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Sensor-based detection of individual walkability perception to promote healthy communities

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ABSTRACT

People living in walkable areas are more likely to maintain a physically active lifestyle. Adverse elements of the built environment (e.g. demolished houses, damaged sidewalks) can cause physical or emotional distress, and negatively affect walkability patterns. Individuals are likely to perceive walkability of a place in distinct ways and can be differentially impacted by the built environment. This paper quantifies walkability perception of the built environment using data from "in-the-moment" interactions between pedestrians and the built environment, captured by wearable physiological and accelerometry sensors. Prominent temporal change patterns in physiological reactivity (i.e., electrodermal activity, heart rate) and gait are captured through a physiological saliency cue (PSC), which comprises the input of a machine learning model automatically estimating pedestrians' perceived walkability. Contextual information from user's location is further used to augment the features. Results obtained on 25 participants in a field experiment indicate that the PSC measures can reliably detect individual perception of walkability, often more accurately compared to the aggregate measures from the corresponding raw signals. Inclusion of contextual information further improves the performance. Findings from this study can enhance our understanding on the association between walkability and the built environment, and lead to more effective planning and public health strategies that contribute to community health.

1. Introduction

Physical activity is an important health variable with wide ranging effects on physical and mental health(WHO (2010)). Regular physical activity can reduce the risks of developing chronic conditions, such as coronary heart disease, hypertension, diabetes, colon cancer, and breast cancer in women, as well as decrease premature mortality risk(Bouchard et al. (2012)). Individuals reporting regular exercise are less likely to meet mental health diagnosis criteria for depression and a range of anxiety disorders(Saxena et al. (2005)). Physical activity further comprises an effective strategy to promote health in the elderly, and preserve, or even improve, their cognitive performance(Vogel et al. (2009)). In addition, physical activity in adolescence comprises an important contributing factor of physically active adults(Hallac et al. (2019)).

Walkability has been identified both as a means and an indicator of promoting public health due to its potential to complement individual strategies in addressing key health concerns(Sallis et al. (2012)). Walking is the most common form of physical activity and a highly effective way to help people improve their health. Research demonstrates that the way a community is designed, built, and maintained, directly affects walkability(Berke et al. (2007); Burdette & Hill (2008)). Walkable communities can promote physical activity and social interactions, improve

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residents' feelings of safety, and contribute to reducing air pollution, through pedestrian-friendly community layout, rich and diverse natural features and open spaces, and mixed land uses that provide diverse everyday destinations(King et al. (2011); Kwon et al. (2017)). Thus, walkable communities comprise a better place to live(Sallis et al. (2015)) and hold the key to sustainable cities(Zhu et al. (2014)).

One's decision to walk can be made easier by improving elements of the built environment. Behavioral and urban scientists have identified transportation and recreation as the two primary motivations for walking(Zuniga-Teran et al. (2017b)). While walking for transportation has been mostly associated to the neighborhood design, recreational walking has been linked with a variety of factors. Among others, these include the street connectivity (i.e., the extent to which the community layout provides short routes to reach different destinations), diversity of land usage (e.g., commercial, residential), traffic safety (e.g., sidewalks, traffic lights, hazardous objects, barking dogs), and aesthetic, thermal, and physical experience (e.g., trees, shade, graffiti, trash, broken houses, streetscaping)(Karb (2010); Gebreab et al. (2017)). Adverse elements of the built environment, also called physical disorders, can cause residents' discomfort and emotional distress, therefore preventing them from walking in the community(Sales et al. (2013)). Physical disorders can introduce physical and cognitive demands in the built environment, being the source of physical and emotional distress. Physical distress can be manifested as gait difficulty, fatigue, or balance problem(Jun & Hur (2015); Mayne (2020)). Emotional distress refers to the negative affect occurring when a pedestrian perceives a situation in the built environment as threatening or harmful(Mayne et al. (2018); Mayne (2020); Zuniga-Teran et al. (2017a)). Capturing pedestrians' physical and emotional distress can provide a way to track walkability in a cost-effective manner with high spatio-temporal resolution, contributing to monitoring adverse and decaying elements of the built environment and providing residents with personalized route planning suggestions.

Walkability is typically measured through questionnaires and focus group discussions(Lockett et al. (2005); Gallagher et al. (2010)), as part of which researchers or community stakeholders administer surveys and conduct discussions to identify walkable areas in the community(Rosenberg et al. (2013)). For example, the Walk Score(WalkScore.com (2014)) is a scale that captures important aspects of neighborhood walkability(Brown et al. (2013); Hirsch et al. (2014)), such as density of retail destinations, recreational open spaces, street intersections, and residential land uses. Questionnaires and focus group discussions can reveal elements of the built environment that are generally challenging to the public. Yet, they also depict several limitations, since the collection of self reports and coordination of focus group discussions is a lengthy process that requires significant human resources. Moreover, people are often reluctant to answer long surveys, which can result in unreliable or missing data(Short et al. (2009)). Finally, individuals may perceive an identical stimuli from the built environment in different ways, thus creating large inter-individual variability, which adds to the complexity of the nature of human-built environment interactions(Geller (1980)). Surveys and focus groups fail to record "in-the-moment" reactions which may vary from person to person(Khusainov et al. (2013)). These limitations call for a sensor-based approach that allows to capture residents' momentary motion-based and physiological reactions to elements of the built environment providing estimates of physical and emotional distress in a personalized manner(Talen & Koschinsky (2013)).

Previous work has leveraged advances in mobile computing and wearable technologies to estimate the walkability of the built environment(Kim et al. (2016); Deakin & Al Waer (2011); Zanwar et al. (2021); Lee et al. (2020c); Zanwar et al. (2020)). Many efforts rely on computer vision techniques to detect negative visual stimuli that hinder walkability(Ahn et al. (2020); Ham et al. (2016)). Most of the time, such computer vision methods focus on a "one-size-fits-all" approach that fails to capture individual perception of walkability, which can differ across pedestrians(King et al. (2016)). Other researchers have used radar and GPS signals to quantify pedestrians' general motion patterns and detect physical disorders(Kanhere (2013)). Grounded on the evidence that physical and emotional distress can affect one's perception of walkability(Jun & Hur (2015); Mayne (2020); Marquet & Miralles-Guasch (2015); Zuniga-Teran et al. (2017a)), a new line of research has utilized wearable devices to capture physical and emotional distress toward elements of the built environment through tracking pedestrians' physiology (e.g., Electrodermal Activity (EDA), Heart Rate (HR)) and accelerometry(Lee et al. (2020b); Yadav et al. (2018); Yates et al. (2017); Kim et al. (2020c,a)). EDA is an indicator of emotional distress(McCorry (2007); Boucsein (2012)), as it captures the increased sweat activity from the activation of sweat glands of the sympathetic part (i.e., "flight-or-fight") of the autonomic nervous system (ANS)(Gordan et al. (2015)). HR is a measure of heart activity, which tends to rise at the onset of emotional distress(Kudielka et al. (2004); Sarker et al. (2016)). Accelerometry signals include gait parameters that are indicative of motion and balance difficulty(Ahn et al. (2019); Yang et al. (2017); Jebelli et al. (2016)). Yadav *et al.* and Kim *et al.* utilized the EDA, HR, and gait signals to capture pedestrians' distress while walking and subsequently, identify stressful elements of a neighborhood(Yadav et al. (2018); Kim et al. (2020b, 2019b)). In these studies, a physiological saliency cue (PSC) was introduced to capture relative differences in physiological reactivity and gait patterns between different locations of the neighborhood. While this work has explored the use of physiological measures to capture elements of the built environment that are generally adverse to pedestrians, the automatic estimation of one's walkability perception from such measures–as in the work presented here–is not yet addressed.

Prior work on mobile computing supports that the integration of context in ambulatory measurement can contribute to the better understanding of sensor data in everyday settings(Chen & Kotz (2000)). Context refers to "*any information used to characterize the situation*" of a user or an entity(Abowd et al. (1999)). Contextual information usually comprises of user location or activity, time of day, nearby people or devices, and environment characteristics, such as season and temperature(Musumba & Nyongesa (2013)). Machine learning methodologies have the ability to perform context reasoning and deduct knowledge of a user's surroundings in order to better explain his/her current state(Perera et al. (2013)). User location, specifically, plays a significant role in context-aware computing and has demonstrated significant performance improvements when estimating human outcomes related to physical health(Pourhomayoun et al. (2015)) and emotional well-being(Wang et al. (2014); Timmons et al. (2017)). This work considers user location as the contextual information used to augment the proposed automatic walkability estimation system. Our rationale behind this is that user location encodes physical characteristics of the built environment, which can directly affect one's perceived walkability and complement physiology and accelerometry measures.

Here, we propose an automatic method to estimate pedestrians' individual perception of walkability in the built environment using physiology and accelerometry signals, captured in-the-moment by wearable physiological sensors and inertial measurement unit (IMU) devices. We leverage the PSC extracted based on the EDA, HR, and gait signals to quantify differences in physiology and accelerometry across several points of interest (POI) in a predefined route, each with various perceived levels of walkability. The PSC features comprise the input to a machine learning model that automatically estimates each participant's perceived walkability (i.e., high/low) over each POI of the built environment. We integrate contextual

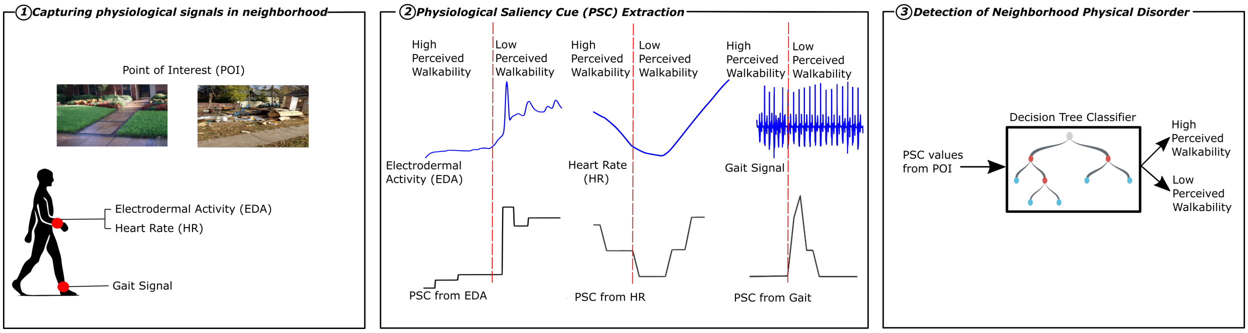


Fig. 1. Overview of proposed method. (1) Physiological signals captured using wearable devices, while participants are walking along the Point of Interests (POI) of the neighborhood. (2) Physiological saliency cue (PSC) extracted from various signals reflects perceived walkability in the POI. (3) PSC values obtained from each POI, used to classify between low and high perceived walkability.

information through an additional input index to the machine learning model that includes the POI's location. We further compare the performance of the proposed PSC measures against aggregate measures that rely on the mean of EDA, HR, and gait signals. Figure 1 presents an overview of the proposed approach, which is evaluated through data obtained from 25 participants in a field experiment. Our results indicate that the PSC features can reliably detect individual perception of walkability, often more accurately compared to the aggregate measures from the raw signals. Inclusion of contextual information further improves the predictive performance. This work lays the foundation of utilizing physiology and accelerometry signals from wearable devices combined with signal processing and machine learning methods to automatically identify perceived walkability of the built environment, which can contribute to the design of applications for personalized route suggestion, and ultimately promote physical activity and contribute to healthy communities and sustainable cities.

2. Related Work

The last decade has experienced a significant increase in research focusing on the effect of the built environment on physical, emotional, and mental health. This is largely attributed to the growing interest in smart cities(Deakin & Al Waer (2011); McLaren & Agyeman (2015)) and digital twin city models(Mohammadi & Taylor (2017); Ahn et al. (2020)). Smart cities incorporate the use of information and communication technology within all their functional activities–from designing sustainable cities to promoting the health and well-being of its citizens. Digital twin city models facilitate this process by leveraging the knowledge obtained from big data and Internet-of-Things (IoT) to create a dynamic digital representation of the built environment and its interaction with humans(Cooper (2018)). Therefore, it is evident that a better understanding of the interplay between humans and the built environment contributes to the planning and design of walkable environments, which in turn can benefit physical and emotional health. An important part of this process includes estimating individuals' perceived walkability in the built environment, which directly affects one's choice and motivation to walk and therefore engage in physical activity(Zuniga-Teran et al. (2017b); Kwon et al. (2017)).

Early research on walkability has employed qualitative measures, such as questionnaires, interviews, and focus group discussions, to understand residents' perception of the built environment(Rosenberg et al. (2013); Lockett et al. (2005); Gallagher et al. (2010)). Rosenberg *et al.* conducted interviews with residents of King County, Washington to identify physical disorders within the community and their impact on walkability(Rosenberg et al. (2013)). Participants wore a GPS sensor for three days prior to their interview. The recorded GPS locations were discussed during the interview, then coded by the researchers. Lockett et al. (2005) used crowdsourced photographs from Ottawa, Canada as touchstones for discussion with the city's residents. Through several rounds of discussions, distress eliciting elements impacting the walkability of the corresponding neighborhood were identified. A similar approach by Gallagher et al. (2010) leveraged focus groups discussions and photos of the community to identify barriers to walkability in Detroit, Michigan. Despite the valuable insights, qualitative measures are confounded by recall bias Wright et al. (2012), since participants need to remember and retrospect upon their experience with the built environment.

Sensor-based measures captured in real-time (i.e., while participants are interacting with the built environment) can provide complementary information to self-reports Bell et al. (2018), therefore improving our understanding on factors of walkability. Prior work has leveraged multiple modalities, including images, location, accelerometry, and physiology, to quantify walkability patterns. Ham et al. (2016) discussed the use of camera-equipped unmanned aerial vehicles for monitoring civil infrastructure systems. Kanhere (2013) explored participatory sensing by crowdsourcing data from smartphone devices in order to estimate road conditions (e.g., potholes, bumps) through accelerometry and positioning system data. In an effort to quantify pedestrians' momentary responses to elements of the built environment, King et al. (2016) used accelerometry from smartphone devices to measure and visualize residents' physical activity in neighborhoods of California, upstate New York, Arizona, Mexico, Israel, Colombia, and Chile. Beyond accelerometry, a recent line of work has quantified residents' interaction with and emotional distress toward elements of the built environment through physiological signals. Grounded on knowledge from neurophysiology that evidences the association of physiological reactivity and emotional distress(Hoehn-Saric & McLeod (1988); Dawson et al. (2017)), Chrisinger & King (2018) explored the use of EDA for identifying positively and negatively perceived POIs in the urban environment (i.e., low traffic versus high traffic, open space versus deteriorated buildings). Tilley et al. (2017) and Neale et al. (2017) assessed pedestrians' neural response in different scenarios of urban settings (i.e., urban green space, busy urban environment) using electroencephalography (EEG) signals. Lee et al. (2020b) measured the collective stress

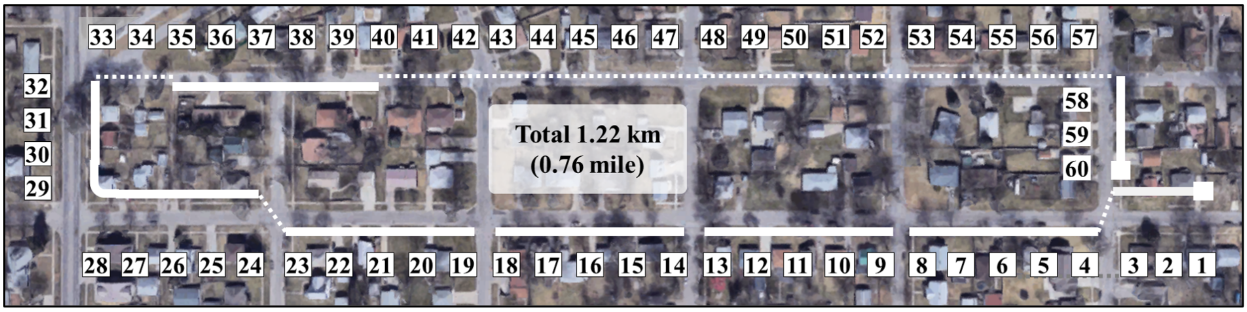


Fig. 2. Predefined walkway used for data collection purposes.

perceived by elderly adults in the built environment and pinpointed locations of environmental barriers through EDA measurements and geocoding. This work further addressed the issue of automatically detecting pedestrian distress elicited by physical disorders in the built environment through machine learning methodologies (e.g., bagging tree). The physiological measures employed in these studies include well-examined time- and frequency-based indices, such as the average level of the EDA signal Chrisinger & King (2018) and energy content of the EEG Tilley et al. (2017); Neale et al. (2017).

While aggregate measures of physiology and accelerometry provide a reliable estimate of one's overall physical and emotional distress, they do not always allow to capture the fine-grain temporal fluctuation in the corresponding signals, which is inherently associated with momentary responses to stimuli of the built environment. Saliency detection approaches have been introduced in computer vision and have the ability to focus on objects of the image that "stand out" by capturing contrast within a visual neighborhood(Fu et al. (2013); Cong et al. (2018)). Motivated by the intuitiveness and effectiveness of saliency detection in computer vision, this method can be extended in capturing prominent responses in physiological signals by identifying distinctive areas of the input. Yadav et al. (2018) and Kim et al. (2019b) proposed a physiological saliency measure to capture the general perception of physical disorders in the built environment across participants. PSC quantifies the difference or prominence of a target segment in a physiological signal compared to others. PSC measures were computed using EDA and gait signals, and were found indicative of the physical disorders in the built environment through statistical analysis. This paper leverages the PSC measure in combination with machine learning models to automatically estimate pedestrians' perceived walkability in the built environment.

With the emergence of mobile sensor networks in the last decade, context awareness has been an integral part of ubiquitous computing systems allowing to fully leverage information captured by wearable devices(Perera et al. (2013)). Contextual factors refer to situational information about an event or an entity (e.g. time of the day, location, weather)(Abowd et al. (1999); Musumba & Nyongesa (2013)). Prior work has incorporated contextual factors with physiological and accelerometry signals to augment the estimation performance of human outcomes. Gjoreski et al. (2017) proposed a stress detection method using the EDA, HR and accelerometry data obtained from a wrist-worn sensor. The combination of contextual features (e.g. time of the day, day of the week, prior high intensity physical activity) with physiological data exhibited significant boost in the performance of the stress detection task. Bavaresco et al. (2020) prototyped a context-aware system for psychotherapy assistance in the wild using physiological and accelerometry signals, where location and time were used as contextual features. Inspired by this prior work, the current paper uses the location of participants as a contextual feature to augment the feature space resulting from the physiological and accelerometry signals.

The contributions of this work compared to previous approaches(Lee et al. (2020a); Kim et al. (2020b)) are as follows: (1) We examine the PSC measure computed from EDA, HR, and gait signals as an input to machine learning models and present a detailed analysis of its predictive performance for estimating perceived walkability in the built environment; (2) We enrich the physiological feature space with contextual information for improving the accuracy of distress estimation; and (3) We consider individual differences in terms of walkability perception (i.e., through individual-specific ratings) and pedestrian experience (i.e., by learning physiological reactivity patterns of a given individual).

3. Data Description

The data analyzed in this paper come from 30 participants (i.e., 15 men, 15 women) walking in the Havelock neighborhood in Lincoln, Nebraska. Data collection was performed in a field experiment(Kim et al. (2020b)) conducted during November 11, 2017 to November 18, 2017 between 10 am and 4 pm, with an average temperature of 64.2° Fahrenheit (17.92° Celsius). Participants were instructed to walk along a predefined path of the neighborhood. This path contained several physical disorders that might elicit distress and physical discomfort, such as broken housing, absence of sidewalk, dead tree branches, and barking dogs, thus impacting perceived walkability (Figure 2).

Participants' physiological responses were recorded from the wrist-mounted Empatica E4 sensor(Empatica), while gait patterns were captured by the right ankle-mounted APDM Opal IMU sensor(Inc.). Participants also carried a smartphone that registered their GPS location using the Geo Tracker app(Tracker). The Empatica E4 device collected EDA sampled at 4 Hz through two dry electrodes and HR data sampled at 1 Hz through a photoplethysmogram (PPG) sensor. The Opal sensor acquired IMU data at a sampling rate of 125 Hz. All data streams were synchronized using the GPS coordinates and timestamps from the sensors along the corresponding time and location.

The predefined path that participants were asked to walk for this experiment was 1.24 km (0.77 miles) in length and included 60 points of interest (POI), which contained various physical disorders (Figure 2). POIs were identified by the research team conducting the experiment and may include built environment elements of common interest(Kim et al. (2020b)), such as uneven sidewalk, no sidewalk, dead branches and leaves overhanging a sidewalk, demolished house, barking dogs, tree limb, and a container for gas storage. Participants were instructed to walk

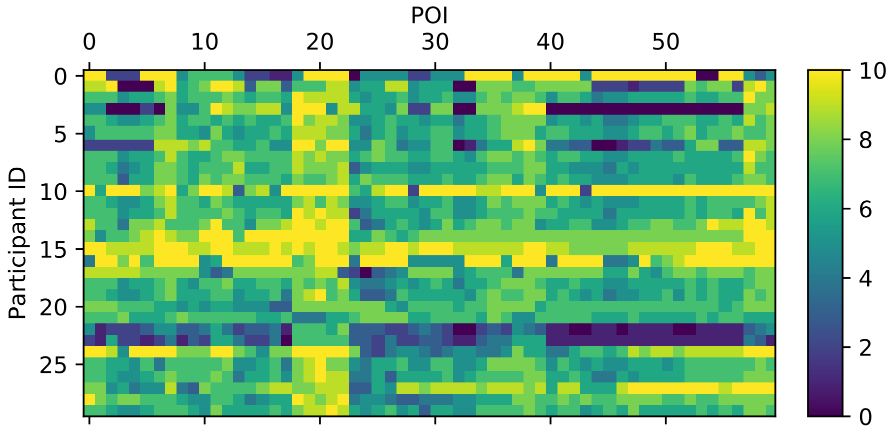


Fig. 3. Distribution of walkability ratings provided by participants for each point of interest (POI).

along this path twice. Their physiological and gait signals were recorded in the first round. During the second round, a research team member accompanied the participants along the same path and solicited their ratings on the walkability of each POI on a scale of 0 to 10, where 10 indicates the least walkable(Kim et al. (2019a); Yadav et al. (2018)). The scale of rating is explained with the help of the National Highway Traffic Safety Administration's walkability checklist(NHTSA.gov). These ratings serve as the ground truth of perceived walkability from each participant (Section 4). Figure 3 presents the distribution of these ratings. Most participants rated POIs 18-25 the least walkable, while POIs 5-6 the most walkable. However, inter-individual differences appear in the way participants rate other POIs (e.g., POI 45-50, which is an area with no sidewalk), indicating that subject-specific factors might influence these walkability ratings(Chrisinger & King (2018)).

4. Methodology

In this section, we present the different steps of the proposed sensor-based method for estimating perceived walkability for each pedestrian. The pre-processing of the data is described in Section 4.1. Section 4.2 provides the description of the physiological saliency detection measures from the sensor-based data, while Section 4.3 presents the calculation of the aggregate measures used as a baseline. The description of contextual features is provided in Section 4.4. Finally, the detailed explanation of the machine learning model for estimating perceived walkability is presented in Section 4.5.

4.1. Data Pre-processing

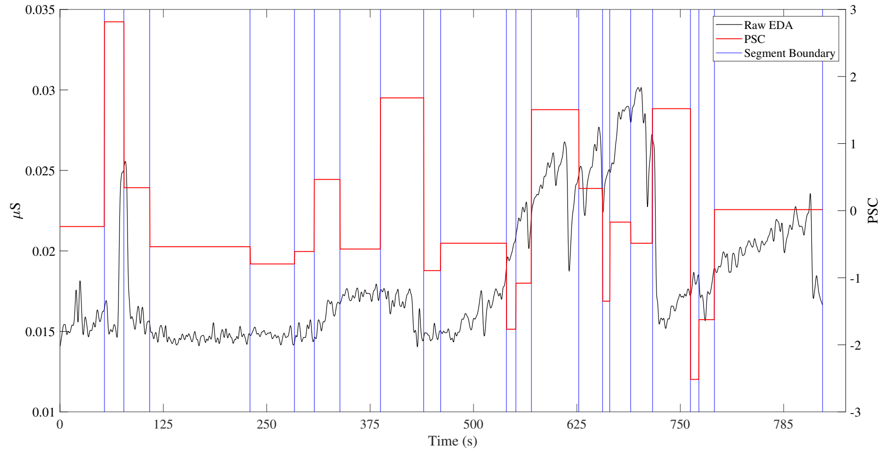
Sensors administered in this experiment are often prone to noise, temperature effects, and motion artifacts. Therefore, physiological data collected using these sensors require thorough inspection and pre-processing. Visual inspection of the EDA signals indicated that data from five participants depicted no fluctuation, which is typically due to loss of contact between the skin and the sensor. For this reason, signals from these five participants were excluded from the analysis, resulting in data from a total of 25 participants. To further remove the high frequency noise from the EDA signal, a Bateman low-pass filter was used(Dawson et al. (2017)). The window length of the filter is set to 24 samples (i.e., 6 seconds). IMU data was pre-processed through a Butterworth low-pass filter of 4 Hz cut-off frequency(Wang et al. (2011)).

4.2. Physiological saliency cue (PSC)

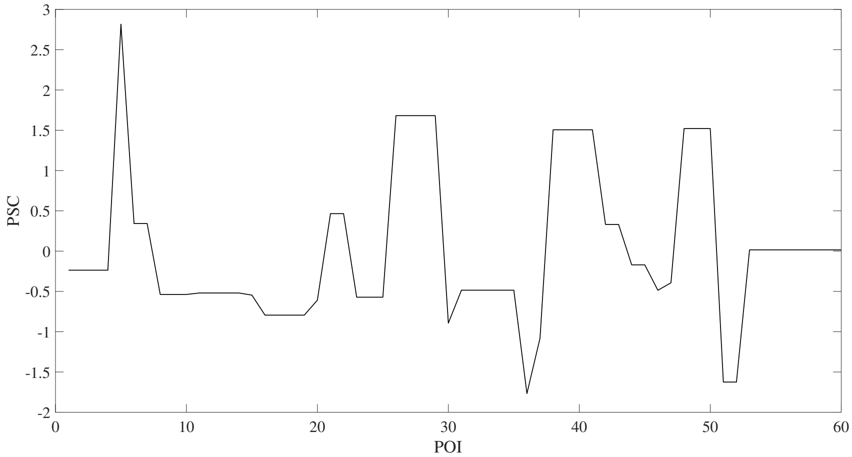
In this subsection, we will describe the method that was used to calculate the PSC measures, which comprised of the signal segmentation step, the feature extraction from the EDA, HR, and gait signals, and the measurement of the distinctiveness of a target signal segment compared to the others.

4.2.1. Signal segmentation

We follow a data-driven segmentation process to determine segments in the collected signals. Instead of identifying intervals through pre-defined temporal criteria (e.g., analysis window of predefined length), data-driven segmentation can contribute to extracting physiology and accelerometry features over meaningful segments of the signals without artificially constraining their boundaries. We employ a bottom-up segmentation method, which is commonly used in time series analysis(Truong et al. (2019)) and numerous fields, such as climate forecasting(Reeves et al. (2007)), computer networks(Tartakovsky et al. (2006)), financial pattern analysis(Keogh et al. (2001)), and physiological time-series clustering(Kim et al. (2019b)). According to this, the number and position of change points within a time series are randomly initialized and subsequently, estimated in an iterative way. The internal similarity of each segment compared to the other segments is used as a criterion to refine the signal segmentation(Kim et al. (2020b)). Figure 4(a) presents the outcome of the bottom-up segmentation process (blue vertical lines) for a sample EDA signal (black line).



(a) Bottom-up segmentation of sample EDA signal with calculated PSC.



(b) Mapping of PSC measure to each POI.

Fig. 4. Example of a bottom-up segmentation process, followed by the physiological saliency cue (PSC) calculation from raw electrodermal activity (EDA) signal. PSC from signal segments are mapped to the physical points of interest (POIs) in the built environment.

4.2.2. Feature extraction

Table 1 presents the features computed from the EDA, HR, and gait signals over the segments extracted from the bottom-up segmentation (Section 4.2.1). We capture the tonic component (i.e., general levels) of the EDA signal through the skin conductance level (SCL), and the phasic (i.e., fluctuations) component via the frequency and mean amplitude of the skin conductance responses (SCR)(Dawson et al. (2017)), as commonly used in prior work(Lee et al. (2020a); Kim et al. (2020b)). Automatic detection of SCRs in the EDA signal was conducted using the Ledalab software(Benedek & Kaernbach (2010b,a)). We further calculate the mean HR for each signal segment, which is a widely used measure of distress(Mashhadi et al. (2015); Bisadi et al. (2017)). Finally, four spatio-temporal features are extracted from the gait signal, including the stride time, stride distance, average velocity, and maximum foot clearance(Yang et al. (2020); Yang & Ahn (2019); Duchowny et al. (2019); Kim et al. (2017)).

4.2.3. Measurement of physiological saliency cue (PSC)

PSC measurements were obtained in order to capture prominent temporal patterns in signal segments. PSC quantifies the "distinctiveness" of a segment compared to the other segments in the signal(Fu et al. (2013)). We adopt the approach used by Kim et al. (2020b) and Yadav et al. (2018), where the PSC of feature f_{ij} from the j^{th} signal segment of participant i is calculated as follows:

$$PSC_{ij} = \sum_{k=1}^{a} \frac{t_{ij}}{T_i} \frac{f_{ij} - f_{ik}}{\sum_{m=1}^{a} f_{im}} \tag{1}$$

where a is the number of signal segments, T_i is duration of entire signal, and t_{ij} is the duration of the j-th segment for the i^{th} participant. A signal segment with significantly different feature values compared to the other segments, exhibits higher distinctiveness, and therefore larger PSC

Table 1. List of features obtained from various sensor-based signals.

Modality	Feature
Electrodermal activity	Skin conductance level Skin conductance response amplitude Skin conductance response frequency
Heart rate	Mean heart rate
Gait	Stride time Stride distance Average velocity Maximum foot clearance

measure. We note that the PSC measure in (1) also takes directionality into account. Thus, we obtain large positive (or negative) PSC measure if a target segment depicts substantially higher (or lower) feature values compared to the other segments of the signal. Figure 4(a) presents the PSC values (red line) of a sample EDA signal. In this example, prominent changes in the EDA signal occurring around the 90^{th} second are also reflected in the PSC measure.

Perceived walkability is measured for each POI along the predefined route (Section 3), which is not necessarily aligned with the data driven signal segmentation (Section 4.2.1). A signal segment might span more than one POIs (Section 3), or vice-versa, a POI might include more than one signal segments. For this reason, we assign a PSC score to each POI as follows. If a POI contains multiple signal segments, the PSC of the larger signal segment is taken into account for this POI. If a signal segment spans multiple POIs, then the corresponding PSC values will be the same across the POIs. Figure 4(b) presents an example of the PSC features being mapped from the signal segments to the POIs. The features extracted with this approach will be referred to as "*PSC features*" in the rest of the paper.

4.3. Aggregate measures as baseline features

As a baseline to the *PSC features*, we extract aggregate statistical measures from the raw physiological signals. We calculate the mean value of each feature (Table 1) over the length of each POI, which is referred to as "*Aggregate measures*." This is a common practice in previous work that uses physiological signals to detect individual distress(Lee et al. (2020b); Chrisinger & King (2018); Koldijk et al. (2014)).

4.4. Contextual features

We further integrate contextual information that augments the sensor-based *PSC features* and the *Aggregate measures*. Similar to prior work(Bavaresco et al. (2020); Gjoreski et al. (2017)), the ID of each POI, which reflects the location of the POI for the predefined route in our experiment, is used as a contextual feature. From a practical perspective, the proposed contextual feature can be easily obtained through GPS coordinates in real-life applications. We expect that the machine learning models (Section 4.5) will learn interactions between the physical location and the sensor-based features in association to the outcome of interest (i.e., perceived walkability).

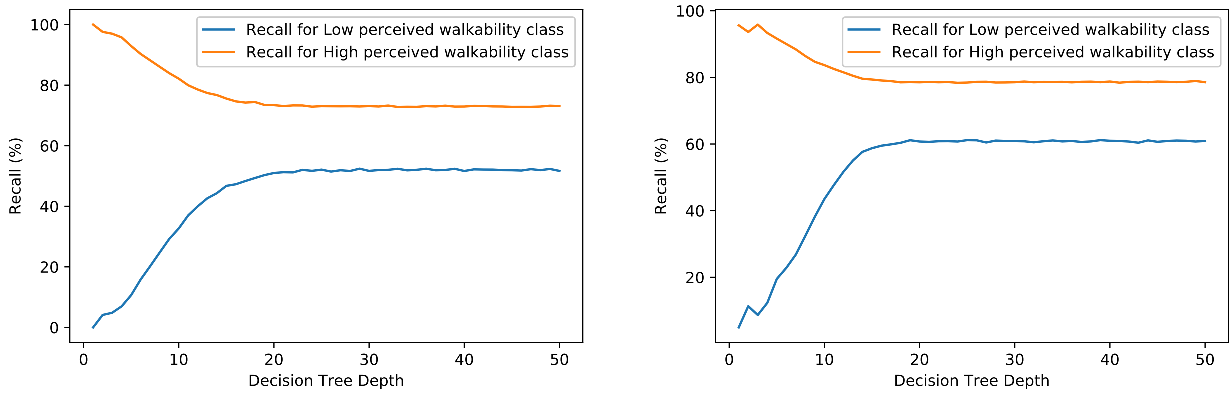
4.5. Estimation of perceived walkability

The goal of the machine learning model is to estimate participants' perceived walkability in each POI. Each participant provided a perceived walkability rating for each POI on a scale of 0 to 10 (Section 3). This resulted in 60 ratings per participant and 1500 ratings for all 25 participants. We formulate a binary classification problem and convert the provided ratings into 2 classes (i.e., high perceived walkability, low perceived walkability) in two different ways.

- *Participant-dependent walkability score*: Grounded on prior work indicating inter-individual differences in the way individuals perceive and rate a target stimulus(Koldijk et al. (2014); Metallinou & Narayanan (2013)), low and high perceived walkability is determined on the basis of the median walkability rating computed for each participant. Samples for a specific participant with higher rating than the threshold are considered to be in the low walkability class for that participant, while the remaining samples are assigned to the high walkability class. This results in 465 samples with low walkability and 1035 samples with high walkability, which will be used in the machine learning experiments.

- *Participant-independent walkability score*: To compare with the above subject-dependent setting, we further introduce a participant-independent walkability score. According to this, the median of the ratings computed over all participants for a specific POI is considered as a threshold value for binarizing the ratings. Samples for a specific POI with ratings lower than the corresponding threshold are assigned to the high walkability class, and the remaining ones contribute to the low walkability class. This method results in 517 samples with low walkability and 983 samples with high walkability.

We use a decision tree to classify between high and low walkability due to its interpretability and effectiveness in relatively small datasets(Lee et al. (2020a,b)). We experiment with the two different settings of binarizing the perceived walkability (i.e., *Participant-dependent walkability score*, *Participant-independent walkability score*). The input to the decision tree comprises of the *PSC features* or the *Aggregate measures*, both computed based on the three different modalities (Sections 4.2, 4.3), as well as their combination with the contextual information (Section 4.4). The depth of the decision tree is determined through hyperparameter tuning by examining different values between 1 and 50 via cross-validation.



(a) *Participant-dependent walkability score* (b) *Participant-independent walkability score*

Fig. 5. Performance of the decision tree model that classifies between low and high perceived walkability classes using various depth sizes.

We investigate the performance of the model through two types of cross-validation. First, a stratified 5-fold cross-validation is conducted, where the training and testing sets are split such that there is no participant overlap across folds. This is referred to as *Participant-independent cross-validation*. In this approach, samples from a given participant are either in the training or in the testing set, therefore evaluating the classification model in a subject-independent scenario. Next, a 10-fold cross-validation is performed, according to which the data samples are randomly split into folds. In this case, different samples from the same participant can be in the train and test set, therefore this is referred to as *Participant-dependent cross-validation*, contributing to the model learning subject-specific physiology and gait patterns related to walkability perception. The unweighted average recall (UAR) serves as a performance metric, as the low and high walkability classes are not fully balanced. UAR is computed as the average recall of the low and high walkability classes and is a commonly used evaluation metric for classification in the case of unbalanced class distributions, where simple accuracy might provide misleading results(Schuller et al. (2013); Polzehl et al. (2009)).

5. Results

5.1. Hyperparameter Tuning

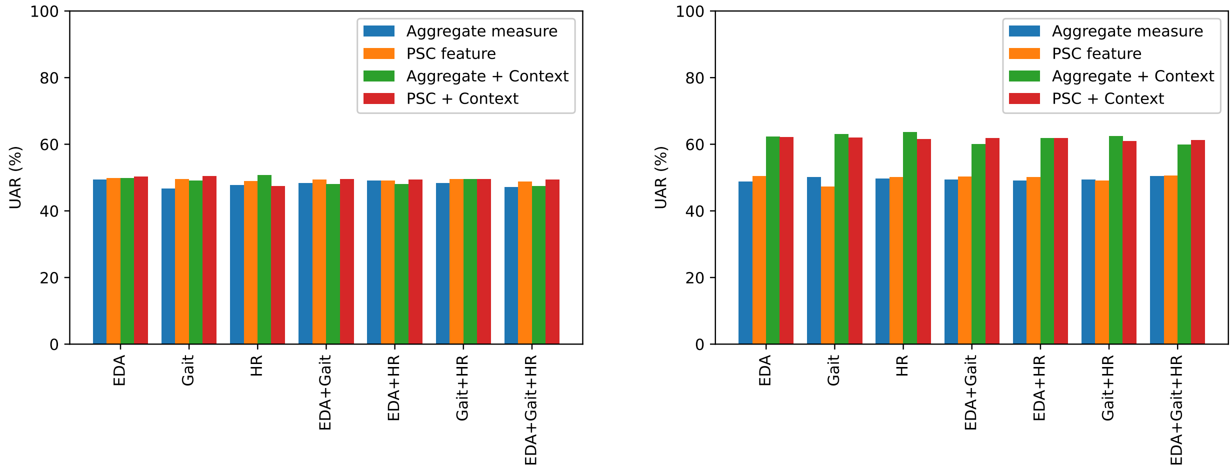
The depth of the decision tree is selected through hyperparameter tuning. Depth values between 1 to 50 are examined. Classification is performed using both types of labels (i.e., *Participant-dependent walkability score*, *Participant-independent walkability score*), as described in Section 4.5. The result of hyperparameter tuning is shown in Figure 5, where the recall of the high and low perceived walkability classes are presented. Detecting cases in which participants perceive low walkability of the built environment is important for our domain, therefore hyperparameters that yield higher recall for the low perceived walkability class will be more beneficial for the purposes of this application. We observe that with an increasing tree depth, the recall of the low perceived walkability class increases, while the recall of the high perceived walkability class slightly decreases. These evaluation metrics start to saturate with a tree depth of 20, therefore we select this as the tree depth for further analysis.

5.2. Classification between low and high perceived walkability

The results from the classification experiments between the low and high perceived walkability classes are provided using both types of labels (i.e., *Participant-dependent walkability score*, *Participant-independent walkability score*) and both cross-validation frameworks (i.e., *Participant-independent cross-validation*, *Participant-dependent cross-validation*), as described in Section 4.5. Figures 6 and 7 present the UAR results for each modality and their combinations.

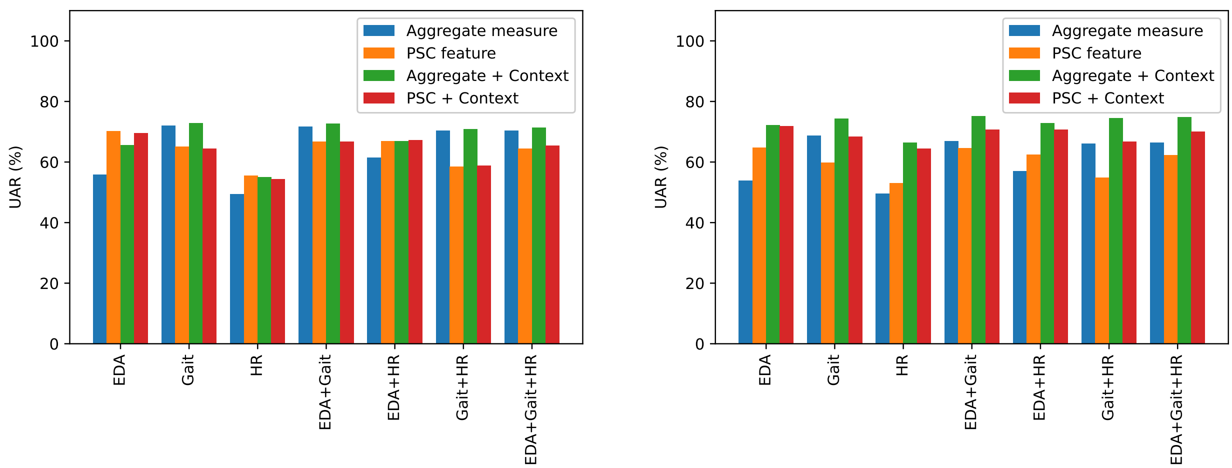
5.2.1. Participant-specific effects

We first examine the effect of participant-specific information in terms of determining the low and high perceived walkability classes. The classification experiments conducted using the *Participant-dependent walkability score* yield on average higher UAR compared to the ones conducted using the *Participant-independent walkability score*, suggesting the inter-individual differences in terms of walkability perception. This pattern is most prominent in the *Participant-independent cross-validation* framework (Figure 6), where the UAR yielding from the *Participant-independent walkability score* is close to chance level (i.e., 50%), while the corresponding UAR for the *Participant-dependent walkability score* reaches 60% (e.g., combination of *Context* and *Aggregate measures*, combination of *Context* and *PSC features*). Table 2 presents the result of a paired t-test comparing the UAR metrics obtained using the *Participant-independent walkability score* and the *Participant-dependent walkability score*. The UAR based on *Participant-dependent walkability score* is significantly higher than their independent counterpart for the majority of modalities. We also note that the *Participant-dependent cross-validation* framework (Figure 7), outperforms the *Participant-independent cross-validation* (Figure 6), which further indicates the present of subject dependencies in the physiology and gait information. It is likely that the decision tree trained using the *Participant-dependent cross-validation* is able to learn subject-specific patterns of the corresponding input data that contribute to the walkability perception.



(a) *Participant-independent walkability score* (b) *Participant-dependent walkability score*

Fig. 6. Unweighted Average Recall (UAR) for *Participant-independent cross-validation*.



(a) *Participant-independent walkability score* (b) *Participant-dependent walkability score*

Fig. 7. Unweighted Average Recall (UAR) for *Participant-dependent cross-validation*.

5.2.2. Comparison between Aggregate measures and PSC features

Next, we compare the performance between *Aggregate measures*, which are computed as the statistical mean of physiology and gait signals (Section 4.3), and *PSC features*, which represent the distinctiveness (or prominence) of features for each POI in comparison to the others (Section 4.2). *PSC features* perform slightly better than *Aggregate measures* when EDA, HR, or their combination are used as modalities. A potential reason for this might be due to the fact that *Aggregate measures* rely on statistical aggregates of the corresponding physiological data, therefore important temporal information about signal fluctuations is often lost. *PSC features* can likely capture finer-grain information from the original EDA and HR signal, which is also reflected in the results. Table 3 further shows the results of a paired t-test when comparing the UAR metrics between the *Aggregate measures* and the *PSC features* for the *Participant-dependent cross-validation*. Statistical results indicate a significant difference in UAR between the two with the *PSC features* outperforming the *Aggregate measures* in the majority of cases. The *Aggregate measures* computed solely on the gait measures perform better compared to the *PSC features* for the same measures. We suspect that the reason for this is that raw gait features are already strongly associated with the movement of participants, therefore saliency calculation based on the gait measures does not contribute much to accurately estimating the walkability perception. In contrast, EDA and HR are much more subtle in nature. Therefore, the corresponding *Aggregate measures* do not capture subtle variations in the signals, which are likely quantified by the *PSC features*.

5.2.3. Comparison of different modalities

We next investigate differences in performance between the various modalities. HR appears to perform worse compared to the EDA and gait modalities. Gait patterns individually and in combination with others perform the best exhibiting 65-68% UAR for both *Participant-independent walkability score* and *Participant-dependent walkability score*. When all three modalities are combined, we further obtain improved UAR of 70.3%

Table 2. Results of two-sided paired t-tests comparing unweighted average recall (UAR) obtained from *PSC features* with context using *Participant-independent walkability score* and *Participant-dependent walkability score* in 10 folds of *Participant-dependent cross-validation*.

Modality	UAR (*Participant-independent score*)	UAR (*Participant-dependent score*)	t-test result
EDA	69.62	71.97	$t(9) = -2.19$
Gait	64.53	68.49	$t(9) = -2.63^{**}$
HR	54.33	64.44	$t(9) = -6.84^{**}$
EDA+Gait	66.79	70.67	$t(9) = -1.17$
EDA+HR	67.32	70.71	$t(9) = -2.28^{*}$
Gait+HR	58.87	66.82	$t(9) = -3.71^{**}$
EDA+Gait+HR	65.49	70.1	$t(9) = -3.21^{*}$

*: $p < 0.05$, **: $p < 0.01$

Table 3. Results of two-sided paired t-tests comparing unweighted average recall (UAR, %) obtained from *Aggregate measures* and *PSC features* in 10 folds of *Participant-dependent cross-validation*.

Modality	*Participant-independent walkability score*			*Participant-dependent walkability score*		
	UAR (*Aggregate*)	UAR (*PSC*)	t-test result	UAR (*Aggregate*)	UAR (*PSC*)	t-test result
EDA	55.84	70.31	$t(9) = -6.85^{**}$	53.92	64.85	$t(10) = -5.87^{**}$
Gait	72.14	65.21	$t(9) = 3.58^{**}$	68.79	59.78	$t(10) = 7.71^{**}$
HR	49.45	55.54	$t(9) = -2.97^{*}$	49.64	53.07	$t(10) = -1.31$
EDA+Gait	71.71	66.75	$t(9) = 2.18$	66.88	64.63	$t(10) = 2.27^{*}$
EDA+HR	61.46	66.89	$t(9) = -2.38^{*}$	56.98	62.52	$t(10) = -2.25$
Gait+HR	70.4	58.56	$t(9) = 4.74^{**}$	66.08	54.84	$t(10) = 5.47^{**}$
EDA+Gait+HR	70.39	64.45	$t(9) = 3.70^{**}$	66.37	62.26	$t(10) = 3.10^{*}$

*: $p < 0.05$, **: $p < 0.01$

for the *Participant-dependent cross-validation* (Figure 7).

5.2.4. *Effect of Context*

Results exhibit the usefulness of the context in correctly classifying between the low and high perceived walkability classes. Table 4 shows the results of paired t-tests that compare the UARs with and without the use of context, where the decision trees are trained using *Participant-dependent cross-validation* framework with *PSC features* and the *Participant-dependent walkability score*. Results depict significant improvement over all modalities when context is added in the feature set. The use of context increases the UAR for both the *Participant-dependent walkability score* and *Participant-independent walkability score* (Figure 7), further signifying the importance of this element. When all modalities are used in combination with context for the *Participant-dependent walkability score*, the *Aggregate measures* exhibit 74.85% UAR, while *PSC features* present 70.1% UAR. This is the best performance yielding from the raw features across all settings. The best performance from *PSC features* is obtained by combining EDA and context, where 71.97% UAR is achieved.

6. Discussion

This paper demonstrates the potential of using physiology and gait signals to estimate perceived walkability in the built environment. Walkability is a key factor to physical activity(Sallis et al. (2012); Fulton et al. (2018)), positive health outcomes(WHO (2010)), and healthy communities(Berke et al. (2007); King et al. (2011)). The subjectivity and inherent inter-individual variability of perceived walkability, the unbalanced distribution of low and high walkability classes, and the inherently complex feature spaces yielding from sensor-based measures collected "in-the-wild", render the task of perceived walkability estimation quite challenging. This paper addressed these challenges in the following ways.

To examine subject-dependent effects in perceived walkability, we introduced two types of labels (i.e., *Participant-independent walkability score*, *Participant-dependent walkability score*) and two types of frameworks (i.e., *Participant-independent cross-validation*) in the classification experiments. We observed high subject dependency in terms of the model's ability to capture physiology and gait patterns of walkability with the *Participant-dependent cross-validation* consistently outperforming the *Participant-independent cross-validation*. Results further depicted some dependency of walkability perception to the individual-level, since the UARs obtained using the *Participant-dependent walkability score* are many times higher compared to the ones yielding by the *Participant-independent walkability score*. Prior work depicts similar results, since environmental barriers in daily trips are found to be perceived in a highly subject-specific manner(Lee et al. (2020a); Dewulf et al. (2012); Ariffin & Zahari (2013); Lee & Shepley (2020)). Perception of distress also varies across individuals, and therefore, physiological responses can be also highly diverse(Koldijk et al. (2014); Can et al. (2019); Schmidt et al. (2018)). Thus, integrating knowledge about individual perception may comprise a useful approach to address this issue.

In order to tackle the inherent complexity of the task of interest, we examined a multimodal set of features representative of both ANS reactivity and physical motion parameters. EDA and gait patterns emerged as the most discriminative indices in estimating perceived walkability, while HR appeared to be the least effective. This might be caused by the motion artifacts in the data obtained from the PPG sensors. A robust motion artifact cancellation process may help in increasing the predictive performance of HR. The combination of all measures increased the UAR, which suggests

Table 4. Results of two-sided paired t-tests comparing unweighted average recall (UAR) obtained from *PSC features* (with and without context) in 10 folds of *Participant-dependent cross-validation* with *Participant-dependent walkability score*.

Modality	UAR (*PSC*)	UAR (*PSC*+Context)	t-test result
EDA	64.85	71.97	$t(9) = -3.85^{**}$
Gait	59.78	68.49	$t(9) = -4.34^{**}$
HR	53.07	64.44	$t(9) = -7.81^{**}$
EDA+Gait	64.63	70.67	$t(9) = -4.77^{**}$
EDA+HR	62.52	70.71	$t(9) = -8.79^{**}$
Gait+HR	54.84	66.82	$t(9) = -7.73^{**}$
EDA+Gait+HR	62.26	70.1	$t(9) = -6.71^{**}$

*: $p < 0.05$, **: $p < 0.01$

that a multimodal approach can be beneficial for detecting distress in the urban environment. Beyond aggregate statistical measures of physiology and gait, which are commonly used in prior work(Lee et al. (2020b); Yates et al. (2017); Yang et al. (2019); Jebelli et al. (2016)), we further examine saliency-based measures to capture the distinctiveness of the input signal for a POI of interest. *PSC features* tend to capture subtle differences in HR and EDA due to the adverse environmental stimuli of physical disorders, with the proposed PSCs outperforming the statistical indices when computed using the physiological measures of HR and EDA. *Aggregate measures* seem not to be able to achieve that, potentially due to the fact that they provide aggregate measures over a signal segment and fail to capture fine-grain signal fluctuations. Similar findings related to the limitation of aggregate statistical measures computed from physiological signals have been found in previous work(Chaspari et al. (2016, 2017); Nirjhar et al. (2020)). On the contrary, statistical measures perform well for the gait, potentially due to the fact that this signal is highly inter-connected with motion-based walkability patterns(Ahn et al. (2019); Yang et al. (2017, 2019); Jebelli et al. (2016)). We further added contextual information for augmenting the performance of the machine learning models that estimate perceived walkability in the built environment. Our results indicate that context plays a vital role in this task, since the integration of context in the feature space significantly improved performance in all experimental settings. These are in line with previous work, that has also demonstrated the importance of using contextual information for estimating human outcomes(Fox et al. (2017); Koldijk et al. (2014)).

To address the unbalanced distribution of classes, we used a decision tree whose hyperparameters were tuned through a balanced recall metric, rather than unbalanced accuracy. High recall for the low perceived walkability class is ensured in the hyperparameter tuning process, so that the model is able to accurately detect low perceived walkability instances with reduced false-negatives. Grounded on prior work, suggesting the importance of low perceived walkability in inhibiting physical activity and ultimately contributing to poor health outcomes(Sallis et al. (2012); Fulton et al. (2018); WHO (2010)), we highlight here the significance of designing an automated system with high recall for the low perceived walkability class in real-life applications. Although there are still several hurdles in terms of applying the current research to real-life practice, we envision that implications of this work can contribute to accurately diagnosing physical disorders in the built environment that affect perceived walkability in a personalized manner. The proposed models can offer a basis for monitoring the condition of the built environment, which could be utilized by government policymakers, urban practitioners, private operators, and citizens. Furthermore, this approach can be leveraged to cater to specific demographic groups (e.g., children, disabled people, and elderly) by means of mobility planning (e.g., daily walking trips in a safe and comfortable manner) and leisure. Currently, our model estimates perceived walkability from offline data. A successful model derived from these experiments can help in creating an online algorithm, which can be integrated into a personalized intervention module. Therefore, this work can contribute to urban bioinformatics, since crowdsourcing of physiological data from wearable devices is likely to be widely used in the not too distant future(Rumsfeld et al. (2016); Guo et al. (2015)).

Despite the encouraging results on estimating distress in the urban environment, the methodology proposed in this paper presents several limitations. The number of participants in this experiment ($N = 25$) is fairly limited, therefore the design of a generalized model may require additional data. The participants of this study did not belong to a sensitive population (e.g., elderly, disabled), therefore further experimentation with populations of interest can highlight specific needs and contribute to modifying community and public health policies related to the built environment in an informed data-driven manner. In addition to these, the estimation of perceived walkability has been formulated as a binary classification problem. A multi-class setup or a regression model can be more helpful in designing a system with increased resolution at the output. Moreover, the features related to the heart activity are computed based on the time domain. Measures extracted on the frequency domain or other domains (e.g., Wavelets) can potentially increase the predictive power of the models. Finally, contextual information was integrated using a simple, but effective, measure that reflects the location of a POI in the urban environment. Additional contextual information from visual cues (e.g., visual-based saliency detection of elements of the built environment) and audio (e.g., ambient noise) might be particularly beneficial as part of future experimentation.

7. Conclusion

This paper examined a machine learning model that used physiology and gait to detect perceived walkability in the built environment with implications in physical activity and overall community health. A field experiment was conducted to collect physiology, gait, and self-reported walkability ratings. We presented a comparative analysis with 25 participants that considered the predictive power of physiological saliency features, statistical measures, and contextual information for accurately detecting perceived walkability. A decision tree model was used in a *Participant-independent cross-validation* and a *Participant-dependent cross-validation* framework with two types of perceived walkability labelling methods. Our results indicate that the multimodal approach that combines both physiology and gait measures is more useful in classifying between low and high perceived walkability compared to the unimodal approach. Moreover, PSC measures based on the EDA and HR signals performed better compared to the corresponding aggregate measures, signifying the importance of capturing fine-grain temporal fluctuations in the signals. Integration of context further significantly benefited classification performance. This work sets the foundation for future experiments of personalized online detection of urban distress elements to ensure walkability and promote healthy communities.

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