Heliyon 10 (2024) e35620

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Feasibility of using electrodermal activity responses to assess level of crowdedness of pedestrian paths

Heejung Lee [a], Sungjoo Hwang [a,*], Seungjun Ahn [b]

[a] Department of Architectural and Urban Systems Engineering, Ewha Womans University, 52 Ewhayeodae-Gil, Seodaemun-Gu, Seoul, 03760, South Korea

[b] Department of Civil and Environmental Engineering, Hongik University, P506, 94 Wausanro, Mapo-gu, Seoul, 04066, South Korea

ARTICLE INFO

Keywords:
Electrodermal activity
Pedestrian level of service
Wearable devices
Physiological data
Skin conductance responses
Crowdedness management

ABSTRACT

As urban populations grow, it's imperative to evaluate and enhance the quality of pedestrian paths from the user's perspective. Crowdedness, associated with discomfort and safety, is crucial in determining the overall walking quality and user experience. Previously utilized methods for measuring crowdedness, such as travel diaries and floating population surveys, were limited to collecting perceptual data from sporadic surveys with restricted spatial coverage. Similarly, methods based on CCTV or mobile service data have been used but present issues with blind spots and fail to consider pedestrian perspectives. Against this background, this study explores the feasibility of assessing crowdedness levels by measuring subjects' physiological responses in a laboratory setting based on visual images of real and virtual environments. This study hypothesizes that the amount of people or vehicles passing by affects the electrodermal activity (EDA) of pedestrians, indicating the comfort level of using the environment. Experimental EDA data were measured using a wearable device while the subjects were watching videos showing different pedestrian traffic flows. Representative EDA signal features (e.g., skin conductance responses) were extracted after data pre-processing. Noticeable changes in EDA responses are observed when subjects countered specific environmental variations, such as differing volumes of passing people, on pedestrian paths. The findings suggest that EDA data can be instrumental in differentiating crowdedness levels on pedestrian paths. This study contributes to the body of knowledge by demonstrating the potential of EDA data to characterize the crowdedness experienced by pedestrians. This aids in the development of a novel, quantitative method to gauge pedestrian path crowdedness and to discern contributing factors, such as path width.

1. Introduction

Due to rapid urbanization and population growth, interest in improving the management of the crowdedness of pedestrian paths continues to grow. The goal is to reduce the associated discomfort and safety concerns on these paths [1]. Thus, to achieve a walking-friendly environment, analyzing traffic volumes and the capacity of pedestrian paths is crucial because the crowdedness significantly impacts the walkability of an environment. The crowdedness has thus been a critical factor in determining pedestrian level of service (PLOS), which is an approach to assess the quality of pedestrian paths. PLOS [2]. The original version of PLOS, tailored

* Corresponding author.
E-mail addresses: ahhssdd12@ewhain.net (H. Lee), hwangsj@ewha.ac.kr (S. Hwang), jun.ahn@hongik.ac.kr (S. Ahn).

https://doi.org/10.1016/j.heliyon.2024.e35620
Received 9 September 2023; Received in revised form 21 January 2024; Accepted 31 July 2024
Available online 7 August 2024
2405-8440/

from the level of service in the transportation domain as a qualitative measure of road performance based on the ratio of traffic volume to road capacity [3], classified the different performances of pedestrian facilities from Grade A (best condition) to Grade F (worst condition) based on flow rate, average walking speed, occupied space, and other parameters (e.g., flow characteristics, physical elements of the constructed environment) [2]. The most recent version of PLOS considers many attributes, such as land use, population structure, and physical and environmental attributes of paths, and has a greater emphasis on users' perceived comfort and safety, rather than mostly focusing on flow characteristics as in the early versions. Nevertheless, not only is the crowdedness of pedestrian paths still an important factor in determining PLOS and measuring path quality, but it also has a huge impact on user's perceptions [4,5].

Many qualitative and quantitative measures have been used to measure the level of crowdedness experienced by pedestrians. National and local governments conduct household travel diary surveys and floating population surveys for statistical purposes, with many studies using the survey results to infer flow rates and levels of crowdedness in specific areas. Still, they are difficult to utilize for specific paths at an alley level [6–10]. Researchers have recently attempted to use computer vision technologies to automatically assess pedestrian flows from closed-circuit television (CCTV) videos. However, this approach also has several limitations because the CCTV coverage is limited, regardless of the number of devices deployed. Additionally, CCTV videos only provide images showing the crowdedness of an area; hence, capturing the feelings and subjective experiences of users regarding the level of crowdedness remains difficult.

In recent years, wearable sensors capable of measuring human physiological responses to external stimuli have gained popularity in various fields of research. Physiological data enable the possibility of using these responses for assessing the level of crowdedness perceived by pedestrians. This is due to physiological data being regarded as an expression of autonomic nervous system activity in response to psychological and emotional stimuli, such as pedestrian flows. However, attempts to use human physiological sensing to assess pedestrian path crowdedness levels are scarce.

Against this background, this study examines the potential of assessing the crowdedness of pedestrian paths based on electrodermal activity (EDA). As a first step, confirming that physiological data, such as EDA responses, vary when a subject is exposed to external stimuli (such as other pedestrians or fast-approaching vehicles) is required. Researchers suggest that physiological responses undergo meaningful changes when subjects are exposed to unfamiliar stimuli [11]. Previous research indicates the possibility of using physiological data, such as EDA, for assessing people's experience in response to environmental conditions; however, this idea has not been rigorously tested in the context of the crowdedness of paths experienced by pedestrians.

The ultimate goal of this research is to test the feasibility of using physiological data collected through EDA sensors to assess the level of crowdedness. Three objectives are involved. First, confirming that significant changes in EDA responses occur when a subject is exposed to particular types of environmental changes (such as the passage of different people) while controlling other variables (e.g., noise, illuminance, ambient temperature, physical obstructions, street amenities, and pedestrian movement) is necessary. In particular, whether EDA changes in the real-world experiment are due to physiological variations caused by crowdedness or the physical movement of pedestrians, which are critical sources of EDA responses, is difficult to ascertain [12]. Moreover, real-world EDA data are extremely difficult to interpret when a subject is physically moving and simultaneously exposed to all stimuli. Therefore, a controlled laboratory setting is required before a real-world experiment is conducted to observe the relationship between crowdedness and physiological responses. Second, the possibility of observing significant EDA changes must be tested when the subject responds to environmental changes (e.g., various levels of crowdedness) while walking in the real world. Third and finally, the possibility of discriminating distinct levels of the crowdedness based on EDA as well as other physiological and movement data obtained by sensors must be confirmed.

This study focuses on the first step described above, i.e., testing the hypothesis that changes in the condition of pedestrian paths (such as the number of pedestrians and vehicles passing by) affect EDA. Thus, the study aims to identify the physiological response signals against varying degrees of crowdedness as visualized in the videos. Concurrently, the effect of the movement of a subject in the laboratory setting is minimized to ensure that the variations in the detected physiological data are attributable to the experimental treatment.

2. Literature review

2.1. The importance of crowdedness in PLOS and pedestrian perception

The initial version of PLOS by the Highway Capacity Manual (HCM) measures the satisfaction level of pedestrians using the transportation system based on factors such as density, speed, and the degree of road congestion [2,4]. It is divided into six levels (Levels A–F). Level A indicates the highest PLOS level, implying the least crowded and most comfortable condition. As the PLOS level descends to Level F, the PLOS index decreases [13]. The standard method for assessing the PLOS level relies on the average pedestrian space (m^2/pedestrian). The supporting standards include pedestrian speed (m/s) and pedestrian unit flow rate (pedestrian/min/m) [4]. The modified versions of the PLOS assessment method consider not only pedestrian flow but also environmental factors that may affect comfort, convenience, safety, security, and economy in the walking environment. Nag et al. [13] reported that the PLOS criteria could primarily be divided into flow characteristics of pedestrian and vehicle traffic as well as physical elements and user perception of the constructed walking environment. Their study showed that the factors perceived by pedestrians (such as comfort, convenience, safety, absence of shade, automobile-only roads, bus stops, and number of vehicle lanes) could reduce satisfaction and affect decision-making. Further, Bloomberg & Burden [14] described three main factors affecting PLOS: sidewalk environment, pedestrian characteristics, and flow characteristics. Sidewalk environment components are related to the physical walking environment.

Pedestrian characteristics are related to socioeconomic information, behavior, physical ability, and pedestrian perception. Flow characteristics are related to pedestrian and vehicle traffic flow characteristics. In this regard, Vallejo-Borda et al. [5] have clarified the evolution of the PLOS concept, explaining that it was initially based predominantly on flow characteristics but has since evolved to include a variety of attributes, such as user perception.

Georgiou et al. [4] identified three methods for analyzing the factors affecting PLOS based on reports in the literature (Table 1). First, quantitative methods measure the available space of transportation facilities and traffic characteristics based on speed and capacity. For example, the HCM proposed a methodology that considers pedestrian speed, pedestrian flow, and other quantitative criteria such as age, gender, group size, and purpose of movement [2]. Transport for London (TfL) published "Pedestrian Comfort Levels (PCLs)" for assessing pedestrian facilities (e.g., sidewalks and crossings) considering various factors (land type and impact of street facilities) [15]. Landis et al. [16] used stepwise multivariate regression analysis to confirm that PLOS derived from the traffic volume and speed of cars and pedestrians was a statistically significant factor for achieving user satisfaction.

Second, qualitative methods measure PLOS in terms of safety, comfort, and accessibility. Jaskiewicz [17] introduced nine qualitative measures to evaluate the goodness of pedestrian infrastructure, including the degree of finish of road edges, complexity of route network, building connections, space complexity, protruding components, awnings components, and physical components. Other factors include various roof lines, shock absorbers, tree shades, sidewalk construction and condition, vehicle speed, and lighting. Rahaman et al. [18] found that perceived safety, comfort, accessibility, public transportation service, and land use attractiveness were factors significantly affecting PLOS. Florez et al. [19] introduced the term "Quality of Pedestrian Level of Service (Q-PLOS)." The Q-PLOS model was aimed at reflecting the demand of pedestrians in infrastructure design. They showed that accessibility, comfort, reliability, convenience, security, safety, and sociality were the most influential characteristics.

Third, mixed methods are employed for analyzing both quantitative and qualitative factors, which are in line with recent trends in PLOS measurement. For example, Hidayat et al. [20] used a mixed analysis model for assessing sidewalks based on pedestrian behavior in Jakarta and Bangkok. Among other quantitative variables, sidewalk comfort and pedestrian perceptions of street vendor activities were included in the assessment list. Christopolou et al. [21] also proposed a mixed model to analyze urban areas in Greece, considering not only pedestrian movement parameters but also traffic, environmental, and sidewalk parameters. Daniel et al. [22] developed a "pedestrian footpath level of service (FOOT-LOS)" model, considering all physical properties, location characteristics, and pedestrian properties for measuring the PLOS of pedestrian paths. More recent studies on the walkability and service quality of pedestrian paths have incorporated both objective and subjective measures by utilizing multivariate attributes [23,24], such as land use and street type affecting pedestrian perception [25], pedestrian comfort due to other pedestrians, physical environment, and ammenities [26], and the building characteristics and continuity of the path affecting pedestrian pleasantness [27]. These studies have revealed that factors influencing PLOS can be categorized as either quantitative or qualitative; although they function independently, there is also a degree of interaction between them. Moreover, user perception is acknowledged as a pivotal factor in the assessment of PLOS [28,29]. Rodriguez-Valencia et al. [30] demonstrated that user perception is a key predictor of pedestrian quality of service when comparing the explanatory power with other attributes.

The review of PLOS-related literature indicated that the emphasis on how users experience and perceive pedestrian paths has been increasing. Additionally, pedestrian flow rate and crowdedness are consistently recognized as important quantitative factors in PLOS, even as other qualitative factors gain importance. In this respect, various methods have been devised to measure the crowdedness of paths, including the analysis of survey data, statistical data, location-based mobile service data, and videos. Methods for identifying floating populations using mobile communication signals or Wi-Fi probes were tested [31,32]. However, this technique was unable to identify pedestrian flows in small areas (such as alleyways) because the minimum area that the method could measure was wider than the normal size of alleys. Street view images have been used to approximate pedestrian volume [33]. A video recognition system was also tested to count the number of pedestrians passing by Kim et al. [34]'s study. However, this method was constrained by blind spots

Table 1
Factors affecting PLOS.

Factors	Factor description	Example
Quantitative	Available space and traffic characteristics of infrastructure	- Pedestrian speed - Pedestrian unit flow rate - Area type - Impact of street furniture - Lateral separation between pedestrians and motor vehicle - Overall condition of sidewalk
Qualitative	Safety, comfort, and accessibility	- Safety and security - Convenience and comfort - Mobility and infrastructure - Perceived pedestrian satisfaction - Socio-demographic characteristics (e.g., gender, age, occupation, and car ownership) - Trip characteristics
Mixed	Quantitative and qualitative characteristics are considered	- Pedestrian perception of sidewalk comfort and street vendor activities - Environmental and sidewalk parameters (e.g., width, height, and ramp presence) - Physical attributes - Location characteristics - User attributes

in areas where CCTV cameras were not installed. In addition, only quantitative features (e.g., physical flow rate) were measured because it was challenging to obtain the crowdedness of paths as experienced by users using the aforementioned methods.

Accordingly, the assessment of the crowdedness reflecting pedestrian perception is necessary to enhance the quality of pedestrian paths. To this end, understanding the effects of crowdedness on human perception is required. In this regard, Engelniederhammer et al. [11] found that the shorter the distance among pedestrians, the greater the invasion of personal space. Hall [35] defined personal space as a distance of 45–75 cm around an individual. Within this radius, a person can reach out and grab or hold another person. The invasion of private space is intrusive and can induce physiological responses, such as increased heart rate, sweating, and increased blood pressure [36]. A considerable distance from strangers reduces the likelihood of physical aggression and risk of disease transmission [37]. Many studies have investigated the shape and size of personal space. However, the results of these studies vary. For example, Newman and Pollack [38] found that personal space was more important at the rear (∼120 cm) than at the sides and in front (∼60 cm) of a person. In contrast, Hayduk found that personal space was more significant in front of a subject than at the rear; personal space was rated zero at the rear when subjects could not move their heads [39,40]. Engelniederhammer et al. [11] also defined 0–2 m as the range of personal space that has psychological and physiological effects when invaded by other people or objects. The personal space in these studies describes the personal space of test subjects while standing or sitting. Other pedestrians may also have a similar desire to maintain a certain comfortable distance from other people or objects [41]. In addition, the invasion of perceived personal space can cause pedestrians to cross a street faster than usual [42,43]. Kaya and Erkip [44] demonstrated that people in highly crowded environments exhibited more withdrawal behaviors than in environments with fewer people. This indicated that they were uncomfortable and defensive because they felt that their personal space was not protected.

2.2. Pedestrian experience based on physiological sensing data

The EDA of pedestrians is an autonomic nervous system indicator that directly shows the activation of the sympathetic nervous system without the effect of the parasympathetic nervous system. It records electrical resistance changes in the skin [45] and measures electrical conductance as eccrine glands release sweat on the skin's surface [45,46]. Events that are psychologically salient can be identified by observing skin conductance fluctuations linked to specific brain circuits [45,47]. Accordingly, the EDA has been widely tested as a tool to investigate a range of psychological states, such as stress, depression, anxiety, attention disorder, pain, and information processing [45,48–50].

Cacioppo et al. [48] reported that EDA signals have three components: skin conductance level, which is related to tonic activities; skin conductance response (SCR), which is related to phasic activities; and artifacts. Typically, a tonic response ranges between 2 and 20 μS and represents a general trend in activation levels [51]. In analyzing EDA signals, the tonic level is typically removed for two reasons [51]. First, further clarification on how psychological events relate to tonic changes is required [51]. Second, EDA baselines are rarely consistent within or among individuals due to hydration status, recording site, eccrine sweat gland density at the recording site, and psychological state [51].

In contrast, SCRs are rapid responses superimposed on the tonic response that can be more directly linked to psychological events [52]. They typically have a predictable shape characterized by rise time, amplitude, and half-recovery time. In healthy adults, the rise time is typically 1–3 s; amplitude frequently varies. The minimum rise time and half-recovery time are set to be 0.01–0.05 μs and 2–10 s, respectively [48].

Lee et al. [53] measured the stress experienced by pedestrians in a built environment by measuring the EDA and analyzed stress hotspots based on geographic information systems. LaJeunesse et al. [54] endeavored to quantify the performance of pedestrian facilities from the perspective of pedestrians. The quantification was based on the physiological measurements of heart rate and EDA in various traffic situations to investigate the factors affecting the comfort of walking. They confirmed that the stress level of participating pedestrians was related to road conditions. Engelniederhammer et al. [11] investigated the emotional response of pedestrians residing in densely populated cities by measuring the EDA, skin temperature, and ambient temperature. They hypothesized that the high population density of a city led to the invasion of the entire personal space of a pedestrian, triggering emotional responses, particularly negative emotions such as stress and aggression. Their study found that pedestrians adversely reacted upon recognizing that a certain level of their personal space (a maximum of 2 m) was invaded while walking.

Previous findings indicate the potential of utilizing EDA monitoring in assessing pedestrian responses, such as stress or discomfort. However, studies on measuring the level of crowdedness from pedestrian responses are limited. Therefore, this study aims to investigate the possibility of assessing the crowdedness from a pedestrian's subjective experience and feelings (e.g., stress and discomfort), which are affected by the level of congestion in pedestrian paths, based on the EDA data.

3. Research design and methods

The overall research process is as follows. First, a research site was selected, and videos of walking that visualized various levels of crowdedness on the selected pedestrian paths were created; the videos had two versions: real and virtual reality. The creation of real-world videos is necessary such that only the effect of changes in the level of crowdedness with minimal impact from other influencing factors (such as noise, illuminance, ambient temperature, and physical obstructions) can be observed. On the same pedestrian path, however, crowdedness is expected to vary depending on the time of day or surrounding conditions. Inevitably, this variation can lead to changes in several of the aforementioned variables and affect pedestrians. In view of this, virtual reality videos in which other influencing variables are perfectly controlled are used with real-world videos in this study. Second, the subjects watched both versions of videos representing various crowdedness levels; concurrently, the wearable device collected EDA data from the participants. Third, the collected data were processed and analyzed using MATLAB-based Ledalab software to extract essential signal features. Finally, the processed EDA data were statistically analyzed and compared with the EDA responses to visual inputs representing different levels of crowdedness.

3.1. Videos creation for different PLOS levels

The research site is a narrow pedestrian path near Sinchon Station in Seoul, Korea. It is in a commercial area where few people are present in the morning; however, it is typically overly crowded during the day. Accordingly, the site is considered suitable for recording varying extents of congestion in the area. The path is approximately 419 m long.

After selecting the research site, the authors recorded videos of walking using smartphones: iPhone 12 pro and gimbal (ATOM). The camera was fixed at eye level such that the recorded videos could stimulate the feeling of walking along the path. The videos were created to show different levels of crowdedness on the pedestrian path by recording them at different times of the day (e.g., quiet environment in the early morning and crowded space in the evening) to visualize various crowdedness levels. While collecting data using the recorded videos, the authors observed that external factors, such as noise, illumination, temperature, and changing obstructions, possibly affected the results. The videos of virtual walking were produced using Lumion (virtual environment modeling software) to fully control these factors; accordingly, the videos can be used in the experiment. Fig. 1 displays real and virtual environment versions of videos designed to visualize various crowdedness levels, represented as pedestrian flow rates. The videos simulating low crowdedness levels were created to depict HCM's initial version of PLOS Level A, focusing on flow characteristics. Meanwhile, the videos simulating high crowdedness levels were created to represent HCM's initial version of PLOS Level B [2]. Crowdedness levels are distinguished based on the pedestrian unit flow rate (pedestrian/m/min), as illustrated in Fig. 1(see Fig. 2).

3.2. Laboratory experiments

The participants in the experiment were requested to watch videos showing a real-world walking environment and a virtual model of the same environment while wearing an EDA sensor in a laboratory setting. Each of the total 37 subjects watched the same four videos (two videos of the actual environment and two videos of the virtual environment) via a wide-screen monitor. Each video was approximately 3 min long with a 30-s break between two successive videos. The order of watching the videos was not determined in advance; it was randomized to control the priming effect [55]. The subjects in this study voluntarily participated and signed a consent form as required by the Institutional Review Board. The participants were healthy adults in the age range of 19–60 years. The EDA data were collected from the subjects using Empatica E4, a wearable physiological sensing device for research purposes. The required sample size was calculated using G*Power 3.1.9.7 software based on a significance level of 0.05, a power of 0.8, and a medium effect size of 0.5 for two-tailed Wilcoxon signed-rank tests [56]. At least two different crowdedness levels were considered; the calculated minimum sample size was 35. The 37 subjects who participated in the study were deemed suitable for the experiment; the dropout rate was also considered.

3.3. EDA data processing and statistical analysis

Ledalab [51] was used for EDA data processing in this study. First, the raw EDA data collected from the subjects were imported, and then these data and video timelines were synchronized. Second, a low-pass filter was applied to remove significant signal noise in the

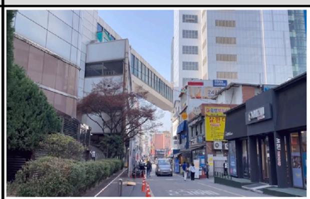
Video Type / Crowdedness	Virtual Reality Video	Real World Video	Flow Rate (pedestrian/m/min)
Low Level Crowdedness			7–8
High Level Crowdedness			16–17

Fig. 1. Videos of walking used in the experiment.

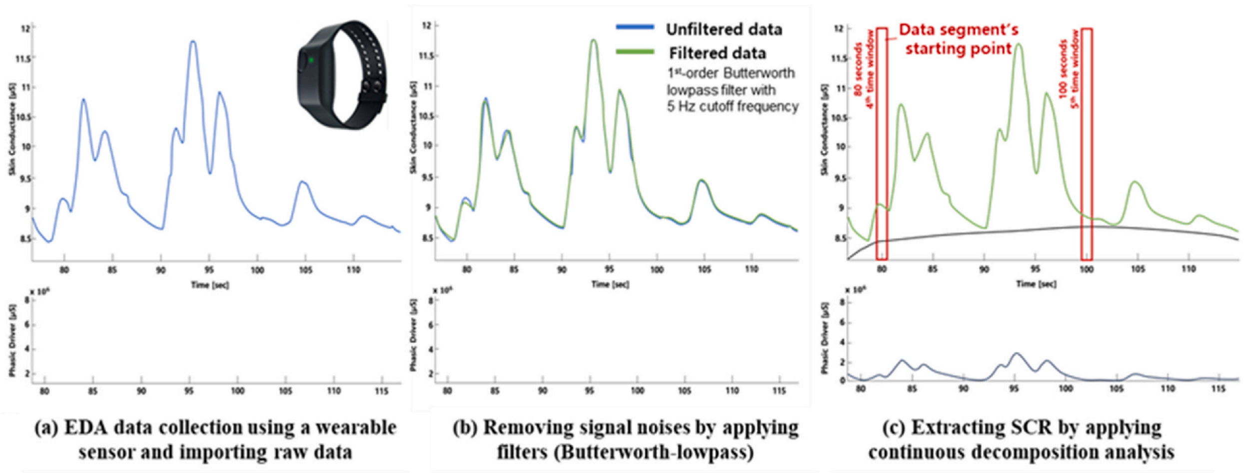


Fig. 2. Data collection and processing.

data. Third, the EDA data were analyzed using decomposition methods. Continuous decomposition analysis (CDA) and discrete decomposition analysis (DDA) have been widely used in the decomposition of skin conductance data. Although DDA is useful for studying SCR-based physiological models, it requires more computational time than CDA [57]. The implementation of CDA benefits the analysis of all unbiased scores of phasic and tonic activities, providing more straightforward measures of phasic activities. Accordingly, CDA is recommended for analyzing large skin conductance data using Ledalab software [57]. In this study, the collected EDA data were decomposed by CDA into continuous signals of phasic activity (i.e., skin conductance response) and tonic activity (i.e., skin conductance level) [51,58]. The signal characteristics of the underlying sudomotor nerve activity could be retrieved by unbiased

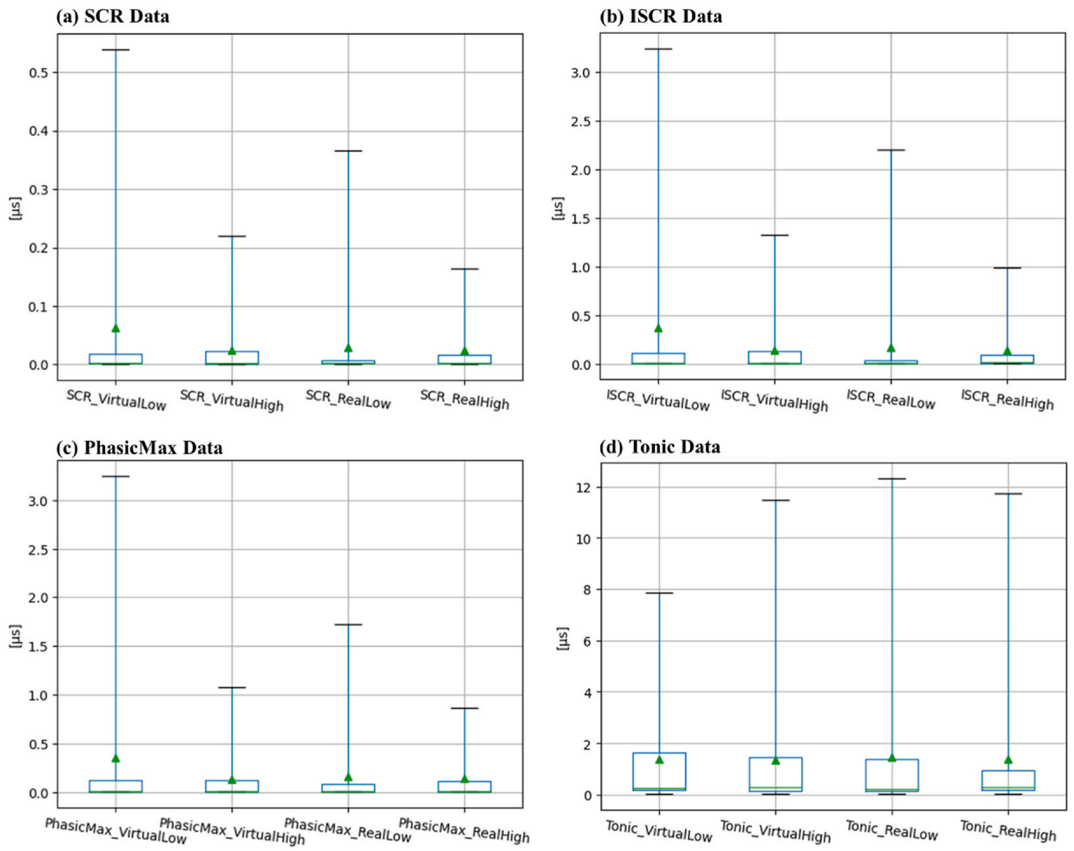


Fig. 3. Boxplots of (a) SCR data; (b) ISCR data; (c) PhasicMax data; and (d) Tonic data.

scores of phasic and tonic activities; consequently, all analyses improved [51,59]. The signal characteristics of basal motor neuron activity are recovered using CDA by decomposing and analyzing the skin conduction data into continuous signals of step-by-step sensory activity [51,59]. Finally, four significant signal features (SCR, Integral of SCR (ISCR), PhasicMax, and tonic data) were extracted. The SCR is an average phasic change in the electrical conductivity of skin [60], reflecting stimulus-specific responses or non-specific responses [51]. The ISCR, which is integral to SCR, is the area of the phasic driver and is equal to the SCR multiplied by the size of the response window. The ISCR is useful because it includes information on both amplitude and frequency of significant SCRs. The maximum values of phasic activity are denoted as PhasicMax data. The mean tonic activities of decomposed components are the tonic data [51]. Although the number of significant SCRs representing frequency and the sum of amplitudes of significant SCRs can be calculated, they were excluded from the analysis because their values were sensitive to the pre-determined threshold and strongly associated with ISCR.

Depending on the normality test result, non-parametric Wilcoxon signed-rank tests were implemented to compare EDA signal features under different PLOS conditions in virtual reality and real-world videos. For in-depth analysis, four significant features (SCR, ISCR, PhasicMax, and tonic data) were analyzed by dividing the data into 20-s segments. Then, values of signal features and the number of approaching people were compared.

4. Results

The descriptive statistics of EDA signal features (SCR, ISCR, PhasicMax, and tonic data) for each of the four videos (virtual-reality video showing low and high pedestrian flow rates as well as real-world videos showing low and high pedestrian flow rates) are shown in Fig. 3 and summarized in Table 2. The graphs in Fig. 3 indicate that the features associated with phasic activities, such as SCR, ISCR, and PhasicMax (excluding tonic data), show high values when flow rates are low in both virtual reality and real-world videos.

Before determining whether the differences in EDA signal features between low and high flow rate samples are statistically significant, a normality test is performed. This test is conducted to determine whether the data satisfies the normality condition. Because the number of subjects is less than 300, the Shapiro–Wilk test is used. Test results in Table 3 show that the significance level of each dataset is 0.000, which does not exceed the significance level of 0.05. Thus, the data cannot be assumed as normally distributed.

Accordingly, the Wilcoxon signed-rank test, a non-parametric statistical hypothesis test, was conducted to compare the EDA features between low and high pedestrian flow rate samples. Specifically, SCR, ISCR, PhasicMax, and tonic data were compared between low and high pedestrian flow rate samples of the virtual reality and real-world videos.

For the real-world videos, the significance level of the difference between low and high pedestrian flow rate samples is 0.492 for both SCR and ISCR data. This result indicates that for the SCR and ISCR data, the difference between low and high pedestrian flow rate samples is not statistically significant based on $\alpha = 0.05$. Similarly, the difference between low and high pedestrian flow rate samples is insignificant for the PhasicMax and tonic data with significance levels of 0.994 and 0.769, respectively; Table 4 summarizes the results. Because the ISCR is an integral of SCR, the rank-based non-parametric test produces identical statistics between SCR and ISCR.

For the virtual reality video, the significance of the difference between the low and high flow rate samples was 0.028 for both SCR and ISCR data, indicating a statistically significant difference between the two samples. Similar to the case of the real-world video, the difference between low and high pedestrian flow rate samples was insignificant for the PhasicMax and tonic data, with significance levels of 0.069 and 0.411, respectively. Table 5 summarizes these results.

Engelniederhammer et al. [11] reported that pedestrians invaded the personal space of other pedestrians more frequently when the distance separating them was short. The invasion of private space was perceived as an intrusion and triggered physiological reactions, such as increased heart rate, sweating, and increased blood pressure [36]. Accordingly, the real-world and virtual reality videos where pedestrians and vehicles are shown to pass by personal space (1) within a 2-m radius or less and (2) within a 5-m radius or less are considered as videos related to events causing changes in EDA features. Engelniederhammer et al. [11] specified that when a

Table 2
Descriptive statistics of EDA signal features.

EDA Signal Features	Video Type	Average	Standard Deviation	Median
SCR	Virtual, low flow rate	0.0627	0.1310	0.0024
	Virtual, high flow rate	0.0248	0.0486	0.0020
	Real, low flow rate	0.0293	0.0734	0.0022
	Real, high flow rate	0.0248	0.0460	0.0024
ISCR	Virtual, low flow rate	0.3760	0.7857	0.0144
	Virtual, high flow rate	0.1486	0.2913	0.0120
	Real, low flow rate	0.1762	0.4403	0.0136
	Real, high flow rate	0.1487	0.2760	0.0146
Phasic	Virtual, low flow rate	0.3569	0.7472	0.0076
	Virtual, high flow rate	0.1295	0.2448	0.0083
	Real, low flow rate	0.1599	0.3693	0.0077
	Real, high flow rate	0.1406	0.2554	0.0088
Tonic	Virtual, low flow rate	1.3776	2.2276	0.2492
	Virtual, high flow rate	1.3454	2.6306	0.2868
	Real, low flow rate	1.4633	2.8637	0.2011
	Real, high flow rate	1.3848	2.7572	0.2909

Table 3
Normality test results of each dataset.

Signal Features	Video Type	Shapiro–Wilk test		
		Statistics	Df	Significance level
SCR	Virtual, low flow rate	0.539	37	**0.000**
	Virtual, high flow rate	0.555	37	**0.000**
	Real, low flow rate	0.430	37	**0.000**
	Real, high flow rate	0.554	37	**0.000**
ISCR	Virtual, low flow rate	0.539	37	**0.000**
	Virtual, high flow rate	0.555	37	**0.000**
	Real, low flow rate	0.430	37	**0.000**
	Real, high flow rate	0.554	37	**0.000**
Phasic	Virtual, low flow rate	0.544	37	**0.000**
	Virtual, high flow rate	0.585	37	**0.000**
	Real, low flow rate	0.478	37	**0.000**
	Real, high flow rate	0.578	37	**0.000**
Tonic	Virtual, low flow rate	0.613	37	**0.000**
	Virtual, high flow rate	0.511	37	**0.000**
	Real, low flow rate	0.518	37	**0.000**
	Real, high flow rate	0.511	37	**0.000**

Table 4
Wilcoxon signed-rank test results for real-world video data.

	SCR (Real Low–High Flow Rates)	ISCR (Real Low–High Flow Rates)	PhasicMax (Real Low–High Flow Rates)	Tonic (Real Low–High Flow Rates)
Total N	37	37	37	37
Test statistic	397.000	397.000	351.000	371.000
Standard error	66.285	66.285	66.285	66.285
Standardized test statistic	0.686	0.686	−0.008	0.294
Significance	**0.492**	**0.492**	**0.994**	**0.769**

Table 5
Wilcoxon test results for virtual reality video data.

	SCR (Virtual Low–High Flow Rates)	ISCR (Virtual Low–High Flow Rates)	PhasicMax (Virtual Low–High Flow Rates)	Tonic (Virtual Low–High Flow Rates)
Total N	37	37	37	37
Test statistic	206.000	206.000	231.000	297.000
Standard error	66.285	66.285	66.285	66.285
Standardized test statistic	−2.195	−2.195	−1.818	−0.822
Significance	**0.028***	**0.028***	**0.069**	**0.411**

*$p < 0.05$.

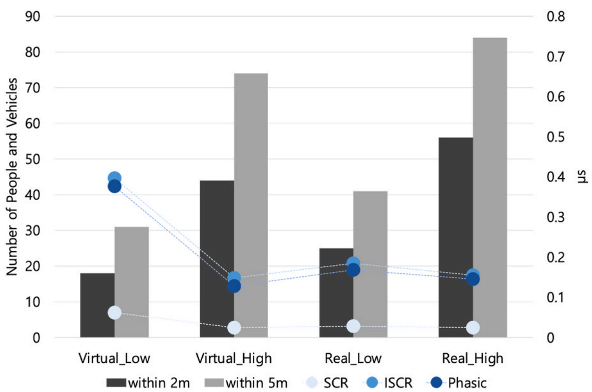


Fig. 4. Personal space invasion of passing people and vehicles as shown in videos and indicated by EDA signal features.

pedestrian approached another within a radius of approximately 2 m, this approach had a psychological effect. Fig. 4 clearly shows that the SCR, ISCR, and PhasicMax values are high in less crowded areas. Moreover, considerable personal space invasion events occur in both virtual reality and real-world video versions (including videos showing low pedestrian flow rates). The SCR and ISCR data thus tend to have a higher increase when flow rates are low. This is possibly because of the more sensitive reaction of a pedestrian to personal space invasion (e.g., pedestrians approaching each other within a 2-m radius in a less-crowded environment).

Fig. 5 shows the changes in EDA features and personal space invasion events in 20-s video segments. A significant increase in SCR, ISCR, and PhasicMax data is observed when the invasion of personal space event occurs within a 2-m radius in a less crowded environment (e.g., 20 s in Figs. 5(a) and 80 s in Fig. 5, (a) and (c)). Such increase is also observed when personal space invasion events within a 2-m radius frequently occur compared with events where pedestrians approach others within a 5-m radius (e.g., 40 s in Fig. 5 (b) or 60 s in Fig. 5(d)). Hence, physiological activation has a high probability when the number of personal space invasion events occurring within a 2-m radius is high compared with the total number of pedestrians rather than the absolute number of people.

5. Discussion

5.1. Discussion on the results

At distinct levels of crowdedness, statistically significant differences in EDA features (including SCR and ISCR) were observed while the subjects viewed the virtual reality videos. These differences were observed because other factors possibly affecting EDA data, such as vehicle noise, illuminance, and physical obstructions, were fully controlled in the virtual reality videos. However, the effect of viewing real-world videos was statistically insignificant, possibly because of several uncontrolled real-world factors, although the tendency for changes in EDA features is similar to that when viewing virtual reality videos. The EDA data are hypothesized to have a positive or negative relationship with crowdedness in pedestrian paths. However, more substantial evidence of a negative relationship between EDA (particularly phasic activity related to SCR) and level of crowdedness is shown by the results. In other words, the change in phasic EDA activity (such as SCR and ISCR, which are responses to specific and discontinuous stimuli) is relatively inconsiderable in a crowded walking environment because pedestrians may become more accustomed to the presence of numerous people and vehicles. In contrast, if a pedestrian or vehicle suddenly appears in a non-crowded environment and invades personal space, phasic SCR and ISCR data can increase, representing an immediate response toward unusual and unfamiliar external stimuli. In this regard, Engelniederhammer et al. [11] proposed that the physiological responses of individuals significantly vary when confronted with an unfamiliar stimulus (e.g., a person passes in an uncrowded area); their responses differ when they encounter a familiar stimulus (e.g., passing people in crowded areas). This is because the invasion of personal space by strangers causes discomfort, acting as an unfamiliar and disturbing stimulus that can cause anxiety, stress, or emotional arousal [11,61,62]. Such psychological changes stimulate the sympathetic nervous system and lead to subsequent changes in EDA, consistent with our findings.

In contrast, tonic EDA activity is associated with the background level and represents a gradual change in skin conductance level. The change in tonic activity in response to crowdedness is thus insignificant in the results, indicating that viewing real-world and virtual reality videos tends to have similar statistical significance.

In summary, the results of viewing virtual reality videos on phasic EDA activities, such as SCR and ISCR, showed the possibility of assessing the volume and density of pedestrians on a path by measuring physiological reactions. Moreover, although the scope of personal space varies among studies, the prominent EDA responses to personal space invasion (e.g., within a 2-m radius) may be useful for understanding the crowdedness of paths perceived by individuals.

5.2. Contributions

Although many qualitative and quantitative methods, such as survey-based or mobile-data-based ones, have been used to measure the level of crowdedness, the continuous collection and monitoring of the crowdedness of pedestrian paths in a wide range of areas at the alley level is difficult to perform. Additionally, previous methods do not consider how pedestrians respond and feel, which limits understanding the level of crowdedness experienced by pedestrians in terms of their comfort. In contrast, this study explores the collection of pedestrian physiological data using wearable sensors and then utilizes them to measure the level of crowdedness of paths from the perspective of human responses. This study thus demonstrates the feasibility of utilizing the physiological responses to varying levels of crowdedness considering pedestrian perception. Additionally, rather than simply increasing the number of physiological responses, such as EDA, in crowded areas, this study obtains a counterintuitive finding: passersby and vehicles in less crowded areas act as unfamiliar stimuli. These stimuli result in significant EDA responses, which are effective in providing a direction for EDA-based crowdedness measurement. Results show that EDA does not completely discriminate the level of crowdedness accurately. However, in predicting the level of crowdedness using machine learning algorithms by integrating sensor data, features related to phasic activity rather than tonic activity can be used as distinct features for crowdedness measurement.

5.3. Limitations, future works, and expected applications

The current study only compares human responses at two levels of crowdedness because real-world cases with extremely crowded situations are infrequently encountered. However, if the experiment is conducted using various levels of crowdedness, more significant results in the relationship between EDA and the level of crowdedness are to be expected. Advancements in instruments capable of accurate physiological data measurements, advanced signal processing, and sophisticated feature extraction can contribute to this

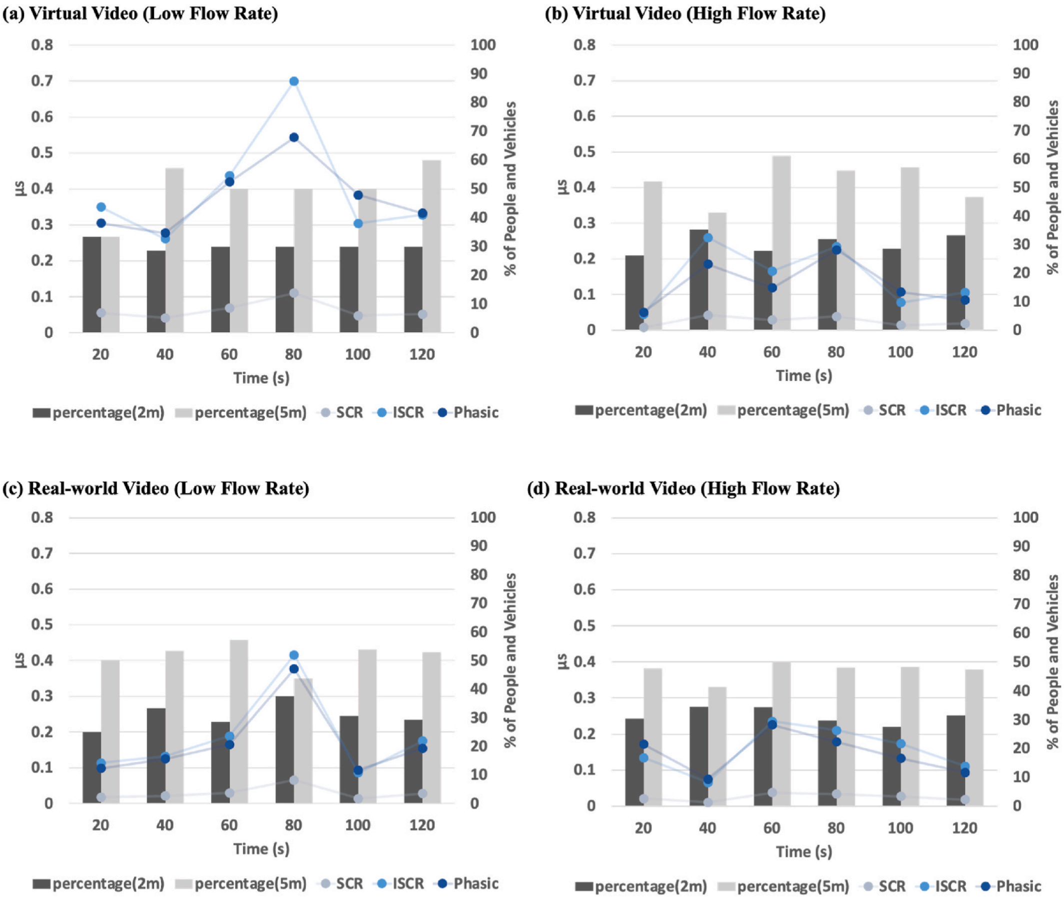


Fig. 5. Personal space invasion and EDA signal features over time: (a) virtual reality video (low flow rate); (b) virtual reality video (high flow rate); (c) real-world video (low flow rate); and (d) real-world video (high flow rate).

improved accuracy in distinguishing different levels of crowdedness.

Future studies where subjects walk in various real-world environments with various levels of crowdedness must also be conducted. However, external environmental factors can detrimentally affect EDA; hence, they must be measured and controlled using environmental sensors. Moreover, a subject's movements can influence EDA; hence, this impact must be adjusted by measuring movements using an embedded accelerometer. Data on human movement acceleration are also expected to support the assessment of different crowdedness levels. These data include various physical movement patterns (e.g., gait instability when avoiding other pedestrians) captured in crowded spaces. By conducting a user survey in the experiment, the analysis results of sensor data can be compared with the survey-based perception of pedestrians to improve the reliability of research results.

With future works and further validation, the research outcome is expected to be used for the physiological sensing-based continuous measurement of the level of crowdedness at the alley level. Using this method, evaluating whether an existing walking path has an appropriate and effective width relative to pedestrian volume becomes possible. This may aid in modifying the walking environment and constructing a more walking-friendly pedestrian path in terms of effective width. Supplementing the research results with data obtained using various instruments, such as accelerometers and global positioning system sensors, is necessary to measure data more accurately. This is because EDA represents activities of the sympathetic nervous system that can be affected by several other factors, such as emotional arousal, cognitive workloads, and intensive movement [12]. In a future study, the authors intend to investigate the feasibility of using integrated EDA and acceleration signals. By capturing the physiological and behavioral responses of pedestrians in a congested area, the accuracy of assessing the level of crowdedness can be improved. The results of such a study will benefit the improvement of walking environments. The extent of walking involved can be considered as a means of not only managing crowdedness in a congested area but also as an effective strategy for surveilling lonesome paths.

6. Conclusions

A method for assessing the level of crowdedness in pedestrian paths was explored in this study by measuring the physiological signals of individuals through wearable sensors. The hypothesis was that vehicles and people passing by affect the EDA of pedestrians while walking on a street. To verify the foregoing, real-world videos of walking were taken, and virtual simulation videos were produced based on these videos. As subjects watched these videos, their EDAs were measured by wearable devices. Then, the EDAs were processed to extract four important signal features, SCR, ISCR, PhasicMax, and tonic data. The Wilcoxon signed-rank test was performed to confirm whether significant EDA changes occurred according to the extent of crowdedness. Results were significant when factors such as noise, illuminance, screen movement, and other real-world factors were controlled in the virtual reality videos. This study demonstrated that EDA can be one of the essential features in discriminating the level of crowdedness; however, relying solely on EDA to accurately measure crowdedness presented challenges. The main contribution of this study is identifying the potential and limitations of using EDA to understand human responses to crowdedness in pedestrian paths. In future research, the authors intend to integrate EDA and acceleration signals to enhance the feasibility of sensor-based assessment of crowdedness by capturing both physiological and behavioral responses of pedestrians. The research results are anticipated to aid in assessing the extent of walking involved in various narrow areas that may be CCTV blind spots. Such assessment can support constructing a more walking-friendly pedestrian path with effective width throughout a city.

Data availability statement

Data will be made available on request.

Ethics declarations

This study was reviewed and approved by the Ewha Womans University Institutional Reviewer Board, with the approval number: ewha-202206-0026-01. All participants provided informed consent to participate in the study.

CRediT authorship contribution statement

Heejung Lee: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis. **Sungjoo Hwang:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Data curation, Conceptualization. **Seungjun Ahn:** Writing – review & editing, Validation, Formal analysis.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Sungjoo Hwang reports financial support was provided by Korea Forest Service. Sungjoo Hwang reports financial support was provided by Korea Agency for Infrastructure Technology Advancement. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This study was carried out with the support of 'R&D Program for Forest Science Technology (Project No. 2021355B10-2123-AC03)' provided by Korea Forest Service (Korea Forestry Promotion Institute). This work is also supported by the Korea Agency for Infrastructure Technology Advancement(KAIA) grant funded by the Ministry of Land, Infrastructure and Transport (Grant KAIA001434041G0003186).

References

[1] J. Wu, S. Lu, Feature analysis and operation evaluation of pedestrian weaving zone, Transport. Res. Rec. 2393 (1) (2013) 66–74, https://doi.org/10.3141/2393-08.
[2] H.C. Manual, Chapter 23, Off-Street Pedestrian and Bicycle Facilities, Transportation Research Board, Washington, DC, 2010. https://onlinepubs.trb.org/onlinepubs/trnews/trnews273hcm2010.pdf.
[3] E.-J. Kim, H.-C. Park, S.-W. Ham, S.-Y. Kho, D.-K. Kim, Extracting vehicle trajectories using unmanned aerial vehicles in congested traffic conditions, J. Adv. Transport. 2019 (2019), https://doi.org/10.1155/2019/9060797.
[4] A. Georgiou, A. Skoufas, S. Basbas, Perceived Pedestrian Level of Service in an urban central network: the case of a medium size Greek city, Case Studies on Transport Policy 9 (2) (2021) 889–905, https://doi.org/10.1016/j.cstp.2021.04.009.
[5] J.A. Vallejo-Borda, V. Cantillo, A. Rodriguez-Valencia, A perception-based cognitive map of the pedestrian perceived quality of service on urban sidewalks, Transport. Res. F Traffic Psychol. Behav. 73 (2020) 107–118, https://doi.org/10.1016/j.trf.2020.06.013.
[6] D.C. Duives, W. Daamen, S.P. Hoogendoorn, Quantification of the level of crowdedness for pedestrian movements, Phys. Stat. Mech. Appl. 427 (2015) 162–180, https://doi.org/10.1016/j.physa.2014.11.054.
[7] S. Kim, Improvements of Travel Survey and Statistical Indicators for Walk Trips; the Seoul Institute: Seoul. Korea, 2015, pp. 1–89. http://global.si.re.kr/sites/default/files/report_data/. %5BTransportation%20Planning%5D%203.%20Improvement%20of%20Travel%20Survey%20and%20Statistical%20Indicators%20for%20Walk%20Trips.pdf.
[8] J. Sharp, E. Murakami, Travel surveys: methodological and technology-related considerations, J. Transport. Stat. 8 (3) (2005) 97–113. https://www.bts.gov/archive/publications/journal_of_transportation_and_statistics/volume_08_number_03/paper_07/index.
[9] A. Richardson, R. Seethaler, Estimating long-distance travel behavior from the most recent trip, TRB Transportation Research Circular E-C026—Personal Travel: The Long and Short of It (2001). https://trid.trb.org/view/686699.
[10] M.P. Fisher II, Exploring Targeted Long-Distance Travel Survey Sampling Frame Approaches to Support Travel Survey Collection, Auburn University, 2022. https://www.proquest.com/openview/5be1d3ff5b0bc80bdf813a956a7134fb/1?pq-origsite=gscholar&cbl=18750&diss=y.

[11] A. Engelniederhammer, G. Papastefanou, L. Xiang, Crowding density in urban environment and its effects on emotional responding of pedestrians: using wearable device technology with sensors capturing proximity and psychophysiological emotion responses while walking in the street, J. Hum. Behav. Soc. Environ. 29 (5) (2019) 630–646, https://doi.org/10.1080/10911359.2019.1579149.
[12] M.-Z. Poh, N.C. Swenson, R.W. Picard, A wearable sensor for unobtrusive, long-term assessment of electrodermal activity, IEEE Trans. Biomed. Eng. 57 (5) (2010) 1243–1252, https://doi.org/10.1109/TBME.2009.2038487.
[13] D. Nag, A.K. Goswami, A. Gupta, J. Sen, Assessing urban sidewalk networks based on three constructs: a synthesis of pedestrian level of service literature, Transport Rev. 40 (2) (2020) 204–240, https://doi.org/10.1080/01441647.2019.1703841.
[14] M.R. Bloomberg, A.M. Burden, New York city pedestrian level of service study phase I. https://www.nyc.gov/assets/planning/download/pdf/plans/transportation/td_fullpedlosb.pdf, 2006.
[15] E. Finch, G. Iverson, J. Dye, Pedestrian comfort guidance for London, in: European Transport Conference, 2010Association for European Transport (AET), 2010. https://content.tfl.gov.uk/pedestrian-comfort-guidance-technical-guide.pdf.
[16] B.W. Landis, V.R. Vattikuti, R.M. Ottenberg, D.S. McLeod, M. Guttenplan, Modeling the roadside walking environment: pedestrian level of service, Transport. Res. Rec. 1773 (1) (2001) 82–88, https://doi.org/10.3141/1773-10.
[17] F. Jaskiewicz, Pedestrian level of service based on trip quality, Transportation Research Circular, TRB (2000). https://trid.trb.org/view.aspx?id=686656.
[18] K.R. Rahaman, N. Ohmori, N. Harata, Evaluation of the roadside walkway environment of Dhaka city, in: Proceedings of the Eastern Asia Society for Transportation Studies, 2005. https://www.academia.edu/download/29936082/1751.pdf.
[19] J. Florez, J. Muniz, L. Portugal, Pedestrian quality of service: lessons from maracanã stadium, Procedia-Social and Behavioral Sciences 160 (2014) 130–139, https://doi.org/10.1016/j.sbspro.2014.12.124.
[20] N. Hidayat, K. Choocharukul, K. Kishi, Pedestrian level of service model incorporating pedestrian perception for sidewalk with vendor activities, in: Proceedings of the Eastern Asia Society for Transportation Studies, vol. 8, Eastern Asia Society for Transportation Studies, 2011, https://doi.org/10.11175/eastpro.2011.0.197.0. The 9th International Conference of Eastern Asia Society for Transportation Studies, 2011.
[21] P. Christopoulou, M. Pitsiava-Latinopoulou, Development of a model for the estimation of pedestrian level of service in Greek urban areas, Procedia-Social and Behavioral Sciences 48 (2012) 1691–1701, https://doi.org/10.1016/j.sbspro.2012.06.1144.
[22] B.D. Daniel, S.N.M. Nor, M.M. Rohani, J. Prasetijo, M.Y. Aman, K. Ambak, Pedestrian footpath level of service (FOOT-LOS) model for Johor Bahru, in: MATEC Web of Conferences, EDP Sciences, 2016, https://doi.org/10.1051/matecconf/20164703006.
[23] F. Fonseca, G. Papageorgiou, S. Tondelli, P. Ribeiro, E. Conticelli, M. Jabbari, R. Ramos, Perceived walkability and respective urban determinants: insights from Bologna and Porto, Sustainability 14 (15) (2022) 9089, https://doi.org/10.3390/su14159089.
[24] W. Gao, Y. Qian, H. Chen, Z. Zhong, M. Zhou, F. Aminpour, Assessment of sidewalk walkability: integrating objective and subjective measures of identical context-based sidewalk features, Sustain. Cities Soc. 87 (2022) 104142, https://doi.org/10.1016/j.scs.2022.104142.
[25] S. Lee, M. Han, K. Rhee, B. Bae, Identification of factors affecting pedestrian satisfaction toward land use and street type, Sustainability 13 (19) (2021) 10725, https://doi.org/10.3390/su131910725.
[26] L. Eboli, C. Forciniti, G. Mazzulla, M.G. Bellizzi, Establishing performance criteria for evaluating pedestrian environments, Sustainability 15 (4) (2023) 3523, https://doi.org/10.3390/su15043523.
[27] C. Forciniti, L. Eboli, What makes a pedestrian path pleasant? Analysis of young pedestrians' perceptions, Urban Science 7 (2) (2023) 44.
[28] T. Ahmed, M. Moeinaddini, M. Almoshaogeh, A. Jamal, I. Nawaz, F. Alharbi, A new pedestrian crossing level of service (PCLOS) method for promoting safe pedestrian crossing in urban areas, Int. J. Environ. Res. Publ. Health 18 (16) (2021) 8813, https://doi.org/10.3390/ijerph18168813.
[29] T. Campisi, G. Tesoriere, A. Skoufas, D. Zeglis, C. Andronis, S. Basbas, Perceived pedestrian level of service: the case of Thessaloniki, Greece, Transport. Res. Procedia 60 (2022) 124–131, https://doi.org/10.1016/j.trpro.2021.12.017.
[30] A. Rodriguez-Valencia, G.A. Barrero, H.A. Ortiz-Ramirez, J.A. Vallejo-Borda, Power of user perception on pedestrian quality of service, Transport. Res. Rec. 2674 (5) (2020) 250–258, https://doi.org/10.1177/0361198120914611.
[31] H.-C. Kwak, J.Y. Song, J.K. Eom, K.T. Kim, A study on factors influencing floating population using mobile phone data in urban area, Journal of The Korean Society For Urban Railway 6 (4) (2018) 373–381, https://doi.org/10.24284/JKOSUR.2018.12.6.4.373.
[32] J. Hou, E. Zhang, Y. Long, Measuring pedestrian flows in public spaces: inferring walking for transport and recreation using Wi-Fi probes, Build. Environ. 230 (2023) 109999, https://doi.org/10.1016/j.buildenv.2023.109999.
[33] L. Chen, Y. Lu, Q. Sheng, Y. Ye, R. Wang, Y. Liu, Estimating pedestrian volume using Street View images: a large-scale validation test, Comput. Environ. Urban Syst. 81 (2020) 101481, https://doi.org/10.1016/j.compenvurbsys.2020.101481.
[34] J. Kim, D. Shin, J. Kim, C. Kwon, H. Byun, Optical flow based vehicle counting and speed estimation in CCTV videos, Journal of Broadcast Engineering 22 (4) (2017) 448–461, https://doi.org/10.5909/JBE.2017.22.4.448.
[35] E.T. Hall, The Hidden Dimension (Anchor Books a Doubleday Anchor Book) by, Anchor, 1966. https://www.academia.edu/43785083/The_Hidden_Dimension_Edward_Hall.
[36] R.D. Middlemist, E.S. Knowles, C.F. Matter, Personal space invasions in the lavatory: suggestive evidence for arousal, J. Pers. Soc. Psychol. 33 (5) (1976) 541, https://doi.org/10.1037/0022-3514.33.5.541.
[37] J. Troko, P. Myles, J. Gibson, A. Hashim, J. Enstone, S. Kingdon, C. Packham, S. Amin, A. Hayward, J.N. Van-Tam, Is public transport a risk factor for acute respiratory infection? BMC Infect. Dis. 11 (1) (2011) 1–6, https://doi.org/10.1186/1471-2334-11-16.
[38] R.C. Newman, D. Pollack, Proxemics in deviant adolescents, J. Consult. Clin. Psychol. 40 (1) (1973) 6, https://doi.org/10.1037/h0033961.
[39] L.A. Hayduk, The shape of personal space: an experimental investigation, Canadian Journal of Behavioural Science/Revue canadienne des sciences du comportement 13 (1) (1981) 87, https://doi.org/10.1037/h0081114.
[40] L.A. Hayduk, S. Mainprize, Personal space of the blind, Soc. Psychol. Q. (1980) 216–223, https://doi.org/10.2307/3033624.
[41] M. Costa, Interpersonal distances in group walking, J. Nonverbal Behav. 34 (2010) 15–26, https://doi.org/10.1007/s10919-009-0077-y.
[42] R.J. Smith, E.S. Knowles, Attributional consequences of personal space invasions, Pers. Soc. Psychol. Bull. 4 (3) (1978) 429–433, https://doi.org/10.1177/014616727800400314.
[43] V.J. Konečni, L. Libuser, H. Morton, E.B. Ebbesen, Effects of a violation of personal space on escape and helping responses, J. Exp. Soc. Psychol. 11 (3) (1975) 288–299, https://doi.org/10.1016/s0022-1031(75)80029-1.
[44] N. Kaya, F. Erkip, Invasion of personal space under the condition of short-term crowding: a case study on an automatic teller machine, J. Environ. Psychol. 19 (2) (1999) 183–189, https://doi.org/10.1006/jevp.1999.0125.
[45] M. Kelsey, M. Akcakaya, I.R. Kleckner, R.V. Palumbo, L.F. Barrett, K.S. Quigley, M.S. Goodwin, Applications of sparse recovery and dictionary learning to enhance analysis of ambulatory electrodermal activity data, Biomed. Signal Process Control 40 (2018) 58–70, https://doi.org/10.1016/j.bspc.2017.08.024.
[46] W. Boucsein, Electrodermal Activity, Springer Science & Business Media, 2012, https://doi.org/10.1007/978-1-4614-1126-0.
[47] P.J. Lang, M.M. Bradley, Emotion and the motivational brain, Biol. Psychol. 84 (3) (2010) 437–450, https://doi.org/10.1016/j.biopsycho.2009.10.007.
[48] J.T. Cacioppo, L.G. Tassinary, G. Berntson, Handbook of Psychophysiology, Cambridge university press, 2007, https://doi.org/10.13140/2.1.2871.1369. https://www.academia.edu/34699451/Handbook_of_Psychophysiology.
[49] A. Sano, R.W. Picard, Stress recognition using wearable sensors and mobile phones, in: 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction, IEEE, 2013, https://doi.org/10.1109/acii.2013.117.
[50] S. Doberenz, W.T. Roth, E. Wollburg, N.I. Maslowski, S. Kim, Methodological considerations in ambulatory skin conductance monitoring, Int. J. Psychophysiol. 80 (2) (2011) 87–95, https://doi.org/10.1016/j.ijpsycho.2011.02.002.
[51] M. Benedek, C. Kaernbach, A continuous measure of phasic electrodermal activity, J. Neurosci. Methods 190 (1) (2010) 80–91, https://doi.org/10.1016/j.jneumeth.2010.04.028.
[52] D.M. Alexander, C. Trengove, P. Johnston, T. Cooper, J. August, E. Gordon, Separating individual skin conductance responses in a short interstimulus-interval paradigm, J. Neurosci. Methods 146 (1) (2005) 116–123, https://doi.org/10.1016/j.jneumeth.2005.02.001.

[53] G. Lee, B. Choi, C.R. Ahn, S. Lee, Wearable biosensor and hotspot analysis–based framework to detect stress hotspots for advancing elderly's mobility, J. Manag. Eng. 36 (3) (2020) 04020010, https://doi.org/10.1061/(asce)me.1943-5479.0000753.
[54] S. LaJeunesse, P. Ryus, W. Kumfer, S. Kothuri, K. Nordback, Measuring pedestrian level of stress in urban environments: naturalistic walking pilot study, Transport. Res. Rec. 2675 (10) (2021) 109–119, https://doi.org/10.1177/03611981211010183.
[55] A.M. Rivers, J. Sherman, Experimental design and the reliability of priming effects: reconsidering the" train wreck", PsyArXiv (2018), https://doi.org/10.31234/osf.io/r7pd3.
[56] F. Faul, E. Erdfelder, A. Buchner, A.-G. Lang, Statistical power analyses using G* Power 3.1: tests for correlation and regression analyses, Behav. Res. Methods 41 (4) (2009) 1149–1160, https://doi.org/10.3758/BRM.41.4.1149.
[57] M. Benedek, C. Kaernbach, Decomposition of skin conductance data by means of nonnegative deconvolution, Psychophysiology 47 (4) (2010) 647–658, https://doi.org/10.1111/j.1469-8986.2009.00972.x.
[58] H.F. Posada-Quintero, K.H. Chon, Innovations in electrodermal activity data collection and signal processing: a systematic review, Sensors 20 (2) (2020) 479, https://doi.org/10.3390/s20020479.
[59] D. Caruelle, A. Gustafsson, P. Shams, L. Lervik-Olsen, The use of electrodermal activity (EDA) measurement to understand consumer emotions–A literature review and a call for action, J. Bus. Res. 104 (2019) 146–160, https://doi.org/10.1016/j.jbusres.2019.06.041.
[60] J.J. Braithwaite, D.G. Watson, R. Jones, M. Rowe, A guide for analysing electrodermal activity (EDA) & skin conductance responses (SCRs) for psychological experiments, Psychophysiology 49 (1) (2013) 1017–1034. https://www.birmingham.ac.uk/documents/college-les/psych/saal/guide-electrodermal-activity.pdf.
[61] I. Vine, Crowding and stress: 2. a personal space approach, Curr. Psychol. Rev. 2 (1) (1982) 1–18, https://doi.org/10.1007/BF02684452.
[62] A. Wabnegger, V. Leutgeb, A. Schienle, Differential amygdala activation during simulated personal space intrusion by men and women, Neuroscience 330 (2016) 12–16, https://doi.org/10.1016/j.neuroscience.2016.05.023.