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CHAPTER FOUR

Data and data collection for pedestrian planning

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Contents

Abstract

Data is essential for effective urban planning and management. This chapter provides a comprehensive overview of data and data collection techniques for pedestrian planning, aiming to provide researchers and practitioners insights into selecting suitable data and data collection techniques based on their specific pedestrian planning needs. This chapter begins by outlining the taxonomy of data for pedestrian planning, identifying the types of pedestrian behaviour, data types, and data features that are important for pedestrian planning considerations. It specifically identifies four types of data that are essential for pedestrian planning, namely environmental and infrastructure data, traffic data, personal characteristics, and physiological data. This

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chapter provides a comprehensive overview of each type of data used in pedestrian planning and where these data can be sourced. Moreover, this chapter provides an in-depth overview of different data collection techniques used in pedestrian planning, including sensors, crowd sourcing, and eXtended Reality. The advantages and limitations of each technique are also discussed, offering practical insights for employing them for data collection purposes. In summary, this chapter serves as a comprehensive guide to understanding the why, what, where, and how of using data to enhance pedestrian planning. It offers the readers the knowledge to collect and use data effectively, which ultimately supports the designing, planning, and management of pedestrian-friendly urban environments.

1. Introduction

Walking is an essential mode of transportation in today's urban environments. The behaviour of pedestrians is complex and multidimensional, as pedestrians interact continuously and dynamically with their environment, consisting of their infrastructural surroundings and the people in it. Pedestrian planning refers to the process of designing, implementing, and managing infrastructure and policies that prioritize and enhance the safety, accessibility and comfort of pedestrians in urban areas. Another term often used in relation to pedestrian planning is Transit oriented development (Qiang et al., 2022) integrating transit and land-use. Pedestrian planning aims to create environments that encourage walking as a primary mode of transportation, promote physical activity, improve public health, reduce traffic congestion, and enhance the overall liveability of cities and communities. Pedestrian planning relies on a variety of data to effectively design and manage pedestrian-friendly environments. This does not only involve data on pedestrian counts, demographic data, safety data, land use, and data on the various transportation networks, but the comprehensive understanding of pedestrian behaviour is of great significance.

This chapter begins with Section 2, which introduces the taxonomy of data for pedestrian planning, covering essential pedestrian behaviour, types of data, and critical data features. Following this, Section 3 delves into the four key types of data crucial for urban planning, explaining their usage in pedestrian planning and identifying where these data can be found. Section 4 presents the most commonly employed data collection techniques, discussing their respective advantages and limitations. Finally, Section 5 provides a summary of the chapter's key points.

2. Taxonomy of data for pedestrian planning

As indicated in the introduction, pedestrian planning consists of two main elements, namely the design of pedestrian-friendly infrastructure and the management thereof. Pedestrian planning starts with (the design of) the land use and transport infrastructure. This infrastructure should be designed such that its use, for all modes of transport including pedestrians, is safe and attractive. The usage of infrastructure depends on its turn on pedestrian behaviour, including user preferences, socio-economic factors and priorities. In the following, we further detail this pedestrian behaviour, and based on this we identify the requirements for the data and their features for the pedestrian planning process.

2.1 Pedestrian behaviour

(Feng et al., 2021a) provides an overview of the types of pedestrian behaviour. For pedestrian planning, chapter 6 identifies relevant behaviours, activity choice, destination choice, departure time choice, mode choice, route choice, and operational movement choice. All these behaviours are related, not only to each other, but also to other elements of pedestrian planning. Fig. 1 provides a conceptual model, that identifies

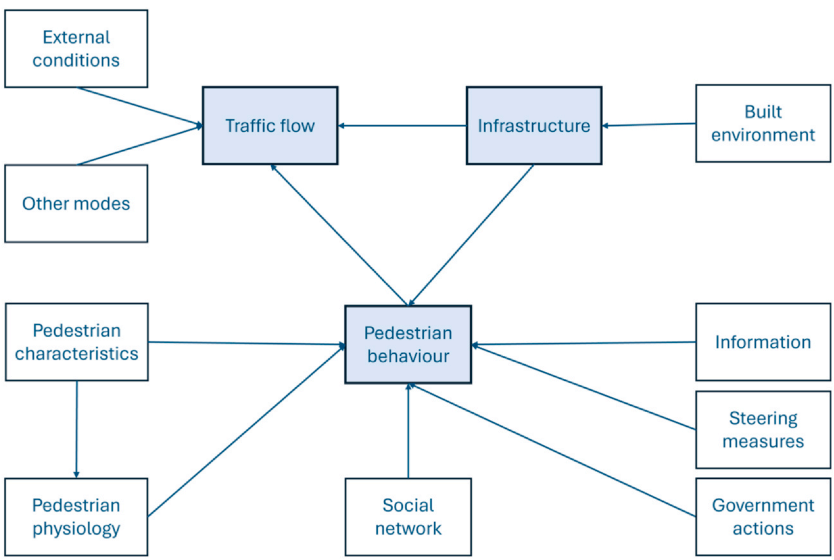

Fig. 1 Conceptual model for pedestrian behaviour in relation to pedestrian planning.

these relations. Knowledge is needed on all elements of the conceptual model, and that for the (pedestrian) planning for a specific area, the corresponding information (and thus data) is required.

2.2 Types of data

We distinguish in the remainder of this chapter three groups of data, namely environment and infrastructure data, use of the infrastructure, and personal characteristics (pedestrians and their demographics), and finally physiological data. Each group in itself entails many different types of data, corresponding to the large amount of data used in literature on pedestrian planning (Qiang et al., 2022).

We can structure data sources along three dimensions: time, space, and granularity (Daamen et al. 2020). The time scale ranges from several microseconds (e.g. delay in propagation of information in autonomous vehicles) to multiple years (e.g. changes of household composition). The spatial scale ranges from a cross-section (e.g. lateral distance between pedestrians) to a whole city (e.g. origin-destination patterns). Finally, the granularity scale relates to the information available on the individual travellers, where low granularity implies little information (e.g. for social media data), while high granularity implies a lot of information per person (e.g. for people participating in a VR experiment). In a way, this granularity is linked to the distinction between microscopic (individual) and macroscopic (aggregate or flow) perspectives.

In pedestrian planning, both real-time and historical data play crucial roles, each offering distinct advantages and serving different purposes. Real-time data refers to information that is collected and available immediately as events occur. In the context of pedestrian planning, this includes live data on pedestrian movements, conditions, and incidents. Real-time data is typically used for immediate insights and responses, safety and emergency management and managing pedestrian flows. On the other hand, historical data refers to information that has been collected over a period and stored for analysis. This includes past records of pedestrian counts, survey results, and incident reports. Applications of historical data can be found in comprehensive understanding of long-term patterns and trends, informed decision-making for future planning and the evaluation of policies and interventions.

Experiments and field observations are two distinct methodologies used to gather data and understand pedestrian behaviour. Experiments involve manipulating certain variables in a controlled environment to observe the effects on pedestrian behaviour. This approach allows for precise measurement and isolation of variables, the ability to establish causal relationships and it provides a safe and ethical testing of potentially disruptive or hazardous scenarios. Its limitations are the possible lack of validity and/or real-world complexity, which makes it harder and sometimes even impossible to generalize to real-world conditions. At the same time, it can be resource-intensive and time-consuming. Field observations involve the direct observation of pedestrian behaviour in real-world settings without manipulating the environment. This approach provides rich, contextual data about how pedestrians interact with their environment naturally. The resulting data have a high validity, are cost-effective and relatively easy to conduct. However, the researcher has limited control over external variables, making it harder to establish causality. Moreover, the data may have potential observer bias and subjective interpretations, while it may require extensive time and effort to gather sufficient data.

2.3 Data features

Understanding the features of data is essential for effectively collecting and analysing different types of data to derive key information for understanding pedestrian behaviour.

Accuracy refers to how close the collected data points are to the true values. The closer the collected data are to the true values, the higher the accuracy. ***Validity*** refers to the extent to which the collected data represents the real-world phenomenon. Several aspects of validity are relevant for pedestrian studies, which include ecological validity, content validity, construct validity, and face validity (Deb et al., 2017). ***Controllability*** relates to the extent to which the data collection process can be managed and influenced by the researchers. This includes the ability to adjust conditions and internal as well as external variables during the data collection process. Another important aspect of data is ***confidentiality***, that is collected data should remain confidential and comply with legal and ethical regulations, such as General Data Protection Regulation (GDPR) (European Parliament and Council of the European Union, 2016) and EU Cybersecurity Act (European Parliament and Council of the European Union, 2019). ***Representativeness*** reflects how well the data reflects the characteristics of the population it is intended to investigate. Data with higher representativeness ensures the derived insights are more generalizable to the broader population. ***Bias*** refers to systematic errors in data collection that lead to inaccuracies or unfair judgments (Pannucci and Wilkins, 2010).

Reproducibility relates to the ability to replicate the data collection process and collect consistent results regarding the data. ***Cost*** refers to the required financial resources for data collection and storage.

3. Types of data for pedestrian planning

A wide variety of data are collected, both by governmental organisations, but also by industry and research institutes and universities. Nowadays, the number of publicly available data sets is keeps growing rapidly, not only in general, but also dedicated to pedestrian planning. The datasets are made available by many persons and organisations and are provided in many different formats. Rather than providing links to existing datasets (which will be outdated in no time), we will provide information on where and how to look for these datasets, and we will give some references of papers using these datasets.

Based on the conceptual model introduced in Fig. 1, we distinguish four main types of data, namely the data on the environment and the infrastructure, data on the use of the infrastructure (traffic), data on personal characteristics and physiological data. In the following, each of these three types of data will be discussed in more detail, including references to papers identifying these data as important for pedestrian planning (first subsection for each type of data). For each type of data, we also have identified whether data sets already exist. If that is the case, we have added with references of papers developing these datasets (second subsection of each type of data).

3.1 Environment and infrastructure

This section introduces the data on the environment and infrastructure, detailing their features and relation to pedestrian planning and pedestrian behaviour. Section 3.1.1 further describes the sources related to the environment and infrastructure, while Section 3.1.2 provides references to existing data sets.

3.1.1 An overview of environment and infrastructure data

A walkability framework is often mentioned as a model that can be adopted in pedestrian planning, not only for micro environments such as university campuses (Abeysinghe et al., 2023), but also in macro environments such as public transport catchment areas (Zeng et al., 2022) and cities as a whole.

These walkability frameworks typically contain neighbourhood environmental attributes and elements (Abeysinghe et al., 2023). Spatial configuration of land use and transport infrastructure does not only directly affect walkability, but it also has a significant impact on mode choice (Limtanakool et al., 2006; Næss, 2012).

The environment and infrastructure cover different features, that can be distinguished as objective and subjective or perceptive features. Where the objective features of different areas can be compared easily, the perceptual qualities of an environment depend on the (subjective) experiences of pedestrians. (Lindelöw et al., 2017) shows that this heterogeneity of preferences should be taken into account in pedestrian planning, as the heterogeneous preferences result in heterogeneous responses for among other things walking frequency.

A wide variety of objective urban physical features that affect walkability and as such pedestrian planning has been mentioned in literature. Sidewalk width, tree canopy, building heights, weather (Abdelfattah and Nasreldin, 2019); shading facilities, obstacle barriers, resting seats around pedestrian walkways, convenience of overpasses and underpasses (Zeng et al., 2022); architectural features such as building floor plans and local landmarks (Durante et al., 2018). Though very relevant, these data are difficult to acquire.

The urban environment is characterized by its richness and multidimensionality of urban streets. The multidimensional nature of streets is typically analyzed using Geographic Information Systems (GIS) due to their ability to efficiently manage multiple layers of information (Orozco Carpio et al., 2024). Recently developed approaches such as 3D modelling, satellite images, and even gamification, allow users to evaluate physical attributes of the urban environment (Gholami et al., 2022; Kumalasari et al., 2023; Bassiri Abyaneh et al., 2021). In addition to simply map urban spaces, point clouds are used to analyze urban environments, optimize walkability, perform path planning and enhance safety when analyzing lighting conditions (Xirui et al., 2022; Xu et al., 2023; Orozco Carpio et al., 2024; Balado et al., 2019). A point cloud consists of numerous three-dimensional (3D) points, each with one or more associated attributes, and is often created using lidar scanners (Fernández-Arango et al., 2022; Zhang et al., 2021).

The environment has been shown to have various perceptual qualities: imageability, legibility, complexity, coherence, enclosure, human scale, linkage, transparency (Abdelfattah and Nasreldin, 2019), aesthetics

(Bhattacharya et al., 2020). More individual reactions to the environment are revealed by a sense of safety, a sense of comfort, and the level of interest (Bereitschaft, 2017).

In addition to the environment, attention should be paid to the design of the infrastructure network. According to (Southworth, 2005), six criteria are relevant to design a successful pedestrian network: (1) connectivity; (2) linkage with other modes; (3) fine grained land use patterns; (4) safety; (5) quality of path; and (6) path context.

3.1.2 Existing data sources

(Wang and Yang, 2019) provide a review and bibliometric analysis on neighborhood walkability. While they provide an overview of 136 papers on the subject of walkability studies using geographical information systems (GIS), they point out that there is a significant data scarcity in comparable and street-level walkability indicators. In the following, some of the most used data sources have been provided.

OpenStreetMap (2024) (OSM, ("Orozco Carpio et al., 2024)) is one of the most widely used platforms for accessing open geographic data, including pedestrian network information (Bessho et al., 2023; Shartova et al., 2023). Most of the data in OSM originates from data of public authorities (Rhoads et al., 2023) but its maintenance, and thus data addition and data checking, is in hands of community of volunteers ('mappers') via open collaboration. Given the increased importance of OSM leading to many public and private actors relying on it, large corporations including Microsoft and Apple have employed editors to increase the data coverage in particular areas of interest (Anderson et al., 2019; Schröder-Bergen et al., 2022). Especially in China, other maps such as Baidu map and Gaodu maps (for PoIs) are available as well (Qiang et al., 2022). In addition to the geographic information, OSM also provides a variety of features (as used in e.g., (Olivari et al., 2023)). However, this is often not enough information for specific applications, such as accessibility research, or is incomplete for residential or rural locations (Roper et al., 2022). For those purposes, dedicated (open) platforms have been created, such as by (Bessho et al., 2023) and (Bartzokas-Tsiompras et al., 2021).

Walkability tools such as OS-WALK-EU (Fina et al., 2022) and Colouring Australia (Roper et al., 2022) typically use more than only the geographic data. Satellite imagery e.g., by the European Copernicus, provided in the Global Human Settlement Layer ("GHSL - Global Human Settlement Layer," 2024) is a source that provides more information about the environment, among other things about the height contours (both of the landscape and the buildings), but also about the built-up surfaces and height, and the distribution of the population (residence density (Fina et al., 2022)).

3.2 Traffic data

This section introduces the traffic data, detailing their features and relation to pedestrian planning. Section 3.2.1 further describes the different types of traffic data, while Section 3.2.2 provides references to existing data sets.

3.2.1 An overview of traffic data

Traffic related environmental stimuli are shown to impact decision making and the ability of pedestrians to navigate unfamiliar spaces (Durante et al., 2018). These stimuli can be quantified using traffic data, which are related to the use of the infrastructure, both by pedestrians (crowding) and other modes. Chapter 3 (on pedestrian flow and crowd operations) and Chapter 5 (on empirical facts on pedestrian flow) show the data related to pedestrian traffic dynamics, such as flow, speed, and density. These data types can also be used to describe cars, whereas in public transport the time table and the routes become more relevant, including among other things number of stops, frequency and routes (Qiang et al., 2022). Most important type of pedestrian data is the counts of pedestrians at different locations in the urban area (Carter et al., 2020).

3.2.2 Existing data sources on traffic data

There are several data sources on traffic available for researchers, ranging from open datasets to proprietary and sensor-based data. As each country has their dedicated datasets, we will only give here a subset of data sources. A search in the country at hand will provide more specific data sources.

Data sources can either contain a static data set that has been collected in the past and does not undergo further changes, or a real-time data set that is continuously increasing by adding the most recent data. With respect to the first type, we distinguish open data sources and sensor and crowdsourced data. Some examples of this type of data are Google Open Traffic Data (Mostafi and Elgazzar, 2021) and national transportation data archives such as the National Transportation Data Archive (NPMRDS) (Turner and Koeneman, 2018), the UK Department for Transport (Chatterton et al., 2015) and the European Data Portal (Kirstein et al., 2019). Many transportation agencies use highway sensors such as loop detectors to provide traffic volume and speed data. In the Netherlands, NDW (National Data Warehouse, n.d.) maintains the NDW portal, which gives access to a wide variety of road data, including cars and bicycles. For real-time traffic data, governments and dedicated companies typically provide so-called APIs (application programming interface), which is a connection between computer programs allowing to access the data.

3.3 Personal characteristics data

This section introduces personal characteristics data, outlining their features and relevance to pedestrian behaviour. Section 3.3.1 first describes key components of personal characteristics data, and Section 3.3.2 lists several existing data sets.

3.3.1 An overview of personal characteristics data

Personal characteristics are one of the most important factors influencing pedestrian behaviour, which includes socio-demographics, attitude, and habit (Götschi et al., 2017).

Socio-demographics typically include age, gender, education level, income, occupation, ethnicity, and migration background. In literature, studies have investigated the influence of age and gender on activity choice, destination choice, and mode choice (De Vos and Alemi, 2020; Figueroa et al., 2014; Patterson et al., 2005; Rosenbloom, 2004), as well as walking speed (Pinna and Murrau, 2018; Rahman et al., 2012; Willis et al., 2004); education level on activity choice and mode choice (De Paepe et al., 2018; Dingil, Esztergár-Kiss, 2022; Limtanakool et al., 2006); income and occupation on mode choice and activity choice (Dieleman et al., 2002; Ko et al., 2019; Zegras and Srinivasan, 2007); and ethnicity and migration background on mode choice (Blumenberg and Evans, 2010; Mattioli and Scheiner, 2022; Tal and Handy, 2010).

Attitudes are considered an important factor in determining travel behaviour (Mehta, 2008; Nicolas et al., 2017). It is defined as "learned predispositions to respond in a consistently favourable or unfavourable way towards a given object, person, or event" by social psychologists (Hayes 1993). Many studies have examined the relationship between attitudes toward travel modes and mode choice, such as cost, flexibility, availability, comfort, privacy, and car ownership (Arroyo et al., 2020; Elias and Shiftan, 2012; Etminani-Ghasrodashti et al., 2018; Lin et al., 2017).

Habits are broadly defined as patterns of behaviour that are acquired through learning and serve to achieve particular goals or outcomes (Verplanken and Aarts, 1999). Pedestrian behaviour or general travel behaviour can become habitual and lead to automatic performance with less need for decision-making processing when actions are repeated (Ouellette and Wood, 1998). A number of studies have examined the effect of travel-related habitual behaviour on activity choice and mode choice (Hoang-Tung et al., 2017; Murtagh et al., 2012; Ralph and Brown, 2019).

Besides individual characteristics, the social environment of a person, including household, social contacts, and neighbourhood, plays an important role in pedestrian travel behaviour. Studies have found that household variables, such as household size, household income, housing source, presence of children and elderly, and car ownership (Zhou and Wang, 2019), have a significant impact on activity choice and planning, as well as mode choice (e.g., Srinivasan and Ferreira, 2002; Chakrabarti and Joh, 2019; Dieleman et al., 2002). Social contacts refer to the various social connections that potentially shape an individual's travel choices, including family members, friends, colleagues, and the broader population. For instance, studies have examined how the size, composition, and mode choice of an individual's social networks influence activity choice and mode choice (Lin and Wang, 2014; Kowald et al., 2015; Phithakkitnukoon et al., 2017). Many studies have examined the relationship between neighbourhood variables, including land use types (e.g., commercial versus industrial), employment levels, housing demographics, service accessibility, and economics (e.g., average dwelling value) (Manaugh et al., 2010), and travel behaviour such as mode choice and activity choice (Kitamura et al., 1997; Cao et al., 2009; Voulgaris et al., 2017; Aditjandra et al., 2012). A more detailed discussion of the impact of social environment on pedestrian behaviour can be found in Chapter 6: Pedestrian travel choice behavior and Chapter 9: Calibration, Validation & Verification.

3.3.2 Existing data sources on personal characteristics

There are several open-source statistical databases that provide data on individuals and their social environment, including demographics, socioeconomic factors, health, and mobility. Global and regional statistics can be found in the World Bank Open Data (https://data.worldbank.org/), United Nations Data (UNdata, http://data.un.org/), OECD Data (https://www.oecd.org/en.html), Eurostat (https://ec.europa.eu/eurostat/) and Gapminder (http://gapminder.org/). Many countries also have open government data initiatives providing social statistics, such as USA (data.gov), UK (https://ukdataservice.ac.uk/), Germany (https://www.destatis.de/), Canada (https://www.statcan.gc.ca/en/start) and the Netherlands (https://www.cbs.nl/en-gb/our-services/open-data).

There are several national surveys around the world that collect travel behaviour data along the personal characteristics data. For instance, the Dutch National Travel Survey (ODiN in Dutch) contains detailed data regarding travel behaviour (e.g., travel trips, travel time, travel modes, and travel purposes) and personal characteristics (e.g., age, gender, income, level of education) of the Dutch population aged 6 years and over. Participants are invited by letter to complete an online questionnaire, which results in an annual sample of over 45,000 respondents (Mobility; per person, modes of travel, purposes of travel and regions, 2024). Similarly, the Netherlands Mobility Panel features travel behaviour of a fixed group of individuals and households in the Netherlands over several years (MPN data, 2024). Other Dutch mobility panels are the Verplaatsingspanel (NVP) and the CBS Safety monitor. In the United Kingdom, the National Travel Survey collects data on personal travel by residents of England via interviews and a seven-day travel diary. It contains information on travel mode, travel purposes, destination choice, and individual information such as age, gender, social and economic information, occupation, household variables, and vehicle information. Approximately 16,000 individuals participate in the survey per year, (National Travel Survey, 2024). Additionally, the National Travel Attitudes Study data, which is derived from a panel survey of people who have completed the National Travel Survey, runs twice a year and collects data on travel attitudes (National Travel Attitudes Study, 2024). In the United States, the National Household Travel Survey collects data on daily non-commercial travel including travel modes, travel purposes, and travel time, along with personal characteristics, such as age, gender, and household composition (National Household Travel Survey, 2024). Similar datasets are often made available by other countries with similar setups of surveys, such as the National Travel Survey in Canada (National Travel Survey, 2024), the Household Travel Survey in Australia (Household Travel Survey, 2021), and the Mobility Panel in Germany (Mobility Panel Germany, 2024).

There are also several datasets that focus on the impact of personal characteristics on pedestrian movement dynamics. For instance, (Subaih, Maree, Chraibi and Awad, 2018) investigated the impact of gender compositions on pedestrian movement dynamics in a corridor. The movement trajectories of 47 participants (26 females and 21 males) were recorded under different densities and gender compositions. Similarly, (Paetzke et al., 2021) focused on the impact of gender compositions on pedestrian movement speed in single-file movement. A total of 40 females and 40 males participated in the experiment and their movement trajectories of the left and right oval were recorded for each experimental run.

3.4 Physiological data (Yan)

This section introduces physiological data and their relevance to pedestrian behaviour. Section 3.4.1 first describes key components of physiological data, and Section 3.4.2 lists several existing datasets that relate to physiological data.

3.4.1 An overview of physiological data

Physiological data is another type of data source to provide insights into pedestrian behaviour with respect to their stress level, cognitive load, emotional response, and physical exertion. Generally, physiological data can be categorized into biological measurements related to cardiac activity, skin response, muscle engagement, and motion movement (Ahn et al., 2019).

Electrocardiography (ECG) and photoplethysmography (PPG) are the most commonly used indicators to reflect cardiac activity. Literature often uses ***Heart Rate (HR)*** and ***Heart Rate Variability (HRV)*** to measure the impact of environmental factors in the built environment on pedestrian stress level (Ahn et al., 2020; Kim et al., 2020, 2019; Lajeunesse et al., 2021).

Electrodermal activity (EDA) refers to autonomic changes in the electronic properties of the skin, which commonly features ***Skin Conductance Response (SCR)*** and ***Skin Conductance Level (SCL)*** (Braithwaite et al., 2013). EDA is widely used as an indicator of arousal and activation of the sympathetic nervous system. Studies have used EDA data to examine the impact of environmental stimulus (Birenboim et al., 2021; Kim et al., 2020), road infrastructure (Lajeunesse et al., 2021), and crowd density (Engelniederhammer et al., 2019) on pedestrian emotional responses.

Electroencephalography (EEG) measures the electrical activity of the brain recorded by electrodes and it is well established that EEG data can reflect cognitive load and attention (Antonenko et al., 2010). EEG is often used in accessing pedestrian spatial awareness, cognitive processes, and perceptual attention during wayfinding and evacuation (Occhialini et al., 2016; Erkan, 2018; Kalantari et al., 2022; Mavros et al., 2022).

Electromyography (EMG) captures the electrical potentials created by skeletal muscle cells during their contractions (Chen et al., 2011). It is commonly used to reflect obvious or unapparent movement intentions during pedestrian walking, such as stride frequency, stride lengths, and walking patterns (Chen et al., 2011; Courtine and Schieppati, 2003; Gasparini et al., 2020; Wang et al., 2013).

Advanced **motion tracking** technologies, such as eye tracking and full-body motion capturing, provide new possibilities to analyze pedestrian virtual attention and physical movement. Eye tracking data (e.g., gaze patterns, gaze time, and gaze sequences) are widely used to analyze the information acquisition process during wayfinding and evacuation process (Bae et al., 2020; Beek et al., 2024a; Feng et al., 2022b; Wiener et al., 2012). The full-body motion-capturing system records the three-dimensional movement of individuals. While its usage is still in its infancy, (Feldmann et al., 2024) used 3D motion data to understand the human body's reaction to impulses in a crowd regarding inter-person distance, forward velocity, and the margin of stability.

3.4.2 Existing data sources on physiological data

Compared to other data types, there are relatively few available datasets that feature physiological data that is relevant for pedestrian behaviour and planning. For instance, (Di Nardo et al., 2024) provides a dataset composed of long-lasting surface electromyographic signals from 2011 and 2018 during ground walking from 31 young able-bodied subjects (ages 20 to 38 years old). (De Winter et al., 2022) used a Tobii Pro Glasses 2 eye-tracker to record eye movement data of 43 participants (21 females, 22 males) who walked a short route in a parking garage. This study aimed to understand what pedestrians look at when walking through a parking garage. In total, a total of 12,996 fixations were recorded with an average of 302 fixations per participant. Another study aimed to understand how pedestrians react to an external force and how pushes propagate along a row (Feldmann et al., 2022). In this study, motion suits and cameras were used to record pedestrian movement. Five participants, aged 19 to 55 years old, wore Inertial Motion Capturing (MoCap) suits from Xsens and their head trajectories were also recorded with an overhead and side-view camera. The MoCap data was then combined with the head trajectories to gain a complete dataset of each participant's 3D full-body motion in space. Additionally, the intensity of each push was recorded using a pressure sensor LX210:50.50.05 from Xsensor. (Üsten and Sieben, 2021) recorded the heart rate and heart rate variability data using EcgMove 4 to investigate the effects of interruptions on individuals from both psychological and crowd dynamics perspectives.

4. Data collection techniques

Effective data collection plays a vital role in collecting data for the purpose of understanding pedestrian behavior and pedestrian planning. Various data collection techniques have been employed to collect the above-mentioned different types of data. This section categorizes the most commonly applied data collection techniques in the field of pedestrian studies into three main groups, namely sensors (Section 4.1), surveys (Section 4.2), social media (Section 4.3), eXtended Reality (Section 4.4) and laboratory experiments (Section 4.5). The specific techniques within each category are further detailed, discussing their advantages and limitations to highlight their roles in collecting diverse types of data. This also covers some practical insights into how these data collection techniques can be effectively employed for data collection purposes, providing a comprehensive overview for researchers and practitioners in the field. The last subsection relates to data analyses, as sometimes data is collected for a different purpose, but with post processing, it can be used as input for pedestrian planning or to monitor pedestrian flows.

4.1 Sensors

Early pedestrian and bicycle monitoring relied on counting methods and travel surveys, with site counting being the most traditional approach (Lee and Sener, 2020). Manual site counting by human observers used to be the main method to collect pedestrian traffic volumes (Ryus et al., 2014), but more advanced techniques have been developed since (Lee and Sener, 2020).

The Global Positioning System (GPS) is the only viable option for outdoor positioning (Abdulateef and Makki, 2023). GPS offers the advantage of precise location tracking, which is crucial for real-time visualization and crowd management (Blanke et al., 2014; Kapoor and Brar, 2023; Wirz et al., 2012). The position information can be used to calculate crowd count movement data, density, velocity, turbulence, and pressure. The drawback is that signal loss may be experienced in dense urban areas (Ma et al., 2024) or indoors (Abdulateef and Makki, 2023), which can potentially diminish its accuracy and reliability in different environments.

Electromagnetic and radio frequency analysis (Donelli et al., 2021; Fadhlullah and Ismail, 2016; Progri et al., 2007), as well as Bluetooth (Christoe et al., 2021; Fadhlullah and Ismail, 2016; Weppner and Lukowicz, 2013) and WiFi (Garcia-Villalonga and Perez-Navarro, 2015;

Kurkcu and Ozbay, 2017; Li et al., 2014; Wu et al., 2016) are different ways of signal tracking. All three sensing techniques may offer data on crowd signal density and movement patterns, including origin-destination matrices. However, these techniques can only be applied in environments with wireless infrastructure, which makes it less suitable for indoor infrastructure such as underground parking (Piao et al., 2023). While electromagnetic and radio frequency observe the pedestrians directly, Bluetooth and Wi-Fi signal tracking detects devices, which then needs to be translated into crowd counts. The detection process of both Bluetooth and WiFi devices operates in cycles where the sniffer transmits messages across various frequencies and waits for devices to respond. (Michau et al., 2014) found that Bluetooth devices need to remain in discoverable mode for approximately 10 s within the detection zone to be identified. The detection rate is however rather low, around 2 % as reported by (Lesani and Miranda-Moreno, 2018). Compared to Bluetooth, WiFi has a shorter discovery time, allows distance estimation from the sensor based on signal strength, and is considered a more suitable standard for pedestrian data collection (Abedi et al., 2013). The observation methods leverage existing infrastructure and personal devices to gather data, making them cost-effective and less intrusive than other alternatives. However, privacy concerns may arise since individuals might not be aware their devices are being used for data collection. Moreover, the accuracy of these methods may vary depending on device density, the specific technical setup of the sensors, physical conditions as well as weather (Michau et al., 2014).

CCTV footages (Ahuja and Charniya, 2019; Cho et al., 1999; Gerogiannis and Bode, 2024; Sindagi and Patel, 2018; Wang et al., 2022; Zhang et al., 2018). Footages can be either derived from a fixed mounted device, or from mobile devices on vehicles or drones (Jiang et al., 2021; Xiao et al., 2021). CCTV and drone footage offer visual data of the crowd. The advantage of these technologies is that the sensors typically cover large areas, which makes it possible to detect, and thus monitor, abnormal patterns quickly, being essential in crowd monitoring for safety purposes. The implementation or application of these visual tools entails substantial setup and maintenance costs. Moreover, they pose significant privacy concerns, as continuous surveillance is often regarded as intrusive by the public. uB-VisioGeoloc (Scalvini et al., 2024) is a data set consisting of pedestrian navigation (image) data sequences combining visual and spatial information for encountered by a pedestrian walking in an urban outdoor environment.

Stereo vision cameras are traditionally used in autonomous vehicles to track pedestrians around the vehicle (Nguyen et al., 2019). Stereo cameras are used to generate noisy point cloud data (Eppenberger et al., 2020), after which data analytics (typically deep neural networks) are applied to identify static and dynamic objects in the data that can be tracked over time (Mueller and Wuensche, 2017; Konrad et al., 2018; Zhong et al., 2020). Compared to monocular cameras, stereo vision provides the depth information, allowing for accurate pedestrian localization and distance measurements. This depth information also helps to distinguish pedestrians from the background and other topics. While the stereo vision cameras produce large amounts of data, the resulting depth image is privacy proof, as personal information is omitted from the images. While better than monocular cameras, stereo vision still struggles with heavy crowd occlusions compared to overhead sensors.

MmWave radars gained recently significant attention (Gu et al., 2023; Wang et al., 2023) To prevent privacy issues, occlusions and lower accuracy at lower light conditions. mmWave radar sensors are single-chip radar sensors with extremely high resolution and low power consumption (Bhatia et al., 2021). mmWave sensors use software to analyse the reflected signals, hence providing activity sensing, people positioning, and object detection. Simultaneous Localization and Mapping (SLAM) algorithms have been recently used to improve the accuracy of ubiquitous positioning. Among SLAM algorithms, GraphSLAM is the most efficient algorithm for the offline SLAM problem (Schuster et al., 2016). GraphSLAM has been further improved for indoor environments resulting in MMGraphSLAM, which reaches a mean accuracy of 0.52 m (Piao et al., 2023). Also here, further improvements in accuracy have been acquired by combining mmWave sensors with other sensors such as camera vision (Yang et al., 2023).

More recently, also Light Detection and Ranging (LiDAR) sensors are used to detect and track pedestrians (Tanida et al., 2024; Tarko et al., 2018), as they provide a 3D map of their environment. LIDAR is a method for determining distances between an object and the sensor by directing a laser at an object or surface and measuring the time it takes for the reflected light to return to the receiver. Lidar can operate in a fixed direction (e.g., vertical) or scan multiple directions, in which case it is referred to as lidar scanning or 3D laser scanning. The result of the scanning is a point cloud of all objects in its scanning range, for which post-processing is needed to classify the objects (Wu et al., 2020; Zhao et al., 2018), which makes its accuracy dependent on the accuracy of those post-processing algorithms.

Infrared sensors detect infrared (IR) radiation emitted by humans or animals and convert this optical signal into an electronic one. While this technology is advantageous for nighttime surveillance compared to video cameras, it can produce inaccurate results due to occlusions or similar textures (Kristoffersen et al., 2016). Additionally, the camera is cumbersome and has high power consumption. Some of these drawbacks have been accounted for by passive infrared sensors (PIR, (Akhter et al., 2019)). These low-cost, low-power passive sensors respond when an infrared (IR) emitting subject such as (humans or animals) passes through the field of view of a Fresnel lens (Mukhopadhyay et al., 2018). PIR sensors do not violate human privacy. (Akhter et al., 2019) have developed an intelligent algorithm to convert pedestrian detection into pedestrian count, which provides highly accurate results: more than 90 % accurate compared to manual counting.

4.2 Surveys

Traditionally, surveys are the main way to collect data on pedestrians in urban environments (Ryus et al., 2014). Various types of surveys can be utilized to collect (Abeysinghe et al., 2023; Aden et al., 2020; Kumari, 2021). These surveys aim to understand pedestrian behaviours, preferences, and needs, which can inform the design and improvement of pedestrian infrastructure. Typically, the users of the urban environment are targeted for the distribution of surveys, but several researchers also address expert groups (Stangl, 2011), to get more specific background information on the planning process. The primary types of surveys for pedestrian planning include (references are given to examples of studies using these types of data in pedestrian planning):

- Pedestrian intercept survey (Buckley et al., 2017). These surveys gather real-time data on pedestrian experiences, travel patterns, preferences, and perceptions of the walking environment. The surveys are typically conducted by interviewing pedestrians at key locations such as intersections, public spaces, or transit stops.
- Household travel surveys (Choi and Guhathakurta, 2024; Kweon et al., 2023). These surveys aim to understand overall travel behaviour, including walking trips, trip purposes, and mode choices. To this end, daily travel diaries or related questionnaires are administered to households to collect detailed information on travel behaviour (including walking trips) and patterns over a specified period.

- Focused questionnaires. These questionnaires are designed to analyze pedestrian specific travel behavior in detail, often with a focus on one of the aspects of this behavior, such as walkability perception (Moura et al., 2017; Aromal and Naseer, 2022), safety concern (Bazargan et al., 2020; Park and Garcia, 2020) or route choice (Basu et al., 2023; Barros et al., 2015). The questionnaires are typically shorter than household travel surveys, address a smaller and more targeted sample and use on-line forms.
- Walking audits (Annear et al., 2024; Ma et al., 2021). Walking audits are assessments conducted by individuals or groups walking through specific areas to evaluate the pedestrian infrastructure and environment. These audits may cover a wide variety of evaluations concerning e.g., sidewalk conditions, street crossings, lighting, and accessibility features. Dedicated audit tools have been developed (Arellana et al., 2020; Moura et al., 2017).
- Focus groups (Penerbit, 2023; Yadav and Kumari, 2024). Focus groups consist of group discussions with selected participants to gather in-depth insights on specific pre-determined issues. It is a thorough research approach to explore attitudes, motivations, and detailed opinions about walking experiences and infrastructure.
- Public workshops and community meetings (Labbé et al., 2023). Interactive sessions with community members can be organised to discuss pedestrian planning issues and gather feedback. This way, the community can be engaged in the planning process and qualitative data on pedestrian needs and preferences can be collected. Especially when it is not yet clear which data needs to be collected, a workshop has a sufficiently broad setup to collect a wide range of data.

Each of these survey types offers unique insights and can be selected based on the specific goals and context of the pedestrian planning project. One of the potential drawbacks is that the surveys are mainly targeted towards local residents of urban districts and typically have a homogeneous, older audience (Hausmann et al., 2017). Modern means of communication, such as mobile applications and web apps to engage pedestrians while walking are therefore a valuable alternative (Hausmann et al., 2017).

4.3 Social media

By leveraging social media data, pedestrian planners can gain a comprehensive understanding of pedestrian behaviors, preferences, and needs (Aman et al., 2022; Gong et al., 2018). As such, there is a wide variety of applications for social media data:

- Identifying popular routes and areas (Al-Kodmany, 2019; Zhang et al., 2020).
- Understanding public sentiment (Aman et al., 2022; Gong et al., 2019).
- Crowdsourced data collection (He and He, 2023; Yang et al., 2024).
- Temporal analysis of pedestrian activity (Lai and Kontokosta, 2017; Rybarczyk et al., 2018).
- Identifying crowd composition (Gong et al., 2019).

To analyse the social media data, which consists of text and/or pictures, a variety of tools and techniques have been developed, among which Natural Language Processing (NLP, to analyze text data and understand sentiments, themes, and topics discussed by pedestrians) (Aman et al., 2022), computer vision (CV) to analyze the figures in social media data (Aman et al., 2022), geospatial analysis to visualize and analyze location-based data, identifying spatial patterns and trends (Rybarczyk et al., 2018; Suvannadabha et al., 2022), Machine Learning Algorithms to detect patterns, classify data, and predict pedestrian behaviors based on social media activity (Tang et al., 2022; Yang et al., 2024) and sentiment analysis to gauge public opinion and sentiment towards pedestrian infrastructure and policies (Gong et al., 2019).

4.4 eXtended reality (XR)

eXtended Reality (XR) is an umbrella term that covers Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR), which are commonly used terms to describe how technologies create or modify reality via utilizing computer simulation and immersive sensory experiences (Rauschnabel et al., 2022). XR has been increasingly used in pedestrian research due to its advantage of complete experimental control while automatically collecting accurate pedestrian behavioural data. Additionally, XR can collect advanced physiological data with the integration of other biosensors. Furthermore, XR allows participants to be virtually immersed in (dangerous) environments without exposing them to real physical dangers (Feng et al., 2021b).

AR integrates 2D information or 3D virtual objects into a real environment in real time (Azuma, 1997). For example, Google AR glasses display 2D information on the glasses to provide notifications and Pokémon GO game overlays 3D virtual characters onto real-world locations through a smartphone camera. AR can be available through a variety of devices, including mobile phones, headsets, and smart glasses. Mobile AR captures live video feeds of the real-world environment and integrates other sensor data to process and overlay digital content in real time. In contrast, head-mounted-display (HMD) AR requires users to wear a headset (such as Microsoft HoloLens) or smart glasses (such as Magic Leap). There are built-in cameras and sensors in the HMDs to capture and analyse the real-world surroundings of the users. Digital contents are projected directly onto the lenses of the headsets or smart glasses, which allows for a hand-free and more immersive experience. With the ability to project digital content into the real world, AR has been increasingly applied to study pedestrian behaviour and training in the context of emergency evacuations and wayfinding. They can be categorised into two groups, including:

- pedestrian evacuation behaviour, such as evacuation time (Rehman and Cao, 2017; Wada et al., 2021) and evacuation route choice (Ahn and Han, 2012)
- evacuation training (Iguchi et al., 2016; Catal et al., 2020; Paes et al., 2024) and wayfinding performance training (Qiu et al., 2024; Xu et al., 2024)

In contrast to AR, VR commonly immerses users in a simulated virtual environment that can sense the user's position and actions and replace or augment feedback to one or more senses (Sherman and Craig, 2018). For instance, Feng, Duives and Hoogendoorn (2022a) created a virtual replica of a real-life building, allowing participants to immerse themselves and navigate through the entire building. Based on the level of immersion, VR can be generally categorized into non-immersive VR and immersive VR. In non-immersive VR, the virtual environment is displayed on a device like a desktop monitor, and users interact with it using a mouse, keyboard, or joystick (e.g., Feng, Duives and Hoogendoorn, 2021). In immersive VR, the virtual environment immerses participants via sophisticated sensory interfaces, who interact with it using specialized control devices like joysticks or gloves, alongside motion tracking hardware such as eye, head, and motion tracking devices (e.g., Feng, Duives and Hoogendoorn, 2022a). VR has been widely applied to collect data that record pedestrian timestamps, movement coordinates and choice that feature:

- pedestrian route and exit choice (Kobes et al., 2010; Feng, Duives and Hoogendoorn, 2021, 2022a; Zhang et al., 2023; Beek Van Duives et al., 2024)
- pedestrian movement dynamics and performance (Fink et al., 2007; Sanz et al., 2015; Feng, Duives and Hoogendoorn, 2022a; Beek Van Duives et al., 2024)
- social influence on pedestrian behaviour (Kinateder, et al., 2014, 2018; Fu et al., 2021)

Suitability and validity are two important aspects of utilising VR for pedestrian behaviour studies and are receiving increasing attention. Suitability refers to which VR mode (non-immersive or immersive VR) is best suited for studying specific types of pedestrian behaviour. For instance, Duives and Hoogendoorn (2022b) and Dai et al. (2024) compared the adoption of different VR technologies for pedestrian wayfinding studies, such as non-immersive versus immersive VR and 2D versus 3D virtual environments. Validity refers to whether the behavioural results gathered through VR accurately reflect real-world pedestrian behaviour. For instance, Kobes et al. (2010), Kinateder and Warren (2016) and Arias et al. (2022) compared pedestrian evacuation behaviour between a physical and VR experiment; Beek et al. (2024) provided a direct comparison of pedestrian wayfinding behaviour between a field and an identical VR experiment.

MR can be seen as a mix of real and virtual objects within a single display on a spectrum between a fully real and a fully virtual environment (Milgram, 2012). For example, Microsoft HoloLens enables users to interact with holographic objects overlaid onto the real world. Compared to the extensive body of studies that applied VR and AR to study pedestrian behaviour, there are only a few studies that have applied MR to investigate pedestrian behaviour in the context of evacuations (Chen et al., 2022).

Overall, XR provides high accuracy in data collection because it collects data at a high frequency automatically through XR devices (Feng et al., 2021a). Regarding validity, XR provides relatively high validity for pedestrian behaviour at strategic and tactical levels. For instance, (Suma et al., 2010; Li et al., 2019; Ewart and Johnson, 2021; Feng, Duives and Hoogendoorn, 2021; Beek et al., 2024) has shown that results generated via XR are consistent with real-life situations. For pedestrian movement dynamics, AR and MR offer improved ecological validity compared to VR because pedestrians can move within real-life situations. Meanwhile, VR enhances internal validity as it offers a more immersive experience. Similarly, because VR allows researchers to create and modify any virtual environments, it provides a higher level of controllability compared to AR and MR, which are still influenced by real-world surroundings. In terms of representativeness and reproducibility, VR has the advantage since data collection is not restricted to location or time. This allows for conducting the same data collection repetitively at different locations and times (Feng et al., 2021a).

4.5 Laboratory experiments

The previous sections have discussed different techniques to collect data. These techniques can be applied in real-world situations, but also in laboratory settings. Laboratory experiments are often applied to get insights into specific pedestrian behaviours, while real-world studies provide broader insights. Laboratory experiments provide controlled, replicable conditions, where external variables (think of weather, traffic, distractions) can be eliminated (Daamen and Hoogendoorn, 2003). This also makes it possible to repeat the experiments under identical conditions, improving the reliability of the results. Finally, detailed data collection can be performed, using motion capture, eye tracking or tracking sensors (as described earlier in this chapter), while the settings of the sensors can be optimized for the situation at hand (Shi et al., 2018; Feng et al., 2021) provides a systematic literature review on data collection experiments for pedestrian behaviour study. Although experiments are not entirely natural since participants are aware they are being observed, they still involve real human interactions within a physical environment. Overall, experiments offer a reasonable balance between control, measurement accuracy, and realism (Feliciani and Nishinari, 2018; Geoerg et al., 2021) and are particularly effective for studying pedestrian locomotion (Bode et al., 2015; Liao et al., 2017; Wagoum et al., 2017).

Complex pedestrian walking behaviours range from uni-directional to multi-directional movement behaviours. (Duives et al., 2013) presents eight crowd motion base cases and states that the combination of these cover the full range of pedestrian movements. Laboratory experiments are thus often focused on one or more of these motion base cases.

Several papers have been written with overviews of performed laboratory experiments (Shi et al., 2018; Haghani, 2020; Dong et al., 2019). In these papers, more details on the different experiment can be found, including suggestions on how to set them up and best practices.

5. Data analytics and data fusion

Data analytics refers to the process of collecting, processing, analyzing, and interpreting data to extract meaningful insights, patterns, and trends. It involves techniques such as statistical analysis, machine learning, and visualization to support decision-making. This way, existing data sources can be used to get more insights into pedestrian behaviour. Some of these data analytics also increase the accuracy of a sensor, think of smart sensors and beacon systems as described below.

Smart sensors are the combination of data analytics and regular video footage. Using dedicated software applications precise crowd count, size, density, and flow can be derived from video images, but also individual trajectories. The maximum accuracy for outdoor application is 85% (Barthélemy et al., 2019). In addition, the accuracy of detection, tracking and classification is sensitive to external factors, such as weather and lighting conditions (Fu et al., 2015; Thi et al., 2008; Yoneyama et al., 2005). The advantage of smart sensors over traditional CCTV footage is the lower privacy concerns, as the images are directly analysed on the sensor, and only the anonymised derived data leaves the sensor and will further be processed.

To solve the drawback of signal loss in micropositioning, beacon systems can be used, especially for locations that are semi-indoor or where surrounding infrastructure limits signal accessibility. Dedicated systems such as FinderX (Hasan and Hasan, 2021) have been developed, which also reduce the time to find the amenities. For indoor positioning, these beacons are often combined with postprocessing software (machine learning, dead reckoning, Kalman filters) to make the positioning more accurate (Liu et al., 2015; Sung et al., 2018; Wang et al., 2019). These beacon systems suffer from the fact that they need reference points, and the underlying software assumes that the infrastructure remains fixed. In more dynamic environments, a combined system of beacons and CCTV could be used to overcome those problems (Lee et al., 2022).

Data fusion is the process of integrating data from multiple sources to produce more accurate, consistent, and useful information than what would be obtained from individual sources alone. Especially in ITS application a wide variety of methodologies exists to enrich the data (Ounoughi and Yahia, 2023). While applications for indoor pedestrian positioning (Zhao et al., 2019; Huang et al., 2019) and for urban planning (Kashinath et al., 2021; Zou et al., 2025) exist, dedicated examples for pedestrian planning are scarce (Li et al., 2021).

6. Summary

Walking is crucial in urban transportation, where pedestrian behaviour is influenced by the infrastructure and the environment. Pedestrian planning involves designing and managing infrastructure to ensure safety, accessibility, and comfort for pedestrians, encouraging walking, enhancing public health, reducing congestion, and improving urban liveability. This chapter discusses the data that are needed for the design and management of pedestrians in the urban environment.

To identify which data are needed, a conceptual model has been developed for pedestrian behaviour in relation to pedestrian planning. From this conceptual model, four types of data can be derived:

- Environment and infrastructure data, containing details of land use, transport infrastructure, and their impact on pedestrian safety and attractiveness. More specifically, these are data on walkability, urban physical features, and perceptual qualities of environments. Sources include OpenStreetMap and walkability tools like OS-WALK-EU.
- Data on the use of Infrastructure, or traffic data. These data provide information on pedestrian, cyclist and vehicle flow, public transport timetables, vehicle occupancy and routes.
- Data on pedestrian characteristics. Socio-demographic information, attitudes, habits influencing pedestrian behavior, collected through various studies and surveys.
- Physiological data. These data consist of biological measurements like heart rate, skin response, brain activity, and muscle engagement to assess pedestrian stress, cognitive load, and physical exertion.

The data can be structured in several ways. First of all, data for pedestrian planning can be structured along three dimensions: time (ranging from microseconds to several years), space (from cross-sections to whole cities) and granularity (ranging from the individual level (high granularity) to aggregated levels (low granularity)). Another distinction is the difference between real-time and historical data, where real-time data are available immediately (used for managing pedestrian flows, safety, and emergency responses), while historical data is collected over time (used for understanding long-term trends, decision-making, and policy evaluation). The last distinction that has been introduced is the difference between experiments and field observations. Where experiments cover controlled environments to manipulate variables and observe pedestrian behaviour, allowing for precise measurement and establishing causal relationships, provide field observations real-world settings to observe natural pedestrian behaviour, providing rich contextual data with high validity.

Table 1 Comparative overview of features for different types of data.

Data type	**Data feature**							
	Accuracy	**Validity**	**Controllability**	**Confidentiality**	**Representativeness**	**Bias**	**Reproducibility**	**Cost**
Environment and infrastructure data	High	Medium	Low	Low	Medium	Low	Medium	Low
Traffic data	High	Medium	Low	High	High	Low	Medium	Medium
Personal data	Medium	Medium	Medium	High	Medium	High	Low	Low
Physiological data	High	High	High	High	Medium	Low	Low	Medium

Essential features for effective data collection and analysis include accuracy, validity, controllability, confidentiality, representativeness, bias, reproducibility, and cost. The different types of data that have been distinguished before have varying degrees of these features. Table 1 shows a comparative overview of the above-mentioned features for different types of data, namely environment and infrastructure data, traffic data, personal data, and physiological data. Additionally, we provide a quantitative assessment of these features for each data type, ranking them as low, medium, and high based on their relative prominence. This assessment helps in understanding the strengths and limitations of each data type.

The last part of the chapter provides a comprehensive overview of the types and features of data used in pedestrian planning, highlighting the importance of accurate, valid, and representative data for effective urban planning and management. Moreover, it focuses on the techniques that can be used to collect the data, showing references to both data collection and how to apply the data for pedestrian planning.

References

Abdelfattah, D., Nasreldin, R., 2019. Perceptional dimension towards more walkable communities: an assessment tool approach. J. Urban. Res. 33 (1), 172–183.

Abdulateef, A.T., Makki, S.A., 2023. A survey of indoor positioning systembased-smartphone. 2023, AIP Conference Proceedings 4Th International Scientific Conference of Alkafeel University (ISCKU 2022), p. 030005 AIP Publishing.

Abedi, N., Bhaskar, A., Chung, E., 2013. Bluetooth and Wi-Fi MAC address based crowd collection and monitoring: benefits, challenges and enhancement. Proceedings of 36th Australasian Transport Research Forum, Brisbane, Queensland, Australia 1–17.

Abeysinghe, U., Saparamadu, S., Hewawasam, C., 2023. Influence of neighborhood environment attributes on the walkability of university students. In: 2023 Moratuwa Engineering Research Conference (MERCon), pp. 310–315.

Aden, W.A., Zhao, S., Subhan, F., Zhou, H., Ullah, I., 2020. A comparative study on pedestrians' intention to violate traffic rules: the case of China and Djibouti. J. Road. Traffic Eng. 66 (3), 1–9.

Aditjandra, P.T., Cao, X.J., Mulley, C., 2012. Understanding neighbourhood design impact on travel behaviour: an application of structural equations model to a British metropolitan data. Transp. Res. A: Policy Pract. 46 (1), 22–32.

Ahn, J., Han, R., 2012. An indoor augmented-reality evacuation system for the Smartphone using personalized Pedometry. Human-centric Comput. Inf. Sci. 2 (1), 1–23.

Ahn, C.R., Lee, S., Sun, C., Jebelli, H., Yang, K., Choi, B., 2019. Wearable sensing technology applications in construction safety and health. J. Constr. Eng. Manag 145 (11), 1–17.

Ahn, C., Ham, Y., Kim, J., Kim, J., 2020. A digital twin city model for age-friendly communities: capturing environmental distress from multimodal sensory data. In: Proceedings of the Annual Hawaii International Conference on System Sciences, 2020-Janua, pp. 1675–1684.

Ahuja, K.R., Charniya, N.N., 2019. A survey of recent advances in crowd density estimation using image processing. In: 2019 International Conference on Communication and Electronics Systems (ICCES), pp. 1207–1213.

Akhter, F., Khadivizand, S., Lodyga, J., Siddiquei, H.R., Alahi, M.E.E., Mukhopadhyay, S. C., 2019. Design and development of an IoT enabled pedestrian counting and environmental monitoring system for a smart city. In: 2019 13th International Conference on Sensing Technology (ICST), pp. 1–6.

Al-Kodmany, K., 2019. Improving understanding of city spaces for tourism applications. Buildings 9 (8), 187.

Aman, J., Matisziw, T.C., Kim, J.B., Luo, D., 2022. Sensing the City: leveraging geotagged social media posts and street view imagery to model urban streetscapes using deep neural networks. In: Proceedings of the International Conference on Computer-Aided Architectural Design Research in Asia, Association for Computer-Aided Architectural Design Research in Asia pp. 595–604.

Anderson, J., Sarkar, D., Palen, L., 2019. Corporate editors in the evolving landscape of OpenStreetMap. ISPRS Int. J. Geo-Information 8 (5), 232.

Annear, M., Fristedt, S., Laddawong, T., 2024. Walkability in Japan's aging neighborhoods: a comparative audit analysis of pedestrian journeys in urban Tokyo. J. Transp. & Health 35, 101755.

Antonenko, P., Paas, F., Grabner, R., Van Gog, T., 2010. Using electroencephalography to measure cognitive load. Educ. Psychol. Rev. 22 (4), 425–438.

Arellana, J., Saltarín, M., Larrañaga, A.M., Alvarez, V., Henao, C.A., 2020. 'Urban walkability considering pedestrians' perceptions of the built environment: a 10-year review and a case study in a medium-sized city in Latin America. Transp. Rev. 40 (2), 183–203.

Arias, S., Mossberg, A., Nilsson, D., Wahlqvist, J., 2022. A study on evacuation behavior in physical and virtual reality experiments. Fire Technol 58 (2), 817–849.

Aromal, V., Naseer, M.A., 2022. A methodology for the identification of significant factors for the improvement of pedestrian facilities in an urban area. J. Urban. Manag 11 (3), 353–364.

Arroyo, R., Ruiz, T., Mars, L., Rasouli, S., Timmermans, H., 2020. Influence of values, attitudes towards transport modes and companions on travel behavior. Transportation Res. Part. F: Traffic Psychol. Behav 71, 8–22.

Azuma, R.T., 1997. A survey of augmented reality. Teleoperators Virtual Environ 6 (4), 355–385.

Bae, Y.H., Kim, Y.C., Oh, R.S., Son, J.Y., Hong, W.H., Choi, J.H., 2020. Gaze point in the evacuation drills: analysis of eye movement at the indoor wayfinding. Sustainability (Switz.) 12 (7), 1–14.

Balado, J., Díaz-Vilariño, L., Arias, P., Lorenzo, H., 2019. Point clouds for direct pedestrian pathfinding in urban environments. ISPRS J. Photogrammetry Remote. Sens 148, 184–196.

Barros, A.P., Martínez, L.M., Viegas, J.M., 2015. A new approach to understand modal and pedestrians route in Portugal. Transportation Res. Procedia 10, 860–869.

Barthélemy, J., Verstaevel, N., Forehead, H., Perez, P., 2019. Edge-computing video analytics for real-time traffic monitoring in a smart city. Sensors 19 (9), 2048.

Bartzokas-Tsiompras, A., Photis, Y.N., Tsagkis, P., Panagiotopoulos, G., 2021. Microscale walkability indicators for fifty-nine European central urban areas: an open-access tabular dataset and a geospatial web-based platform. Data Brief 36, 107048.

Bassiri Abyaneh, A., Allan, A., Pieters, J., Davison, G., 2021. Developing a GIS-based tourist walkability index based on the AURIN walkability toolkit—case study: Sydney CBD. Urban Informatics and Future Cities. Springer, Cham, Switzerland, pp. 233–256.

Basu, N., Oviedo-Trespalacios, O., King, M., Kamruzzaman, M., Haque, M.M., 2023. What do pedestrians consider when choosing a route? The role of safety, security, and attractiveness perceptions and the built environment during day and night walking. Cities 143, 104551.

Bazargan, H.S., Haghighi, M., Heydari, S.T., Soori, H., Shahkolai, F.R., Motevalian, S.A., Mohammadkhani, M., 2020. Developing and validating a measurement tool to self-report pedestrian safety-related behavior: the pedestrian behavior questionnaire (PBQ). Bull. Emerg. & Trauma 8 (4), 229.

Beek, A., Van, Duives, D.C., et al., 2024. Comparison of pedestrian wayfinding behavior between a real and a virtual multi-story building – A validation study. Transp. Res. C: Emerg. Technol. 163, 104650.

Beek, A., Van, Feng, Y., et al., 2024. Studying the impact of lighting on the pedestrian route choice using virtual reality. Saf. Sci. 174, 106467.

Bereitschaft, B., 2017. Equity in microscale urban design and walkability: a photographic survey of six Pittsburgh streetscapes. Sustainability 9 (7), 1233.

Bessho, M., Usaka, T., Sakamura, K., 2023. Toward open and sustainable data platform for accessible pedestrian network. In: 2023 IEEE International Conference on Big Data (BigData), pp. 4731–4739.

Bhatia, J., et al., 2021. Classification of targets using statistical features from range fft of mmwave fmcw radars. Electronics 10 (16), 1965.

Bhattacharya, T., Dasgupta, S., Sen, J., 2020. An attempt to assess the need and potential of aesthetic regeneration to improve walkability and ergonomic experience of urban space. In: Proceedings of the AHFE 2019 International Conference on Human Factors in Architecture, Sustainable Urban Planning and Infrastructure, July 24–28, 2019, Washington DC, USA 10, pp. 358–370.

Birenboim, A., et al., 2021. The study of walking, walkability and wellbeing in immersive virtual environments. Int. J. Environ. Res. Public. Health 18 (2), 1–18. https://doi.org/10.3390/ijerph18020364.

Blanke, U., et al., 2014. Capturing crowd dynamics at large scale events using participatory GPS-localization. In: 2014 IEEE Ninth International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), pp. 1–7.

Blumenberg, E., Evans, A., 2010. Planning for demographic diversity: the case of immigrants and public transit. J. Public. Transport. 13 (2), 23–45. https://doi.org/10.5038/2375-0901.13.2.2.

Bode, N.W., Holl, S., Mehner, W., Seyfried, A., 2015. Disentangling the impact of social groups on response times and movement dynamics in evacuations. PLoS ONE 10 (3) e0121227.

Braithwaite, J.J.J., et al., 2013. A Guide for analysing electrodermal activity (EDA) & skin conductance responses (SCRs) for psychological experiments 1–42. Available at: http://www.bhamlive.bham.ac.uk/Documents/college-les/psych/saal/guide-electrodermal-activity.pdf%5Cnhttp://www.birmingham.ac.uk/documents/college-les/psych/saal/guide-electrodermal-activity.pdf%0Ahttps://www.birmingham.ac.uk/Documents/college-les/psych/sa.

Buckley, P., Stangl, P., Guinn, J., 2017. Why people walk: modeling foundational and higher order needs based on latent structure. J. Urban. Int. Res. Placemaking Urban. Sustainability 10 (2), 129–149.

Cao, X., Mokhtarian, P.L., Handy, S.L., 2009. Examining the impacts of residential self-selection on travel behaviour: a focus on empirical findings. Transp. Rev. 29 (3), 359–395.

Carter, E., et al., 2020. Enhancing pedestrian mobility in smart cities using big data. J. Manag. Analytics 7 (2), 173–188.

Catal, C., Akbulut, A., Tunali, B., Ulug, E., Ozturk, E., 2020. Evaluation of augmented reality technology for the design of an evacuation training game. Virtual Real 24, 359–368.

Chakrabarti, S., Joh, K., 2019. The effect of parenthood on travel behavior: evidence from the California household travel survey. Transp. Res. A: Policy Pract. 120, 101–115.

Chatterton, T., Barnes, J., Wilson, R.E., Anable, J., Cairns, S., 2015. Use of a novel dataset to explore spatial and social variations in car type, size, usage and emissions. Transp. Res. D: Transp. Environ. 39, 151–164.

Chen, R., et al., 2011. Sensing strides using EMG signal for pedestrian navigation. GPS Solut 15 (2), 161–170. https://doi.org/10.1007/s10291-010-0180-x.

Chen, M., et al., 2022. Mixed reality LVC simulation: a new approach to study pedestrian behaviour. Build. Environ. 207 (PB), 108404. https://doi.org/10.1016/j.buildenv.2021.108404.

Cho, S.-Y., Chow, T.W.S., Leung, C.-T., 1999. A neural-based crowd estimation by hybrid global learning algorithm'. IEEE Trans. Systems, Man, Cybern. Part. B (Cybernetics) 29 (4), 535–541.

Choi, Y., Guhathakurta, S., 2024. Unraveling the diversity in transit-oriented development. Transp. Res. A: Policy Pract. 182, 104020.

Christoe, M.J., et al., 2021. Bluetooth signal attenuation analysis in human body tissue analogues. IEEE Access 9, 85144–85150.

Courtine, G., Schieppati, M., 2003. Human walking along a curved path. II. Gait features and EMG patterns. Eur. J. Neurosci 18 (1), 191–205. https://doi.org/10.1046/j.1460-9568.2003.02737.x.

Daamen, W., et al., 2020. Urban mobility observatory. Traffic Granul. Flow. 2019 457–463.

Daamen, W., Hoogendoorn, S.P., 2003. Experimental research of pedestrian walking behavior. Transportation Research Record Vol 1828. Transportation Research Board, Washington, DC, pp. 20–30.

Dai, Z., Li, D., Feng, Y., Yang, Y., Sun, L., 2024. A study of pedestrian wayfinding behavior based on desktop VR considering both spatial knowledge and visual information. Transp. Res. Part. C: Emerg. Technol. 163, 104651.

De Paepe, L., et al., 2018. Changes in travel behavior during the transition from secondary to higher education: a case study from Ghent, Belgium. J. Transp. Land. Use 11 (1), 477–498. https://doi.org/10.5198/jtlu.2018.1113.

De Vos, J., Alemi, F., 2020. Are young adults car-loving urbanites? Comparing young and older adults' residential location choice, travel behavior and attitudes. Transportation Res. Part. A: Policy Pract 132 (April 2019), 986–998. https://doi.org/10.1016/j.tra.2020.01.004.

De Winter, J.C.F., Bazilinskyy, P., Wesdorp, D., De Vlam, V., Hopmans, B., Visscher, J., Dodou, D., 2022. Supplementary data for the paper: How do pedestrians distribute their visual attention when walking through a parking garage? An eye-tracking study. 4TU. Research Data. https://doi.org/10.4121/13488384.v2.

Deb, S., et al., 2017. Efficacy of virtual reality in pedestrian safety research. Appl. Ergon. 65, 449–460. https://doi.org/10.1016/j.apergo.2017.03.007.

Department for Transport. 2024. National Travel Survey, 2002-2022. [data collection]. 17th Edition. UK Data Service. SN: 5340, http://doi.org/10.5255/UKDA-SN-5340-13. The complete reference is found at https://beta.ukdataservice.ac.uk/datacatalogue/doi/?id=5340.

Di Nardo, F., Morbidoni, C., Fioretti, S., 2024. Surface electromyographic signals collected during long-lasting ground walking of young able-bodied subjects. Available at:. PhysioNet. https://doi.org/10.13026/grdj-qx06.

Dieleman, F.M., Dijst, M., Burghouwt, G., 2002. Urban form and travel behaviour: micro-level household attributes and residential context. Urban. Stud 39 (3), 507–527. https://doi.org/10.1080/00420980220112801.

Dingil, A.E., Esztergár-Kiss, D., 2022. The influence of education level on urban travel decision-making. Period. Polytech. Transp. Eng. 50 (1), 49–57. https://doi.org/10.3311/PPTR.16871.

Donelli, M., Espa, G., others, 2021. A crowd monitoring methodology based on the analysis of the electromagnetic spectrum. Glob. J. Res. Engineering, 2021 39–47.
Dong, H., Zhou, M., Wang, Q., Yang, X., Wang, F.Y., 2019. State-of-the-art pedestrian and evacuation dynamics. IEEE Trans. Intell. Transp Syst. 21 (5), 1849–1866.
Duives, D.C., Daamen, W., Hoogendoorn, S.P., 2013. State-of-the-art crowd motion simulation models. Transp. Res. Part. C: Emerg. Technol. 37, 193–209.
Durante, A., et al., 2018. Understanding the effect of architectural and environmental features on human behavior. In: Advances in Usability and User Experience: Proceedings of the AHFE 2017 International Conference on Usability and User Experience, July 17–21, 2017, The Westin Bonaventure Hotel, Los Angeles, California, USA 8, pp. 521–531.
Elias, W., Shiftan, Y., 2012. The influence of individual's risk perception and attitudes on travel behavior. Transp. Res. Part. A: Policy Pract. 46 (8), 1241–1251. https://doi.org/10.1016/j.tra.2012.05.013.
Engelniederhammer, A., Papastefanou, G., Xiang, L., 2019. Crowding density in urban environment and its effects on emotional responding of pedestrians: using wearable device technology with sensors capturing proximity and psychophysiological emotion responses while walking in the street. J. Hum. Behav. Soc. Environ. 29 (5), 630–646. https://doi.org/10.1080/10911359.2019.1579149.
Eppenberger, T., Cesari, G., Dymczyk, M., Siegwart, R., Dubé, R., 2020. Leveraging stereo-camera data for real-time dynamic obstacle detection and tracking. In: 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), IEEE, pp. 10528–10535.
Erkan, İ., 2018. Examining wayfinding behaviours in architectural spaces using brain imaging with electroencephalography (EEG). Architectural Sci. Rev. 61 (6), 410–428. https://doi.org/10.1080/00038628.2018.1523129.
Etminani-Ghasrodashti, R., Paydar, M., Hamidi, S., 2018. University-related travel behavior: young adults decision-making in Iran. Sustain. Cities Soc. 43 (August), 495–508. https://doi.org/10.1016/j.scs.2018.09.011.
European Parliament and Council of the European Union, 2016. Regulation (EU) 2016/679 (General Data Protection Regulation). Official Journal of the European Union. https://eur-lex.europa.eu/eli/reg/2016/679/oj.
European Parliament and Council of the European Union, 2019. Regulation (EU) 2019/881 (Cybersecurity Act). Official Journal of the European Union. https://eur-lex.europa.eu/eli/reg/2019/881/oj.
Ewart, I.J., Johnson, H., 2021. Virtual reality as a tool to investigate and predict occupant behaviour in the real world: the example of wayfinding. J. Inf. Technol. Constr 26 (August 2020), 286–302. https://doi.org/10.36680/j.itcon.2021.016.
Fadhlullah, S.Y., Ismail, W., 2016. A statistical approach in designing an rf-based human crowd density estimation system. Int. J. Distrib. Sens. Netw 12 (2), 8351017.
Feldmann, S., et al., 2024. Temporal segmentation of motion propagation in response to an external impulse. Saf. Sci. 175 (April 2021), 1–34. https://doi.org/10.1016/j.ssci.2024.106512.
Feliciani, C., Nishinari, K., 2018. Measurement of congestion and intrinsic risk in pedestrian crowds. Transp. Res. Part. C: Emerg. Technol. 91, 124–155.
Feng, Y., Duives, D.C., Hoogendoorn, S.P., 2021. Using virtual reality to study pedestrian exit choice behaviour during evacuations. Saf. Sci. 137, 105158. https://doi.org/10.1016/j.ssci.2021.105158.
Feng, Y., Duives, D., Hoogendoorn, S., 2022a. Development and evaluation of a VR research tool to study wayfinding behaviour in a multi-story building. Saf. Sci. 147, 105573. https://doi.org/10.1016/j.ssci.2021.105573.

Feng, Y., Duives, D.C., Hoogendoorn, S.P., 2022b. Wayfinding behaviour in a multi-level building: a comparative study of HMD VR and Desktop VR. Adv. Eng. Inform. 51, 101475.

Feng, Y., Duives, D., Daamen, W., Hoogendoorn, S., 2021. Data collection methods for studying pedestrian behaviour: a systematic review. Build. Environ. 187, 107329. https://doi.org/10.1016/j.buildenv.2020.107329.

Fernández-Arango, D., Varela-García, F.A., González-Aguilera, D., Lagüela-López, S., 2022. Automatic generation of urban road 3D models for pedestrian studies from LiDAR data. Remote. Sens 14 (5), 1102.

Figueroa, M.J., Nielsen, T.A.S., Siren, A., 2014. Comparing urban form correlations of the travel patterns of older and younger adults. Transp. Policy 35, 10–20. https://doi.org/10.1016/j.tranpol.2014.05.007.

Fina, S., et al., 2022. OS-WALK-EU: an open-source tool to assess health-promoting residential walkability of European city structures. J. Transp. & Health 27, 101486.

Fink, P.W., Foo, P.S., Warren, W.H., 2007. Obstacle avoidance during walking in real and virtual environments. ACM Trans. Appl. Percept. (TAP.) 4 (1), 2es. https://doi.org/10.1145/1227134.1227136.

Forward propagation of a push through a row of five people. https://10.34735/ped.2022.2.

Fu, M., Liu, R., Zhang, Y., 2021. Do people follow neighbors? An immersive virtual reality experimental study of social influence on individual risky decisions during evacuations. Autom. Constr 126, 103644.

Fu, T., Zangenehpour, S., St-Aubin, P., Fu, L., Miranda-Moreno, L.F., 2015. Using microscopic video data measures for driver behavior analysis during adverse winter weather: opportunities and challenges. J. Mod. Transp. 23, 81–92.

Garcia-Villalonga, S., Perez-Navarro, A., 2015. Influence of human absorption of Wi-Fi signal in indoor positioning with Wi-Fi fingerprinting. 2015 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1–10.

Gasparini, F., et al., 2020. EMG for walkability assessment: a comparison betweenelderly and young adults. CEUR Workshop Proceedings of the Italian Workshop on Artificial Intelligence for an Ageing Society 2020 co-located with 19th International Conference of the Italian Association for Artificial Intelligence (AIxIA 2020), pp. 88–100.

Geoerg, P., Schumann, J., Holl, S., Boltes, M., Hofmann, A., 2021. The influence of individual impairments in crowd dynamics. Fire Mater 45 (4), 529–542.

Gerogiannis, A., Bode, N.W.F., 2024. Analysis of long-term observational data on pedestrian road crossings at unmarked locations. Saf. Sci. 172, 106420.

Gholami, M., Torreggiani, D., Tassinari, P., Barbaresi, A., 2022. Developing a 3D city digital twin: enhancing walkability through a green pedestrian network (GPN) in the City of Imola, Italy. Land 11, 1917.

GHSL - Global Human Settlement Layer, 2024. Available at: https://human-settlement.emergency.copernicus.eu.

Gong, V.X., et al., 2018. Using social media for attendees density estimation in city-scale events. IEEE Access 6, 36325–36340.

Gong, V.X., et al., 2019. Estimate sentiment of crowds from social media during city events. Transp. Res. Rec. 2673 (11), 836–850.

Götschi, T., et al., 2017. Towards a comprehensive conceptual framework of active travel behavior: a review and synthesis of published frameworks. Curr. Environ. Health Rep. 4 (3), 286–295. https://doi.org/10.1007/s40572-017-0149-9.

Gu, Z., Regmi, H., Sur, S., 2023. Poster: mmBox: mmWave bounding box for vehicle and pedestrian detection under outdoor environment. In: 2023 IEEE 31st International Conference on Network Protocols (ICNP), pp. 1–2.

Haghani, M., 2020. Empirical methods in pedestrian, crowd and evacuation dynamics: part II. Field methods and controversial topics. Saf. Sci. 129, 104760.

Hasan, Raiful, Hasan, Ragib, 2021. FinderX: a bluetooth beacon-based system for designing sustainable green smart cities. IEEE Consum. Electron. Mag. 11 (1), 65–72.

Hausmann, S., Keller, C., Schlegel, T., 2017. Lessons learned on the design of several tools for participation on foot. IxD&A 35, 205–226.

He, X., He, S.Y., 2023. Using open data and deep learning to explore walkability in Shenzhen, China. Transp. Res. Part. D: Transp. Environ 118, 103696.

Hoang-Tung, N., Kojima, A., Kubota, H., 2017. Transformation from intentions to habits in travel behavior: an awareness of a mediated form of intention. Transp. Res. Part. F: Traffic Psychol. Behav 49, 226–235. https://doi.org/10.1016/j.trf.2017.07.001.

Household Travel Survey, 2021. data.nsw.gov.au. Available at: https://data.nsw.gov.au/data/dataset/household-travel-survey, https://researchdata.edu.au/household-travel-survey.

Huang, H.Y., Hsieh, C.Y., Liu, K.C., Cheng, H.C., Hsu, S.J., Chan, C.T., 2019. Multi-sensor fusion approach for improving map-based indoor pedestrian localization. Sensors 19 (17), 3786.

Iguchi, K., Mitsuhara, H., Shishibori, M., 2016. Evacuation instruction training system using augmented reality and a smartphone-based head mounted display. In: 2016 3rd International Conference on Information and Communication Technologies for Disaster Management (ICT-DM), IEEE, pp. 1–6.

Jiang, Y., et al., 2021. Ultra large-scale crowd monitoring system architecture and design issues. IEEE Internet Things J. 8 (13), 10356–10366. https://doi.org/10.1109/JIOT.2021.3076257.

Kalantari, S., et al., 2022. Evaluating the impacts of color, graphics, and architectural features on wayfinding in healthcare settings using EEG data and virtual response testing. J. Environ. Psychol 79 (December 2021), 101744. https://doi.org/10.1016/j.jenvp.2021.101744.

Kapoor, S.S., Brar, T.S., 2023. Use of smartphones application to identify pedestrian barriers around existing metro stations in Noida. AIoT Technol. Appl. Smart Environ 57, 57.

Kashinath, S.A., Mostafa, S.A., Mustapha, A., Mahdin, H., Lim, D., Mahmoud, M.A., Yang, T.J., 2021. Review of data fusion methods for real-time and multi-sensor traffic flow analysis. IEEE Access 9, 51258–51276.

Kim, J., et al., 2020. Environmental distress and physiological signals: examination of the saliency detection method. J. Comput. Civ. Eng. 34 (6), 1–12. https://doi.org/10.1061/(asce)cp.1943-5487.0000926.

Kim, J., Ahn, C.R., Nam, Y., 2019. The influence of built environment features on crowdsourced physiological responses of pedestrians in neighborhoods. Comput. Environ. Urban. Syst. 75 (September 2018), 161–169. https://doi.org/10.1016/j.compenvurbsys.2019.02.003.

Kinateder, M., Comunale, B., Warren, W.H., 2018. Exit choice in an emergency evacuation scenario is influenced by exit familiarity and neighbor behavior. Saf. Sci. 106, 170–175.

Kinateder, M., Müller, M., Jost, M., Mühlberger, A., Pauli, P., 2014. Social influence in a virtual tunnel fire–influence of conflicting information on evacuation behavior. Appl. Ergon. 45 (6), 1649–1659.

Kinateder, M., Warren, W.H., 2016. Social influence on evacuation behavior in real and virtual environments. Front. Robot. AI 3, 43.

Kirstein, F., Dittwald, B., Dutkowski, S., Glikman, Y., Schimmler, S., Hauswirth, M., 2019. Linked data in the European data portal: a comprehensive platform for applying dcat-ap. In: Electronic Government: 18th IFIP WG 8.5 International Conference, EGOV 2019, San Benedetto Del Tronto, Italy, September 2–4, 2019, Proceedings, Springer International Publishing, 18, pp. 192–204.

Kitamura, R., Mokhtarian, P.L., Laidet, L., 1997. A micro-analysis of land use and travel in five neighborhoods in the San Francisco Bay area. Transportation 24, 125–158.
Ko, J., Lee, S., Byun, M., 2019. Exploring factors associated with commute mode choice: an application of city-level general social survey data. Transp. Policy 75 (May 2017), 36–46. https://doi.org/10.1016/j.tranpol.2018.12.007.
Kobes, M., Helsloot, I., de Vries, B., Post, J., 2010. Exit choice,(pre-) movement time and (pre-) evacuation behaviour in hotel fire evacuation—Behavioural analysis and validation of the use of serious gaming in experimental research. Procedia Eng. 3, 37–51.
Konrad, S.G., Shan, M., Masson, F.R., Worrall, S., Nebot, E., 2018. Pedestrian dynamic and kinematic information obtained from vision sensors. In 2018 IEEE Intelligent Vehicles Symposium(IV), IEEE, pp. 1299-1305.
Kowald, M., Arentze, T.A., Axhausen, K.W., 2015. Individuals' spatial social network choice: model-based analysis of leisure-contact selection. Environ. Plan. B: Plan. Des. 42 (5), 857–869.
Kristoffersen, M.S., et al., 2016. Pedestrian counting with occlusion handling using stereo thermal cameras. Sensors 16 (1), 62.
Kumalasari, D., Koeva, M., Vahdatikhaki, F., Petrova Antonova, D., Kuffer, M., 2023. Planning walkable cities: generative design approach towards digital twin implementation. Remote. Sens 15, 1088.
Kumari, R., 2021. Adaptness assessment of pedestrian street during crises like Covid-19. J. Urban. Environ. Eng. 15 (1), 50–57.
Kurkcu, A., Ozbay, K., 2017. Estimating pedestrian densities, wait times, and flows with wi-fi and bluetooth sensors. Transportation Res. Rec. 2644 (1), 72–82.
Kweon, B.-S., Shin, W.-H., Ellis, C.D., 2023. School walk zone: identifying environments that foster walking and biking to school. Sustainability 15 (4), 2912.
Labbé, D., et al., 2023. Multiple-stakeholder perspectives on accessibility data and the use of socio-technical tools to improve sidewalk accessibility. Disabilities 3 (4), 621–638.
Lai, Y., Kontokosta, C., 2017. Analyzing the drivers of pedestrian activity at high spatial resolution. In: 2017 International Conference on Sustainable Infrastructure: Methodology, ICSI 2017, pp. 303–314.
Lajeunesse, S., et al., 2021. Measuring pedestrian level of stress in urban environments: naturalistic walking pilot study. Transp. Res. Rec. 2675 (10), 109–119. https://doi.org/10.1177/03611981211010183.
Lee, K., Sener, I.N., 2020. Emerging data for pedestrian and bicycle monitoring: sources and applications. Transp. Res. Interdiscip. Perspect 4, 100095.
Lee, M.J.L., Su, M., Hsu, L.-T., 2022. Wi-Fi, CCTV and PDR integrated pedestrian positioning system. In: WiP Proceedings of the Twelfth International Conference on Indoor Positioning and Indoor Navigation - Work-in-Progress Papers.
Lesani, A., Miranda-Moreno, L., 2018. Development and testing of a real-time WiFi-bluetooth system for pedestrian network monitoring, classification, and data extrapolation. IEEE Trans. Intell. Transp. Syst. 20 (4), 1484–1496.
Li, X., Yu, Q., Alzahrani, B., Barnawi, A., Alhindi, A., Alghazzawi, D., Miao, Y., 2021. Data fusion for intelligent crowd monitoring and management systems: a survey. IEEE Access 9, 47069–47083.
Li, H., Zhang, J., Xia, L., Song, W., Bode, N.W., 2019. Comparing the route-choice behavior of pedestrians around obstacles in a virtual experiment and a field study. Transp. Res. Part. C: Emerg. Technol. 107 (December 2018), 120–136. https://doi.org/10.1016/j.trc.2019.08.012.
Li, H., Sun, L., Zhu, H., Lu, X., Cheng, X., 2014. Achieving privacy preservation in WiFi fingerprint-based localization. In: Ieee Infocom 2014-IEEE Conference on Computer Communications, pp. 2337–2345.

Liao, W., Kemloh Wagoum, A.U., Bode, N.W., 2017. Route choice in pedestrians: determinants for initial choices and revising decisions. J. R. Soc. Interface 14 (127), 20160684.

Limtanakool, N., Dijst, M., Schwanen, T., 2006. The influence of socioeconomic characteristics, land use and travel time considerations on mode choice for medium- and longer-distance trips. J. Transp. Geogr 14 (5), 327–341. https://doi.org/10.1016/j.jtrangeo.2005.06.004.

Lin, T., Wang, D., Guan, X., 2017. The built environment, travel attitude, and travel behavior: residential self-selection or residential determination? J. Transp. Geogr 65 (July 2016), 111–122. https://doi.org/10.1016/j.jtrangeo.2017.10.004.

Lin, T., Wang, D., 2014. Social networks and joint/solo activity–travel behavior. Transp. Res. Part. A: Policy Pract 68, 18–31.

Lindelöw, D., et al., 2017. Satisfaction or compensation? The interaction between walking preferences and neighbourhood design. Transp. Res. Part. D: Transp. Environ. 50, 520–532.

Liu, K., et al., 2015. Ship-board pedestrianpositioning method by integrating Dead Reckoning and wireless sensor networks. In: 2015 International Association of Institutes of Navigation World Congress (IAIN), pp. 1–7.

Ma, X., Chau, C.K., Lai, J.H.K., 2021. Critical factors influencing the comfort evaluation for recreational walking in urban street environments. Cities 116, 103286.

Ma, S., Wang, P., Lee, H., 2024. An enhanced hidden markov model for map-matching in pedestrian navigation. Electronics 13 (9), 1685.

Manaugh, K., Miranda-Moreno, L.F., El-Geneidy, A.M., 2010. The effect of neighbourhood characteristics, accessibility, home–work location, and demographics on commuting distances. Transportation 37, 627–646.

Mattioli, G., Scheiner, J., 2022. The impact of migration background, ethnicity and social network dispersion on air and car travel in the UK. Travel. Behav. Soc. 27 (ember 2021), 65–78. https://doi.org/10.1016/j.tbs.2021.12.001.

Mavros, P., et al., 2022. A mobile EEG study on the psychophysiological effects of walking and crowding in indoor and outdoor urban environments. Sci. Rep. 12 (1), 1–20. https://doi.org/10.1038/s41598-022-20649-y.

Mehta, V., 2008. Walkable streets: pedestrian behavior, perceptions and attitudes. J. Urbanism 1 (3), 217–245. https://doi.org/10.1080/17549170802529480.

Michau, G.E., et al., 2014. Retrieving dynamic origin-destination matricesfrom Bluetooth data. In: Transportation Research Board (TRB) 93rd Annual Meeting Compendium of Papers, pp. 1–11.

Milgram, P., 2012. A taxonomy of mixed reality visual displays. IEICE Trans. Inf. Syst 77 (12), 1–15. Available at: http://vered.rose.utoronto.ca/people/paul_dir/IEICE94/ieice.html.

Mobility Panel Germany, 2024. https://mobilitaetspanel.ifv.kit.edu/english/survey.php#:~:text=The%20German%20Mobility%20Panel%20is,behaviour%20in%20Germany%20since%201994.

Mobility; Per Person, Modes of Travel, Purposes of Travel and Regions, 2024. Available at: https://opendata.cbs.nl/ODataApi/OData/84710ENG.

Mostafi, S., Elgazzar, K., 2021. An open source tool to extract traffic data from google maps: limitations and challenges. In: 2021 International Symposium on Networks, Computers and Communications (ISNCC), IEEE, pp. 1–8.

Moura, F., Cambra, P., Gonçalves, A.B., 2017. Measuring walkability for distinct pedestrian groups with a participatory assessment method: a case study in Lisbon. Landsc. Urban. Plan 157, 282–296.

MPN Data. 2024. https://www.mpndata.nl/.

Mueller, G.R., Wuensche, H.J., 2017. Continuous stereo camera calibration in urban scenarios. In: 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), IEEE, pp. 1–6.
Mukhopadhyay, B., Srirangarajan, S., Kar, S., 2018. Modeling the analog response of passive infrared sensor. Sens. Actuators A: Phys 279, 65–74.
Murtagh, S., Rowe, D.A., Elliott, M.A., McMinn, D., Nelson, N.M., 2012. Predicting active school travel: The role of planned behavior and habit strength. Int. J. Behav. Nutr. Phys. Act. 9, 1–9.
Næss, P., 2012. Urban form and travel behavior: experience from a Nordic context. J. Transp. Land. Use 5 (2), 21–45. https://doi.org/10.5198/jtlu.v5i2.314.
National Data Warehouse, n.d. NDW - National Data Warehouse for Traffic Data. National Data Warehouse. https://www.ndw.nu/.
National Household Travel Survey, 2024. Available at: https://nhts.ornl.gov.
National Travel Attitudes Study, 2024. Available at: https://www.gov.uk/government/collections/national-travel-attitudes-study-ntas.
Nguyen, U., Rottensteiner, F., Heipke, C., 2019. Confidence-aware pedestrian tracking using a stereo camera. ISPRS Ann. Photogrammetry, Remote. Sens. Spat. Inf. Sci. 4, 53–60.
Nicolas, A., Bouzat, S., Kuperman, M.N., 2017. Pedestrian flows through a narrow doorway: effect of individual behaviours on the global flow and microscopic dynamics. Transp. Res. Part. B: Methodol 99, 30–43. https://doi.org/10.1016/j.trb.2017.01.008.
Occhialini, M., et al., 2016. Fire exit signs: the use of neurological activity analysis for quantitative evaluations on their perceptiveness in a virtual environment. Fire Saf. J. 82, 63–75. https://doi.org/10.1016/j.firesaf.2016.03.003.
Olivari, B., et al., 2023. Are Italian cities already 15-minute? Presenting the next proximity index: a novel and scalable way to measure it, based on open data. J. Urban. Mobil 4, 100057.
OpenStreetMap, 2024. Available at: http://www.openstreetmap.org (Accessed 5 June 2024).
Orozco Carpio, P.R., Viñals, M.J., López-González, M.C., 2024. 3D point cloud and GIS approach to assess street physical attributes. Smart Cities 7 (3), 991–1006.
Ouellette, J.A., Wood, W., 1998. Habit and intention in everyday life: the multiple processes by which past behavior predicts future behavior. Psychological Bull 124, 54–74. (Available at). https://api.semanticscholar.org/CorpusID:18838893.
Ounoughi, C., Yahia, S.B., 2023. Data fusion for ITS: a systematic literature review. Inf. Fusion 89, 267–291.
Paes, D., Feng, Z., King, M., Shad, H.K., Sasikumar, P., Pujoni, D., Lovreglio, R., 2024. Optical see-through augmented reality fire safety training for building occupants. Autom. Constr 162, 105371.
Paetzke, S., Beermann, M., Chraibi, M., Seyfried, A., Gend, A.S. Composition single-file exp. 2021. https://10.34735/ped.2021.5.
Pannucci, C.J., Wilkins, E.G., 2010. Identifying and avoiding bias in research. Plastic Reconstructive Surg 126 (2), 619–625. https://doi.org/10.1097/PRS.0b013e3181de24bc.
Park, Y., Garcia, M., 2020. Pedestrian safety perception and urban street settings. Int. J. Sustain. Transportation 14 (11), 860–871.
Patterson, Z., Ewing, G., Haider, M., 2005. Gender-based analysis of work trip mode choice of commuters in suburban Montreal, Canada, with stated preference data. Transp. Res. Rec. 1924, 85–93. https://doi.org/10.3141/1924-11.
Penerbit, U.M.T., 2023. Socio-Spatial Transformation Model of urban architectural elements: the perspective of local communities in the Corridor of Boulevard II, The Coast of Manado City, Indonesia. J. Sustainability Sci. Manag 18 (3), 125–146.
Phithakkitnukoon, S., Sukhvibul, T., Demissie, M., Smoreda, Z., Natwichai, J., Bento, C., 2017. Inferring social influence in transport mode choice using mobile phone data. EPJ Data Sci. 6, 1–29.

Piao, W., Zhao, X., Li, Z., 2023. MMGraphSLAM: autonomous indoor positioning based on millimeter wave GraphSLAM. Measurement 220, 113300.
Pinna, F., Murrau, R., 2018. Age factor and pedestrian speed on sidewalks. https://10.3390/su10114084.
Progri, I.F., et al., 2007. Indoor geolocation using FCDMA pseudolites: signal structure and performance analysis. Navigation 54 (3), 241–256.
Qiang, D., Zhang, L., Huang, X., 2022. Quantitative evaluation of TOD performance based on multi-source data: a case study of Shanghai. Front. public. health 10, 820694.
Qiu, Z., Ashour, M., Zhou, X., Kalantari, S., 2024. NavMarkAR: a landmark-based augmented reality (AR) wayfinding system for enhancing older adults' spatial learning. Adv. Eng. Inform 62, 102635.
Rahman, K., et al., 2012. Analysis of pedestrian free flow walking speed in a least developing country: a factorial design study. Res. J. Appl. Sciences, Eng. Technol 4 (21), 4299–4304.
Ralph, K.M., Brown, A.E., 2019. The role of habit and residential location in travel behavior change programs, a field experiment. Transportation 46 (3), 719–734.
Rauschnabel, P.A., et al., 2022. What is XR? Towards a framework for augmented and virtual reality. Comput. Hum. Behav 133 (January), 107289. https://doi.org/10.1016/j.chb.2022.107289.
Rehman, U., Cao, S., 2017. Augmented-reality-based indoor navigation: a comparative analysis of handheld devices versus google glass. IEEE Trans. Human-Machine Syst 47 (1), 140–151.
Rhoads, D., et al., 2023. Sidewalk networks: review and outlook. Computers, Environ. Urban. Syst 106, 102031.
Roper, J., et al., 2022. Colouring Australia: a participatory open data platform. ISPRS Ann. Photogrammetry, Remote. Sens. Spat. Inf. Sci. 10, 229–235.
Rosenbloom, S., 2004. Understanding women's and men's travel patterns. In: Research on Women's Issues in Transportation, Volume 1: Conference Overview and Plenary Papers.
Rybarczyk, G., et al., 2018. Travel and us: the impact of mode share on sentiment using geo-social media and GIS. J. Locat. Based Serv 12 (1), 40–62.
Ryus, P., Ferguson, E., Laustsen, K.M., Schneider, R.J., Proulx, F.R., Hull, T., Miranda-Moreno, L., 2014. Guidebook on pedestrian and bicycle volume data collection. NCHRP Report 797, National Cooperative Highway Research Program.
Sanz, F.A., Olivier, A.H., Bruder, G., Pettré, J., Lécuyer, A., 2015. Virtual proxemics: locomotion in the presence of obstacles in large immersive projection environments. 2015 IEEE Virtual Real. (vr) 75–80 (IEEE).
Scalvini, F., et al., 2024. uB-VisioGeoloc: an image sequences dataset of pedestrian navigation including geolocalised-inertial information and spatial sound rendering of the urban environment's obstacles. Data Brief 53, 110088.
Schröder-Bergen, S., et al., 2022. De/colonizing OpenStreetMap? Local mappers, humanitarian and commercial actors and the changing modes of collaborative mapping. GeoJournal 87 (6), 5051–5066.
Schuster, F., et al., 2016. Landmark based radar SLAM using graph optimization. In: 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), pp. 2559–2564.
Shartova, N.V., Mironova, E.E., Grischenko, M.Y., 2023. Spatial disparities of street walkability in Moscow in the context of healthy urban environment. Cities 141, 104469.
Sherman, W.R., Craig, A.B., 2018. Understanding Virtual Reality: Interface, Application, and Design. Morgan Kaufmann.

Shi, X., Ye, Z., Shiwakoti, N., Grembek, O., 2018. A state-of-the-art review on empirical data collection for external governed pedestrians complex movement. J. Adv. Transportation 2018 (1), 1063043.
Sindagi, V.A., Patel, V.M., 2018. A survey of recent advances in cnn-based single image crowd counting and density estimation. Pattern Recognit. Lett 107, 3–16.
Southworth, M., 2005. Designing the walkable city. J. urban. Plan. Dev. 131 (4), 246–257.
Srinivasan, S., Ferreira, J., 2002. Travel behavior at the household level: understanding linkages with residential choice. Transportation Res. Part. D: Transp. Environ 7 (3), 225–242.
Stangl, P., 2011. The US pedestrian plan: linking practice and research. Plan. Pract. Res. 26 (3), 289–305.
Subaih, R., Maree, M., Chraibi, M., Awad, S., Zanoon, T., 2018. Experimental investigation on the alleged gender-differences in pedestrian dynamics: A study reveals no gender differences in pedestrian movement behavior. IEEE Access 8, 33748–33757.
Suma, E., et al., 2010. Evaluation of the cognitive effects of travel technique in complex real and virtual environments. IEEE Trans. Vis. Computer Graph 16 (4), 690–702. https://doi.org/10.1109/TVCG.2009.93.
Sung, K., Lee, D.K., 'Roy', Kim, H., 2018. Indoor pedestrian localization using iBeacon and improved Kalman filter. Sensors 18 (6), 1722.
Suvannadabha, P., Busayarat, C., Supnithi, T., 2022. The analytical tools for tourism development through social media data and spatial morphological analysis. Nakhara: J. Environ. Des. Plan 21 (3), 223.
Tal, G., Handy, S., 2010. Travel behavior of immigrants: an analysis of the 2001 national household transportation survey. Transp. Policy 17 (2), 85–93. https://doi.org/10.1016/j.tranpol.2009.11.003.
Tang, Y., et al., 2022. Exploring the impact of built environment attributes on social followings using social media data and deep learning. ISPRS Int. J. Geo-Information 11 (6), 325.
Tanida, S., et al., 2024. Investigating the congestion levels on a mesoscopic scale during outdoor events. J. Disaster Res. 19 (2), 347–358.
Tarko, A., et al., 2018. Detecting and tracking vehicles, pedestrians, and bicyclists at intersections with a stationary LiDAR. In: 18th International Conference Road Safety on Five Continents (RS5C 2018), Jeju Island, South Korea, May 16–18, 2018.
Thi, T.H., et al., 2008. Vehicle classification at nighttime using eigenspaces and support vector machine. 2008 Congr. Image Signal. Process 422–426.
Turner, S.M., Koeneman, P., 2018. Validating the national performance management research data set (NPMRDS) for South Dakota (No. SD2013–08-F). South Dakota. Dept. of Transportation. Office of Research.
Üsten, E., Sieben, A., 2021. Interruption study 2: moving crowd interruption. https://10.34735/ped.2021.12.
Verplanken, B., Aarts, H., 1999. Habit, attitude, and planned behaviour: Is habit an empty construct or an interesting case of goal-directed automaticity? Eur. Rev. Soc. Psychol 10 (1), 101–134. https://doi.org/10.1080/14792779943000035.
Voulgaris, C.T., Taylor, B.D., Blumenberg, E., Brown, A., Ralph, K., 2017. Synergistic neighborhood relationships with travel behavior: an analysis of travel in 30,000 US neighborhoods. J. Transp. Land. Use 10 (1), 437–461.
Wada, T., et al., 2021. New evacuation guidance using augmented reality for emergency rescue evacuation support system (ERESS). ACM International Conference Proceeding Series, pp. 1–6. https://10.1145/3458744.3473347.
Wagoum, A.K., Tordeux, A., Liao, W., 2017. Understanding human queuing behaviour at exits: an empirical study. R. Soc. Open. Sci. 4 (1), 160896.

Wang, Q., et al., 2013. Electromyography-based locomotion pattern recognition and personal positioning toward improved context-awareness applications. IEEE Trans. Systems, Man, Cybern. Part. A:Systems Hum. 43 (5), 1216–1227. https://doi.org/10.1109/TSMC.2013.2256857.
Wang, S., et al., 2019. IBeacon/INS data fusion location algorithm based on unscented kalman filter. J. Electron. Inf. Technol 41 (9), 2209–2216.
Wang, R., et al., 2022. AAC: automatic augmentation for crowd counting. Neurocomputing 500, 90–98.
Wang, H., Yang, Y., 2019. Neighbourhood walkability: a review and bibliometric analysis. Cities 93, 43–61.
Wang, W., et al., 2023. A long-term study of mmWave sensing in an outdoor urban scenario. In: 2023 19th International Conference on Distributed Computing in Smart Systems and the Internet of Things (DCOSS-IoT), pp. 240–247.
Weppner, J., Lukowicz, P., 2013 Bluetooth based collaborative crowd density estimation with mobile phones. In: 2013 IEEE international conference on pervasive computing and communications (PerCom), pp. 193–200.
Wiener, J.M., et al., 2012. Gaze behaviour during space perception and spatial decision making. Psychological Res. 76 (6), 713–729. https://doi.org/10.1007/s00426-011-0397-5.
Willis, A., et al., 2004. Human movement behaviour in urban spaces: implications for the design and modelling of effective pedestrian environments. Environ. Plan. B: Plan. Des. 31 (6), 805–828. https://doi.org/10.1068/b3060.
Wirz, M., et al., 2012. Inferring crowd conditions from pedestrians' location traces for real-time crowd monitoring during city-scale mass gatherings. In: 2012 IEEE 21st International Workshop on Enabling Technologies: Infrastructure for Collaborative Enterprises, pp. 367–372.
Wu, C., et al., 2016. Mitigating large errors in WiFi-based indoor localization for smartphones. IEEE Trans. Vehicular Technol 66 (7), 6246–6257.
Wu, J., et al., 2020. An improved vehicle-pedestrian near-crash identification method with a roadside LiDAR sensor. J. Saf. Res. 73, 211–224.
Xiao, W., et al., 2021. A blockchain-based secure crowd monitoring system using UAV swarm. IEEE Netw 35 (1), 108–115.
Xirui, M., Yueqian, S., Jinhu, W., Teng, H., 2022. Hierarchical extraction method for street lamp point cloud considering relative distance. Laser Optoelectron. Prog 59, 1–8.
Xu, J., Jia, X., Cheng, Z., 2023. Detection method of street tree trunks from point clouds based on multilayer aggregation. Laser Optoelectron. Prog 60, 1228009.
Xu, F., Zhou, T., You, H., Du, J., 2024. Improving indoor wayfinding with AR-enabled egocentric cues: a comparative study. Adv. Eng. Inform 59, 102265.
Yadav, A., Kumari, R., 2024. Gender safety perspective in urban planning: the case of pedestrian mobility in Kanpur city. Cities 147, 104845.
Yang, J., Fricker, P., Jung, A., 2024. From intangible to tangible: the role of big data and machine learning in walkability studies. Comput. Environ. Urban. Syst. 109, 102087.
Yang, C., Huan, S., Wu, L., Weng, Q., Xiong, W., 2023. Fusion of millimeter-wave radar and camera vision for pedestrian tracking. In: 2023 5th International Conference on Communications, Information System and Computer Engineering (CISCE), pp. 317–321.
Yoneyama, A., Yeh, C.-H., Kuo, C.-C.J., 2005. Robust vehicle and traffic information extraction for highway surveillance. EURASIP J. Adv. Signal. Process 2005, 1–17.
Zegras, P.C., Srinivasan, S., 2007. Household income, travel behavior, location, and accessibility: sketches from two different developing contexts. Transp. Res. Rec. 2038, 128–138. https://doi.org/10.3141/2038-17.

Zeng, P., Xu, W., Liu, B., Guo, Y., Shi, L., Xing, M., 2022. Walkability assessment of metro catchment area: a machine learning method based on the fusion of subject-objective perspectives. Front. Public. Health 10, 1086277.
Zhang, Y., Chang, F., Wang, M., Zhang, F., Han, C., 2018. Auxiliary learning for crowd counting via count-net. Neurocomputing 273, 190–198.
Zhang, G.T., Verbree, E., Wang, X.J., 2021. An approach to map visibility in the built environment from airborne LiDAR point clouds. IEEE Access 9, 44150–44161.
Zhang, M., Xu, R., Siu, M.F.F., Luo, X., 2023. Human decision change in crowd evacuation: a virtual reality-based study. J. Build. Eng. 68, 106041.
Zhang, F., Zu, J., Hu, M., Zhu, D., Kang, Y., Gao, S., Huang, Z., 2020. Uncovering inconspicuous places using social media check-ins and street view images. Comput. Environ. Urban. Syst. 81, 101478.
Zhao, H., Cheng, W., Yang, N., Qiu, S., Wang, Z., Wang, J., 2019. Smartphone-based 3D indoor pedestrian positioning through multi-modal data fusion. Sensors 19 (20), 4554.
Zhao, J., Xu, H., Wu, D., Liu, H., 2018. An artificial neural network to identify pedestrians and vehicles from roadside 360-degree LiDAR data. In: Proceedings of Transportation Research Board (TRB) 97th Annual Meeting Compendium of Papers.
Zhong, J., Sun, H., Cao, W., He, Z., 2020. Pedestrian motion trajectory prediction with stereo-based 3D deep pose estimation and trajectory learning. IEEE Access 8, 23480–23486.
Zhou, M., Wang, D., 2019. Investigating inter-generational changes in activity-travel behavior: a disaggregate approach. Transportation 46 (5), 1643–1687.
Zou, X., Yan, Y., Hao, X., Hu, Y., Wen, H., Liu, E., Liang, Y., 2025. Deep learning for cross-domain data fusion in urban computing: taxonomy, advances, and outlook. Inf. Fusion 113, 102606.