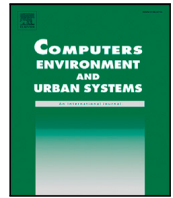




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Walking smart in the heat: A dynamic shade-oriented pathfinding approach to enhance pedestrian comfort in arid cities

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ABSTRACT

In recent decades, rapid population growth in Middle Eastern cities has led to increased motorization and rising carbon emissions, particularly in car-oriented, high-density urban environments like Dubai. In response, cities are expanding their public transportation systems and promoting walking and cycling. However, scorching temperatures make the choice of active mobility challenging. This study presents a methodology to evaluate pedestrian walking environments by comparing the alignment between the shortest and optimal shadiest paths around metro stations in Dubai. Unlike existing models that apply a constant shade reward, we develop an optimal shadiest path method that assigns dynamic rewards to buildings, trees, and indoor shade, which better reflects real-world conditions. Additionally, we highlight the often-overlooked role of indoor paths in enhancing pedestrian thermal comfort, particularly in arid cities. To quantify both the shortcut effect and the shade improvement of indoor paths, we introduce the Indoor Contribution Index (ICI), a metric that assesses the role of indoor routes in improving pedestrian thermal comfort and walking efficiency. The results reveal that, on average, the optimal shadiest path is 1.3% longer than the shortest path, with an 8.9% increase in building shade and an 8.8% decrease in sun exposure compared to the shortest path. Additionally, both temporal factors and spatial characteristics significantly influence the utility of indoor routes in enhancing thermal walking comfort. Our findings highlight the need for further research into smart pathfinding algorithms that can guide pedestrians through hot environments, as well as the integration of indoor networks into urban mobility systems, particularly in Middle Eastern cities and other regions with harsh outdoor conditions.

1. Introduction

The population in Middle Eastern cities has grown rapidly over the past two decades (Dubai Statistics Center, 2023; Planning and Statistics Authority, Qatar, 2024; Statistics Centre, Abu Dhabi, 2024), placing increasing demands on urban infrastructure, particularly transportation systems. For instance, Dubai's population increased from 1.32 million in 2005 to 3.65 million in 2023 (Dubai Statistics Center, 2023). In response, the city has expanded its metro network, covering 74 km with 49 stations and serving over 600,000 daily riders as of 2022 (Gugler et al., 2021), with plans to grow to 197 stations by 2030 (Roads and Transport Authority, Dubai, 2024).

While these investments in public transportation have been instrumental in accommodating the city's expanding population, the number of vehicles has also increased significantly. By 2015, there were 540

vehicles per 1000 inhabitants in Dubai, surpassing the rates in cities like London and New York (Qamhaieh & Chakravarty, 2020). This surge in both population and vehicle numbers has, unsurprisingly, led to higher carbon emissions (Pal & Eltahir, 2016). To address these challenges, Dubai has introduced its "20-min city" plan (Dubai Municipality, 2024), which aims to enhance the areas around metro stations, making it easier for residents to reach their destinations on foot or by bicycle. This initiative will require the city to further develop its urban environment to be more pedestrian-friendly.

However, creating a pedestrian-friendly environment in hot and arid cities such as Dubai presents considerable challenges. Dubai's climate is classified as arid, characterized by high temperatures, intense sunlight, and minimal rainfall throughout the year. The extreme heat, particularly during the summer months when average daily high temperatures often exceed 40 °C (Pal & Eltahir, 2016; WorldData.info, 2024), makes

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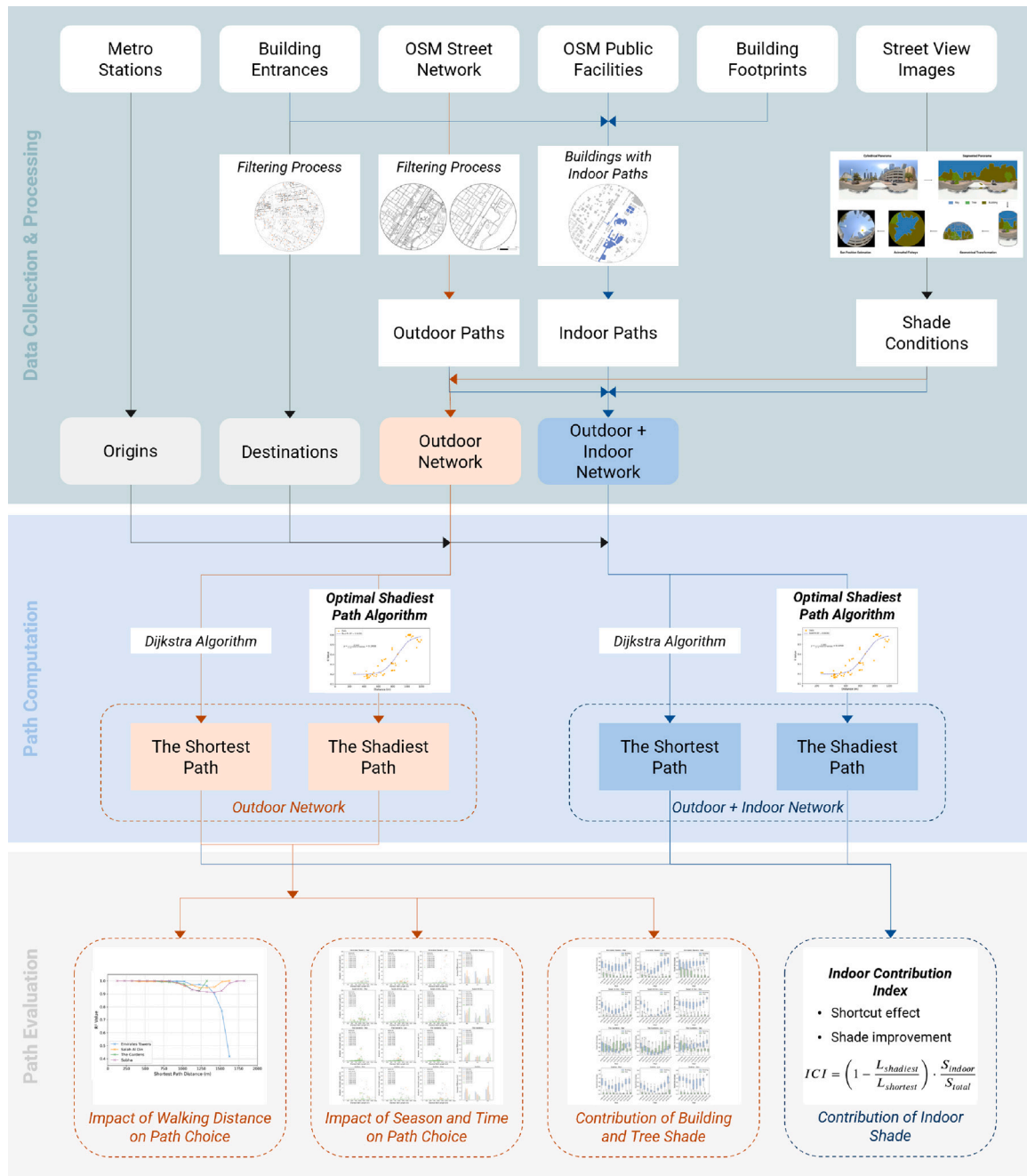


Fig. 1. Methodology flowchart outlining the process from data collection and preprocessing to path computation and multi-criteria evaluation.

walking outdoors uncomfortable and potentially hazardous. Furthermore, due to its proximity to the nearby gulf, the city's humidity level can be significant, with relative humidity reaching above 80%, particularly during the summer months. This combination of heat and humidity creates challenging outdoor conditions for pedestrians, highlighting the importance of improving walkability and outdoor thermal comfort.

In cities like Dubai, where air temperatures are consistently high and wind is generally weak throughout the year, solar radiation becomes the dominant factor affecting pedestrian comfort (Fabros, 2009). Therefore, shading has been identified as a key intervention to mitigate heat stress (Lin et al., 2010; Middel et al., 2016; Nasrollahi et al., 2021; Watanabe et al., 2014), as it reduces direct solar radiation (Armson et al., 2012; Halawa et al., 2014; Tan et al., 2014), thereby lowering surface and air temperatures in the surrounding areas. Ideally, sidewalks in Dubai should be fully shaded by trees to provide continuous

relief throughout the day. However, the harsh climate often hinders tree growth and leads to high maintenance costs, leaving many pedestrian paths without sufficient shade. To mitigate this, a practice in Dubai is for pedestrians to use indoor, typically air-conditioned pathways within public and commercial buildings. These indoor pathways provide convenient shortcuts and allow people to avoid the discomfort of walking in the heat.

One way to assess whether a city is pedestrian-friendly is by examining the alignment between the shortest path and the shadiest path. This comparison helps evaluate how well walking efficiency corresponds with pedestrian thermal comfort, an increasingly important concern in hot-climate cities. The goal of this study is to develop a more realistic and human-centered pedestrian navigation model that integrates both outdoor and indoor environmental conditions, enabling smarter pathfinding under extreme heat. While the shortest path is typically

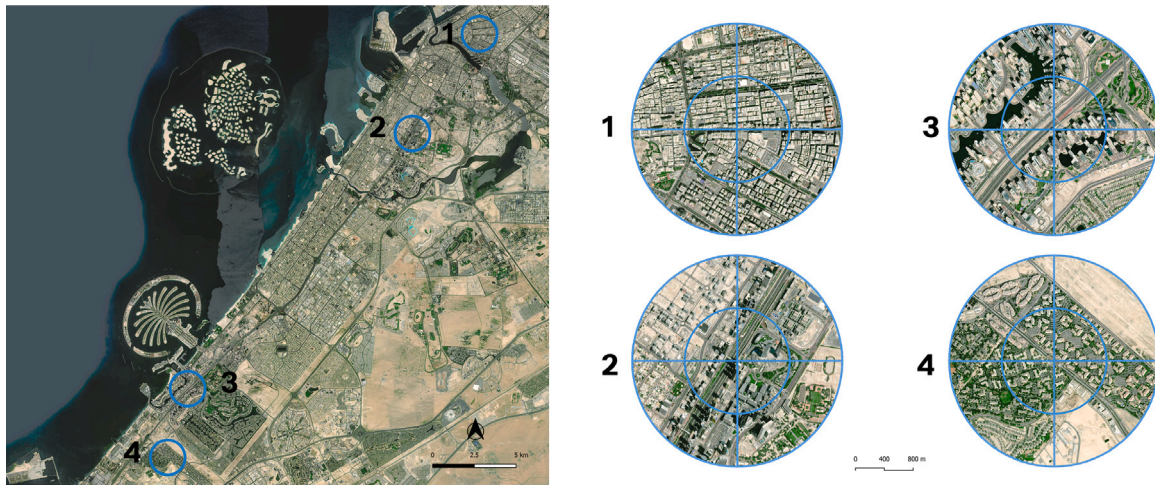


Fig. 2. Locations of the four selected metro stations in Dubai: (1) Salah Al Din, (2) Emirates Towers, (3) Sobha, and (4) The Gardens. Two buffer zones (500 m and 1000 m) were generated around each station to define the study areas. Each buffer was further divided into four directional quarters to analyze walking patterns relative to direction.

calculated using the well-known Dijkstra algorithm (Dijkstra, 1959), current approaches to identifying the optimal shadiest path reveal three key gaps.

First, most existing studies apply a static cost-benefit model, assigning a fixed penalty for sun exposure or a constant reward for shade (Feng et al., 2024; Li et al., 2022; López-Pazos et al., 2017; Peng et al., 2021; Vartholomaos, 2023; Wolf et al., 2024). However, empirical evidence indicates a correlation between pedestrian fatigue and shade preference: as walking distance increases, pedestrians may exhibit a stronger preference for shaded areas due to increased physical exertion. This suggests that the perceived value of shade increases with walking distance, and therefore, the reward for shade should be dynamic rather than constant.

Second, most algorithms for finding the shadiest path do not differentiate between building shade and tree shade (Feng et al., 2024; Li et al., 2022; López-Pazos et al., 2017; Vartholomaos, 2023; Wolf et al., 2024). In urban environments, shade typically originates from either buildings or trees, with building shade offering two main advantages over tree shade. First, it generally covers larger areas due to the greater size and volume of buildings. Second, it is more consistent and complete, fully blocking sunlight and creating predictable shaded zones across space and time. In contrast, tree shade is typically partial, dynamic, and dappled, as it is shaped by the movement of leaves and the position of the sun, resulting in more variable and fragmented coverage. Given these differences, tree shade and building shade should be assigned distinct reward values in pathfinding algorithms.

Third, existing studies largely overlook the potential of indoor paths as part of the pedestrian network, such as shopping malls and covered walkways. While indoor navigation has been explored in other contexts such as emergency evacuation (Inoue et al., 2008), it is rarely incorporated into thermal comfort-based routing models. This omission is especially significant in hot climates, where indoor environments often provide the most effective relief from outdoor heat.

To address these gaps, we developed an optimal shadiest path method that dynamically assigns rewards to building shade, tree shade, and indoor shade based on the cumulative walking distance. This approach offers a more realistic representation of pedestrian behavior compared to existing models. We applied this method to a case study in Dubai, comparing the shortest path and the optimal shadiest path from metro stations to destinations within 500- and 1000-m buffers. These buffer zones were chosen to capture the critical final walking distance, acknowledging metro stations as key transit hubs. The comparison was conducted across different seasons and times of day, with indoor paths also integrated into the analysis. The degree of alignment between the

shortest and optimal shadiest paths serves as an indicator of how well the areas surrounding metro stations support pedestrian mobility and thermal comfort.

2. Methods

An overview of the methodological framework is illustrated in Fig. 1.

2.1. Study area

This study focuses on understanding the deviation between the shortest path and the optimal shadiest path around Dubai's metro stations. Four metro stations were selected for their diverse characteristics including surrounding street network, building and tree densities, building heights, and land use (Fig. 2). Sobha station is surrounded by high-rise buildings, while Emirates Towers features high-rise buildings at its center with low-rise structures in the surrounding areas. In contrast, Salah Al Din and The Gardens stations are predominantly surrounded by low-rise residential buildings. The Salah Al Din area, a primarily low-income residential zone, has limited tree coverage, whereas The Gardens station, located in a high-income residential area, features abundant tree-lined sidewalks.

Two buffers, with a radius of 500 m and 1000 m respectively, were created around each metro station to define the study areas. Each buffer was divided into four directional quarters to account for how walking direction may influence the relevance of shaded paths. Within each quarter, up to 20 random destinations were selected from the building entrance data, with five of them located within the 500-m buffer (Fig. A.2). To avoid clustering, a minimum distance of 100 m between selected points was enforced. Due to limited building entrance data in some quarters, fewer than 20 points were selected in certain cases. As a result, the final number of building entrances used as destinations was: 80 for Salah Al Din, 73 for Emirates Towers, 71 for Sobha, and 74 for The Gardens.

2.2. Walking path network

2.2.1. Outdoor paths

To determine outdoor sidewalk paths for pedestrians, we used publicly available OpenStreetMap (OSM) data as the initial source. The OSM street network was then converted into a graph of nodes and edges using the OSM4Routing library (rust-transit, 2024). We applied two primary filters: (1) the road must be accessible to pedestrians, and

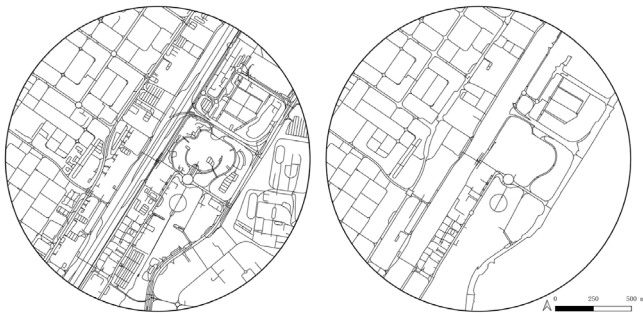


Fig. 3. Outdoor pedestrian network around Emirates Towers station before (left) and after (right) the filtering process to ensure that paths are both accessible and suitable for pedestrian use.

(2) it must be suitable for pedestrian use. Specifically, we retained only roads tagged with the “foot” route designation, which indicates that the road is walkable without restrictions related to fitness, equipment, or weather conditions (OpenStreetMap contributors, 2017). Since the metro station serves as our starting node, we removed isolated nodes from the graph, ensuring that every node is reachable from the metro station. Fig. 3 showcases the outdoor network before and after the described filtering process.

2.2.2. Indoor paths

To identify accessible buildings, we utilized publicly available building footprints from OSM, along with the locations of public facilities from the same source. Additionally, we incorporated building entrance data provided by the city’s digital open portal (Digital Dubai Office, 2024). First, we filtered out buildings with fewer than two entrances, as these do not significantly contribute to the pedestrian network. We then focused on buildings’ public facilities, under the assumption that these are accessible to pedestrians. To exclude residential buildings with ground-floor public facilities, such as shops and restaurants, that do not form a coherent pedestrian path, we offset the building footprints inward by 12 m using QGIS’s buffer processing tool. This offset was empirically selected to filter out such buildings while retaining structures with centrally located public facilities, such as shopping malls or multifunctional complexes, which are more conducive to internal pedestrian circulation.

In shopping complexes, central communal areas play a crucial role in fostering social interaction and enhancing the shopping experience (Dawson & Lord, 2012). These spaces are designed to be pedestrian-friendly. To construct an indoor pedestrian network for our study, we assumed 20% of the area to be communal (Marcus & Francis, 1997). We offset building footprints inward to simulate layouts representing these pedestrian-accessible spaces, ensuring a realistic depiction of indoor movement areas. We then connected building entrances to these layouts using the nearest distance to form indoor nodes. Additionally, we generated centroids for the inner areas and connected them to the indoor nodes, forming a complete indoor network for each building. For buildings with complex layouts that cannot be simplified through uniform scaling without losing essential structural or navigational features, such as multiple corridors, disconnected subareas, or irregular internal shapes, we created multiple centroids to more accurately represent pedestrian routes between entrances. Fig. 4 illustrates an indoor network example from a shopping mall at Salah Al Din metro station.

In the case of buildings with a long length and narrow width — such as linear underground malls or transit corridors, where the length of the building footprint significantly exceeds its width, often by an order of magnitude — offsetting the footprint inward did not consistently generate a suitable common area. For such buildings, we used key points of the building footprint to create an inner polyline. We then

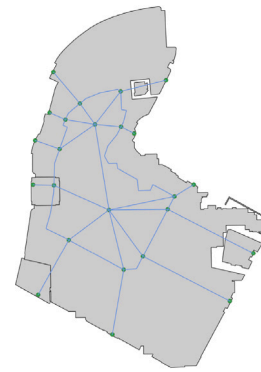


Fig. 4. Example of the indoor pedestrian network within a shopping mall located at the Salah Al Din metro station.

connected the key points to the entrances to form an indoor network. This approach allows for the representation of the likely movement of pedestrians through the building by capturing the central circulation axis or the primary walkable zone.

To validate the indoor path network, we conducted on-site observations and collected GPS data while walking between building entrances. For each indoor building, we examined the accessibility of the building for pedestrians, the presence of building entrances, and the connectivity of these entrances with a complete indoor path. While this method confirmed true/false positives for modeled paths, it is acknowledged that certain potential pathways might have been overlooked.

2.3. Computing the shortest and optimal shadiest paths

2.3.1. The shortest path

To calculate the shortest path between nodes, we used the Dijkstra algorithm (Dijkstra, 1959) for each pair of origin (metro station) and destination (building entrance). The algorithm iteratively selects the node with the smallest known distance from the starting node and updates the shortest paths to its neighboring nodes until the optimal shortest path is determined.

2.3.2. The optimal shadiest path

The shadiest path is determined by assigning rewards to building shade, tree shade, and indoor shade, effectively making shaded segments appear shorter than their actual physical distance. The optimal shadiest path is then the one with the minimal adjusted distance between the origin and the destination.

The shadiest path consists of two components: outdoor shaded paths and indoor paths. Indoor paths are considered shaded as they fall within covered buildings, with minimal or no sun exposure. To estimate shade for outdoor sidewalks, we utilized panoramic images collected at 2.5-m intervals along each filtered path using a GoPro Max camera. These images can be manually collected or sourced from external platforms such as Google Street View (GSV), Apple Maps, Bing Maps, or other similar services. It is important to note that the coverage of these services varies globally, and the use of their imagery for research or commercial purposes is subject to the rules and restrictions imposed by the respective owners.

For each panorama image obtained, we panoptically segmented sky, buildings, and trees using the Detectron2 Field Pyramid Network (FPN) model (Wu et al., 2019). The segmented panoramas were then geometrically transformed into cylindrical, spherical, and finally hemispherical fisheye views to model shade cover in a street canyon setting (Li et al., 2022). Given that shade is temporally and spatially dependent, we implemented a sun position estimation algorithm based on temporal inputs (time of day and date) and spatial inputs (latitude and longitude). Shade was determined by comparing the computed

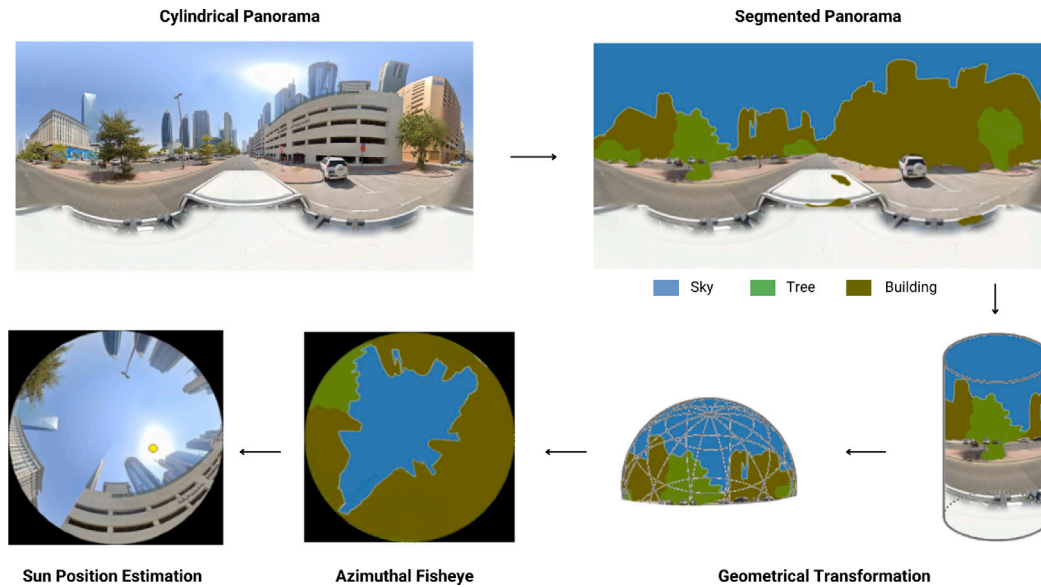


Fig. 5. Shade estimation involves segmenting a cylindrical image into three components: sky, trees, and buildings. The segmented image is then geometrically transformed from a cylindrical view to a hemispherical view. Finally, it is converted into an azimuthal fisheye view, where the estimated sun position is used to assess the shade.

sun position with the segmentation mask in the fisheye view; if the sun falls on a pixel classified as a tree or building, the corresponding location is considered shaded by that element. It is important to note that all hemispherical images were oriented to face magnetic north using the GoPro camera's magnetometer heading readings. This step is crucial to ensure that the estimated sun position aligns accurately with the actual sun position in the hemispherical images. Shade was then estimated by comparing the sun position to the segmentation mask in the hemispherical image, determining whether a given point was exposed to direct sunlight or shaded by buildings or trees.

To validate our results, we compared the shade estimations against the actual shade conditions at the time the image was captured. As illustrated in the sun position estimation step in Fig. 5, the yellow dot represents the estimated sun position, which aligns with the actual sun position at the time of image capture.

According to Dubai's historical weather data (National Center of Meteorology, 2025), the maximum air temperature consistently exceeds 26 °C year-round (Fig. A.3). Combined with high solar radiation due to persistently low cloud cover, the maximum Universal Thermal Climate Index (UTCI) during daytime remains above the threshold for thermal stress (26 °C) in all months, though not uniformly across all hours. Consequently, thermal stress is a year-round concern. To capture diverse shade conditions throughout the year, our study focuses on three key dates: June 21st (summer solstice), December 21st (winter solstice), and March 21st, between 8:00 AM and 5:00 PM.

As most panorama images were collected by car, two measures were taken to avoid underestimating shade due to the distance from the actual sidewalk. First, we ensured that car routes were as close to the sidewalks as possible when capturing the images—within approximately three meters at most, measured from the centroids of the car path and the sidewalk. Images beyond this distance were either discarded or recaptured to ensure the reliability of the shade measurements. Second, we introduced a one-hour time window in our analysis. For instance, if the shade estimation at 8:00 AM indicated the point was shaded by buildings (shade value = 1), but exposed to direct sunlight at 9:00 AM (shade value = 0), we assigned the maximum shade value of 1 for the 8:00–9:00 AM time window. This approach accounted for the fact that shadows shift slightly over the course of an hour, and pedestrians may adjust their route slightly to take advantage of nearby shade. Therefore, as long as a shadow exists within the one-hour

window at a given location, there is a high likelihood that pedestrians will be able to find shade along the sidewalk.

The initial shade estimation was based on point panorama data collected at 2.5-m intervals. For each edge in the network, we calculated the length of building shade, tree shade, and sun exposure with respect to the month and time of day. These values were later used in determining the optimal shadiest path.

2.3.3. The optimal shadiest path algorithm

In the absence of pedestrian behavior data specific to Dubai, either from experimental studies or real-world movement tracked through cellphone GPS data, our study utilized data from an experimental study conducted in Singapore to understand pedestrians' preferences for shade. Both cities experience year-round thermal stress, characterized by consistently high temperatures, high humidity, and relatively weak winds (Fig. A.3). While the climates share similarities, they are not identical, which could result in variations in pedestrian behavior. Nonetheless, in the absence of localized data, the Singapore dataset provides a valuable approximation for demonstrating our methodology.

Our goal for finding the optimal shadiest path is to minimize sun exposure by giving different rewards to building shade, tree shade and indoor shade. Researchers in Singapore found that on average, shade from trees is perceived as half intense as shade from buildings (Melnikov et al., 2022). Therefore, in our reward model, we assigned a reward of θ to building shade, and a reward of 0.5θ to tree shade.

In the Singapore study (Melnikov et al., 2022), participants were asked to complete tasks numbered 1–13, each requiring them to choose between a shorter path and a longer path with more shade. During the experiment, all participants were provided with a map clearly illustrating both route options, ensuring that route choices reflected active shade preference rather than accidental selection. From this database, we selected tasks in which the shorter path (Path A) had a longer sun exposure distance compared to the relatively longer shaded path (Path B). We then focused on responses where participants chose the longer, shaded path (Path B), as these instances reveal the minimum level of shade preference sufficient to justify taking a longer route. This represents a conservative estimate of pedestrian shade valuation, since it only accounts for scenarios where shade benefits outweighed the distance penalty. Based on these selected responses, we calculated the shade reward θ by assigning reduced weights (less than 1) to shaded

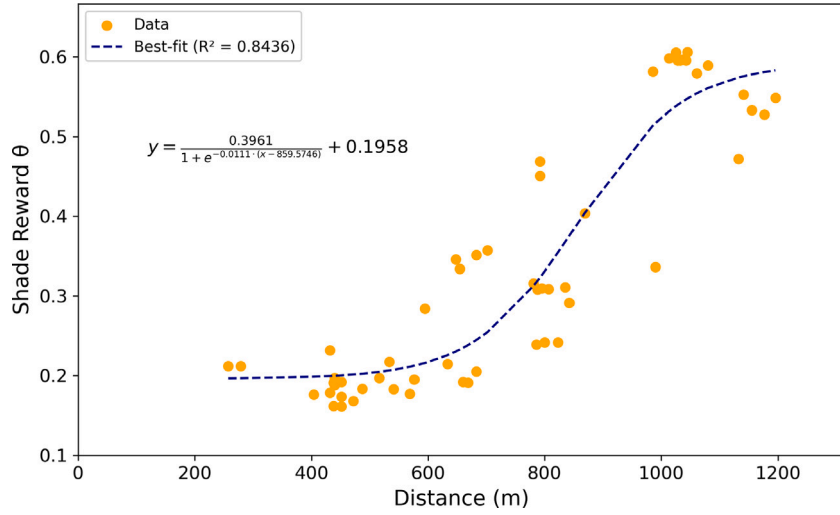


Fig. 6. The relationship between shade rewards and walking distances, shown as a sigmoid function. These results are derived from a publicly available pedestrian behavior database collected in Singapore (Melnikov et al., 2022).

segments, so that the effective walking distance under building or tree shade becomes shorter than the actual physical distance. The reward θ is then determined as the point at which the weighted lengths of the shorter, sunnier path (Path A) and the longer, shadier path (Path B) are equal.

$$\begin{aligned} L_A^{\text{Sun}} + (1 - 0.5\theta)L_A^{\text{Tree}} + (1 - \theta)L_A^{\text{Building}} \\ = L_B^{\text{Sun}} + (1 - 0.5\theta)L_B^{\text{Tree}} + (1 - \theta)L_B^{\text{Building}} \end{aligned} \quad (1)$$

$$\therefore \theta = \frac{(L_B^{\text{Sun}} - L_A^{\text{Sun}}) + (L_B^{\text{Tree}} - L_A^{\text{Tree}}) + (L_B^{\text{Building}} - L_A^{\text{Building}})}{0.5(L_B^{\text{Tree}} - L_A^{\text{Tree}}) + (L_B^{\text{Building}} - L_A^{\text{Building}})} \quad (2)$$

where L_A^{Sun} , L_A^{Tree} , and L_A^{Building} refer to the lengths of sun exposure, tree shade, and building shade in Path A, respectively; L_B^{Sun} , L_B^{Tree} , and L_B^{Building} are the lengths of sun exposure, tree shade, and building shade in Path B, respectively.

Using the selected behavioral data, we found that the correlation between shade reward θ and past walking distance (L_{past}) follows a sigmoidal curve equation, as shown in Eq. (3) below. Our analysis reveals a strong correlation between these two parameters, with an R^2 value of 0.84 (Fig. 6). In our analysis, data points with a L_{past} less than 150 m were excluded from the analysis, as the behavioral data were largely influenced by the two paths used in tasks 1 and 2 of the Singapore study (Melnikov et al., 2022).

$$\theta = \frac{0.3961}{1 + e^{-0.0111 \cdot (L_{\text{past}} - 859.5746)}} + 0.1958 \quad (3)$$

where L_{past} represents the distance a pedestrian has traveled from the origin to their current location.

In our framework, θ represents the marginal trade-off between walking distance and shade—the point at which the shorter Path A and the shadier Path B are theoretically equivalent when shade rewards are applied. This serves as an equilibrium reference value for quantifying the reward of shade. In practice, individual pedestrian choices may deviate from this marginal value, causing the fitted sigmoid function to shift horizontally to represent stronger or weaker shade preferences. To capture this variability, we conducted a parametric sensitivity analysis (Sections 2.5.2 and 3.3.2) to examine how left or right shifts of the sigmoid curve influence the results.

The optimal shadiest path was then calculated using a Dijkstra cost function $g(u)$ that is the cost of the path from the start node to the

current node u . Each edge (u, v) holds information about the actual length of the edge L_{Actual} , the total shade length L_{Shade} along the edge, the length of tree shade L_{Tree} , the length of building shade L_{Building} , the length of indoor shade L_{Indoor} , and the length of sun exposure L_{Sun} . For each neighboring node v_n of the current node u , the tentative shade cost $\tilde{g}(v_n)$ (the accumulated shade length along the path up to this point) is calculated through

$$\tilde{g}(v_n) = g(u) + S(u, v_n, L_{\text{Shade}}) \quad (4)$$

where the shade function $S(u, v_n, L_{\text{Shade}})$ is based on the hypothesis that people's preferences for shade will be changing while they are continually walking. The change is reflected by giving a lower cost of shade path length based on the shade source which is defined using Eq. (5).

$$L_{\text{Shade}} = L_{\text{Sun}} + (1 - 0.5\theta)L_{\text{Tree}} + (1 - \theta)L_{\text{Building}} + (1 - 1.5\theta)L_{\text{Indoor}} \quad (5)$$

In our study, indoor shade was assigned a higher reward due to the cooler temperatures typically found in indoor environments, making them more comfortable for pedestrians. To evaluate the impact of varying indoor shade rewards on the selection of optimal shadiest paths, we conducted a sensitivity analysis. This analysis examined how varying the indoor shade reward impacts the number of optimal shadiest paths utilizing indoor shade as the reward value increased from 1.1 θ to 1.5 θ in increments of 0.1 θ (Fig. A.4). Here, the number of optimal shadiest paths refers to the average across all selected dates and times. To further explore the potential of indoor shade in contributing to optimal shadiest paths, we present the analysis based on an indoor shade reward of 1.5 θ . This provides a deeper understanding of its role in enhancing pedestrian comfort in the studied networks.

2.4. Evaluating the shortest and optimal shadiest paths

This section analyzes how travel distance, solar exposure (influenced by seasonal and diurnal variations), and built environment characteristics (including network layout and shading features) influence pedestrian decision-making in hot climates. We employed two network models to compute the shortest and optimal shadiest paths: one that included indoor pathways and another that considered only the outdoor network. We analyzed various scenarios in the comparison, including walking distance, season, and time of day. Additionally, we evaluated the individual contributions of tree shade, building shade, and indoor shade to the formation of the optimal shadiest path.

Table 1

Summary of indoor contribution metrics for shortest and optimal shadiest paths using the combined indoor–outdoor network.

Metric	Description	Expression
Indoor network ratio	Proportion of indoor network length to the total indoor + outdoor network length at each station.	$\frac{\sum \text{indoor network}}{\sum \text{indoor} + \text{outdoor network}}$
Indoor use in shortest paths	Share of shortest paths that include indoor segments.	$\frac{\#ST_{in_net}^{indoor}}{\#ST_{in_net}}$
Indoor length in shortest paths	Share of total indoor length in shortest paths that include indoor segments.	$\frac{\sum \text{indoor paths for } ST_{in_net}^{indoor}}{\sum ST_{in_net}^{indoor}}$
Indoor use in optimal shadiest paths	Share of optimal shadiest paths that include indoor segments.	$\frac{\#SD_{in_net}^{indoor}}{\#SD_{in_net}}$
Indoor length in optimal shadiest paths	Share of total indoor length in optimal shadiest paths that include indoor segments.	$\frac{\sum \text{indoor paths for } SD_{in_net}^{indoor}}{\sum SD_{in_net}^{indoor}}$
Additional indoor use in shadiest paths	Share of optimal shadiest paths that include additional indoor segments not used in the shortest path.	$\frac{\#SDT_{in_net}^{indoor}}{\#SD_{in_net}}$
Additional indoor length in shadiest paths	Share of total indoor length in optimal shadiest paths that include additional indoor segments compared to the shortest path.	$\frac{\sum \text{indoor paths for } SDT_{in_net}^{indoor}}{\sum SDT_{in_net}^{indoor}}$

Σ : The total lengths. #: The total number. ST_{in_net} : The shortest path based on the indoor + outdoor network. $ST_{in_net}^{indoor}$: The shortest path that includes indoor paths. SD_{in_net} : The optimal shadiest path based on the indoor + outdoor network. $SD_{in_net}^{indoor}$: The optimal shadiest path that includes indoor paths. $SDT_{in_net}^{indoor}$: The optimal shadiest path that includes additional indoor paths compared to the shortest path.

2.4.1. The shortest versus the optimal shadiest path on the outdoor network

To investigate how walking distance influences the correlation between the shortest and the optimal shadiest path lengths, we performed a rolling regression analysis using a sliding window of 250 m and a step size of 100 m. This approach allows us to observe how the correlation evolves with walking distance, providing a more nuanced understanding of how shading influences routing decisions across different spatial scales. In the analysis, rolling R^2 values were used to represent the strength of correlation between the shortest walking path lengths and the optimal shadiest path lengths.

To examine the impact of season and time of day on path choice, we used a scatter plot to analyze how the difference between the shortest and optimal shadiest path lengths varies with the shortest path length across different seasons and times of day.

Additionally, we used a box plot to examine the contribution of building and tree shade in shaping the optimal shadiest path by analyzing the percentage of each path covered by building and tree shade across different seasons and times of day.

2.4.2. Effects of indoor shade on path choice

We assessed the contribution of indoor shade by incorporating indoor paths into the network and analyzing both the shortest and optimal shadiest paths for the same set of destinations. By adding nodes and edges representing indoor walkways, we observed how the inclusion of these routes altered the path configurations. First, we compared the shortest and optimal shadiest paths within the indoor–outdoor network to evaluate how shade-based rewards shift route selection. The metrics used in this analysis are summarized in Table 1. Then, to further assess the impact of indoor routes, we compared the shortest path computed using only the outdoor network with the optimal shadiest path derived from the combined indoor–outdoor network. This allowed us to isolate the contribution of indoor shade and identify cases where indoor routes not only improved thermal comfort but also shortened travel distance by acting as shortcuts.

To quantify both the shortcut effect and the shade improvement of indoor paths, an Indoor Contribution Index (ICI) was defined as:

$$ICI = \left(1 - \frac{L_{shadiest}}{L_{shortest}}\right) \cdot \frac{S_{indoor}}{S_{total}} \quad (6)$$

where: $L_{shadiest}$: Length of the shadiest path with indoor sections. $L_{shortest}$: Length of the shortest path using only the outdoor network.

S_{indoor} : Shaded length contributed by indoor segments. S_{total} : Total shaded length on the shadiest path (indoor + outdoor).

The first factor $1 - \frac{L_{shadiest}}{L_{shortest}}$ captures the shortcut effect. When $L_{shadiest} < L_{shortest}$ (indoor as a shortcut): this factor is positive, representing a gain in both shorter distance and shade. When $L_{shadiest} > L_{shortest}$ (indoor adds distance): this factor is negative, penalizing longer paths even if they offer more shade. The second factor $\frac{S_{indoor}}{S_{total}}$ represents the improvement in shade, showing the proportion of shade contributed by the indoor paths.

A positive ICI indicates that indoor paths provide both shade improvement and a shortcut, enhancing both thermal comfort and walking efficiency. A negative ICI reflects a trade-off: indoor paths increase the overall distance but contribute substantial shade. Importantly, a negative ICI does not necessarily imply an undesirable route; it highlights the balance between added thermal comfort and additional walking effort. A larger negative value suggests that the inclusion of indoor segments significantly increases the path length, thereby reducing the overall benefit even if shade improves. An ICI close to zero indicates that indoor paths contribute minimally to either distance reduction or shade enhancement.

2.5. Justifying of the reward function

We employed two approaches to justify the logic behind the sigmoid reward function. The first approach involved an ENVI-met thermal walk simulation to examine whether pedestrians' skin and core temperature variations while walking align with our hypothesis. The second approach involved a parametric sensitivity analysis of the sigmoid function.

2.5.1. ENVI-met thermal walk simulation

We developed our methodology based on the hypothesis that as walking distance increases, pedestrians may show a stronger preference for shaded areas due to rising physical exertion. We conducted an ENVI-met thermal walk simulation using the BioMet 5.7.1 model to examine whether pedestrians' skin and core temperature variations while walking through sun-exposed and shaded areas align with our hypothesis.

The simulation was designed with a typical urban setting in Singapore on a clear summer day. The study area featured a representative urban environment with a mix of high-rise and mid-rise buildings, open

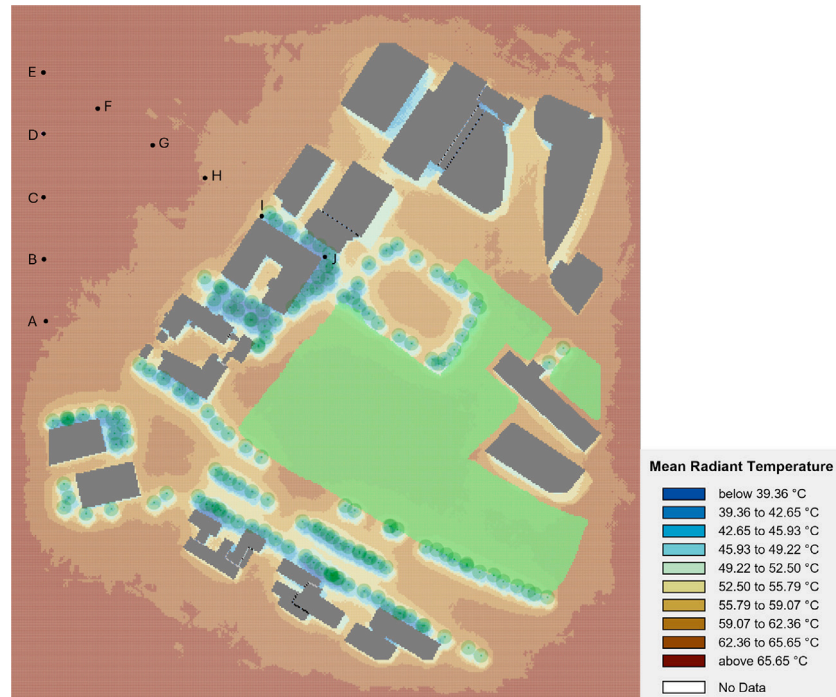


Fig. 7. ENVI-met simulation output showing the spatial distribution of mean radiant temperature (MRT) across the study area.

spaces, and shaded areas created by native trees and structures. We defined the surface properties (reflectance, absorption, and emissivity) based on Singapore's BCA Code for Environmental Sustainability of Buildings (Building and Construction Authority, 2008) and site-specific measurements. Tree characteristics were modeled using data from common tree species in Singapore. The simulation domain was 796 m × 878 m, with a spatial resolution of 2 m horizontally and 3 m vertically. To improve the precision of microclimatic variations near the pedestrian walking environment, each grid in the bottom layer was subdivided into five smaller grids.

We used meteorological inputs (including air temperature, humidity, wind speed and direction, and solar radiation) from a nearby weather station to ensure realistic environmental conditions.

The simulation ran from 10 AM to 2 PM, with the 2 PM results used for the thermal walk simulation (Fig. 7). The preceding four hours were simulated to enhance the accuracy of the microclimatic conditions at 2 PM.

A virtual pedestrian, modeled as a 35-year-old male using default physiological settings, was set to walk along a predefined path that included both sun-exposed and shaded segments. The simulation varied the length of sun exposure while keeping the shaded segment length constant to assess how prolonged sun exposure influences shade-seeking behavior. A total of 13 routes were selected for analysis, as summarized in Table 2. The walking speed was set at 1.34 m/s, reflecting a natural pedestrian pace.

The simulation captured changes in the pedestrian's skin and core temperatures. The results were analyzed to understand the impact of different sun-to-shade transition patterns on pedestrian thermal comfort.

2.5.2. Parametric sensitivity analysis of the sigmoid function

When applying our method to other cities with different climate conditions and pedestrian behaviors, the sigmoid function may take on different shapes to reflect local thermal preferences. To explore the sensitivity of our approach, we varied the four parameters of the sigmoid function and calculated the average percentage difference between the shortest and optimal shadiest paths on all the dates and

Table 2

Routes and their paths selected for the ENVI-met thermal walk simulation (paths colored in orange indicate sun-exposed segments, while paths in blue indicate shaded segments).

Route	Path
Route 1	E → D → C → B → A → B → C → D → E → F → G → H → I → J
Route 2	D → C → B → A → B → C → D → E → F → G → H → I → J
Route 3	C → B → A → B → C → D → E → F → G → H → I → J
Route 4	B → A → B → C → D → E → F → G → H → I → J
Route 5	A → B → C → D → E → F → G → H → I → J
Route 6	B → C → D → E → F → G → H → I → J
Route 7	C → D → E → F → G → H → I → J
Route 8	D → E → F → G → H → I → J
Route 9	E → F → G → H → I → J
Route 10	F → G → H → I → J
Route 11	G → H → I → J
Route 12	H → I → J
Route 13	I → J

times considered. The specific values considered for each parameter are listed below.

$$\theta = \frac{A}{1 + e^{\beta \cdot (L_{\text{past}} - X_0)}} + y_0 \quad (7)$$

where: $A = 0.2, 0.3, 0.5, 0.6$; $\beta = 0.005, 0.008, 0.015, 0.018$; $X_0 = 650, 750, 950, 1050$; and $y_0 = 0.10, 0.15, 0.25, 0.30$.

3. Results

3.1. The shortest versus the optimal shadiest path on the outdoor network

3.1.1. Impact of walking distance on path choice

A rolling regression analysis was used to explore how walking distance affects the difference in path length between the shortest and optimal shadiest routes (Fig. 8). Overall, the optimal shadiest path length exhibits a strong linear correlation with the shortest path length, with most R^2 values exceeding 0.9. However, as walking distance increases, the alignment between the shortest and optimal shadiest paths tends to decline, particularly when the distance exceeds 1000 m.

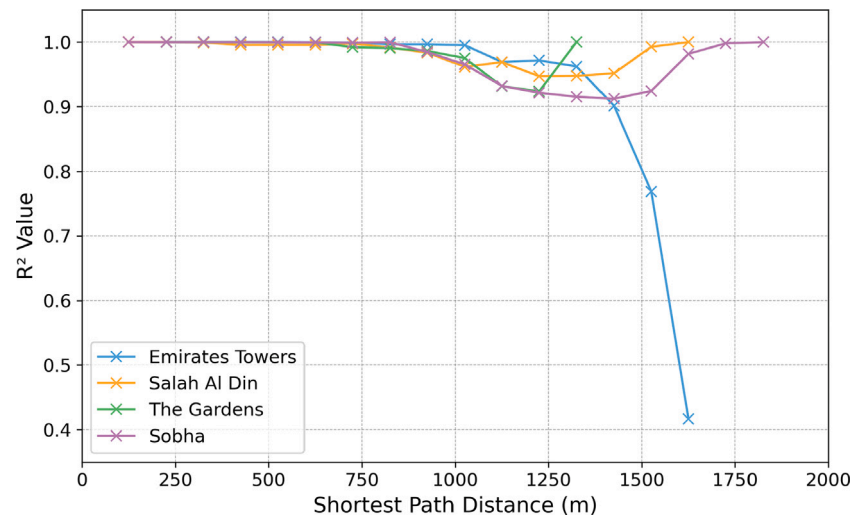


Fig. 8. Rolling R^2 values representing the strength of correlation between the shortest walking path lengths and the optimal shadiest path lengths across four metro stations.

The extent of this decline appears to be influenced by the spatial distribution of shade sources within the network. For instance, in the case of Emirates Towers, tall buildings are concentrated in the center of the network, while the outer areas have few or no tall structures.

Additionally, we observed differences between stations. For instance, at The Gardens station, which has the most complex path network, all shortest and optimal shadiest paths for random destinations within the two buffers are less than 1500 m. These random destinations are evenly distributed within the buffer, covering various walking distances without clustering together. In contrast, Sobha station, with its simpler network, requires pedestrians to walk longer distances to reach their destinations. This explains why the correlation between the optimal shadiest and shortest paths remains high at Sobha Station even within the 1500–2000 m range—pedestrians have limited options in choosing their paths.

Table A.1 in the Appendix presents the average deviation percentage between the shortest and the optimal shadiest paths in the outdoor network, categorized by station, month, and time period. It also includes the average percentages of building shade, tree shade, and sun exposure as proportions of the total length for both the optimal shadiest and the shortest paths. Overall, the optimal shadiest path is, on average, 1.3% longer than the shortest path. In comparison to the shortest path, the percentage of building shade increases by 8.9%, while the percentage of sun exposure decreases by 8.8%.

3.1.2. Impact of season and time on path choice

Fig. 9 illustrates how the difference between the shortest and optimal shadiest path lengths varies with the shortest path length across different seasons and times of day. In general, the shortest and optimal shadiest paths tend to align when the area is either fully exposed to direct sunlight or fully shaded. For the two stations primarily covered by high-rise buildings (Emirates Towers and Sobha), the deviation between the shortest and optimal shadiest paths is typically lowest in the late afternoon when most areas are shaded. In June, the deviation between the two paths remains low even during noon time. This is because most areas remain unshaded during midday, resulting in greater alignment between the shortest and optimal shadiest paths. However, as the sun's path drifts southward and sits lower in the sky during March and December compared to June, some areas experience shade even at noon, causing pedestrians to seek shadier routes that deviate from the shortest path. Interestingly, at The Gardens station, which is largely covered by trees, the difference between the shortest and optimal shadiest paths increases as the day progresses, and the differences among the three seasons are relatively minimal. This is because

the shade provided by tall, dense trees is more consistent throughout the day, whereas building shade varies significantly with time. Additionally, Salah Al Din station exhibits the largest deviation between the shortest and optimal shadiest paths in March and December. This is primarily due to the area's coverage by low residential buildings and the limited presence of trees, which reduces the availability of consistent shade.

3.1.3. Contribution of building and tree shade

To better understand the contribution of building and tree shade in shaping the optimal shadiest path, we analyzed the percentage of optimal shadiest paths covered by building and tree shade across different seasons and times of day (Fig. 10). In areas predominantly covered by buildings, the percentage of building shade is highest between 4–5 PM and lowest at noon, irrespective of the season. Among the three seasons, December has the highest building shade coverage, followed by March and June. This pattern reflects the influence of the sun path's position, as buildings provide more shade when the sun is lower in the sky. Additionally, taller buildings tend to offer greater shade coverage, which aligns with the findings that stations with taller buildings, such as Emirates Towers and Sobha, have higher building shade percentages. Although Salah Al Din station has lower building heights, the building shade percentages here are still relatively substantial due to a high building density. In contrast to the other stations, The Gardens station shows a significant portion of shade coming from trees throughout the day across different seasons. In June, tree shade percentage remains dominant even in the late afternoon. However, as the sun's path gradually drifts southward during March and December, building shade outweighs tree shade during the afternoon when the sun angle is low.

3.2. Effects of indoor shade on path choice

Two pairs of the shortest and optimal shadiest paths were computed and compared: one pair was based solely on the outdoor network, while the other incorporated both outdoor and indoor networks. Fig. 11 presents an example of these two path pairs.

To assess the impact of indoor paths on the deviation between the shortest and optimal shadiest paths, the combined outdoor-indoor network was analyzed. Table 3 summarizes the percentage of indoor network, which accounts for 10.8%, 3.8%, and 3.4% of the total combined network length at Emirates Towers, Salah Al Din, and Sobha Metro Station, respectively. By incorporating indoor shortcuts, 16 out of 73, 10 out of 80, and 3 out of 71 shortest paths utilize indoor routes at the aforementioned stations. For these paths, the indoor

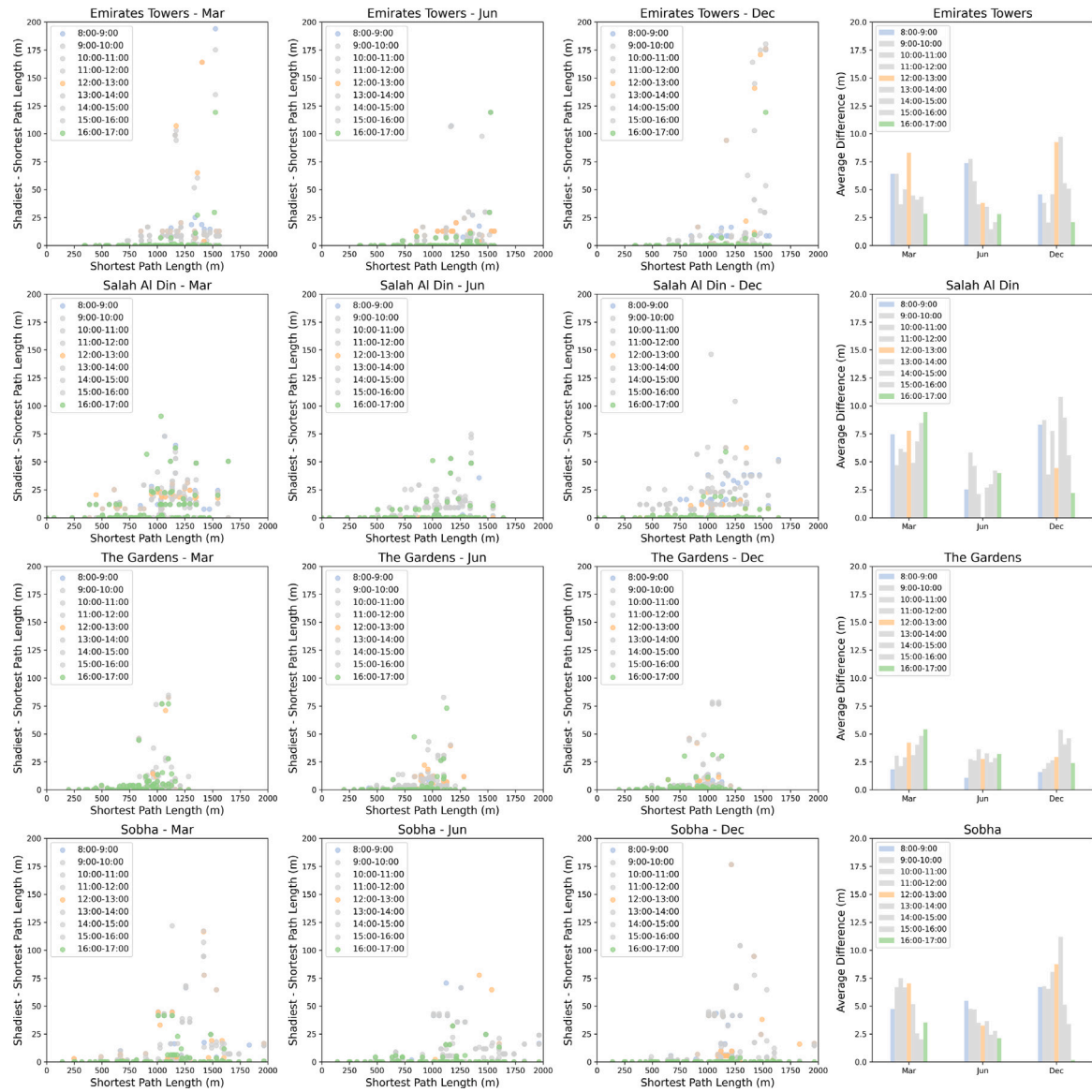


Fig. 9. Difference in path length between the optimal shadiest path and the shortest path across different seasons and times of day at four metro stations.

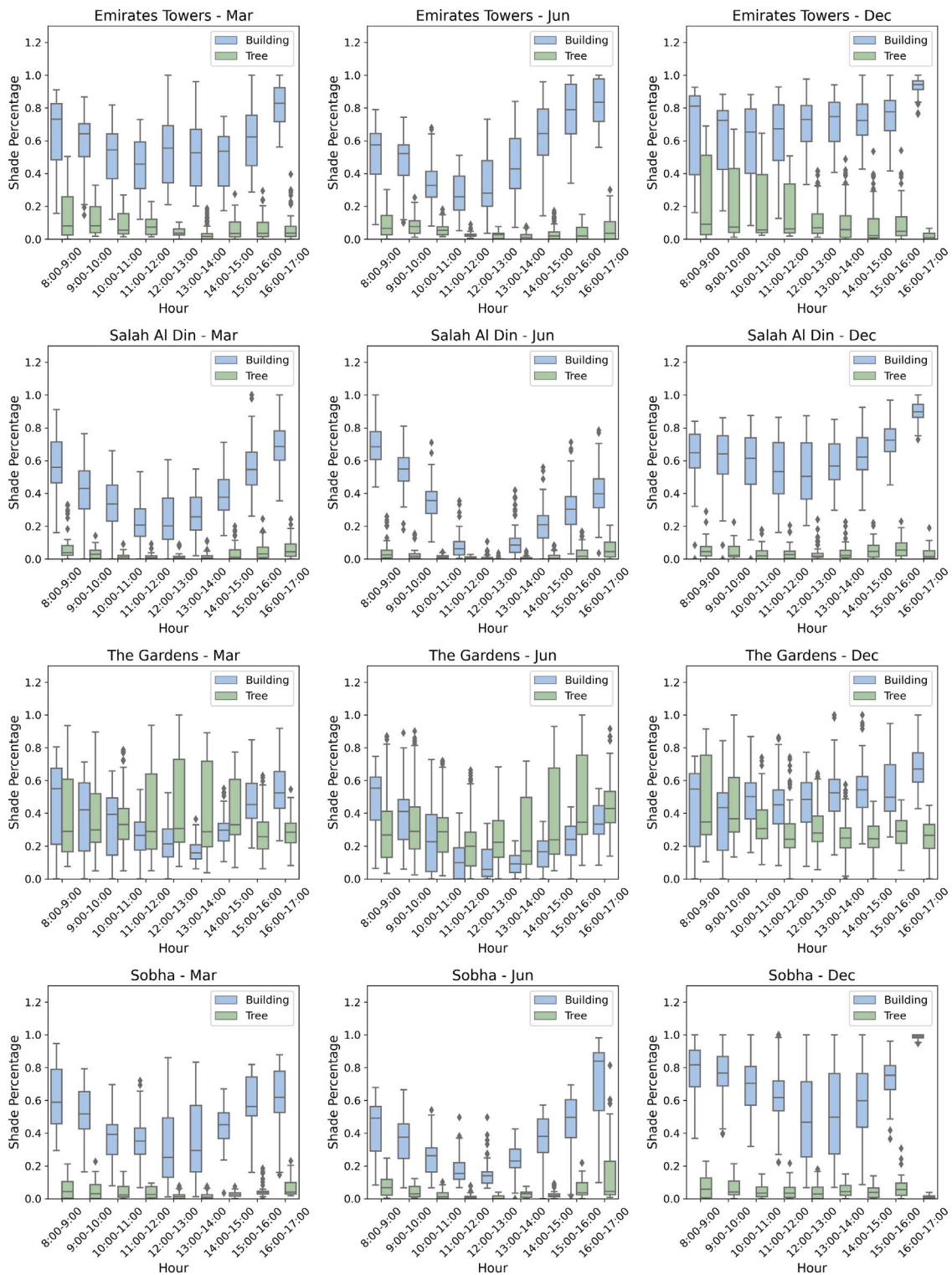


Fig. 10. Contribution of building and tree shade in shaping the optimal shadiest path, expressed as the percentage of each path covered by these shade elements.

segments constitute 16.5%, 24.7%, and 12.3% of the total path length, respectively, indicating a significant contribution of indoor routes to shortening the overall path.

The optimal shadiest path is subject to variations based on time and date, and Table 3 highlights differences for three time periods in June. When indoor shading is considered, 18 out of 73, 16 out of 80, and 3 out of 71 optimal shadiest paths utilize indoor routes between 12–1

PM at Emirates Towers, Salah Al Din, and Sobha Metro Station, respectively. However, some of these optimal shadiest paths overlap with the shortest paths that also use indoor routes. To exclude such cases, Table 3 also presents the number of optimal shadiest paths that incorporate indoor segments where the corresponding shortest path does not. For these shadiest paths, indoor shading constitutes approximately 24% and 28% of the total path length at Emirates Towers and Salah Al Din,



Fig. 11. Three representative pairs comparing the shortest path vs. the optimal shadiest path during 8:00–9:00 AM on 21st December at Salah Al Din metro station. The left map shows routes calculated using the outdoor network only, while the right map incorporates the combined outdoor-indoor network, illustrating differences in pedestrian route choices when indoor pathways are included.

Table 3

The shortest path (outdoor + indoor network) vs. the optimal shadiest path (outdoor + indoor network) across three stations: Emirates Towers, Salah Al Din, and Sobha for different time ranges.

Metric	Emirates Towers			Salah Al Din			Sobha		
$\frac{\sum \text{indoor network}}{\sum \text{indoor} + \text{outdoor network}}$	10.8%			3.8%			3.4%		
$\frac{\#ST_{in_net}^{indoor}}{\#ST_{in_net}}$	16/73			10/80			3/71		
$\frac{\sum \text{indoor paths for } ST_{in_net}^{indoor}}{\sum ST_{in_net}^{indoor}}$	16.5%			24.7%			12.3%		
	8–9	12–13	16–17	8–9	12–13	16–17	8–9	12–13	16–17
$\frac{\#SD_{in_net}^{indoor}}{\#SD_{in_net}}$	19/73	18/73	17/73	11/80	16/80	14/80	3/71	3/71	3/71
$\frac{\sum \text{indoor paths for } SD_{in_net}^{indoor}}{\sum SD_{in_net}^{indoor}}$	21.0%	20.9%	20.3%	26.8%	24.4%	25.8%	12.3%	12.3%	12.3%
$\frac{\#SDT_{in_net}^{indoor}}{\#SD_{in_net}}$	6/73	5/73	4/73	4/80	6/80	4/80	0/71	0/71	0/71
$\frac{\sum \text{indoor paths for } SDT_{in_net}^{indoor}}{\sum SDT_{in_net}^{indoor}}$	24.1%	24.5%	22.3%	28.7%	24.0%	28.7%	–	–	–

$\sum$: The total lengths. $\#$: The total number. ST_{in_net} : The shortest path based on the indoor + outdoor network. $ST_{in_net}^{indoor}$: The shortest path that includes indoor paths. SD_{in_net} : The optimal shadiest path based on the indoor + outdoor network. $SD_{in_net}^{indoor}$: The optimal shadiest path that includes indoor paths. $SDT_{in_net}^{indoor}$: The optimal shadiest path that includes additional indoor paths compared to the shortest path.

respectively.

Fig. 12 displays the Indoor Contribution Index (ICI) values for the three stations that have accessible indoor paths. The ICI values indicate the shade contribution of indoor paths compared to outdoor paths. Emirates Towers exhibits a broader range of ICI values, with high negative values up to -0.26 . Sobha shows a narrower range with most ICI values clustered around 0, suggesting limited shade improvement through indoor paths. The effectiveness of indoor paths in providing shade benefits varies by station, season, and time of day. As the sun's position changes, the availability and alignment of shaded segments also shift. Emirates Towers demonstrates the greatest seasonal responsiveness, particularly in June, with significant shade improvements due to the favorable positioning of indoor connections. In contrast, stations like Sobha show limited benefits, likely due to simpler street layouts with fewer routing alternatives, which reduce opportunities for indoor paths to meaningfully alter the walking configuration. These variations underscore how both temporal factors and spatial characteristics influence the utility of indoor routes in enhancing thermal walking comfort.

3.3. Justification of the reward function

3.3.1. ENVI-met thermal walk simulation

The observed skin and core temperature trends from the ENVI-met simulation results (Fig. 13) demonstrate the physiological benefits of shade, particularly after prolonged sun exposure.

Skin temperature consistently rises with walking distance, with steeper slopes observed during prolonged sun exposure. However, upon entering shaded areas, the rate of increase moderates, highlighting the cooling effect of shade. This cooling effect becomes more pronounced when pedestrians have been exposed to the sun for longer distances. Further insights can be drawn from the skin temperature change rate plot, which shows sharp increases during sun exposure, followed by decreases upon transitioning to shade. A distinct turning point appears at approximately 300 m, beyond which prolonged sun exposure not only raises skin temperature but also accelerates its rate of change. Notably, the transition to shade after this point results in a more substantial decline in the skin temperature change rate, reinforcing the growing importance of shade for thermal relief as walking distance increases.

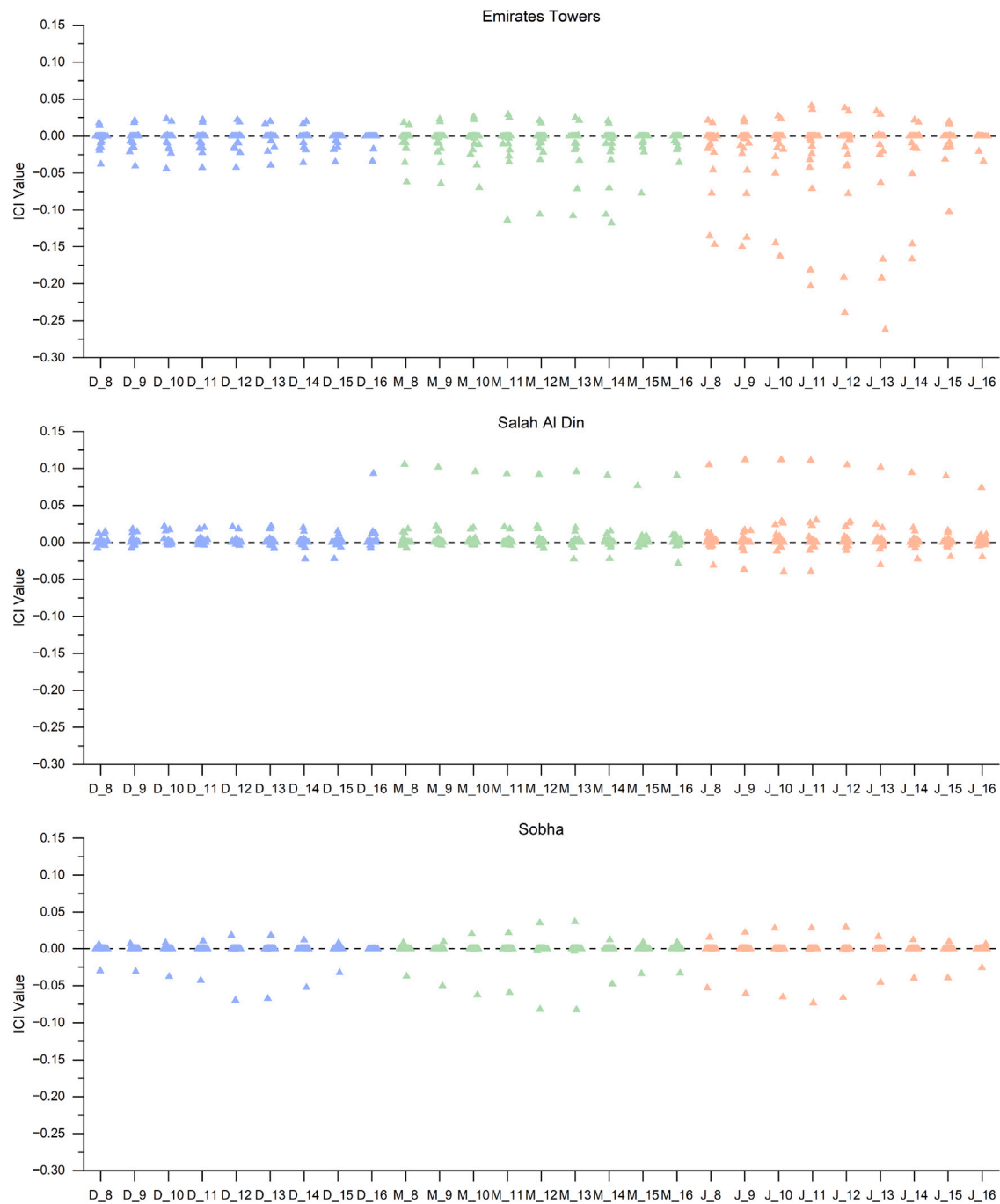


Fig. 12. Distribution of Indoor Contribution Index (ICI) values across different hours (8 to 16) and seasons (D: December; M: March; J: June) at three metro stations featuring indoor pathways. Positive values indicate the optimal shadiest path yields greater shade and a shorter distance due to indoor shortcuts; negative values indicate greater shade is achieved at the expense of increased walking distance.

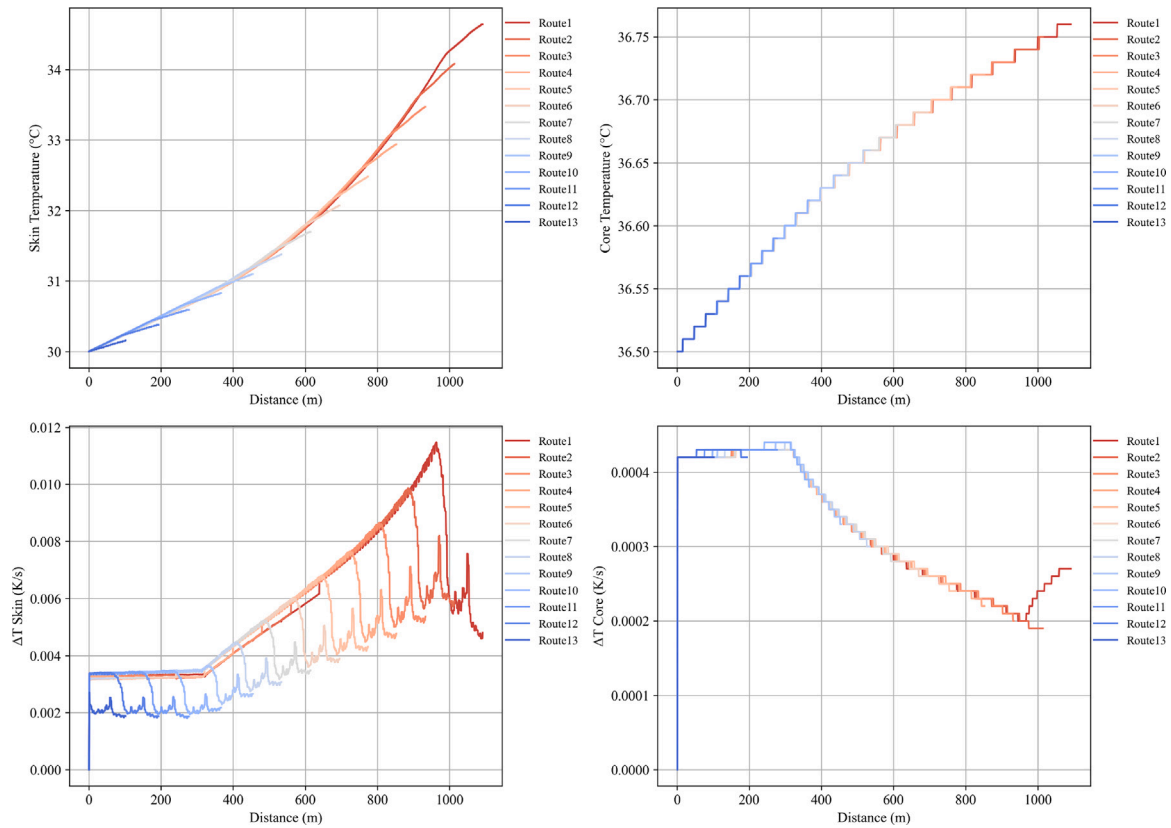


Fig. 13. Skin and core temperature trends from ENVI-met simulations illustrating the physiological benefits of shade during pedestrian movement. Thirteen routes with varying sun exposure lengths and constant shade segments are modeled to assess temperature responses after prolonged sun exposure.

Core temperature, on the other hand, shows a gradual increase as pedestrians continue walking. While core temperature is less sensitive to immediate environmental changes than skin temperature, prolonged sun exposure still exerts a cumulative effect. The core temperature change rate plot also shows a similar turning point at around 300 m. After this point, the rate of change decreases as pedestrians continue walking. However, when walking distances exceed 1000 m, the rate of core temperature change rises again.

3.3.2. Parametric sensitivity analysis of the sigmoid function

The sigmoid function sensitivity analysis examines how variations in the four parameters of the sigmoid function influence the shade reward and the resulting percentage difference between the shortest and optimal shadiest paths at two metro stations, Emirates Towers and Salah Al Din (Fig. 14).

For both metro stations, a higher asymptote (A) increases the percentage difference between the shortest and optimal shadiest paths, indicating that a higher baseline reward for shade encourages pedestrians to prioritize shaded routes. However, higher growth rates (β) lead to a steeper transition in the shade reward curve, promoting a more rapid increase in shade preference over shorter distances. While Emirates Towers shows a slight increase in the difference percentage with a higher growth rate, the effect at Salah Al Din is less consistent. This discrepancy suggests that while a steeper reward curve can influence shade-seeking behavior, its impact may vary by location. The transition point (X_0), which determines when the shade reward begins to rise significantly, also plays a crucial role. At both stations, the percentage difference between the two paths decreases with a higher transition point, indicating that delaying the shade reward may reduce the incentive for pedestrians to deviate from the shortest path. Additionally, increasing the offset (y_0) raises the overall reward for shade across all distances. While Emirates Towers exhibits a slight

increase in the difference percentage with a higher offset, Salah Al Din shows a more pronounced rise.

Overall, the percentage difference between the two paths remains within 2.2% across all parameter variations. This consistency suggests that the robustness of the sigmoid reward function in our study may be influenced by the specific context of Dubai. However, this robustness may not necessarily apply to other cities with different climate conditions and urban layouts. In regions with milder climates, variable shading patterns, or diverse pedestrian behaviors, the sigmoid function could exhibit greater sensitivity to parameter adjustments, necessitating more careful calibration to accurately reflect local shade-seeking tendencies.

4. Discussion

As Middle Eastern cities continue to grow rapidly and pursue goals to reduce carbon emissions, such as expanding their transit network and implementing policies like the “20-min city”, it is crucial to prepare these cities to become more pedestrian and environment friendly. However, the region’s harsh climate presents significant challenges in achieving outdoor thermal comfort for pedestrians. This study uses Dubai as a case study to assess how well the city’s shortest paths align with the optimal shadiest paths, in order to understand whether walking efficiency coincides with thermal comfort. The study focuses on four metro stations in Dubai due to the manual effort required to collect street-view data. However, the methodology is adaptable to other metro stations across the city and beyond. Key applications include: assisting authorities in identifying areas with insufficient shade and implementing interventions such as tree planting or artificial shading along sidewalks; and developing mobile apps to guide pedestrians toward the optimal shadiest path for their journey, enhancing thermal comfort and overall walkability.

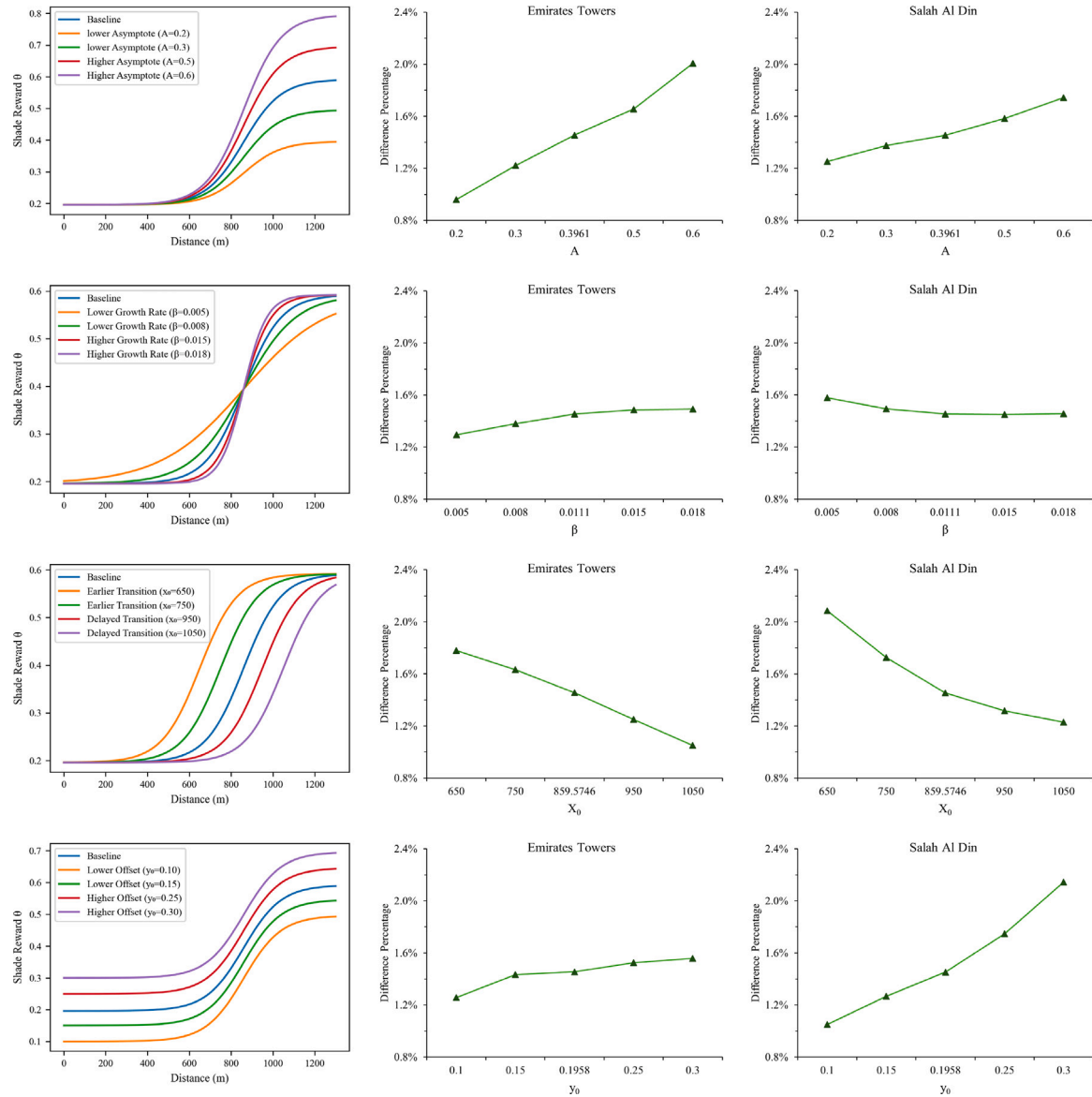


Fig. 14. Sensitivity analysis of the sigmoid function parameters illustrating their effects on the shade reward and the resulting percentage difference between the shortest and optimal shadiest paths at two metro stations, Emirates Towers and Salah Al Din.

Our findings indicate that the optimal shadiest path is, on average, only 1.3% longer than the shortest path, with a significant increase in building shade (8.9%) and reduction in sun exposure (8.8%). These results highlight the potential for optimizing existing urban infrastructure by strategically increasing shading interventions to improve thermal comfort without significantly increasing walking distances.

This high correlation between the shortest and optimal shadiest paths can be attributed to several factors:

1. A lack of tree coverage or the predominance of tree-lined sidewalks in the study areas creates a binary shade scenario, where paths are either mostly shaded or mostly exposed.

2. According to the path choice model, a shaded path may be too long to compensate for the penalties associated with sun exposure on the shortest path. Consequently, the algorithm tends to select either the shortest path or a moderately shaded path that does not deviate significantly from the shortest route.

4.1. Dynamic shade reward

One key contribution of this study is an optimal shadiest path method that assigns dynamic rewards to building shade, tree shade and indoor shade based on walking distance. The sensitivity analysis of the sigmoid reward function shows that the percentage difference between the shortest and optimal shadiest paths remains relatively stable (within 2.2%) across all parameter variations, demonstrating robustness in the Dubai context. However, this robustness may not generalize to cities with milder climates, more variable shading patterns, or more diverse pedestrian behaviors. While the sigmoid function describing the relationship between shade reward and walking distance may vary in other contexts, the principle of assigning dynamic rewards to shade remains broadly applicable.

Existing studies on shadiest paths typically either penalize sun exposure or reward shade, without considering that pedestrians' preferences for the shadiest path over the shortest path may change as they walk (Wolf et al., 2024). One approach to determining these penalties or rewards is to base them on pedestrian behavior. For instance, researchers in Singapore found that walking in the sun is perceived as 16% longer than walking in the shade over the same distance (Melnikov et al., 2022). However, the exact penalty or reward is influenced by various factors, such as climate conditions. A recent study highlighted the difficulty of determining precise penalties for sun exposure. To address this, they assigned penalties (α) of 1.1, 1.25, 1.5, 2, 4, and 10 to sun exposure, covering realistic scenarios ($\alpha \leq 1.5$) and extreme conditions ($\alpha = 10$) (Wolf et al., 2024).

Our approach is based on the hypothesis that as walking distance increases, pedestrians may exhibit a stronger preference for shaded areas due to increased exertion. This hypothesis is supported by evidence from an open-source database in Singapore (Melnikov et al., 2022). Notably, our analysis differs from the prior Singapore study by incorporating the effect of accumulated walking distance on route-choice decisions. The hypothesis is also supported by strong correlations between pedestrians' current skin surface temperature, heat storage, and their past thermal experiences (Xie et al., 2022; Zhao et al., 2024). Additionally, research also demonstrates that pedestrians' current thermal sensations are influenced by their previous experiences (Xie et al., 2022; Zhao et al., 2024).

4.2. Building shade versus tree shade

Another novelty of our optimal shadiest path method is the assignment of different rewards to building shade and tree shade, whereas most existing studies do not distinguish between types of shade (Wolf et al., 2024).

Our analysis reveals that the distribution of building and tree shade along optimal shadiest paths is strongly influenced by urban morphology and seasonal-diurnal solar dynamics. High-rise, dense districts

offer extensive building shade, particularly in the late afternoon and during winter (December), when the sun is lower and casts longer shadows. In contrast, low-rise neighborhoods rely primarily on tree shade, which is especially valuable around midday and during summer (June), when building shadows are shorter. These results highlight the complementary roles of buildings and trees in shaping pedestrian thermal comfort. Understanding these patterns is essential for designing walkable urban environments, informing both strategic tree planting in exposed streets and building form optimization to enhance pedestrian shade.

While dense high-rise buildings are optimal for providing more consistent shade along pedestrian paths, they can introduce other challenges. Urban heat can be absorbed and stored in building surfaces, making the environment less comfortable for pedestrians, particularly at night (Nugroho et al., 2022; Saroglou et al., 2017). Additionally, high-rise buildings can interfere with the release of heat into the atmosphere, exacerbating the nighttime urban heat island effect (Huang, Lee et al., 2021; Huang, Song et al., 2021). As a result, relying on buildings as a primary source of shade requires careful urban planning and consideration of these potential thermal impacts.

A key advantage of tree shade is its proximity to sidewalks, which allows it to compensate for the lack of building shade during midday hours. This close alignment with pedestrian paths ensures consistent shading even when the sun is at its peak, providing critical thermal relief during the hottest parts of the day (Colter et al., 2019; Morakinyo et al., 2017). However, tree shade also presents several challenges. First, maintaining trees in hot and arid cities demands significant resources (Yin et al., 2015). Second, trees can increase local humidity levels, potentially reducing pedestrians' thermal comfort, especially in humid cities like Dubai (Chakraborty et al., 2022). Therefore, understanding which types of trees are best suited to provide shade in such climates, while minimizing resource use and negative environmental impacts, is an area that warrants further exploration.

4.3. Indoor shade

Another contribution of our study is the inclusion of indoor paths, emphasizing their potential in enhancing the outdoor walking experience for pedestrians in Middle Eastern countries. Indoor shade has two key advantages over building and tree shade. First, it remains consistent throughout the day and across seasons, making it a more reliable source of shade. Second, it provides a significantly cooler walking environment, as indoor temperatures are typically much lower than outdoor conditions. Given the limited research on the use of indoor paths for pedestrian commuting, this study does not aim to generalize findings but rather to underscore their importance as an alternative for reducing the distance between origins and destinations while offering a relatively cooler and shaded walking environment.

To quantify both the shortcut effect and the shade enhancement provided by indoor paths, we introduce the Indoor Contribution Index (ICI). The ICI analysis reveals that the effectiveness of indoor routes is driven by the interplay between urban spatial configuration and solar dynamics. Indoor paths offer the greatest benefits in complex, high-density urban environments, where multiple routing options allow pedestrians to strategically utilize indoor segments as the sun's position shifts throughout the day and across seasons. In contrast, simpler street networks with limited connectivity and fewer indoor alternatives provide minimal improvements, as pedestrians have little flexibility to adjust their routes to take advantage of indoor shade.

The indoor paths considered in our study are located within shopping malls or complex buildings that include shopping areas. These buildings are typically open during daytime hours, which aligns with the times when pedestrians are most likely to seek shaded routes. As a result, accessibility to these indoor paths is generally not a significant concern in this context. However, when scaling this approach to include a broader range of indoor accessible buildings, accessibility

may become a critical factor due to the varying operational hours of different buildings. One limitation of our study is that it does not account for indoor paths that span multiple floors. Additionally, while passing through shopping malls, pedestrians may be distracted by shops or impacted by crowded conditions, potentially reducing their walking speed compared to outdoor walking (Liu & Zlatanova, 2023; Liu et al., 2024). These factors could influence the overall efficiency and experience of using indoor paths for commuting purposes. Furthermore, the dynamic thermal comfort experienced during the transition from indoor to outdoor environments presents an important area for further exploration (Höppe, 2002; Katavoutas et al., 2015).

4.4. Future work

Further research could be conducted to enhance this study and address its limitations.

First, the optimal shadiest path equation was developed based on an open-source experimental database, which was derived from an experiment conducted in Singapore. Although climate-specific variations are expected, the similarity in consistently hot and humid conditions between Singapore and Dubai makes the database a useful proxy in the absence of equivalent data for Dubai (Meteorological Service Singapore, 2025; National Center of Meteorology, 2025). Future research could benefit from experimental studies or real-world pedestrian movement data to validate and refine the model for the local context. Moreover, while this study aims to present a method for calculating the optimal shadiest path, additional pedestrian behavior data are necessary to adapt the formula to different climates and regions. This would enable the development of formulas that better align with people's thermal preferences under various climate conditions.

Second, this paper uses several metro stations in Dubai as a case study to demonstrate the methodology. Expanding the analysis to cover more areas is expected to yield more interesting and meaningful findings that could guide urban planning efforts to create more pedestrian-friendly cities.

Third, the current pathfinding model does not account for seasonal variations or time-of-day differences due to Dubai's consistently high temperatures throughout the year. However, incorporating a factor to account for these variations could enhance the model's applicability. This would require access to detailed pedestrian behavior data for validation, which is currently unavailable. Future research could explore gathering and incorporating such data to refine the model further.

5. Conclusions

This study introduces a comprehensive methodology to evaluate outdoor walking environments by analyzing the alignment between the shortest and optimal shadiest paths around metro stations in Dubai. The goal is to assess how walking efficiency corresponds with thermal comfort under varying seasonal conditions, times of day, walking distances, and urban design configurations.

The methodology encompasses: (1) constructing outdoor and indoor pedestrian networks using open-source data; (2) calculating street segment shade conditions through street view imagery and Visual AI techniques; (3) computing the optimal shadiest path using a custom-developed pathfinding algorithm; and (4) evaluating the differences between the shortest and optimal shadiest paths, including a quantification of the contributions from building shade, tree shade, and indoor shade. This methodology is transferable to other cities, though the pathfinding algorithm must be calibrated with local pedestrian behavior data, particularly in regions with different climatic conditions and cultural walking norms.

The findings indicate that the shadiest path is, on average, only 1.3% longer than the shortest path, with a significant increase in building shade (8.9%) and reduction in sun exposure (8.8%), suggesting that

effective shading strategies can be implemented without compromising pedestrian efficiency.

A key contribution of this study is the development of a pathfinding algorithm that integrates dynamic rewards for building shade, tree shade, and indoor shade. This addresses a major gap in the existing literature, which typically applies fixed penalties for sun exposure or constant rewards for shade. This dynamic approach provides a valuable tool for urban designers and planners, offering actionable insights into how shading strategies can be optimized to enhance pedestrian thermal comfort and walkability.

In addition to outdoor shading, this study emphasizes the potential role of indoor paths in enhancing pedestrian comfort, particularly in cities where extreme heat makes outdoor walking challenging. Indoor routes offer shaded, cooler environments and can sometimes serve as shortcuts, reducing overall walking distance. To quantify these dual benefits, we introduce the Indoor Contribution Index (ICI), a metric that captures both the thermal comfort enhancement and the route efficiency gained from using indoor paths. The findings from various metro stations reveal that both temporal factors (e.g., season and time of day) and spatial characteristics (e.g., the complexity of walking path networks) significantly influence the utility of indoor routes in enhancing thermal walking comfort. Despite the significant role indoor environments can play in pedestrian mobility, especially in hot climates, this aspect remains largely underexplored in current literature. Our findings highlight the need for further research on the integration of indoor networks into urban mobility systems, particularly in Middle Eastern cities and other regions facing harsh outdoor conditions.

CRedit authorship contribution statement

Jianxiu Wen: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Diaa Addeen Abuhani:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Martina Mazzarello:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Fabio Duarte:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Leslie Norford:** Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization. **Ruohan Xu:** Writing – review & editing, Software. **Nyuk Hien Wong:** Writing – review & editing, Resources. **Carlo Ratti:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT in order to proofread and enhance the clarity of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Fig. A.1. Platform setup for street view image collection: a GoPro MAX camera mounted on a vehicle, enabling panoramic data capture along the surveyed routes.

Appendix. Supplementary material

A.1. Street view data acquisition and processing

Street View Images were obtained using a GoPro MAX camera mounted on a vehicle via a mounting platform (See Fig. A.1). The camera is equipped with a GPS module and a magnetometer along with other telemetry data sources. Although the majority of images were captured from the vehicle, some pedestrian paths were inaccessible by car; therefore, these areas were surveyed on foot to capture as many pedestrian routes as possible. Each video captured was later converted to frames with a window of 4 s for vehicle-captured videos and 2 s for pedestrian-captured videos. Telemetry data were extracted using ffmpeg (FFmpeg Developers, 2023), with each frame image file named using a unique random identifier, latitude, longitude, and yaw angle extracted from the GPS and magnetometer readings, respectively.

A.2. Information of the four selected stations

Fig. A.2 illustrates the building footprint and entrance data, and the outdoor and indoor network of the four selected stations.

A.3. Comparison of historical weather data in dubai and Singapore

Fig. A.3 compares historical temperature and humidity data for Dubai (1974–2023) and Singapore (1984–2024).

A.4. Indoor shade reward sensitivity analysis

The results of indoor shade sensitivity analysis (Fig. A.4) show that for Emirates Towers and Salah Al Din stations, as the indoor shade reward increases, the number of optimal shadiest paths incorporating indoor shade also increases. However, for Sobha station, the simpler network structure results in a constant number of optimal shadiest paths using indoor shade, regardless of the reward variation.

A.5. Sample shade condition map

See Fig. A.5.

A.6. Deviation between the shortest and the optimal shadiest path

As used in Table A.1, DP: The percentage of the deviation between the optimal shadiest and the shortest path relative to the total length of the shortest path. $BS_{shadiest}$: The percentage of building shade length relative to the total length of the optimal shadiest path. $TS_{shadiest}$: The percentage of tree shade length relative to the total length of the optimal shadiest path. $Sun_{shadiest}$: The percentage of sun exposure length relative to the total length of the optimal shadiest path. $BS_{shortest}$: The percentage of building shade length relative to the total length of the shortest path. $TS_{shortest}$: The percentage of tree shade length relative to the total length of the shortest path. $Sun_{shortest}$: The percentage of sun exposure length relative to the total length of the shortest path.

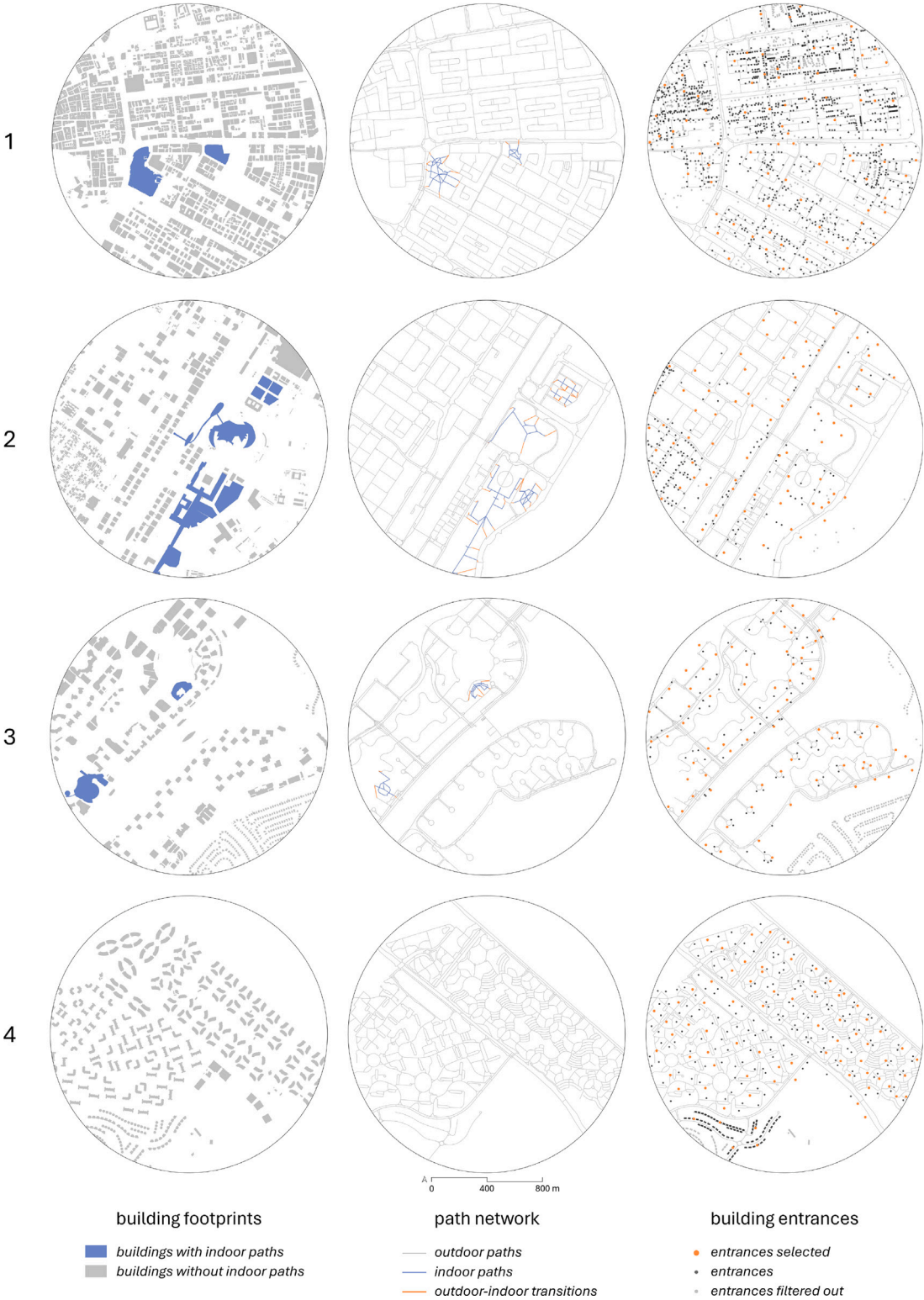


Fig. A.2. Building footprint, entrances, and outdoor and indoor network of the selected stations: 1. Salah Al Din; 2. Emirates Towers; 3. Sobha; 4. The Gardens.

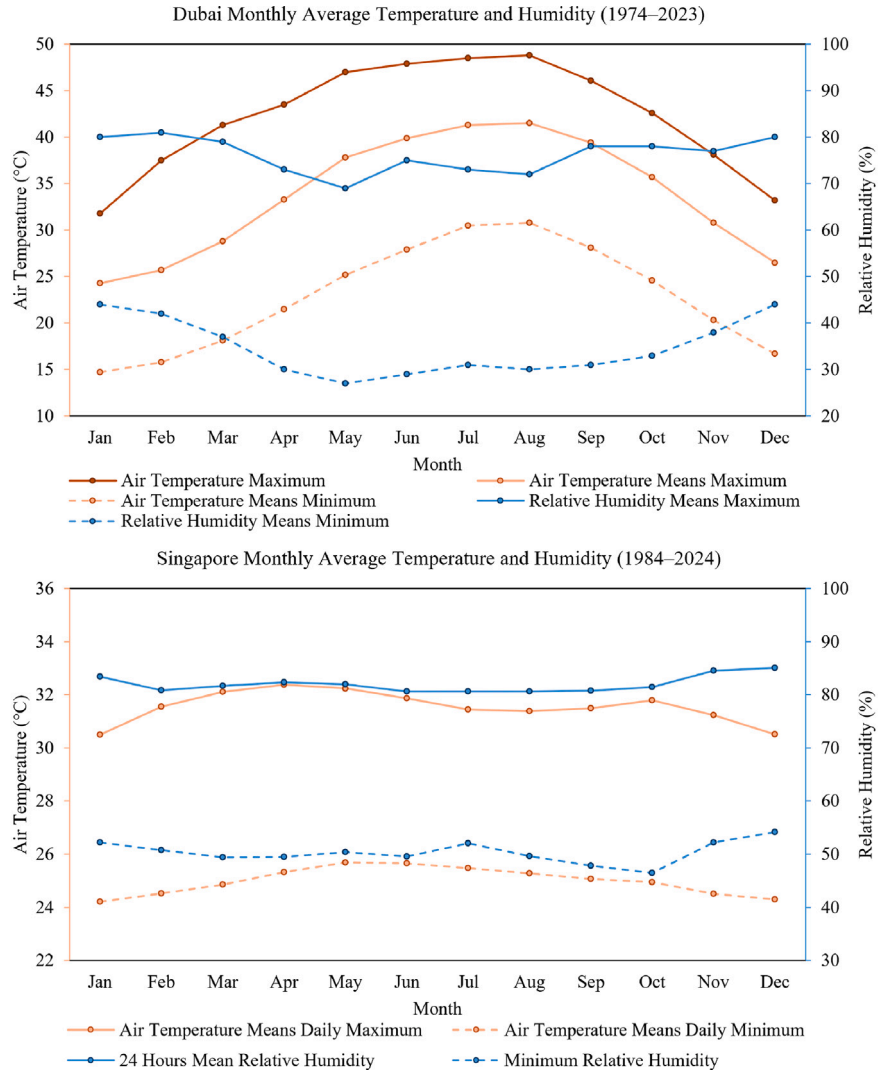


Fig. A.3. Comparison of historical monthly average temperature and relative humidity between Dubai (Meteorological Service Singapore, 2025) and Singapore (National Center of Meteorology, 2025).

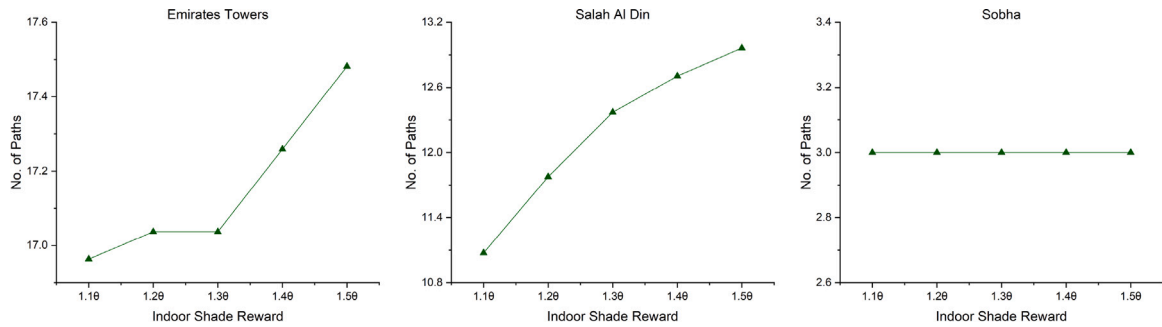


Fig. A.4. Sensitivity analysis of indoor shade reward impact on the number of optimal shadiest paths utilizing indoor shade at three metro stations with indoor networks.



Fig. A.5. Shade conditions between 8:00–9:00 AM on 21 December at Salah Al Din station, showing building footprints, indoor paths, outdoor paths (sun-exposed, tree-shaded, and building-shaded), and indoor–outdoor transitions.

Table A.1

The deviation between the shortest and the optimal shadiest path on the outdoor network.

Station	Month	Time	DP	$BS_{shadiest}$	$TS_{shadiest}$	$Sun_{shadiest}$	$BS_{shortest}$	$TS_{shortest}$	$Sun_{shortest}$
Salah Al Din	Mar	8:00–9:00	1.68%	72.03%	4.13%	23.85%	57.32%	4.40%	38.28%
		9:00–10:00	1.35%	49.81%	2.10%	48.08%	38.88%	2.68%	58.44%
		10:00–11:00	1.97%	44.52%	1.61%	53.87%	30.35%	1.51%	68.14%
		11:00–12:00	1.74%	34.69%	0.54%	64.77%	21.17%	0.77%	78.07%
		12:00–13:00	1.84%	37.77%	0.81%	61.41%	20.60%	0.55%	78.84%
		13:00–14:00	1.51%	39.90%	1.00%	59.11%	20.25%	0.91%	78.84%
		14:00–15:00	1.44%	42.55%	2.46%	54.98%	28.75%	1.92%	69.33%
		15:00–16:00	1.75%	55.43%	3.07%	41.49%	39.14%	2.45%	58.41%
		16:00–17:00	1.89%	68.84%	4.25%	26.91%	56.47%	4.33%	39.20%
	Jun	8:00–9:00	0.94%	74.18%	3.55%	22.27%	65.18%	4.84%	29.98%
		9:00–10:00	1.43%	59.87%	1.26%	38.86%	48.33%	2.22%	49.45%
		10:00–11:00	1.27%	38.16%	1.55%	60.30%	28.65%	1.04%	70.31%
		11:00–12:00	1.50%	22.31%	0.58%	77.11%	8.06%	0.17%	91.78%
		12:00–13:00	0.03%	0.94%	0.40%	98.66%	0.27%	0.40%	99.34%
		13:00–14:00	1.02%	20.42%	0.57%	79.01%	11.18%	0.35%	88.47%
		14:00–15:00	1.20%	28.27%	0.78%	70.95%	17.67%	0.91%	81.42%
		15:00–16:00	1.48%	37.46%	1.72%	60.82%	23.25%	2.42%	74.32%
		16:00–17:00	1.24%	48.45%	3.22%	48.33%	37.84%	3.92%	58.24%
	Dec	8:00–9:00	1.79%	67.27%	5.06%	27.67%	55.50%	4.44%	40.05%
		9:00–10:00	2.09%	66.26%	3.67%	30.07%	53.12%	4.73%	42.15%
		10:00–11:00	1.12%	65.79%	2.68%	31.54%	53.90%	2.94%	43.16%
		11:00–12:00	2.01%	64.32%	3.36%	32.31%	50.75%	2.60%	46.65%
		12:00–13:00	1.27%	66.65%	2.14%	31.22%	53.38%	1.89%	44.73%
		13:00–14:00	1.90%	63.43%	2.81%	33.76%	49.42%	2.16%	48.42%
		14:00–15:00	1.62%	65.43%	4.42%	30.15%	52.42%	4.13%	43.44%
		15:00–16:00	1.38%	74.11%	4.40%	21.49%	62.33%	4.48%	33.20%
		16:00–17:00	0.76%	92.99%	1.84%	5.17%	81.16%	2.76%	16.08%
	Average		1.45%	51.92%	2.37%	45.71%	39.46%	2.44%	58.10%
Emirates Towers	Mar	8:00–9:00	1.22%	54.80%	22.85%	22.35%	48.03%	24.77%	27.20%
		9:00–10:00	1.40%	55.72%	13.69%	30.59%	46.54%	15.28%	38.19%
		10:00–11:00	0.82%	50.47%	10.82%	38.71%	40.22%	11.89%	47.89%
		11:00–12:00	1.18%	46.84%	8.68%	44.48%	36.69%	9.19%	54.13%
		12:00–13:00	2.70%	56.35%	4.89%	38.76%	42.88%	5.48%	51.64%
		13:00–14:00	1.74%	62.32%	2.64%	35.04%	51.24%	2.84%	45.93%
		14:00–15:00	1.39%	59.74%	7.55%	32.71%	50.33%	9.51%	40.17%
		15:00–16:00	1.67%	65.88%	10.39%	23.73%	55.13%	12.71%	32.16%
		16:00–17:00	1.11%	81.72%	4.09%	14.19%	77.06%	5.64%	17.30%

(continued on next page)

Table A.1 (continued).

Station	Month	Time	DP	$BS_{shadiest}$	$TS_{shadiest}$	$Sun_{shadiest}$	$BS_{shortest}$	$TS_{shortest}$	$Sun_{shortest}$
Emirates Towers	Jun	8:00–9:00	1.38%	52.65%	10.96%	36.40%	44.51%	11.96%	43.53%
		9:00–10:00	1.65%	51.81%	7.96%	40.23%	43.26%	8.39%	48.35%
		10:00–11:00	1.34%	40.40%	5.13%	54.47%	31.17%	5.50%	63.33%
		11:00–12:00	1.02%	30.40%	2.03%	67.58%	22.59%	2.33%	75.08%
		12:00–13:00	0.96%	41.63%	1.89%	56.48%	31.73%	2.52%	65.75%
		13:00–14:00	1.27%	58.46%	1.25%	40.29%	50.73%	1.61%	47.65%
		14:00–15:00	0.79%	70.08%	4.98%	24.94%	60.56%	8.63%	30.81%
		15:00–16:00	0.61%	73.92%	4.20%	21.88%	67.94%	7.02%	25.05%
		16:00–17:00	1.25%	79.20%	8.97%	11.83%	72.89%	11.10%	16.01%
	Dec	8:00–9:00	1.43%	42.31%	47.39%	10.31%	34.62%	47.67%	17.71%
		9:00–10:00	1.46%	50.19%	33.72%	16.10%	43.11%	35.67%	21.22%
		10:00–11:00	1.06%	55.17%	23.77%	21.07%	47.89%	24.56%	27.55%
		11:00–12:00	1.69%	67.02%	11.22%	21.77%	58.48%	12.11%	29.41%
		12:00–13:00	2.57%	59.83%	16.10%	24.07%	50.87%	16.62%	32.51%
		13:00–14:00	3.67%	63.52%	21.81%	14.67%	52.15%	22.16%	25.69%
		14:00–15:00	1.31%	70.78%	11.93%	17.29%	62.86%	15.58%	21.56%
		15:00–16:00	1.09%	72.18%	14.18%	13.65%	66.16%	15.85%	17.99%
		16:00–17:00	1.50%	92.45%	1.50%	6.05%	88.56%	2.83%	8.61%
	Average		1.46%	59.48%	11.65%	28.88%	51.05%	12.94%	36.02%
Sobha	Mar	8:00–9:00	1.35%	54.91%	8.09%	37.00%	45.41%	5.82%	48.78%
		9:00–10:00	1.75%	54.87%	7.20%	37.94%	42.58%	4.73%	52.69%
		10:00–11:00	1.83%	39.52%	7.43%	53.06%	28.19%	4.76%	67.05%
		11:00–12:00	1.38%	39.69%	5.99%	54.32%	30.02%	4.60%	65.39%
		12:00–13:00	1.40%	45.30%	2.30%	52.40%	38.90%	1.76%	59.34%
		13:00–14:00	1.80%	43.64%	1.84%	54.52%	34.93%	0.90%	64.17%
		14:00–15:00	0.80%	42.37%	1.73%	55.90%	38.85%	1.75%	59.40%
		15:00–16:00	0.80%	61.84%	3.74%	34.42%	56.38%	4.25%	39.37%
		16:00–17:00	0.87%	63.44%	7.92%	28.65%	57.95%	6.73%	35.33%
	Jun	8:00–9:00	2.08%	44.86%	9.66%	45.48%	31.50%	7.19%	61.31%
		9:00–10:00	1.57%	38.32%	5.79%	55.89%	28.81%	3.21%	67.98%
		10:00–11:00	1.42%	25.57%	2.15%	72.28%	18.83%	0.64%	80.54%
		11:00–12:00	0.97%	18.09%	1.93%	79.99%	13.57%	0.81%	85.62%
		12:00–13:00	1.87%	19.14%	1.31%	79.55%	13.69%	1.54%	84.78%
		13:00–14:00	0.94%	27.59%	3.90%	68.50%	22.72%	3.23%	74.06%
		14:00–15:00	0.62%	40.56%	2.78%	56.66%	36.14%	3.43%	60.43%
		15:00–16:00	0.96%	45.46%	7.34%	47.19%	38.61%	7.06%	54.33%
		16:00–17:00	0.74%	65.84%	16.49%	17.68%	61.88%	14.67%	23.46%
Sobha	Dec	8:00–9:00	1.72%	72.22%	10.83%	16.95%	59.75%	7.91%	32.34%
		9:00–10:00	1.46%	71.97%	10.79%	17.24%	61.74%	8.40%	29.86%
		10:00–11:00	1.15%	65.66%	6.29%	28.06%	57.65%	6.29%	36.06%
		11:00–12:00	1.63%	64.72%	6.69%	28.59%	53.24%	5.62%	41.14%
		12:00–13:00	2.38%	62.21%	5.33%	32.46%	48.23%	5.53%	46.25%
		13:00–14:00	2.98%	53.99%	6.75%	39.26%	40.48%	6.10%	53.43%
		14:00–15:00	1.59%	55.78%	5.96%	38.26%	45.80%	4.69%	49.51%
		15:00–16:00	1.50%	73.67%	6.17%	20.16%	61.61%	7.87%	30.53%
		16:00–17:00	0.19%	99.03%	0.89%	0.08%	98.81%	1.11%	0.08%
	Average		1.40%	51.49%	5.83%	42.69%	43.20%	4.84%	51.97%
The Gardens	Mar	8:00–9:00	0.42%	57.28%	32.66%	10.05%	52.74%	34.70%	12.56%
		9:00–10:00	0.59%	42.45%	30.10%	27.45%	36.51%	31.62%	31.88%
		10:00–11:00	0.51%	41.31%	25.48%	33.21%	34.33%	26.69%	38.98%
		11:00–12:00	0.69%	34.41%	30.66%	34.93%	28.02%	28.10%	43.88%
		12:00–13:00	0.88%	30.00%	39.17%	30.83%	22.25%	37.59%	40.16%
		13:00–14:00	1.01%	18.30%	39.08%	42.62%	11.57%	37.16%	51.27%
		14:00–15:00	1.11%	28.94%	37.88%	33.18%	20.06%	38.42%	41.52%
		15:00–16:00	1.06%	50.20%	25.87%	23.93%	41.95%	27.02%	31.04%
		16:00–17:00	1.15%	53.49%	30.62%	15.89%	42.94%	34.73%	22.33%
	Jun	8:00–9:00	0.39%	59.69%	21.51%	18.80%	55.34%	23.50%	21.17%
		9:00–10:00	0.66%	36.77%	28.44%	34.79%	31.46%	26.98%	41.55%
		10:00–11:00	0.61%	23.05%	26.76%	50.19%	17.54%	24.68%	57.78%
		11:00–12:00	1.07%	15.52%	30.21%	54.27%	11.27%	22.05%	66.68%
		12:00–13:00	0.95%	14.19%	34.43%	51.37%	10.73%	29.55%	59.71%
		13:00–14:00	0.78%	13.90%	19.45%	66.65%	9.69%	16.15%	74.16%
		14:00–15:00	0.58%	20.23%	28.71%	51.06%	13.99%	27.56%	58.45%
		15:00–16:00	0.95%	29.26%	39.01%	31.73%	24.51%	37.21%	38.28%
		16:00–17:00	1.48%	40.80%	42.46%	16.74%	32.26%	42.60%	25.14%
	Dec	8:00–9:00	0.40%	54.17%	41.60%	4.23%	50.76%	42.32%	6.91%
		9:00–10:00	0.46%	40.77%	38.33%	20.90%	34.54%	38.97%	26.50%
		10:00–11:00	0.47%	46.17%	32.55%	21.28%	40.11%	33.35%	26.54%
		11:00–12:00	0.58%	46.74%	27.27%	25.98%	41.21%	27.01%	31.77%
		12:00–13:00	0.79%	48.55%	30.40%	21.05%	42.62%	31.21%	26.17%
		13:00–14:00	1.08%	51.72%	26.29%	21.99%	44.16%	25.40%	30.44%
		14:00–15:00	0.87%	57.01%	27.34%	15.65%	48.90%	27.88%	23.22%
		15:00–16:00	1.04%	52.38%	34.01%	13.61%	42.94%	37.35%	19.71%
		16:00–17:00	0.60%	63.67%	29.60%	6.73%	55.88%	35.88%	8.24%
	Average		0.78%	39.67%	31.48%	28.86%	33.27%	31.32%	35.41%

Data availability

No data was used for the research described in the article.

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