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REVIEW

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Past, Present, and Future Perspectives on the Integration of AI Into Walkability Assessment Tools: A Systematic Review

Yasin Delavar, Sarah Gamble, and Karla Saldana-Ochoa

School of Architecture, University of Florida, USA

Correspondence: Yasin Delavar (yasin.delavar@ufl.edu)

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Abstract

This study employs a systematic literature review (PRISMA methodology) to investigate the integration of Artificial Intelligence (AI) in walkability assessments conducted between 2012 and 2022. Analyzing 34 articles exploring data types, factors, and AI tools, the review emphasizes the value of utilizing diverse datasets, particularly street view images, to train supersized AI models. This approach fosters efficient, unbiased assessments and offers deep insights into pedestrian environment interactions. Furthermore, AI tools empower walkability assessment by facilitating mapping, scoring, designing pedestrian routes, and uncovering previously unconsidered factors. The current shift from large-scale spatial data analysis (allocentric perspective) to a ground-level view (egocentric perspective) and physical and perceptual features of walking introduces a subjective lens into current walkability assessment tools. However, the efficacy of current methods in addressing non-visual aspects of human perception and their applicability across diverse demographics remains debatable. Finally, the lack of integration of emerging technologies like virtual/augmented reality and digital twin leaves a significant gap in research, inviting further study to determine their efficacy in enhancing the current methods and, in general, understanding the interaction of humans and cities.

Keywords

artificial intelligence; digital twin; human perception; urban built environment; walkability; walkability assessment; walkable environment

1. Introduction

Walkability is a central concept within urban design, planning, and transportation disciplines, with each emphasizing its influence on achieving specific goals (Ewing & Handy, 2009). Southworth (2005) defines walkability as the extent to which the built environment supports and encourages pedestrian activity. This includes prioritizing pedestrian comfort and safety, fostering connectivity between destinations within a reasonable timeframe, and offering visual interest throughout walking journeys. Notably, this definition encompasses various active travel modes, such as utilizing strollers or wheelchairs. Enhancing walkability offers a multitude of benefits for both individuals and communities, impacting public health, transportation efficiency, and environmental sustainability (Sallis et al., 2015).

Walkability fundamentally depends on the dynamic interplay between pedestrians and their surrounding built environment. Pedestrian needs vary based on demographic factors such as age, gender, disability status, and other socio-economic characteristics. Understanding the built environment is equally crucial, as it comprises various spatial, physical, and perceived elements that influence walkability. Data pertaining to these elements can be analyzed from two key perspectives: egocentric (ground-level, user-centric, and subjective) and allocentric (aerial and objective; Mou et al., 2004). Some factors, such as sidewalk connectivity, can be assessed from both viewpoints across various scales: micro (property-to-property), neighborhood (block-to-block), and city (neighborhood-to-neighborhood).

Traditional approaches to walkability assessment often rely on manual methods, such as observation-based scoring. These methods, while prevalent, can be resource-intensive and time-consuming, hindering widespread implementation (McGinn et al., 2007). Therefore, there exists a pressing need for the development of novel and time-saving evaluation instruments.

The emergence of Artificial Intelligence (AI) offers significant potential to revolutionize the walkability assessment process. Integrating AI into these assessments holds promise for increased efficiency, accuracy, and scalability (Koo et al., 2022a). AI algorithms can automate manual processes associated with data gathering and analysis, significantly reducing the time and effort required to produce results. This automation allows communities to receive timely feedback on existing walkability issues and potential improvements.

Innovative tools and technologies leveraging AI can seamlessly integrate diverse data sources and perspectives into the walkability assessment process. The inherent capabilities of AI enable the effective merging of egocentric and allocentric data, subjective and objective data, and qualitative and quantitative information. Through the analysis of this comprehensive dataset using AI algorithms, data-driven assessments can be generated to support more informed urban planning decisions (Delavar et al., in press). This approach ensures that crucial factors such as safety, accessibility, aesthetics, community preferences, and urban indices like morphological structures and sustainability are thoroughly evaluated (Boujari et al., 2024; Hassanzadehkermanshahi & Shirowzhan, 2022; Tehrani et al., 2024; Wang et al., 2019).

Motivated by the importance of walkability in urban environments and harnessing the potential of AI, the present study aims to provide a solid basis for advancing future walkability measurement tools. The study identifies and examines recent research in the field of walkability that incorporates AI methodologies and data analysis that could feed into this domain. Our analysis centers around three key research questions:

> RQ1: How do AI models and emerging technologies enhance understanding of specific aspects of human perception related to walkability, such as safety, comfort, and aesthetics?

RQ2: How can spatial, physical, and perceived walkability features (e.g., street connectivity, barriers, and aesthetics) be effectively extracted and integrated into AI models to provide comprehensive walkability assessments?

RQ3: What specific gaps exist in current research, and what potential applications of AI and emerging technologies remain unexplored?

By systematically analyzing these research questions, this study aims to establish a robust foundation for developing and implementing future walkability assessment tools that are not only technologically advanced but also cater to the unique requirements of various populations. This, in turn, will contribute to the improvement of walkability in urban environments for all.

The remainder of the article is structured as follows. Section 2 briefly reviews some of the past walkability measurement methods. Section 3 details the methodology employed for the systematic literature review following the PRISMA guidelines. Section 4 presents a comprehensive analysis and classification of the identified research findings. Finally, Section 5 discusses the future of walkability assessment and outlines promising avenues for future research in this domain.

2. Background on Walkability Assessment

Academics and practitioners utilize various methods to evaluate walkability. Established tools include index systems (McGinn et al., 2007), subjective questionnaires for perceived data, and analysis of big urban data. Publicly accessible assessments include Walkscore (property-level scores) and the US National Walkability Index (census block scores). While these metrics provide walkability scores across the US, they rely solely on allocentric data, neglecting on-the-ground conditions.

The past decade has seen the emergence of street environment platforms like the Systematic Pedestrian and Cycling Environmental Scan (Pikora et al., 2006), and the Scottish Walkability Assessment Tool (Millington et al., 2009). Additionally, US organizations have established guidelines for walkable streetscapes, such as those developed by the National Association of City Transportation Officials (n.d.), the Portland Bureau of Environmental Services (n.d.), and the Austin Transportation Department (n.d.). However, most platforms primarily rely on allocentric data. This disconnection between allocentric and egocentric data highlights the challenge of achieving accurate and relevant assessments. Researchers actively seek solutions to integrate subjective, localized data with automated methods for increased accuracy (Chiang et al., 2017).

Six prior literature reviews related to the topic provide valuable insights into various assessment methods. Three reviews (Blečić et al., 2020; Hasan et al., 2021; Wang et al., 2022) focused on factors influencing walkability evaluation and data collection advancements. The remaining three reviews (Biljecki & Ito, 2021; Cinnamon & Jahiu, 2021; Yongchang Li et al., 2022) specifically addressed the use of street view imagery in walkability research. These prior literature reviews identified two key considerations impacting tool applicability: (a) assessment scale and (b) hierarchical arrangement of related factors.

3. Methodology

The literature review in this article is designed to identify research at the intersection of AI tools and the assessment of the built environment for walkability. The articles are classified based on AI methodologies, more specifically the machine learning processes of teaching (datasets), learning (algorithms), and inference (validation).

We examined studies published from 2012 to 2022 that delve into the specifics of AI methodologies—datasets, algorithms, and validation techniques. As outlined in Table 1, the articles were identified by query keywords in the title, abstract, author keywords, and keywords across Scopus, Web of Science, and ScienceDirect databases. Following PRISMA guidelines (Moher et al., 2009), we excluded research focused solely on pedestrian interaction (pedestrian recognition and pedestrian flow) or active transportation beyond walking (cycling). This rigorous process resulted in 34 articles for in-depth analysis (Figure 1).

The selected articles were analyzed to extract data across five crucial dimensions: general information, objectives, methodology, findings, and limitations. Key study characteristics, study area and population, data types, factors, perspective, physical and perceptual features, and AI tools, are specifically extracted.

3.1. Topic Modeling

A topic modeling analysis investigates the lexical patterns employed in studies to ascertain trends. The technique is a valuable indicator of topics and trends representing the selected literature's corpus by analyzing the abstract content (Ochoa, 2021).

Table 1. Search strings queries within Scopus, Web of Science, and ScienceDirect databases.

Search query strings
("AI") and ("walkability")
("AI," "deep learning," or "machine learning"), ("walkability" or "pedestrian environment"), and ("measurement")
("AI," "deep learning," or "machine learning") and ("walkability" or "pedestrian environment")
("AI," "deep learning," or "machine learning") and ("walkway," "footpath," "pedestrian path," "pedestrian mobility," or "active transportation")
("Automatic information extraction") and ("walkability")
("Automatic information extraction") and ("walkway," "footpath," "pedestrian path," "pedestrian mobility," or "active transportation")
("Image processing," "computer vision," "scene recognition," or "image recognition") and ("walkability")
("Image processing," "computer vision," "scene recognition," or "image recognition") and ("pedestrian" and "walking")
("Measure," "measuring," or "measurement"), ("automated," "automation," "automating," or "automatic"), and ("walkability," "walkway," "pedestrian environment," or "walkable")

Note: These search string queries were conducted within the articles' title, abstract, author keywords, and keywords plus (suggested keywords by the databases).

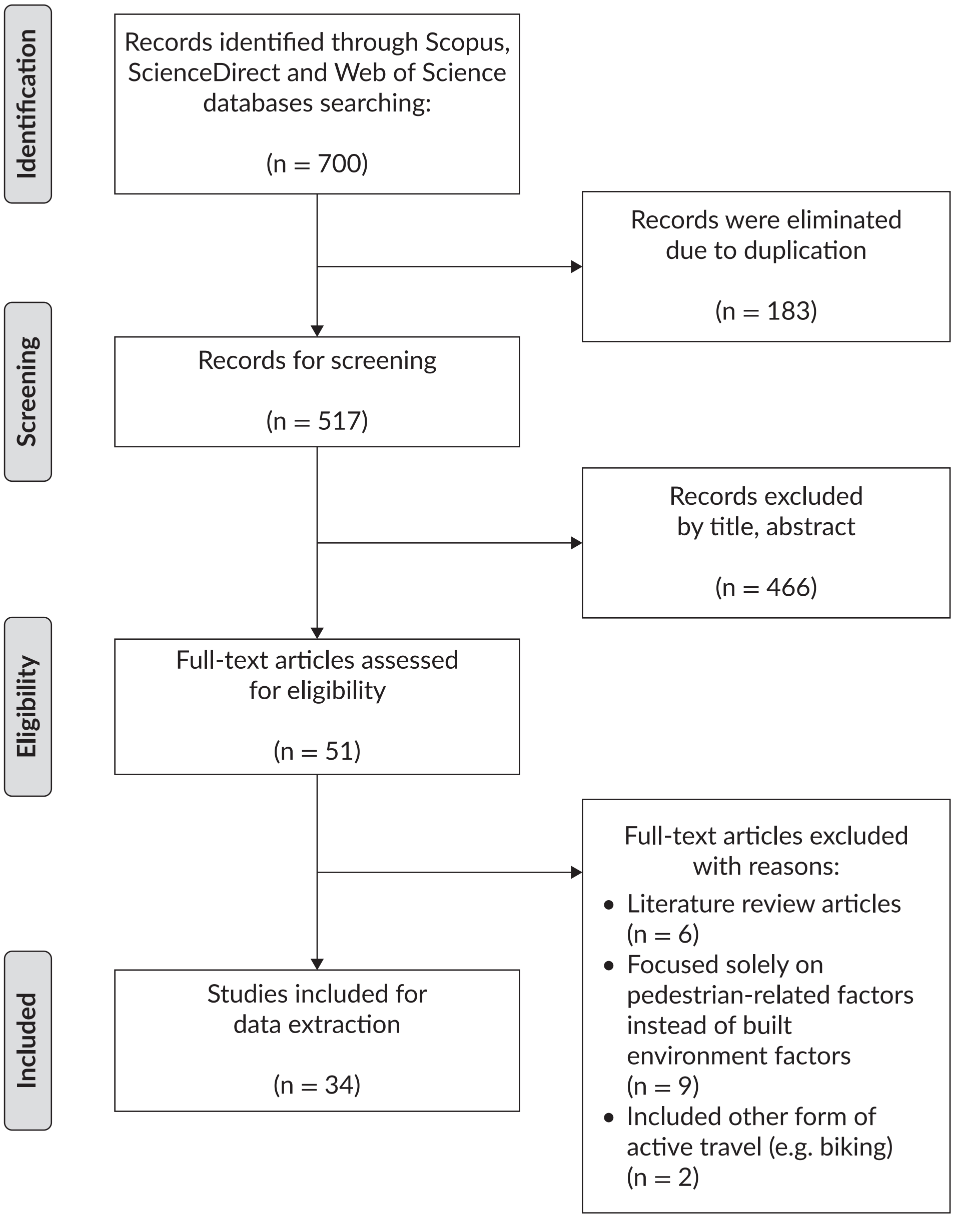

Figure 1. PRISMA flowchart of the systematic review process.

Here, topic modeling reveals the differences and similarities between two sets of studies: one comprising 700 identified articles and the other encompassing a broader selection of 4,967 articles on "walkability" from 2012 to 2022. This additional collection was sourced from the Web of Science using keywords like "walkway," "walkable," "walkability," "pedestrian environment," and "footpath." To compare both searches, topic modeling compiled a list of words from both sets of articles' abstracts and analyzed their frequency (Figures 2 and 3). These words underscore the respective focuses of each topic and provide a quantitative basis for comparison.

The findings of the analysis indicate that while there are some commonalities in both research areas, such as "pedestrian," "environment," and "system," there are also significant differences. In the "walkability and AI" literature, additional terms appeared more frequently, including "learning," "street audit," "imagery," and

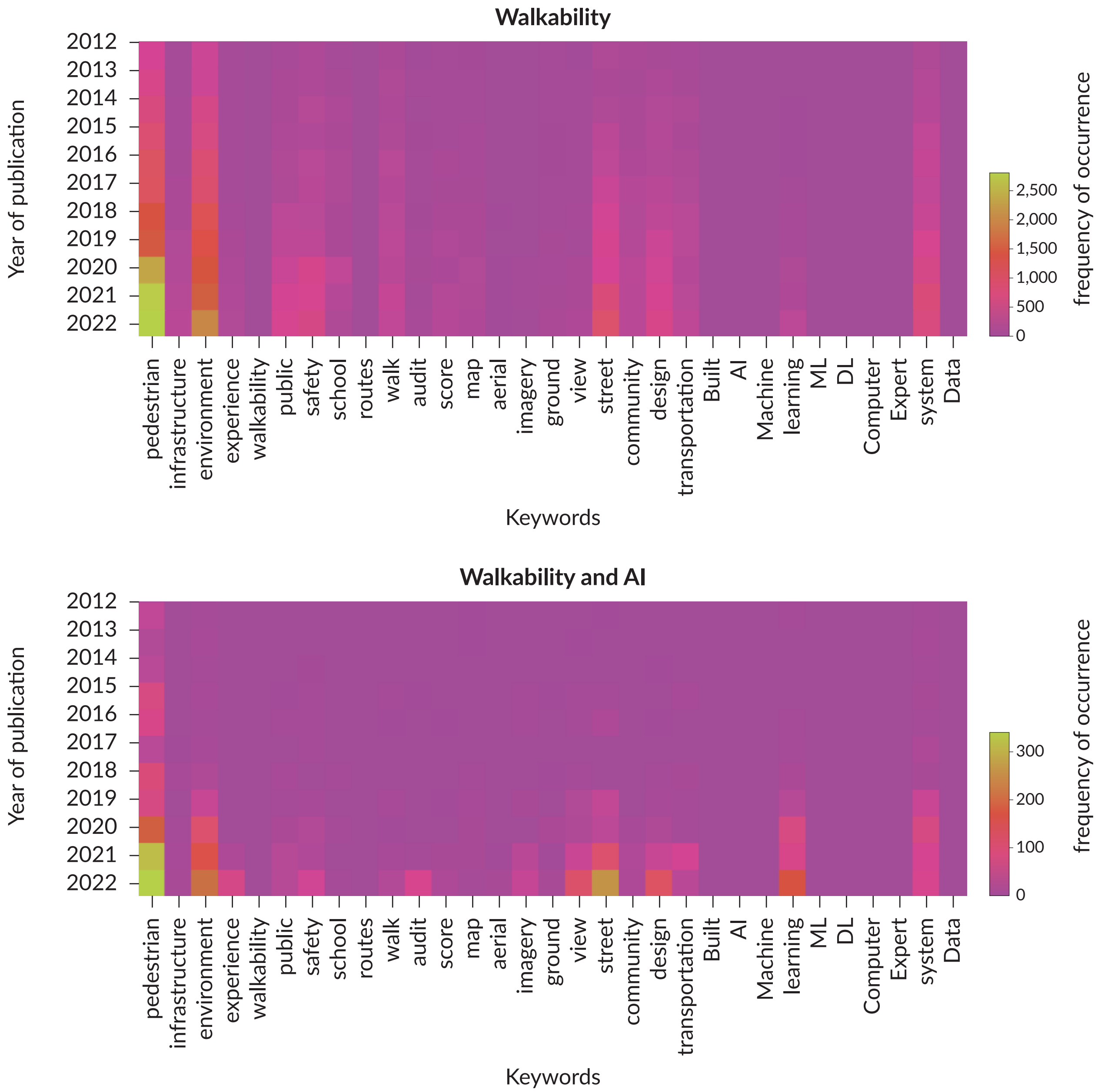

Figure 2. A 10-year analysis of lexical distribution in published literature on "walkability" (top) and "walkability and AI" (bottom).

"view," reflecting the use of AI technologies to improve walkability assessment by analyzing imagery data at the street level. The search for "walkability" alone highlighted terms such as "public," "safety," "walk," and "design," which reflect the focus on urban planning and infrastructure design to improve the quality of the walkability experience.

In the broader "walkability" research articles, the most common words are "environment," "walking," "study," "neighborhood," "area," "city," and "activity." These terms focus on the physical aspects of walkability, such as the built environment, urban design, and promoting walking as a physical activity. On the other hand, the literature on "walkability and AI" highlights different words, including "model," "street," "study," "method,"

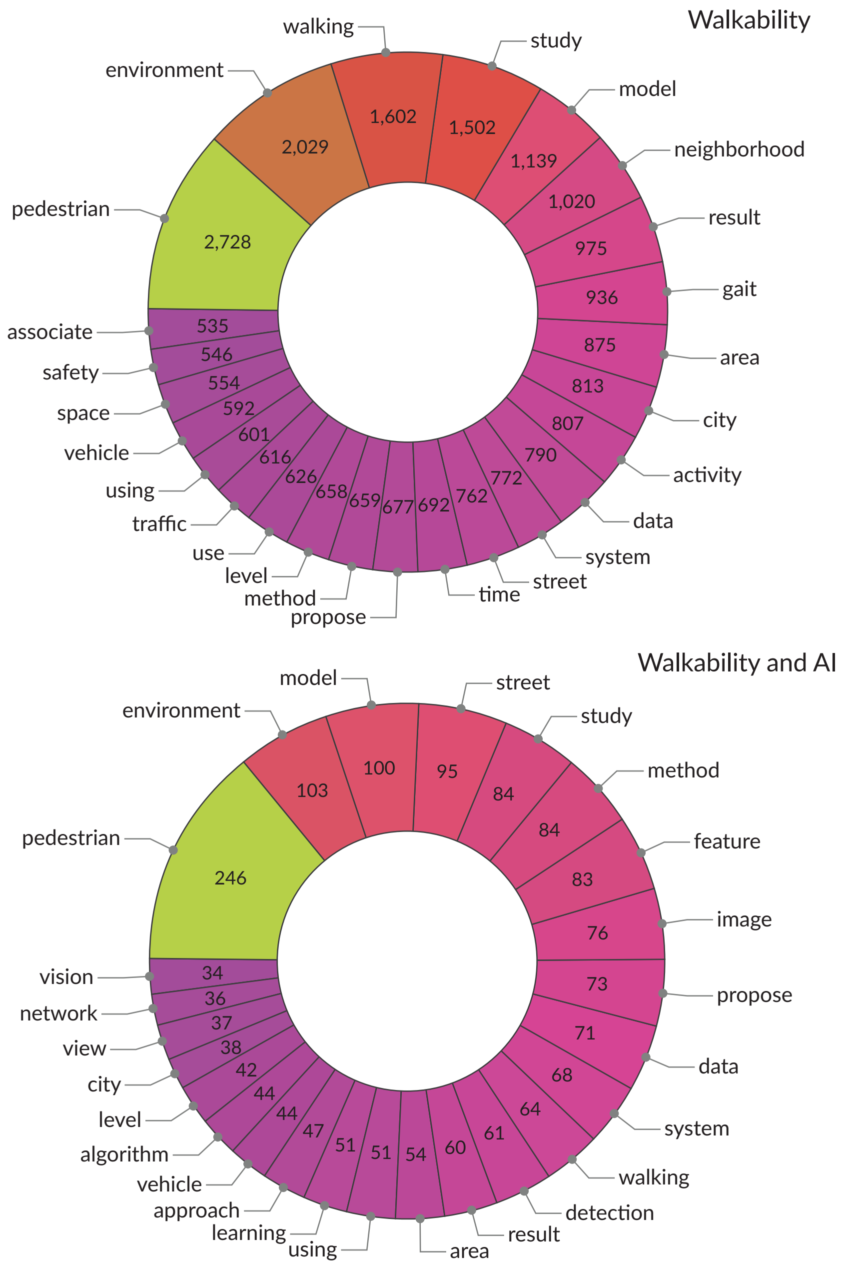

Figure 3. Lexical frequency in published literature on "walkability" (top) and "walkability and AI" (bottom), 2012–2022.

"feature," "image," and "data." These terms indicate a focus on using AI technologies to analyze and improve the subjective features of the walkability of urban environments by developing models and methods that can be applied to street-level imagery data.

4. Results

The table in the Supplementary File summarizes the results and the different attributes considered for the analysis, categorized in the following subsections.

4.1. Use and Perspective

Use classification refers to the specific demographic needs and behaviors that impact walkability, such as the requirements for safe routes for children, accessible pavements for the elderly, and gender-specific safety concerns. Perspective classification, on the other hand, pertains to the vantage point from which walkability is assessed. Egocentric perspectives provide a ground-level, user-centric view that captures the subjective pedestrian experience, while allocentric perspectives offer an aerial, objective view using broader spatial analysis tools like GIS data and aerial imagery. By integrating both use and perspective classifications.

Research spans the globe, with studies in Asia, North America, and Europe leading the way, and sufficient studies in Africa are lacking. Researchers primarily focus on understanding how everyday people navigate walking environments. However, some studies delve deeper into the experiences of elderly pedestrians, people with disabilities, and even university students on campus (see Supplementary File).

Our analysis of 34 articles revealed a preference for egocentric perspectives (17 studies) that leverage street view imagery to understand the pedestrian experience at the street level. In contrast, allocentric approaches, using broader spatial analysis (GIS data, Aerial images, etc.), were used in six articles. Interestingly, eight studies combined these perspectives, potentially to validate findings or explore discrepancies between them. One study stands out in this framework, incorporating physiological data from wearable sensors to analyze and evaluate pedestrian behaviors in the built environment (Bandini & Gasparini, 2020).

4.2. AI in Walkability Assessment

Our approach to classification is based on the three stages of AI's methodology involving: teaching, learning, and inference (Ochoa & Comes, 2021).

4.2.1. Teaching: Data Types, Features, and Factors

In the teaching stage, the focus is on the data. 95% of the revised studies used supersized learning. Therefore, the work was on labeling data, which consists of input data (also known as features) and the corresponding output or label. The algorithm uses this data to learn the underlying patterns and relationships between the input and output data and to create a model that can accurately predict outcomes based on new input. The goal of the teaching stage is to create a model that can generalize and predict with high accuracy the label to new, unseen data.

The reviewed articles utilize labeled data that can be broadly categorized into five types: geospatial data, imagery, historical data, sensor data, and survey. Imagery data appears most frequently among these data types, highlighting its significance in scholarly discussions. The imagery data, which encompasses street view images, aerial images, digital video, and panoramic images, is labeled based on the detection and measurement of street furniture, visual enclosure, openness, greenery, breakage, barriers in sidewalks, and so on.

Geospatial data provides a spatial framework, pinpointing locations, and their associated attributes. Key examples include land-use classification (residential, commercial, and park), street network configuration (highway and local road), street design elements (crosswalks and sidewalks), and public transit infrastructure (bus stops and train stations). Additionally, traffic flow data, often represented by volume and speed measurements, contributes to geospatial characterization.

Sensor data encompasses various measurements utilized in urban design and walkability studies. Remote sensing data from satellites and aircraft collects environmental information such as pollution, light levels, and traffic flow data (Yunqin Li et al., 2020). Notably, geospatial data can also play a role in environmental analysis. By examining street connectivity and land-use patterns, researchers can gain insights into walkability or the distribution of green spaces within a city (Giles-Corti et al., 2014).

Beyond these established categories, sensor data can be further categorized based on the source of measurement. Physiological data from wearable sensors provides insights into human experiences (Bandini & Gasparini, 2020). Examples include biosignals (heart rate and skin conductivity) and GPS data for tracking movement patterns (Miranda et al., 2021). This data offers a unique perspective on the interaction between pedestrian perception and the urban built environment.

Historical data can be incorporated into walkability studies to provide valuable insights. Pedestrian data, often labeled based on the number of pedestrians observed at specific locations and times, offers information on pedestrian volumes and patterns. Additionally, historical accident statistics, categorized by accident type and severity, can shed light on potential safety concerns within the built environment (Bustos et al., 2021).

In the training phase, studies typically employ diverse labeled data types, often combining information from different sources or domains to enhance their models' accuracy (Koo et al., 2022b). For instance, Wang et al. (2019) examined China's elderly using street view images (egocentric) and surveys. They trained a model (Fully Convolutional Network) to find links between walkability features (like enclosure) in the images and self-reported depression/anxiety in the surveys. Adams et al. (2022) compared allocentric and egocentric data (street view, GIS, and surveys) in Phoenix, US, to assess general pedestrian walkability. They used machine learning (convolutional neural network) and expert systems (Decision Support System) to analyze features like sidewalks, crosswalks, and lighting. This allowed them to both evaluate walkability and automate sidewalk feature detection. Similarly, in studies on the evaluation of pedestrian accessibility, the researchers used the GIS features from the OpenStreetMap website and surveys as input for their model (Lucchesi et al., 2023).

4.2.2. Learning: AI Tools

In the learning stage, the model is trained with the test data. The model's accuracy is evaluated based on its performance on this test data. If the model performs well on the test data, it can be considered trained and ready to proceed to the inference stage. In this phase, the choice of algorithms and techniques is influenced by the type of labeled data. The reviewed studies encompass various categories of algorithms, including machine learning, expert systems, computer vision, and robotics.

Machine learning appears most frequently among reviewed algorithms, constituting 58% of the labeled data. Most studies leverage supervised learning techniques like decision trees (Kim et al., 2022) to train models on image data. This focus on imagery is reflected in the dominance of the architecture of convolutional neural networks—referenced in 14 articles. Convolutional neural networks excel at recognizing walkability features, including not just physical aspects like sidewalk width and slope (Zhao et al., 2016) but also factors influencing pedestrian experiences, such as the presence of greenery and shade (Wang et al., 2019). This approach goes beyond traditional safety concerns and incorporates elements influencing how enjoyable a walking environment is.

Studies utilize image segmentation for feature categorization (Lee et al., 2022; Ning et al., 2022), and instance segmentation for object detection, particularly in mapping sidewalk features. Robotics research focuses on developing prototype systems for data collection via computing devices (Bandini & Gasparini, 2020; Zhang et al., 2021). The reviewed literature reveals that researchers commonly use a combination of algorithms. For instance, to evaluate walkability indexes, a study employed the expert systems model to train the GIS features. At the same time, street-view images were used as input for the computer vision model (Yunqin Li et al., 2020). Additionally, expert systems and computer vision were combined to define a walkability index (Miranda et al., 2021).

4.2.3. Inference: Validation and Research Findings

In the inference stage, the trained model makes predictions on new, unseen data. The model takes in the input data and uses the relationships learned during the previous stage to predict. The goal of the inference stage is to use the trained model to make accurate predictions on new data.

Researchers employ various methods to evaluate walkability within the built environment. One approach utilizes walkability indices, including safety, comfort, and accessibility (D'Orso & Migliore, 2018; Yunqin Li et al., 2020, 2022; Yuan & Chen, 2022). These indices assess pedestrian routes based on these factors. Other indices, such as those focusing on desirability (Miranda et al., 2021) or elderly pedestrians (Gorrini & Bandini, 2019), have been developed to provide more specific evaluations of walkability. Additionally, certain studies quantify both physical and perceived features of pedestrian routes (Giles-Corti et al., 2014; Kim et al., 2022; Lee et al., 2022; Ma et al., 2021; Nag & Goswami, 2022; Yang et al., 2022; Yunqin Li et al., 2022; Zhou et al., 2019).

Beyond core walkability factors, some models incorporate additional data to improve prediction accuracy. This data can include factors like walking time (Nagata et al., 2020), time of day (Lai & Kontokosta, 2018), and even biosignals from pedestrians (Kim et al., 2022). These additional considerations highlight the multifaceted nature of walkability and the ongoing efforts to develop increasingly comprehensive models. Certain studies have employed various methods, such as defining a walkability score (Alfosool et al., 2022), rating pedestrian access to urban amenities provided by the city (Blečić, Cecchini, Congiu, et al., 2015; Blečić, Cecchini, & Trunfio, 2015), assessing the resilience of pedestrian pathways (Ku et al., 2022), and evaluating the quality of services available on sidewalks, as means of measuring walkability (Zhao et al., 2016). Some models employ different approaches, such as making predictions by identifying optimal pedestrian accessibility routes (Blečić, Cecchini, Congiu, et al., 2015; Blečić, Cecchini, & Trunfio, 2015) or proposing design solutions and evaluating their impact on walkability (Shao et al., 2021).

Detecting microscale streetscape features associated with pedestrian physical activity is one way to measure walkability, as demonstrated by the effects of these features on walkability (Adams et al., 2022; Blečić et al., 2018). Furthermore, advancements in automation are leading to the development of tools that can automatically detect and map these features. Research by Theodosiou et al. (2022) explore the use of automated barrier and obstacle detection for sidewalk feature data mapping.

The reviewed models also demonstrate another form of inference, which involves automating sidewalk features and data mapping. A trained model could significantly reduce the time and cost of collecting sidewalk mapping data by minimizing the need for human surveyors (Zhang et al., 2021). In another study to assist mobility-disabled users, a model could predict sidewalk features in previously unseen data (Ning et al., 2022). In addition, an attempt to map out walkability elements involves an automated audit that could serve as a highly scalable and dependable alternative to virtual audits (Koo et al., 2022a). Mapping can also be achieved by predicting the hazards on pedestrian routes through classified street images based on the likelihood of pedestrian-vehicle and vehicle-vehicle accidents (Bustos et al., 2021).

Finally, leveraging AI in the field of walkability, inquiries about the correlation between certain factors and walkability. Bandini and Gasparini (2020), Yin and Wang (2016), and Yue et al. (2022) investigate the connection between walkability and mental health, using visual enclosure and levels of depression and anxiety as datasets. Wang et al. (2019) also explore this relationship but with a focus on elderly pedestrians. Additionally, Lucchesi et al. (2023) examine the barriers and incentives of walking and find that areas with low walkability are typically car-oriented and unoccupied, with heavy vehicle traffic and significant vegetation. Conversely, denser areas with proximity to public transportation and lighting are more pedestrian-friendly, encouraging residents to walk.

4.3. Limitations and Existing Gaps

Current walkability assessment methodologies face limitations in data, evaluation methods, and accuracy of AI models. Challenges persist in processing complex data like street view images, adequately considering all relevant factors influencing walkability, and seamlessly integrating data from diverse sources (e.g., GIS and human subject surveys). Beyond technical challenges, there exists a notable gap in representing the experiences of diverse demographics and geographic contexts in walkability assessments. Many existing approaches may not adequately capture the subjective aspects of walkability, including non-visual factors like aesthetics, which are crucial for understanding how different communities perceive and interact with their urban environments. Importantly, these challenges are exacerbated by the limitations in scaling findings from localized studies to larger areas, hindering the applicability of walkability assessments on a broader scale.

In addition to these fundamental challenges, the integration of emerging technologies holds immense potential for revolutionizing walkability research. Devices such as eye-tracking devices, biosensors, wearables, and virtual/augmented reality (VR/AR) platforms, along with digital twin technologies, offer new avenues to enhance the precision and scope of walkability assessments. However, the full utilization of these technologies remains largely unexplored in the context of walkability studies.

A limitation of street-view images for walkability assessment is the misalignment between pedestrian and street-view image viewpoints. This misalignment introduces measurement challenges and distorts 360° panoramic images, affecting the accuracy of walkability evaluation (Lee et al., 2022). Furthermore, current models may not effectively predict transient visual elements such as cars, bicyclists, and pedestrians, which are crucial factors influencing walkability (Ma et al., 2021). Temporal and spatial limitations also impact walkability assessments based on street-view images. Images collected at different years or seasons may not accurately represent the current streetscape, compromising the validity of the assessment (Nagata et al., 2020). Additionally, the uneven spatial distribution of imagery introduces bias in evaluating neighborhood walkability, potentially leading to incomplete or skewed findings (Zhou et al., 2019).

The quantity and quality of street-view images pose challenges to comprehensive walkability assessments. Insufficient images and limited instances of less frequent barriers and obstacles on sidewalks limit the effectiveness of the assessment (Theodosiou et al., 2022). Moreover, the color similarity between sidewalks and vehicle roads can impact the accuracy of segmenting sidewalk pixels and predicting walkability attributes (Yang et al., 2022). To mitigate some limitations, researchers suggest collecting images from the sidewalk point of view, providing a more accurate representation of pedestrians' experiences (Lucchesi et al., 2023).

Non-visual aspects of walkability, including auditory and haptic perception (soundscapes and uneven sidewalks) and air quality (pollution affecting health choices), are often overlooked, limiting the holistic understanding of walkability (Yang et al., 2022). Demographic and area considerations also pose limitations to walkability assessment. In addition to technical assessment, walkability is subjective and varies among individuals, necessitating discussions on indicator weighting to account for these variations. Studies focusing on specific areas and age groups may limit the generalizability of their findings, emphasizing the need for testing diverse demographics and locations (Yunqin Li et al., 2020; Nagata et al., 2020). Furthermore, while using surveys and field observations as a means of labeling data is effective for smaller areas, their application to extensive urban street evaluations presents challenges and impracticalities (Yunqin Li et al., 2020).

5. Discussion

The proliferation of street view imagery and advancements in image processing techniques have facilitated the integration of AI into walkability research. The AI models used in the reviewed studies use algorithms with diverse data sources and architectures. The most common architecture was neural networks, and the applications extended to streetscape feature detection, mapping, scoring, and designing walkable routes. This flexibility highlights the potential of AI to analyze walkability from multiple perspectives. While topic modeling analysis confirmed knowledge about walkability factors, processing street view images presents challenges. These include misalignment with pedestrian viewpoints, image quantity and quality inconsistencies, and color similarity issues. The identified limitations and challenges discussed point to the ongoing need to integrate manual and human data sources into walkability assessments where AI tools cannot fully or accurately assess factors and/or such sources are needed to confirm assessments by fully automated AI tools. With currently available technologies, this study has highlighted the inability of AI to assess experiential factors, human perception of space, and micro-barriers that appear minor or are physically small yet create large barriers to walkability and may conflict with Americans with Disabilities Act standards. Future research should address these limitations and consider non-visual and temporal aspects like noise pollution, air quality, and comfort for a more holistic understanding.

Historically, walkability assessments concentrated on objective factors. However, with AI and street view data, the focus has shifted to a subjective, ground-level pedestrian perspective. AI models can learn to measure perceptual features such as safety or pleasurability by analyzing greenery or building abandonment through image processing. This transformative approach can enhance our understanding of the intricate relationship between the built environment and pedestrians. Despite several advantages over traditional methods, including time savings, comprehensive analysis, reduced bias, and scalability, AI tools constantly evolve to better capture human perception. New technologies like digital twins, eye-tracking devices, biosensors, wearables sensors, and VR/AR offer opportunities to move beyond current methods and achieve a more comprehensive understanding. Existing research lacks training models that leverage these emerging technologies.

6. Conclusion: Further Research and Outlook

With the help of digital twins and VR/AR technologies, it is possible to create a controlled environment for different scenarios of streetscapes. These virtual models can integrate various data sources, including street view imagery, GIS data, and real-time sensor readings. Researchers can manipulate variables like traffic density, building heights, and green space to simulate real-world conditions. The immersive nature allows participants to provide nuanced insights into their perception of safety, comfort, and ease of movement. Additionally, researchers can better understand pedestrian attention patterns by integrating eye-tracking technology. Furthermore, virtual pedestrian agents can be programmed to navigate the environment, providing insights into safety, comfort, and route surface evenness. Participants could virtually walk through simulated environments, providing feedback on their perceived walkability.

Pedestrians can wear AR glasses that overlay digital information, highlighting incentives and barriers in their walking experiences. This time, participants or surveyors could physically walk through physical environments, providing feedback on their perceived walkability. Afterward, AI can analyze video data captured through AR wearables, feedback, and labeled data to automatically identify behavioral walking patterns and environmental interactions. This approach could be particularly beneficial for studying the needs of specific populations, such as children or individuals with disabilities. While acknowledging challenges regarding accessibility, inclusivity, and data privacy, the possibilities offered by digital twins, VR/AR, and AI are undeniable. This approach signifies a shift in walkability assessment, moving beyond current methods to understand the subjective and cognitive experience of walking.

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Conflict of Interests

The authors declare no conflict of interests.

Data Availability

The data that support the findings of this study are available from the corresponding author, Yasin Delavar, upon reasonable request.

Supplementary Material

Supplementary material for this article is available online in the format provided by the authors (unedited).

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About the Authors

Yasin Delavar is a PhD student at the School of Architecture at the University of Florida. His research areas include AI, BIM, Digital Twins, Visualization, and Computational Design. You can visit his website at http://www.yasindelavar.com.

Sarah Gamble is a registered architect, assistant professor, and director of the Certificate in Public Interest Design at the University of Florida School of Architecture. Her professional experience includes design and advocacy work for affordable housing, disaster recovery, downtown development, public art, and more. Her academic research centers on public interest design, with a focus on walkability and walking as a tool for the creative process. She is the co-author of *Environmental Activism by Design* (2023) with Coleman Coker.

Karla Saldana-Ochoa is a professor at the School of Architecture at the University of Florida and a faculty affiliate at the AI2 Center, the Center of Latin American Studies, and FIBER. Karla is the director of SHARE Lab, a research group working on projects to leverage the interaction between artificial and human intelligence as instruments for creativity in architectural design and tools to analyze big data for social good. She collaborates on international projects in Germany, Italy, Switzerland, Mexico, and Ecuador. Karla is an Ecuadorian architect with an MA in landscape architecture and a PhD in architecture from ETH Zurich.