram, R.N.; Markantonakis, K.; Luo, Z.; Watkins, C. Location tracking using smartphone accelerometer and magnetometer traces. In Proceedings of the 14th International Conference on Availability, Reliability and Security, Canterbury, UK, 26–29 August 2019; pp. 1–9.
54. Raturi, V.; Hong, J.; McArthur, D.P.; Livingston, M. The impact of privacy protection measures on the utility of crowdsourced cycling data. *J. Transp. Geogr.* 2021, 92, 103020.
55. Ohlms, P.B.; Dougald, L.E.; MacKnight, H.E. Assessing the Feasibility of a Pedestrian and Bicycle Count Program in Virginia; Virginia Transportation Research Council: Charlottesville, Virginia, 2018.
56. Strelnikova, D. Comparing the Suitability of Strava and Endomondo GPS Tracking Data for Bicycle Travel Pattern Analysis. Bachelor Thesis, Carinthia University of Applied Sciences, Villach, Austria, 2017. Available online: (accessed on 11 June 2021).
57. SFCTA CyclingTraks for iPhone and Android. Available online: (accessed on 12 June 2021).
58. Brown, G. An empirical evaluation of the spatial accuracy of public participation GIS (PPGIS) data. *Appl. Geogr.* 2012, 34, 289–294.
59. Juhász, L.; Novack, T.; Hochmair, H.H.; Qiao, S. Cartographic vandalism in the era of location-based games—The case of openstreetmap and Pokémon GO. *ISPRS Int. J. Geo-Inf.* 2020, 9, 197.

60. Chen, Z.; van Lierop, D.; Ettema, D. Dockless bike-sharing systems: What are the implications? *Transp. Rev.* 2020, 40, 1–21.
61. Davis, L.S. Rolling along the last mile: Bike-sharing programs blossom nationwide. *Planning* 2014, 80, 10–16.
62. DeMaio, P. Bike-sharing: History, impacts, models of provision, and future. *J. public Transp.* 2009, 12, 3.
63. Fishman, E. Bikeshare: A review of recent literature. *Transp. Rev.* 2016, 36, 92–113.
64. Singla, A.; Santoni, M.; Bartók, G.; Mukerji, P.; Meenen, M.; Krause, A. Incentivizing users for balancing bike sharing systems. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Austin, TX, USA, 25–30 January 2015; Volume 29.
65. Buning, R.J.; Lulla, V. Visitor bikeshare usage: Tracking visitor spatiotemporal behavior using big data. *J. Sustain. Tour.* 2020.
66. Cottrill, C.; Gault, P.; Yeboah, G.; Nelson, J.D.; Anable, J.; Budd, T. Tweeting Transit: An examination of social media strategies for transport information management during a large event. *Transp. Res. Part C Emerg. Technol.* 2017, 77, 421–432.
67. Stock, K. Mining location from social media: A systematic review. *Comput. Environ. Urban Syst.* 2018, 71, 209–240.
68. Park, Y.; Kim, M.; Seong, K. Happy neighborhoods: Investigating neighborhood conditions and sentiments of a shrinking city with Twitter data. *Growth Chang.* 2021, 52, 539–566.
69. Rahman, R.; Redwan Shabab, K.; Chandra Roy, K.; Zaki, M.H.; Hasan, S. Real-Time Twitter data mining approach to infer user perception toward active mobility. *Transp. Res. Rec.* 2021.
70. Heesch, K.C.; Langdon, M. The usefulness of GPS bicycle tracking data for evaluating the impact of infrastructure change on cycling behaviour. *Health Promot. J. Aust. Off. J. Aust. Assoc. Health Promot. Prof.* 2016, 27, 222–229.
71. Turner, S.; Martin, M.; Griffin, G.; Le, M.; Das, S.; Wang, R.; Dadashova, B.; Li, X. Exploring Crowdsourced Monitoring Data for Safety; Bureau of Transportation Statistics U.S. Department of Transportation: Washington, DC, USA, 2020.
72. Oguzoglu, U. COVID-19 Lockdowns and Decline in Traffic Related Deaths and Injuries; IZA Discussion Paper No. 13278; IZA Institute of Labor Economics: Bonn, Germany, 2020.
73. Buehler, R.; Pucher, J. COVID-19 Impacts on Cycling, 2019–2020. *Transp. Rev.* 2021.
74. Almanza, E.; Jerrett, M.; Dunton, G.; Seto, E.; Pentz, M.A. A study of community design, greenness, and physical activity in children using satellite, GPS and accelerometer data. *Health Place* 2012, 18, 46–54.

75. Snizek, B.; Nielsen, T.A.S.; Skov-Petersen, H. Mapping bicyclists' experiences in Copenhagen. *J. Transp. Geogr.* 2013, 30, 227–233.
76. Kumar, L.; Mutanga, O. Google Earth ENGINE applications since inception: Usage, trends, and potential. *Remote Sens.* 2018, 10, 1509.
77. Moran, M.E.; Laa, B.; Emberger, G. Six scooter operators, six maps: Spatial coverage and regulation of micromobility in Vienna, Austria. *Case Stud. Transp. Policy* 2020, 8, 658–671.
78. Moran, M. Drawing the map: The creation and regulation of geographic constraints on shared bikes and e-scooters in San Francisco, CA. *J. Transp. Land Use* 2021, 14, 197–218.
79. Jiao, J.; Bai, S. Understanding the shared E-scooter travels in Austin, TX. *ISPRS Int. J. Geo-Inf.* 2020, 9, 135.

---

Retrieved from <https://encyclopedia.pub/entry/history/show/28106>