A multimodal analysis of environmental stress experienced by older adults during outdoor walking trips: Implications for designing new intelligent technologies to enhance walkability in low-income Latino communities

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Abstract

Neighborhood walkability has a significant influence on older adults' physical and mental health. These effects are amplified in underserved communities (e.g., low-income groups, ethnic minorities) which are often associated with worsening pedestrian infrastructure and safety concerns. This paper investigates environmental stressors linked with decreased walkability of older adults from a low-income Latino community, and how these are associated with physiological, physical, environmental, and sociological variables. 68 older adults were recruited from a primarily Hispanic neighborhood, and each collected two-weeks of multimodal data using wearable and smartphone devices. The data included location, acceleration, and physiological data, such as heart rate and electrodermal activity, from participants' outdoor walking trips. Environmental stressors participants encountered during each walking trip were self-reported through a mobile application. The first part of this paper discusses unique challenges faced when working with this under-studied population and strategies used to address these challenges while maintaining scientific rigor. The second part of the paper describes results from the preliminary analysis employing linear mixed models (LMM) and machine learning classifiers to examine potential associations between self-reported and objectively-measured stress levels among participants, as well as the effect of environmental, sociological, and individual variables on physiological stress responses while walking. Findings from this study support new avenues for engaging with and gaining deeper insights into a unique and often overlooked population while laying the groundwork for developing new computational models for quantifying environmental stress using wearable and smartphone devices.

CCS Concepts

• **Human-centered computing → Empirical studies in ubiquitous and mobile computing**; *Empirical studies in accessibility*.

Keywords

Walkability; Pedestrian Stress; Physiology; Gait; Underserved Communities

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1 Introduction

Neighborhood walkability has been shown to be a vital factor in allowing older adults to maintain regular physical activity, and has significant impacts on their mental and physical health as well as their overall quality of life [29, 40]. Walkable communities encourage independent mobility among older adults, allowing the aging population to safely age in place for longer. Increased activity is linked to a decrease in obesity and disease, and increased cognitive independence while aging [7, 13, 47]. Even so, older adults are among the most inactive age groups [43]. Mental conditions caused by aging can make it challenging for older adults to manage environmental stress, further complicating efforts to maintain regular activity [35]. These complications are amplified in underserved communities, such as ethnic minorities and low-income areas, which often contend with poor pedestrian infrastructure, elevated air pollution, higher summer temperatures due to lack of heat adaptation strategies (e.g., urban greenery for shading), elevated crime rates, and limited healthcare access [6, 19, 42]. Rising summer temperatures have been linked to decreased outdoor activity [25] and elevated crime rates [14], an effect pronounced in low-income communities where the unequal impact of heat on quality of life may worsen these effects. Additionally, built environment infrastructure such as sidewalks and street lighting have been found to be more deteriorated in low-socioeconomic status areas, further exacerbating challenges faced by ethnic minority groups [42].

The most common measure of neighborhood walkability is a composite walkability index, which integrates factors such as net residential density, intersection density, retail floor area ratio, and land use mix [12, 32] that are often derived based on Geographic Information Systems (GIS). Despite their effectiveness, these objective environment attributes do not always match with perceived neighborhood walkability and satisfaction [31]. Alternatively, surveys have been employed to capture individuals' perceptions of neighborhood walkability, primarily assessing dimensions of social capital, personal safety, physical signifiers, and general neighborhood descriptors [17]. However, these methods are susceptible to drawbacks such as human subjectivity, bias, and lengthy time commitment. They further lack real-time monitoring capabilities of the built environment, crucial for dynamic urban settings [22], and predominantly focus on the experiences of the 'average' individual while neglecting sensitive populations such as older adults.

Among the older adult population, Latino older adults have been found to be the most socioeconomically disadvantaged subgroup [15]. Although Latino older adults tend to lead longer lives than their white counterparts, they have significantly higher physical disability levels which could be due to physically intensive occupations, high child poverty rates, high rates of metabolic issues, and low education rates [15]. In addition, the Latino population has the lowest rate of health insurance coverage among ethnic groups, further exacerbating health disparities [15]. Ethnic/cultural differences can alter perceptions of distress while walking. Previous research indicates that, beyond elements of physical infrastructure, both positive (e.g., social interaction, community identity) and negative (e.g., crime) attributes of the social environment can contribute to walkability in neighborhoods with predominantly Latino populations [2], highlighting the need for targeted walkability interventions.

Wearable devices combined with GPS tracking have emerged as a proxy to neighborhood walkability and identification of poor pedestrian infrastructure (e.g., broken sidewalk, litter). Biosignals (e.g., heart rate-HR, electrodermal activity-EDA, gait) collected during outdoor walking trips offer the potential to reduce subjectivity in current walkability measures, and can serve as a proxy of pedestrian distress related to uncomfortable walking conditions. Biosignals further capture rapid changes in infrastructure which cannot be measured via traditional methods such as street audits [22]. However, it is important to ensure accessibility and inclusivity of such technological innovations [33], particularly for marginalized groups such as ethnic minorities, who face socioeconomic disparities and often harbor skepticism toward new technologies. This further underscores the importance in designing targeted technologies to meet the unique needs of marginalized populations.

This paper investigates pedestrian stress as a determinant of walkability among older adults residing in a low-income Latino community utilizing multimodal data collected in real-life settings. The first part of the paper discusses the longitudinal multimodal data collected from older adults via wearable and smartphone devices, as well as cultural and technological barriers faced during data collection and strategies used to mitigate those challenges. The second part of the paper leverages the collected data to identify environmental (i.e., ambient temperature, humidity), sociological (i.e., crime rate), and individual (i.e., gender, age, weight, thermal comfort) factors of self-reported stress in walking trips. It further assesses the impact of those factors on the collected biosignal data (i.e., EDA, blood volume pulse-BVP, inertial measurement unit-IMU signals), and examines the potential of machine learning models that use as an input biosignal measures and environmental, sociological, and individual factors in automatically detecting self-reported pedestrian stress elicited from the built environment. Results indicate that humidity, crime rate, gender, and thermal comfort are significantly associated with self-reported stress during walking. They further suggest that changes in EDA, BVP, and IMU can be attributed to self-reported stress elicited by the built environment, alongside factors such as temperature, crime rate, and thermal comfort. These findings are discussed in association to implications in designing inclusive intelligent technologies for reducing pedestrian stress among Latino older adults and promoting walkability.

2 Prior Work

2.1 Factors of neighborhood walkability

The term 'walkability' refers to a measure of the extent to which "the built environment of a neighbourhood encourages people to walk" [49]. An increasing body of research has explored factors of walkability that include both the built environment and neighborhood's social and physical characteristics. Determinants of walkability that pertain to the built environment are the net residential density (i.e., number of housing units per unit of land area), intersection density (i.e., number of intersections, junctions within a neighborhood), retail floor area ratio (FAR) (i.e., total floor area of retail space to the total land area) and mixed land uses (i.e., proximity to a mix of residential, commercial, and recreational destinations) [12]. When these elements are prevalent, they tend to increase opportunity for active transportation and decrease vehicle use. For instance, high net residential density indicates a greater concentration of housing units in a given area, which can support walkability by increasing population density and proximity to amenities. Similarly, higher intersection density accomplished via pedestrian infrastructure (e.g., sidewalks, crosswalks, pedestrian signals) and street connectivity (e.g., short block lengths and frequent intersections) results in more opportunities for pedestrians to change direction, providing direct and efficient routes. Finally, higher retail FAR values and higher mixed land use indicate greater retail development intensity, which can increase access to shops and services within walking distance allowing residents to accomplish daily tasks without relying on automobiles. Low-income communities primarily inhabited by ethnic minorities face increased challenges regarding pedestrian safety [18] and have limited access to local parks [41], a disparity that can be attributed to inequities in the urban planning process [4]. This paper examines elements of the built environment as factors influencing pedestrian stress, subsequently impacting walkability. The components of the built environment are assessed through self-reports to capture participants' unique perceptions of the neighborhood in the focal Hispanic community.

Elements of the social environment relevant to walkability include socioeconomic status, social support, social networks and interaction, social cohesion, social capital, community identity, racial discrimination, safety, and neighborhood disorder [38]. Opportunities for social interaction, community engagement, and a sense of belonging in the community foster a supportive environment for walking. Low crime rates and adequate lighting enhance pedestrian safety and perceptions of security, encouraging walking. While results on crime and neighborhood walkability remain mixed [49], crime is a potential reason for people's reluctance to walk in low-income and minority neighborhoods [10]. This paper considers crime rate, measured via historical data from the local governing body, as a factor affecting pedestrian stress.

Thermal conditions can influence walkability, since thermal stress can degrade the walking experience or lead to significant health risks such as heat exhaustion or heat stroke [30], particularly for older adults who are sensitive to weather conditions and extreme weather events [50]. Pedestrian experience during high heat conditions is affected by factors that pertain both to the built environment and the individuals' characteristics. Elements of the built environment, such as artificial shading, vegetation (e.g., trees, green roofs), and urban furniture (e.g., drinking fountain, benches) [3] can mitigate the adverse effect of high heat on pedestrians. One's ability of thermal adaptation can further moderate vulnerability in thermal extremes and walking comfort. The physiologically equivalent temperature (PET) is a widely used thermal comfort index capturing one's ability to tolerate thermal stress and has been applied to cold and hot conditions and in different climate zone and urban spaces [34, 48]. Here, ambient temperature and thermal comfort, measured via PET, are considered as factors influencing pedestrian stress.

2.2 Multimodal measures of pedestrian stress

Prior work has leveraged a variety of measures, including image, physiology, and acceleration in order to quantify neighborhood walkability and pedestrian stress associated with the built environment. Nagata *et al.* leveraged image data collected via Google Street View (GSV) to assess urban walkability [39]. The authors used an image segmentation method of GSV images via deep learning. Each pixel of an image was classified into 19 different segments (e.g., sky, vegetation, sidewalk) from which street infrastructure and aesthetic information was extracted. Using regression models, each location was given a walkability score and compared to audit scores as well as participants' foot traffic. Although promising, these image-based approaches are subject to limitations. GSV images may be outdated and are not updated frequently enough to keep up with rapidly changing infrastructure which can hinder accuracy levels. In addition, these methods overlook the human-perception component and non-visible factors such as noise levels.

In recent years, researchers have explored pedestrian's movement data as a complementary method for evaluating walkability and assessing elements of the built environment. Kim *et al.* aimed to detect defective sidewalks hampering walkability through data collected via smartphones [20]. Participants carried a smartphone in their front pants pocket which collected IMU and GPS data while they walked a predefined path on a sidewalk. Signal vector magnitude (SVM) was extracted from the IMU signal in order to detect slight gait abnormalities. The study found that IMU irregularities had a high correlation with sidewalk defects with an accuracy of 96.2%, precision of 0.943, and recall of 0.702 in classifying between defective and non-defective sidewalks. This method is centered around people's responses to the environment and allows pedestrians to participate in sidewalk monitoring. These results indicate the feasibility in using IMU data collected from smartphone devices to continuously monitor sidewalk conditions. In order to apply this method to real-life settings, factors such as differences in walking behaviors, diverse sidewalk issues, built environment characteristics, and considerations for minority demographics (e.g., disabled and older individuals) should be taken into account.

Another method being explored to estimate neighborhood walkability, is the use of wearable sensors for detecting pedestrians' distress levels during walking trips through biosignals. One such study, aims to detect distress from participants 20-34 years of age during predefined walking trips within commercial and residential settings by leveraging a multimodal approach, integrating biosignals collected from wearable sensors (e.g., EDA, HR, Gait) in conjunction with image-based data collected via chest-mounted camera to integrate context to the information obtained from personalized biosignals [22]. Data was segmented using timestamps that corresponded to the negative stimuli from the built environment. Each time segment including negative stimuli was compared to the time segments preceding and following the stimuli. The study found that using solely biosignal data or image data resulted in low accuracy levels with each physiological modality achieving 50.37% - 60.38% unweighted average recall (UAR) accuracy and the image data features achieving 52.40%–60.38% UAR accuracy. Meanwhile, combining biosignal and image-based data resulted in up to 91.32% UAR accuracy. In another study, 31 participants walked a predefined path while collecting physiological, movement, and GPS data via wrist sensor, ankle monitor, and smartphone respectively [24]. In addition, video was recorded to pinpoint environmental stressor locations. During the predefined walk, participants encountered a dead animal replica which simulated a negative stimuli. After the predefined walk, participants answered survey questions about how they felt when encountering the stimuli. It was found that participants experienced maximum EDA levels approximately 5.31 seconds after encountering the stimuli. Similarly, participants experienced maximum change in gait measures approximately 4.30 seconds after. Overall, EDA and gait patterns were found to be indicators of negative environmental stimuli.

EDA and BVP responses, aggregated across participants, were used as a proxy measure of pedestrian stress during walking [28]. Results on 20 participants indicate no correlation between participant stress and roadway crossings. However, pedestrian stress increased near main road arteries and in areas with industrial/ mixed land uses. Similarly, high-stress pedestrian experiences in the urban environment, identified via changes in heart rate variability, were associated with issues such as pedestrian-scooter interaction on pedestrian paths, high foot traffic areas, and poor visibility at pedestrian crossings due to inadequate lighting [9]. Finally, a stress index that measured relative change in temperature and EDA was used to identify environmental hotspots in an urban environment [27]. Visual inspection of results indicate that the proposed stress index was associated with spatial locations of self-reported stress.

The contributions of this paper in relation to prior work are as follows: (1) Most studies examining biosignals as a way to capture pedestrian stress focus on predetermined paths [22, 24] or geofenced areas within specific boundaries [9]. We aim to investigate the feasibility of detecting stress in daily-life walking trips, which may be influenced by various factors related to the built environment and other environmental and sociological conditions; (2) Previous research predominantly focuses on young student populations [20, 22, 24, 28], whereas our study analyzes data from a less explored demographic of Latino older adults who may depict unique biosignal patterns of stress elicited from the built environment; (3) While much of the previous research concentrates on identifying overall stress patterns aggregated across pedestrians to generate global trends within a space [9, 27, 28], our study focuses on individual stress responses associated with elements of the built environment. This approach can provide valuable insights into the unique ways older adults experience stress and inform personalized interventions such as customized route planning that could mitigate these effects; and (4) While prior work uses image data to provide environmental context [39], our research uses publicly available sociological and environmental data, without encountering the same privacy concerns associated with visual data.

3 Dataset Description

3.1 Participants

Data included 68 participants from the Magnolia Park/Manchester area in Houston, TX aged between 60 to 90 years recruited from community events. All participants were Latino and live in a 96% Latino neighborhood. Out of the 68 participants, 3 participants did not provide personal demographic data. Among the remaining 65 participants, 13 were male and 52 were female. Furthermore, 5 of our participants indicated the use of walking aids such as walkers or canes. The majority of participants reported earning less than $15,000 a year (Table 1) and have attained below a high school level education (Table 2), providing insight into the population's socioeconomic status.

Income	% Participants
Less than $10,000	33.8%
$10,000 - $14,999	20.0%
$15,000 - $24,999	18.4%
$25,000 to $34,999	3.0%
Don't know / Prefer not to answer	24.6%

Table 1: Distribution of income among participants.

Education Level	% Participants
Less than high school	58.5%
Some high school, but no degree or GED	10.7%
High school diploma or GED	9.2%
Some College	7.6%
Associates Degree	3.0%
Bachelor's Degree	3.0%

Table 2: Education levels among participants.

3.2 Data Collection Protocol

The user study was approved by the research ethics committee at Texas A&M University. Data collection was conducted from January to July 2023 averaging a temperature of 27°C with a low of 5°C and a high of 34°C. After obtaining informed consent, participants were presented the study objectives, protocol, and conducted a tutorial on how to use the study equipment. Each participant was provided with an Empatica E4 sensor and a Google Pixel phone worn around the waist equipped with our customized Daynamica application [1] (Figure 1). The wrist-worn E4 captured BVP and EDA data. The IMU from the smartphone collected participants' acceleration, while the GPS sensor was employed to collect location data. On the first day of their data collection, participants walked a predetermined route approximately 0.65 miles, and took the devices home to continue collecting data on their own for the following 14 days in locations of their choosing. After each walking trip, participants completed a post-walk digital survey administered via the smartphone application [1] where participants were asked to report any encountered stressors while walking, pinpoint the location of these stressors on the map, and rate the perceived stress level on a Likert scale from 1 to 5 for each identified stressor. Participants selected from a list of stressors that included poor walking surface (cracks, holes), unattended dog, litter (dumping, broken glass), people (homeless, rowdy, catcalling, hostile), and uneven walking, or had the option to describe the stressor in their own words.

3.3 Cultural and Technological Barriers in Data Collection & Mitigation Strategies

In conducting data collection, we recognized the importance of adhering to our participants' cultural norms and needs, even so, many adjustments had to be made along the way. Given that Spanish was the primary language spoken in the focal Latino community, our team included bilingual researchers and a bilingual field coordinator who actively participated in participant recruitment and data collection. The field coordinator began by forming meaningful connections with community and local government leaders, and

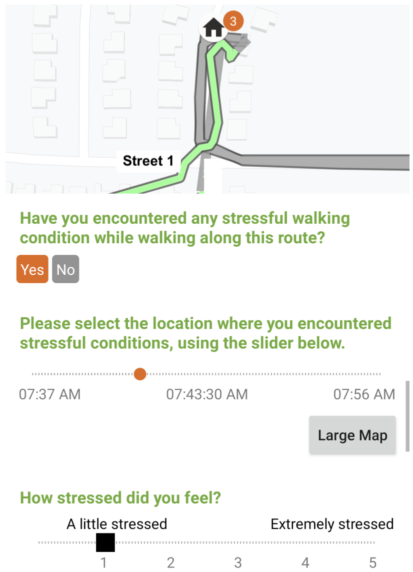

Figure 1: Post-walk survey on the Daynamica application

volunteering in local events. This proved to be vital in gaining community trust and insight into the community culture. In addition, all research materials, including informed consent, surveys, and smartphone interfaces, were translated and provided in English and Spanish. The team was further actively engaged in community meetings and informational sessions to explain research objectives of the project, methods, and potential benefits to the community.

During initial stages of recruitment, many community members were hesitant to participate and declined involvement in research, expressing concerns about their ability to use the data collection devices. In addition, several initial participants felt frustrated trying to learn how to use the devices, even after receiving a tutorial on the study equipment. To help participants feel more comfortable taking part in the study, and to mitigate participant drop-out, the field coordinator became available every morning in-person to address technical issues, promptly assisting participants who needed help learning to use the devices. This also encouraged others to participate as it helped ease their concerns in using new technologies. Even so, some participants needed additional accommodations to successfully and comfortably participate in the study. These participants did not take the data collection devices home with them, and instead, visited the field coordinator every morning during their data collection period to retrieve the devices and receive assistance with setting up. We further allowed for flexible study formats implementing a hybrid survey system. Participants who needed help filling out the post-walk survey through the smartphone application, but felt comfortable collecting sensor data, completed data collection on their own and filled out the post-walk survey on paper. They later worked with the field coordinator to transfer their paper surveys to the smartphone application.

3.4 Description of Resulting Data

In preparing the dataset for analysis, we found that participants walked an average of 14 days within their data collection period. As 27% of E4 data was found to be missing, only trips without missing E4 data were considered. From this subset of trips, 3.9%

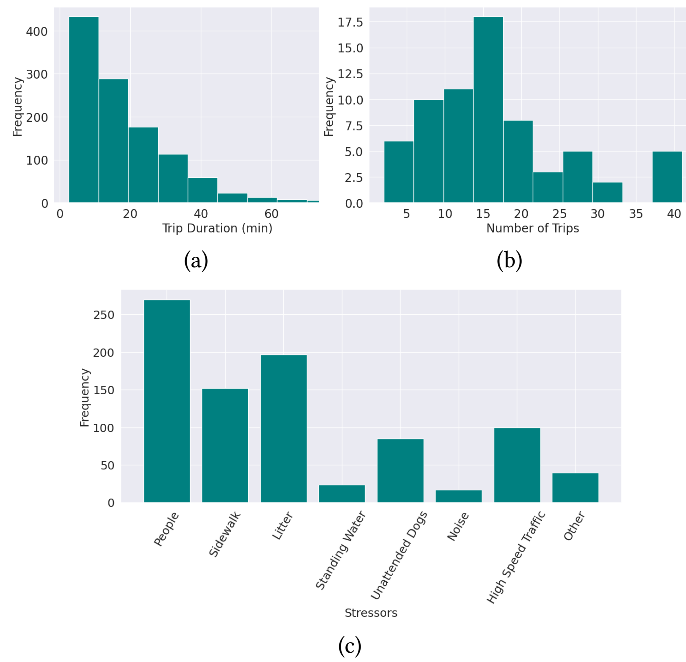

Figure 2: Histograms of (a) trip duration; (b) number of trips per participant; and (c) type of reported stressors.

were missing IMU data. The resulting data included a total of 1,121 trips from the 68 participants. It is important to note that often times, walking trips were split up into multiple smaller trips if participants took breaks during their walk. Participants had an average of 16.4 trips each lasting an average of 18 minutes. Participants reported an average of 8.7 total stressors each throughout their data collection period. The distribution of the number of trips, trip duration per participant, and reported stressors is provided in Figure 2.

4 Methodology

First, we detail the multimodal measures extracted from the wearable and smartphone devices, including variables used in the subsequent analysis (Section 4.1). Next, we outline the statistical analysis conducted using linear mixed models (LMM) to investigate environmental, sociological, and individual factors of older Latino adults' self-reported stress associated with walkability (Section 4.2). Finally, we discuss analysis employing LMM and machine learning models, aimed at assessing the feasibility of utilizing multimodal data to automatically detect pedestrians' self-reported stress (Section 4.3).

4.1 Feature Extraction

A multimodal set of physiological, environmental, sociological, and individual difference measures were extracted for analysis. EDA signals were denoised using a low-pass Butterworth filter to remove frequencies over 1.0 Hz from which a set of statistics was computed on the filtered EDA signal and its tonic and phasic components (Table 3). The skin conductance responses (SCR) were further detected in the EDA signal [36] and the mean amplitude, maximum amplitude, and mean frequency of SCRs was extracted, resulting in a total of 15 EDA features. In addition, BVP signals were filtered to remove frequencies below 0.6 Hz and above 2.0 Hz [23] from which the HR signal was calculated and 3 features extracted.

Type	Measure	Statistic
Biosignals	EDA	mean, max, range, frequency
	Tonic	mean, max, range
	Phasic	mean, max, range
	SCR	mean, max, frequency, max amplitude
	BVP	HR mean, HR max, HR range
	IMU SVM	mean, max, range
	IMU RAV	mean, max, range
Environmental	Temperature	mean
	Humidity	mean
Sociological	Crime rate	frequency
Individual	Gender	n.a.
	Age	n.a
	Weight	n.a
	PET	n.a

Table 3: Summary of extracted multimodal features

Finally, high frequencies over 3 Hz were removed from the IMU data through a low-pass filter [21] from which 6 Sum Vector Magnitude and Resultant Angular Velocity (RAV) features were extracted [8]. All of the physiological features were extracted at the trip-level (Table 3) and z-score normalized for each participant.

Environmental features encompassed ambient temperature and humidity, which were considered due to the significant impact of these factors on EDA signals [5, 37]. The average ambient temperature and humidity levels for each trip were calculated using publicly available historical weather data.

Crime rate was included as a sociological variable and deemed important due to the general assumption that areas with increased crime will cause people to feel unsafe which will negatively impact physical activity [11]. Crime rate was calculated for each trip using crime data from 2019 publicly provided by the city of Houston localized with the GPS data collected through participants' smartphones. We calculated the number of unique crimes (i.e., Disorderly conduct, Aggravated Assault, Robbery) that occurred within a 0.125 mile radius of each trip, the approximate length of a block [26].

Demographic, anthropometric, and thermo-physiological measures were further extracted in order to take into account individual differences that might affect stress and physiological measures. Demographic measures included gender and age, while anthropometric features included weight. Finally, the PET, a personalized measure of thermal comfort [34, 48], was extracted using environmental factors such as air and radiant temperatures; personal demographics such as age, height, weight, and gender; and other variables such as metabolic rate and clothing insulation [48]. Metabolic rate was estimated to 2.45 met based on a study analyzing older adults [44]. Clothing insulation was estimated based on the season, and was estimated as 0.5 clo for summer, 0.9 clo for spring and autumn, and 1.0 clo for winter, aligning with literature [16].

Self-reported stress at the trip-level was calculated by taking the maximum stress reported by the participant in each trip. If no stress was reported, a stress level of 0 was assigned to that trip.

4.2 Factors of pedestrian self-reported stress

In investigating the impact of environmental, sociological, and individual variables on participants' perceived stress levels, we use a LMM that allows us to model the hierarchical nature of the data (i.e., trips nested within participants). The LMM accommodates participant variability by treating participants as random effects, and its equation is as follows:

$$\begin{aligned} X_{ij} =& \beta_0 + \beta_1 \cdot T_{ij} + \beta_2 \cdot H_{ij} + \beta_3 \cdot CR_{ij} + \beta_4 \cdot G_i + \\ & \beta_5 \cdot A_i + \beta_6 \cdot W_i + \beta_7 \cdot PET_{ij} + x_i + \varepsilon \end{aligned} \tag{1}$$

where X_{ij} is the self-reported stress of participant i over trip j, T_{ij} and H_{ij} are the ambient temperature and humidity, respectively, experienced by participant i over trip j, CR_{ij} is crime rate over trip j walked by participant i, and G_i (i.e., $G_i = 0$ for male participants, $G_i = 1$ for female participants), A_i, W_i, and PET_{ij} are participant's i gender, age, weight, and PET, respectively. The variable β_0 indicates the intercept of the LMM, while $\beta_1, ..., \beta_7$ are the fixed-effects coefficients. The latter are the same for all participants and quantify the association between self-reported stress and temperature, humidity, crime rate, gender, age, weight, and PET, respectively. Finally, the variable x_i is a random-effect coefficient which is different for each participant i, while ε indicates the error term.

4.3 Automatic detection of self-reported stress using multimodal data

Here, we examine the feasibility of using biosignal measures for automatically detecting pedestrian self-reported stress. We first conduct a LMM analysis that will allow us to better understand associations between each biosignal measure and self-reported stress, as well as the effect of the aforementioned confounding variables on each biosignal measures. Toward this, we run a LMM that treats each biosignal feature as the dependent variable, along with self-reported stress rating and confounding factors of humidity, temperature, crime rate, and PET as the independent variables:

$$Y_{ij} = c_0 + c_1 \cdot S_{ij} + c_2 \cdot H_{ij} + c_3 \cdot T_{ij} + c_4 \cdot CR_{ij} + c_5 \cdot PET_{ij} + y_i + \varepsilon \tag{2}$$

where Y_{ij} is a biosignal measure recorded from participant i over trip j, S_{ij} is the self-reported stress of participant i over trip j, T_{ij} and H_{ij} are the ambient temperature and humidity, respectively, experienced by participant i over trip j, CR_{ij} is crime rate over trip j walked by participant i, and PET_i is participant's i PET. The variable c_0 is the intercept of the LMM, while the variables $c_1, ..., c_5$ are the fixed-effects coefficients that quantify the association between the physiological measure with self-reported stress, humidity, temperature, crime rate, and PET, respectively. The variable y_i is a random-effect coefficient and ε is the error term. The LMM in 2 is fitted for each physiological variable in Table 3. The LMM described by (2) is run for all biosignal measures as outlined in Table 3.

Machine learning models were used to detect self-reported stress. Trips with a stress rating of 1 or higher were labeled as 'Stress' (515 total) and trips with no reported stress were labeled as 'No-Stress.' (563 total). A random forest classifier and an XGBoost classifier were examined. EDA, HR, IMU, PET and confounding variables were taken as input (i.e., 32 features in total) and the binary stress level as the output. A 5-fold cross validation and a leave-one-subject-out (LOSO) cross-validation were used for both classifiers. Hyperparameter tuning was conducted via LOSO or 5-fold grid search cross-validation considering number of estimators between 5 and 300, and tree depths between 3 and 10. Feature selection was conducted via relative feature importance based on the decrease in impurity to fine-tune the input variables. A total of 18 features were selected

Fixed Effect	Coefficient	P-value
Intercept β_0	2.744	0.000
Temperature β_1	-0.006	0.500
Humidity β_2	0.004	0.030
Crime rate β_3	0.129	0.000
Gender (Female) β_4	-0.260	0.025
Age β_5	-0.010	0.205
Weight β_6	-0.003	0.060
PET β_7	-0.020	0.012

Table 4: Linear mixed model (LMM) results from analyzing the effect of environmental, sociological, and individual variables on self-reported stress.

for classification. Evaluation of the models' performance in classifying between stressful and non-stressful trips was conducted via weighted metrics of recall, precision, and F1-score, where each metric was calculated for the 'Stress' and 'No-stress' class and then averaged for both classes.

5 Results

Through the first LMM in (1), we analyzed the effect of environmental, sociological, and individual variables on self-reported stress (Table 4). Ambient temperature did not have a significant association with reported stress which could be due to the fact that participants reported environmental stressors in the built environment, so while temperature can alter physiology [37], it was not found to influence self-reported stress. Humidity levels had a slight positive correlation with reported stress, which could be due to increased physical discomfort during humid summer days. Crime rate depicted a significant positive correlation with reported stress indicating that participants were more inclined to report environmental stress in areas with previously documented high crime rate. Findings also indicate a significant negative association between self-reported stress and PET, suggesting an increase in self-reported stress levels during decreased thermal comfort. The coefficient corresponding to gender was significant, indicating that women reported lower levels of stress than men. Participant weight and age did not have significant associations with reported stress.

Through the second LMM in (2), we investigated associations between biosignal measures, self-reported stress, and confounding factors. Overall, results indicate moderate associations between a subset of the biosignal measures and self-reported stress, strong associations between biosignal measures (i.e., predominantly EDA measures) and temperature, and weak associations between biosignal measures and humidity, PET, and crime rate (Table 5). EDA range and tonic range depict positive correlations with self-reported stress and ambient temperature. This is expected as EDA is a measure of sympathetic activity, meaning that stressful stimuli can lead to changes in EDA. EDA also reflects sweat production, thus we anticipate an increase in tonic EDA measures with high ambient temperature. EDA Mean, Phasic Mean/Max/Range, Tonic Mean/Max, and SCR Amplitude did not depict significant association with self-reported stress, possibly due to the strong influence of ambient temperature on these measures. Consistent with previous literature, SCR frequency did not have a significant correlation with temperature [37], but SCR Amplitude depicted a slight positive association with temperature. The majority of EDA measures depicted negative associations with PET, indicating that individuals with high thermal comfort depict lower EDA reactivity compared to those with low thermal comfort.

HR measures depicted significant positive associations with self-reported stress and no significant association with temperature. This indicates that an increase in HR variables is linked to self-reported stress, while these measures are not heavily impacted by changes in ambient temperature. SVM Mean exhibited a weak negative correlation with stress levels but no significant correlation with temperature. Interpreting this result alongside the negative association between SCR frequency and self-reported stress, it may suggest that participants move more slowly around stressful stimuli, resulting in a decrease in both acceleration magnitude and the phasic sweat responses. Finally, RAV Mean/Max display positive coefficients with stress and temperature. Prior work indicates that the type of environmental stressor impacts IMU features differently [45], which may explain why SVM and RAV features depict opposite correlations with self-reported stress. A possible explanation could be that participants need to walk around the environmental stimuli such as deteriorated sidewalks or litter, leading to a reduction in acceleration magnitude and an increase in rotation.

Results further reveal interesting patterns in the correlations between physiological measures and crime frequency. EDA Range, tonic range, HR Max, and HR Range depict a significant positive association with crime frequency, suggesting that participants depict an increase in physiology when walking through paths including blocks with higher crime frequencies. Conversely, SCR Frequency demonstrates a negative coefficient and significant p-value with crime rate, suggesting that higher SCR frequencies are associated with lower crime rates. Given that SCRs are triggered by a specific stimuli and the crime rate variable captures an overall pattern of crime for a location rather than individual crime events occurring during the walk, this discrepancy might explain why SCR Frequency depicts negative association with crime rate.

Classification results indicate above chance weighted recall, precision, and F1-score for both classifiers and cross-validation frameworks (Table 6), suggesting the feasibility of automatically detecting pedestrian self-reported stress from biosignals and confounding factors. The type of classifier (i.e., random forest, XGBoost) does not appear to significantly impact the classification result. Within the XGBoost classifier, results do not vary significantly between LOSO and random-split cross-validation, indicating that removing participant dependence via LOSO does not affect the results.

6 Discussion

This paper examined the effect of environmental, sociological, and individual variables of self-reported pedestrian stress of older Latino adults. Findings indicate an increase in self-reported stress on days with high humidity and in regions with high crime rate. Women and individuals with high thermal comfort depict lower levels of self-reported stress. These findings can have important implications for environmental interventions aimed at modifying elements of the built environment to promote walkability in the focal population. Interventions that improve lighting could help mitigate stress in areas with high crime rates. Ensuring that these areas are well-maintained and free of physical disorder (e.g., litter, graffiti) can further create a perception of safety and discourage criminal activity.

	Stress c_1	Humidity c_2	Temperature c_3	Crime Rate c_4	PET c_5
EDA Mean	-0.040 (p = 0.305)	-0.005 (p = 0.038)	0.043 (p = 0.000)	0.015 (p = 0.612)	-0.015 (p = 0.005)
EDA Max	0.038 (p = 0.332)	-0.004 (p = 0.074)	0.041 (p = 0.000)	0.024 (p = 0.428)	-0.013 (p = 0.019)
EDA Range	0.100 (p = 0.010)	-0.004 (p = 0.120)	0.036 (p = 0.000)	0.059 (p = 0.049)	-0.010 (p = 0.077)
Phasic Mean	0.038 (p = 0.389)	0.000 (p = 0.995)	-0.002 (p = 0.888)	0.057 (p = 0.060)	-0.001 (p = 1.000)
Phasic Max	0.023 (p = 0.557)	-0.005 (p = 0.059)	0.033 (p = 0.000)	-0.004 (p = 0.892)	-0.011 (p = 0.061)
Phasic Range	0.035 (p = 0.375)	-0.004 (p = 0.092)	0.035 (p = 0.000)	0.010 (p = 0.727)	-0.011 (p = 0.049)
Tonic Mean	-0.040 (p = 0.305)	-0.005 (p = 0.038)	0.043 (p = 0.000)	0.015 (p = 0.612)	-0.015 (p = 0.005)
Tonic Max	0.041 (p = 0.288)	-0.004 (p = 0.082)	0.041 (p = 0.000)	0.026 (p = 0.389)	-0.013 (p = 0.017)
Tonic Range	0.117 (p = 0.001)	-0.003 (p = 0.153)	0.035 (p = 0.000)	0.068 (p = 0.022)	-0.009 (p = 0.100)
SCR Freq	-0.212 (p = 0.000)	-0.007 (p = 0.023)	0.012 (p = 0.422)	-0.058 (p = 0.052	0.004 (p = 1.000)
SCR Amp	-0.048 (p = 0.219)	-0.003 (p = 0.286)	0.033 (p = 0.000)	-0.025 (p = 0.405)	-0.012 (p = 0.029)
HR Mean	0.132 (p = 0.001)	-0.003 (p = 0.204)	0.009 (p = 0.255)	-0.018 (p = 0.552)	-0.000 (p = 0.993)
HR Max	0.194 (p = 0.000)	0.000 (p = 0.909)	-0.016 (p = 0.285)	0.082 (p = 0.006)	-0.002 (p = 1.000)
HR Range	0.264 (p = 0.000)	0.003 (p = 0.254)	-0.018 (p = 0.219)	0.079 (p = 0.008)	-0.002 (p = 1.000)
SVM Mean	-0.094 (p = 0.031)	-0.001 (p = 0.662)	0.017 (p = 0.243)	-0.045 (p = 0.130)	0.002 (p = 0.000)
SVM Max	-0.028 (p = 0.522)	0.001 (p = 0.707)	0.023 (p = 0.104)	-0.058 (p = 0.050)	0.001 (p = 1.000)
SVM Range	0.078 (p = 0.074)	0.005 (p = 0.072)	0.035 (p = 0.015)	-0.064 (p = 0.030)	-0.004 (p = 1.000
RAV Mean	0.268 (p = 0.000)	0.000 (p = 0.915)	0.033 (p = 0.019)	-0.045 (p = 0.122)	-0.001 (p = 0.000)
RAV Max	0.096 (p = 0.025)	0.000 (p = 0.999)	0.039 (p = 0.006)	0.004 (p = 0.898)	-0.002 (p = 0.710)
RAV Range	-0.046 (p = 0.443)	0.003 (p = 0.456)	0.035 (p = 0.074)	-0.027 (p = 0.513)	0.000 (p = 1.000)

Table 5: Linear mixed model (LMM) results including the coefficients and p-values representing associations between biosignal measures and self-reported stress along with confounding factors.

Model	Balanced Acc	WP	WR	WF1
Random Forest: LOSO	0.666	0.778	0.634	0.664
Random Forest: 5-fold	0.636	0.633	0.631	0.629
XGBoost: LOSO	0.637	0.646	0.643	0.621
XGBoost: 5-fold	0.624	0.626	0.625	0.624

Table 6: Balanced accuracy (Acc), weighted precision (WP), weighed recall (WR), and weighted F1 (WF1) for classifying walking paths between 'Stress' and 'No-stress.'

Additionally, initiatives focusing on improving thermal comfort via increasing shading and green spaces may be important.

Significant associations between self-reports and physiological variables underscore the feasibility of automated systems in detecting environmental stressors. Notably, results reveal significant correlations between EDA, HR, and IMU measures, and self-reported stress levels. Confounding factors such as humidity, crime, PET, and gender could also influence individual's stress reports and should be considered when designing automated systems. These findings hold significant implications for technological interventions aimed at reducing pedestrian stress. Wearable and smartphone devices coupled with machine learning algorithms could be used to suggest walking routes that prioritize pedestrian safety and comfort and provide real-time information on nearby amenities, such as shaded areas or water fountains. Biosignals can serve as evidence to community decision makers, informing policies and environmental interventions, and improving the well-being of older adults. Through reported stressors, we can see the need for specific interventions; 30.51% of stressors were related to people (i.e., homeless, rowdy), 17.18% of were related to sidewalk conditions (i.e., poor walking surface, blocked sidewalk) and 22.25% were related to litter. These insights can lead to interventions such as providing support to homeless individuals, improving sidewalk conditions, and removing litter.

The machine learning experiments in this study consistently achieved above chance accuracy (i.e., 63-66% balanced accuracy) in classifying stressful and non-stressful paths. Although results demonstrate the potential of biosignals captured via wearable sensors to detect environmental stressors, deploying such a system in real-life may encounter limitations. It is essential to assess user experience with such a system and determine if the resulting performance is sufficient to establish trustworthiness among older Latino adults, particularly for applications such as route planning. In this under-studied population, a key question remains regarding whether the achieved accuracy is acceptable or whether it may harbor additional skepticism, potentially hindering adoption of such technologies. Additional environmental factors such as GSV images and GIS data, sociological factors such as specific crimes, or audit data from experts, could further improve accuracies.

Despite promising findings, this study has several limitations to consider. The analysis of this paper was conducted at the route level. While valuable for intelligent route planning purposes, it would be important to identify stressors of the built environment at a higher temporal and spatial resolution. Given prior work highlighting the significance of social cohesion for walkability in Latino communities [46], it would be valuable to incorporate this factor in future work. Additionally, participant weight, age, and gender in the first LMM (2) might better be represented as moderator variables. Finally, it is important to recognize that these findings reflect the characteristics and dynamics of the specific geographical area of the study and may not generalize across different countries due to diverse environmental, sociological, and infrastructural factors.

7 Conclusion

This paper examined the interplay among self-reported stress, biosignal measures, as well as environmental, sociological, and individual factors associated with pedestrian stress of older Latino adults. Several physiological features depicted significant correlations with perceived stress. Likewise, environmental and sociological factors such as crime rate and temperature were found to affect physiology. These findings can inform future interventions aimed at enhancing walkability of older Latino adults.

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