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Space-time analytics of human physiology for urban planning

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ABSTRACT

Recent advancements in mobile sensing and wearable technologies create new opportunities to improve our understanding of how people experience their environment. This understanding can inform urban design decisions. Currently, an important urban design issue is the adaptation of infrastructure to increasing cycle and e-bike use. Using data collected from 12 cyclists on a cycle highway between two municipalities in The Netherlands, we coupled location and wearable emotion data at a high spatiotemporal resolution to model and examine relationships between cyclists' emotional arousal (operationalized as skin conductance responses) and visual stimuli from the environment (operationalized as extent of visible land cover type). We specifically took a within-participants multilevel modeling approach to determine relationships between different types of viewable land cover area and emotional arousal, while controlling for speed, direction, distance to roads, and directional change. Surprisingly, our model suggests ride segments with views of larger natural, recreational, agricultural, and forested areas were more emotionally arousing for participants. Conversely, segments with views of larger developed areas were less arousing. The presented methodological framework, spatial-emotional analyses, and findings from multilevel modeling provide new opportunities for spatial, data-driven approaches to portable sensing and urban planning research. Furthermore, our findings have implications for design of infrastructure to optimize cycling experiences.

1. Introduction

Emotions play a major role in our day-to-day lives, shaping how we perceive and experience the world. Emotions are intense, short-lived, complex reactions to personally meaningful stimuli (Oatley, Keltner, & Jenkins, 2006). An important source of personally meaningful stimuli are the places in which people live. Bumper-to-bumper traffic, large noisy crowds, and beautiful architecture, all evoke emotional responses. While we may feel happy and secure in one place, we might feel worried and unhappy in another (Korpela, 2002). Furthermore, it is well-known that such reactions involve interactions between stimuli and individual differences such as personality, biological sex, and age (Larsen & Diener, 1987).

How we emotionally respond to a place depends on a wide variety of factors (Kirillova, Fu, Lehto, & Cai, 2014). Urban planning and design efforts focus on controlling these factors to make experiences of cities as positive as possible. Related research examining how emotions develop over urban spaces is quickly growing (i Agust'ı, Rutllant, & Fortea, 2019; Shoval, Schvimer, & Tamir, 2018) including urban cycling experiences (Schmidkunz, Schroth, Zeile, & Kias, 2019; Gamble, Snizek, & Nielsen, 2017; Zeile et al., 2016; Snizek et al., 2013). Cycling's recent boom in popularity, and considerable efforts to redesign city transportation infrastructures around cycling, warrants a closer look at cyclists' experiences within and between cities. Two technological developments point to a need for further research. First, existing cycling infrastructure is being enhanced to accommodate the increasing spread of e-bikes enabling higher average cycling speeds over mid-range distances (5–20 km; Schleinitz, Petzoldt, Franke-Bartholdt, Krems, & Gehlert, 2017). Second, increasingly accurate and affordable biometric technologies make it possible to measure cyclists' emotions in a continuous, time-based, and unobtrusive way. These technologies have been applied to urban experiences of walking, but only rarely to cycling.

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To address this gap, we used wearable location and emotion tracking of 12 cyclists on an intercity cycling highway to determine how the land cover type within their field of view affects their emotional arousal. Findings can inform urban design approaches for building public spaces that effectively evoke the emotions and experiences urban planning strategies demand.

2. Background

Emotions are biologically-based responses to stimuli (Scherer, 2005). Evoked in situations that are seen as personally relevant, emotions constitute the main driving force of human behavior (Ekman, 1992). Physical characteristics of locations such as cities can evoke an emotion (Mody, Willis, & Kerstein, 2009), causing them to be experienced as attractive, boring, or dangerous, for example (Korpela, 2002).

Emotions thus play a crucial role in the mental construction and recollection of urban experiences. In the context of leisure and tourism, Bastiaansen et al. (2019) proposed a model based on cognitive psychology and neuroscience which demonstrates the importance of emotions for understanding experience. The model takes external and internal stimuli as a starting point, which together comprise an individual's continuous stream of consciousness. Because this stream is overwhelmingly rich in information, the mind marshals models for periods of time such as 'breakfast' and 'commute' to separate the stream of consciousness into discrete experiential episodes. Emotional arousal varies from one episode to the next, but also within each episode. If emotional arousal peaks beyond a certain threshold during a given episode, that episode prompts an action tendency (Fredrickson, 1998) and is thus likely to be remembered and acted upon. Based on this model, emotion acts as a 'switch' to determine if a given experiential episode influences memory and behavior. Thus, Bastiaansen et al. (2019) stress that to measure experience, the crucial outcome to focus on is emotion. Furthermore, they assert that emotion develops continuously over time, and should therefore be measured using the newly available wealth of physiological methods such as wearable skin conductance or heart rate (variability) measurements, in addition to self-report methods.

Certain physiological measures have been shown to be especially sensitive to emotions (Bradley & Lang, 2000; Lench, Flores, & Bench, 2011). These measures are useful for studying whether the physical layout of an environment, along with its built and natural structures, can evoke particular emotions in its users and in turn, affect the way it is perceived and experienced (Hille, 1999). One well-established physiological marker of emotion is skin conductance. Also termed electrodermal activity (EDA) or galvanic skin response (GSR), skin conductance refers to increases in the skin's ability to conduct electricity caused by an opening of the sweat glands. Two electrodes passing a weak current between one another, as those worn on the bottom of a wristband, can detect this change. Technologies such as the Empatica E4 (Empatica, 2019), a wearable wristband designed to measure skin conductance, make such measurement accessible in mobile field contexts.

Variations in skin conductance comprise physiological responses to discrete environmental stimuli. Hence, they are not only considered to be a reliable index of emotional arousal (Bradley et al., 2008), but when combined with location tracking, reveal the spatial distribution of emotional arousal (Birenboim, Dijst, Ettema, et al., 2019; Shoval et al., 2018). Coupling location measurements with physiological signals enables measuring the experiences of urban design interventions, such as singage or marking of cycling routes. Previously, research measuring the emotional effects of urban design has been largely limited to cross-sectional or repeated measures (Snizek et al., 2013) through self-report-based questionnaires or qualitative methods. The combination of physiological emotion measurement with location tracking holds several advantages over traditional self-report procedures: it is free from the well-known recall biases of self-report measures (Wirtz, Kruger, Scollon, & Diener, 2003), it reduces burden on participants, avoids disrupting the experience being measured, is ecologically valid, and can log in-situ, continuous, high spatiotemporal resolution measurements of emotional arousal (Bastiaansen et al., 2019; Birenboim, Dijst, Scheepers, et al., 2019). By ecologically valid, we mean that physiological measurements assess experiences as they naturally happen, without researcher intervention, in their appropriate environmental context.

Ecological validity of most previous physiological research on emotions has suffered from participants' laboratory experiences being rather different than a real-life visit to an urban space. While recent studies on cycling experience have made considerable advancements in simulating real-world environments in laboratory settings, they still tend to be perceived as artificial. This was observed in Birenboim, Dijst, Scheepers, et al. (2019), which demonstrated how even though immersive virtual environments offer higher levels of realism to participants, they are still found to be artificial in test–retest reliability. Similar outcomes were observed in Ellard (2017)'s research, which explored connections between emotion and urban design using high-immersion virtual environments. With wearable recording equipment now readily available, physiological measurements are increasingly being used in ecologically-valid urban settings (Birenboim, Dijst, Scheepers, et al., 2019; i Agust'ı et al., 2019; Shoval et al., 2018). The results of mobile in-situ emotion measurements are directly applicable to urban planning for decision support and the evaluation of ongoing planning processes (Resch et al., 2015; Nold et al., 2009). Urban planners can gain valuable insight into which spatial configurations and environmental features (e.g., open green spaces, dense urban spaces) trigger emotional arousal in visitors and residents. Emotionally stimulating areas can be identified and then emphasized or removed, respectively.

Previous research has linked physiological measures of emotional arousal with location (Nold et al., 2009; Zeile et al., 2009; Sagl, Resch, & Blaschke, 2015; Resch et al., 2015). The interest in mapping emotion has since continued to grow within urban spatial analytics (Birenboim, Reinau, Shoval, & Harder, 2015; Birenboim, 2016; Birenboim, Dijst, Scheepers, et al., 2019; Shoval et al., 2018; Hijazi et al., 2016; Zeile, Höffken, & Papastefanou, 2009, Zeile et al., 2013, Zeile et al., 2015, Zeile et al., 2016). These studies are based on urban walking experiences, and the measured data are usually interpreted in terms of proximity to urban features. Yet, being *near* a certain urban feature does not mean that it is actually *experienced* or even sensed. Many of these studies' analyses involve deriving a map and describing it, without statistical modeling (with the exception of Hijazi et al., 2016).

Two notable studies (Schmidkunz et al., 2019; Zeile et al., 2016) combined skin conductance recording with location tracking of a cycling experience, focusing on stress and safety in urban cycling contexts. By taking a bio-physiological sensing based, mixed-methods approach, these studies demonstrate how infrastructure inter-user conflict can play a principal role in sparking emotional responses from cyclists. However, these studies are qualitatively described, rather than being modeled statistically, making comparison from one study to another difficult. Moreover, experiences of combined urban and inter-urban travel using e-bikes have yet to be covered.

Cycle highways are a relatively new type of urban infrastructure that offer healthy and environmentally-friendly alternatives to motorized transportation within and between nearby cities. Planning cycling highways for optimal rider experience is important to ensure they are used, and that their users benefit from these investments. Stressful or unpleasant cycling experiences are likely to be recalled and unlikely to be repeated, reducing cycle use and possibly contributing to increased automobile use. Furthermore, the increased popularity of e-bikes presents differing infrastructure requirements, and new challenges to solve. For example, conventional signs are designed for average cycling speeds of 15 km/h, whereas most riders on e-bikes can easily reach 25 km/h (Solymosi, Bowers, & Fujiyama, 2015). Current infrastructure includes rough paving, sharp turns, and small signs parallel to the direction of travel, which are inadequate for navigating at these higher speeds. Thus, mapping and statistically analyzing cyclists' experiences can help gather

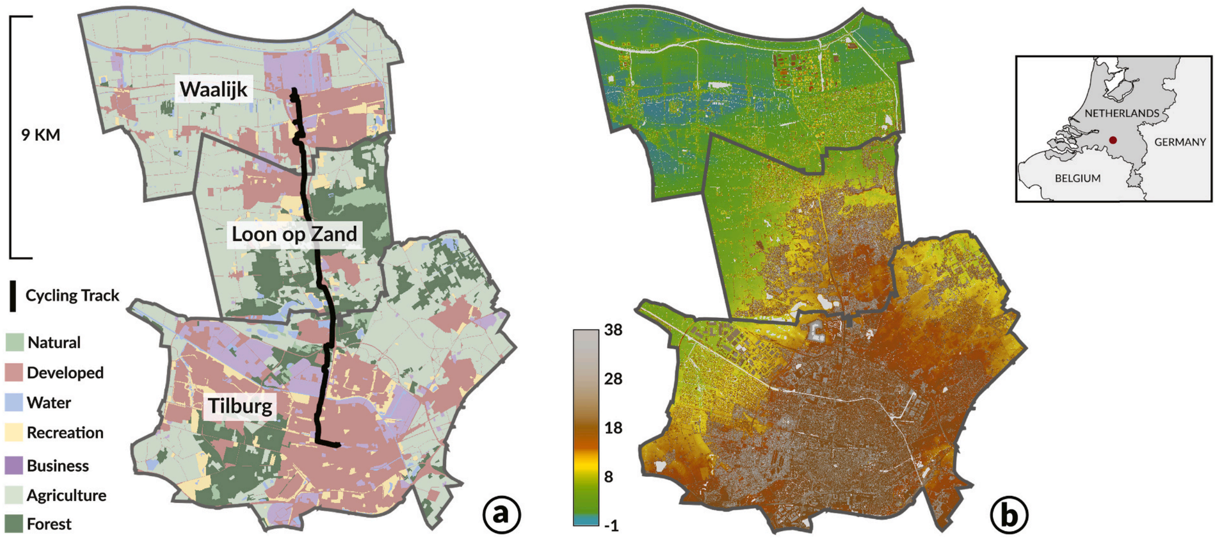

Fig. 1. Study area containing the cycling highway participants took connecting the municipalities of Tilburg, Loon op Zand, and Waalwijk: (a) land cover type and the cycling route, buildings, and vegetation; (b) digital surface model including elevation [m] of bare ground, buildings, and vegetation. Both data layers were developed at half-meter resolution.

insights into spatiotemporal dynamics of emotional arousal, and help city planners respond to changing infrastructure requirements. We expect areas where infrastructure poses a known problem to lead to more emotional arousal in users. We also believe that unique sights along the route will trigger emotional arousal. Furthermore, we focus on experience of visual stimuli, as sight is the dominant sense in triggering emotional responses (Kalat, 2015), and the other senses are difficult to model across space using secondary geospatial data.

Our goal in the present study is to extend the existing research in several ways: First, we apply physiological methods to the experience of cycle highways and using e-bikes for urban and inter-urban travel. Second, by calculating viewsheds of what cyclists would see at a dense systematic sample of points along their ride, we link their experience not only to a location, but to a metric of the actual visual stimuli present at a given location. Third, we move beyond merely mapping relationships between visual stimuli and emotional arousal by modeling it statistically with multilevel models, which nest stimulus-arousal effects within participants. Fourth, we surpass aggregated considerations of space and time by developing a dynamic, interactive, web-based mapping system to visualize fine-grained dynamics of environmental exposure and experience. Overall, our approach serves two main goals:

1. Establish a methodological framework for spatiotemporal modeling of emotional reactions to urban experiences and develop a dynamic web-based mapping system to interactively visualize these reactions.
2. Determine how environmental stimuli along a cycle highway influence e-bike users' emotional arousal.

To carry out these objectives, we established the following research question:

1. How does extent of a given land cover type in a electric bicycle rider's view affect her or his level of emotional arousal, while controlling for ride speed, direction, and distance to automobile roads, and how do changes in direction (turns) explain additional variation in skin conductance when the other variables are accounted for?

We address these goals and question in the context of e-bike rides on a cycle highway connecting the Dutch cities of Tilburg and Waalwijk.

3. Methods & data

3.1. Study region

Our study took place on the F261 cycle highway from Tilburg via Loon op Zand to Waalwijk, Netherlands (Fig. 1). It has been established as a demonstration route for research on how various traffic situations and bicycle infrastructure affect cyclists' experiences. It is 18 km long, is approximately evenly divided between urban and rural environments, and connects the municipalities of Tilburg, Loon op Zand, and Waalwijk. Tilburg is one of the Netherlands' larger cities (6th; 219,632 residents) and has an urban, industrialized character, with numerous factories and businesses.

North from Tilburg, the cycle highway moves past two of the country's most important tourism attractions: the Efteling, which is the world's oldest theme park, having opened in 1952, and the Loonse en Drunense Duinen, a national park containing a unique inland dune field. These two attractions flank the village of Loon op Zand. The cycle highway's north end terminates in the town of Waalwijk, which is significantly smaller than Tilburg (population 48,240) but features large shopping centers on its southern side. In this area, the cycle highway also crosses the busy A59 motorway. Thus, the ride featured a mix of urban and rural landscapes, with frequent changes in land cover type across the viewshed (Fig. 1).

3.2. Procedure & participants

12 participants (4 female, 8 male) unfamiliar with the cycling route were recruited for this study. Half ($N = 6$) of participants' ages ranged from 18 to 24 years old ($M = 21$), while the remaining half were 55 years or older ($M = 65$). We used a purposive sampling approach in selecting participants. Since we were focusing on a newly designed type of infrastructure, we chose half of our sample from an older population, who are likely to cycle recreationally, often while exploring new locations, and use existing infrastructure to do so. For comparative purposes and ease of recruitment, younger individuals were selected for the other half of the sample, who were majorly students. In selecting from these two populations, we eliminated groups for which we thought the new infrastructure was less relevant, especially in terms of the unique e-bike oriented signage. This approach specifically allowed us to exclude individuals who have perhaps become too accustom to their daily ride, or

sport cyclists who use personal navigation units. While relevant to data collection procedures, statistically modeling differences between the older and younger subgroups was beyond the scope of the present paper. However, we recommend future research efforts to carry out such a comparative investigation, as differences in personality, biological sex, and age can all substantially modulate the evaluation and memory encoding of emotional experiences (Larsen & Diener, 1987).

Participants were asked to provide information on their weekly cycling habits. Younger participants, mostly university students, reported cycling functionally 3 days a week ($M = 20.4$ min per day), while those 55 years or older cycled 2.5 days a week ($M = 22.6$ min per day). Recreationally, younger participants cycled roughly 1 day a week ($M = 23.4$ min per day) and older participants cycled 2 days a week ($M = 4$ h per day).

Participants were instructed to stay on the cycle highway for the entirety of the route. None of the participants were familiar with the route and they all used the signposting, infrastructural layout, and other indicators to find their way. Participants were randomly split in half for the direction of the ride. Half of participants cycled in the direction from Tilburg to Waalwijk, while the other half cycled in the opposite direction. Gazelle e-bikes were ridden by participants, with electric pedaling support limited to a speed of 25 km/h, in line with Dutch law. Cycling faster than 25 km/h means that the electrical support stopped and cycling became more strenuous. Thus, riders were not able to exceed this point. The bicycles offered three levels of powered assistance, from which participants were free to choose. A researcher riding along with participants used the same make and model of bicycle.

The choice to have a researcher 'ride along' with participants presents a compromise among several limitations faced during data collection. On one hand, we wanted participants to navigate the cycle highway by themselves. This was in consideration of data collection's secondary focus—the function of signage and wayfinding. On the other hand, we wanted participants to stay on the cycle highway to spatially align their experiences as much as possible. Thus, we had a researcher ride along with participants to correct any navigation errors, rather than explain the route beforehand or provide any type of navigation technology. Otherwise, it is likely any effects of signage would have been overlooked. This approach thus gave us the opportunity to: 1) allow participants to self-sufficiently navigate the cycle highway and 2) ensure they remained on the F261 cycle highway. Prior to their cycling journey, they were given clear instructions not to converse with the researcher nor ask them questions when cycling. The researcher only interrupted when participants became lost, or started going in an incorrect direction. Additionally, the researcher recorded any locations where participants may have hesitated or became confused. As soon as they completed their cycling journey, the researcher administered post-interviews to each participant. During which, the researcher used the information gathered on potentially confusing regions of the cycle highway to unveil how participants might have felt during such situations or what may have caused these situations, such as improper signage (Hoeke, de Kruijf, & Soemers, 2019).

3.3. Mobile data collection

3.3.1. Location & speed

Location data were collected through a dedicated smartphone application. The application utilized both the smart phones' GPS and the cellular network location to record participants' location as well as speed and approximate elevation (see Fig. 2). Collected time-stamps (Table 1) allowed for synchronization with skin conductance response data, a key aspect when analyzing skin conductivity as it allows for accurate logging of start- and end-times of specific physiological episodes.

Table 1
Descriptions, sampling devices, processing software, and sampling rates associated with various human movement, physiology, and environmental location data variables.

Variable	Description	Device [Software]	Sampling Rate
Human Movement & Physiology			
Init_time	Time stamp in Unix time	Empatica [Ledalab]	4Hz
Init_time_mat	Time stamp in datetime format	Empatica [Ledalab]	4Hz
Time	Sampled at a frequency (s)	Empatica [Ledalab]	4Hz
Datatype	Type of data (SCR or GPS)	Empatica [Ledalab]	4Hz
Conductance	Raw Electrodermal Activity (EDA)	Empatica [Ledalab]	4Hz
Conductance_z	Z-transformed EDA	Empatica [Ledalab]	4Hz
Tonic_z	Z-transformed SCL	Empatica [Ledalab]	4Hz
Phasic	Raw SCR	Empatica [Ledalab]	4Hz
Phasic_z	Z-transformed SCR	Empatica [Ledalab]	4Hz
Environmental Location			
Latitude	Coordinate data (northing)	Mobile GPS [R — GRASS]	1Hz
Longitude	Coordinate data (easting)	Mobile GPS [R — GRASS]	1Hz
Altitude	Height above sea level (m)	Mobile GPS [R — GRASS]	1Hz
Distance	Meters from starting point	Mobile GPS [R — GRASS]	1Hz
Speed	Current velocity (km/h)	Mobile GPS [R — GRASS]	1Hz

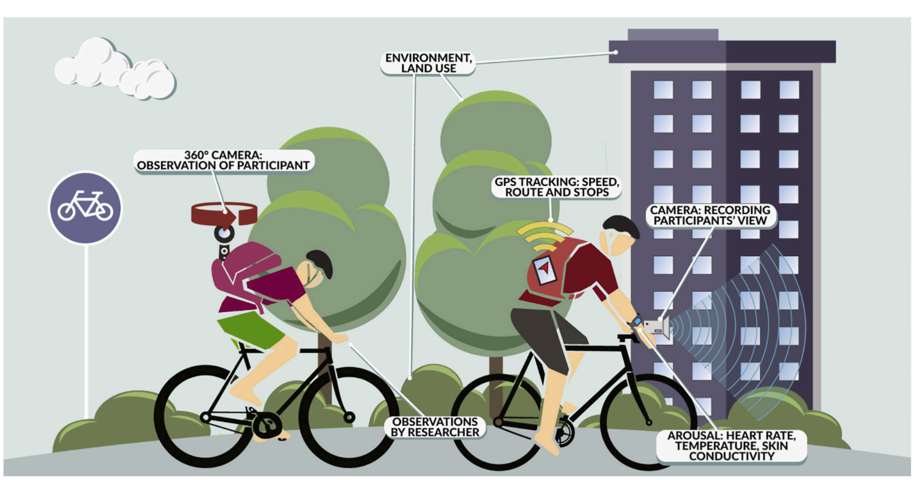

Fig. 2. Data capturing process.

The high sampling frequency of the location data (Table 1) resulted in an unrealistic, noisy speed variability. We used weighted moving average with a 60-s moving window to compute smoothed speed along the cycle highway for each participant. The weights were linearly decreasing from 1 at the current point to 0 at the window limits and subsequently, the weights were re-normalized so that they summed to 1. In this manner, the mean was unaffected while the noise decreased roughly by an order of magnitude, while longer intervals of break in speed due to stops were still well represented.

3.3.2. Emotional arousal

We used skin conductance responses as a continuous, time-varying measure of emotional arousal. As cyclists biked along the track, their skin conductance was measured using a wrist-worn Empatica E4 wearable, which uses two active electrodes on the bottom of the wrist. Skin conductance was recorded at a rate of 4 Hz. It is well-established that raw skin conductance signals result from two separate processes—rapid responses to emotional stimuli, and gradual change due to differences in temperature, physical activity, and the wearing of a sensor against the skin (Braithwaite, Watson, Jones, & Rowe, 2013). The former component, known as phasic skin conductance or skin conductance responses (SCR), is the metric which indicates immediate peripheral nervous responses to emotion stimuli.

Skin conductance responses were derived from the raw skin conductance signal in Ledalab (Karenbach, 2005), a MATLAB-based (MATLAB, 2018) software for the analysis of raw EDA data. To carry out this process, we first used a moving window of 20 s on raw, unprocessed skin conductance data to identify deviations of 3 standard deviations or more as potential motion artifacts. These deviations were visually inspected and if they failed to conform to a standard, physiologically-plausible shape for a SCR—specifically a decline which lasted at least 3 or more seconds after a peak—were replaced with linear interpolation. Cleaned data were then deconvoluted using the Ledalab toolbox into phasic and tonic components. Ledalab implements the method of continuous deconvolution, wherein frequencies of change are used to mathematically separate out changes in nerve activity that drive skin conductance responses, and gradual changes due to skin conductance level. The former is considered a valid and reliable metric of emotional arousal, with a baseline near 0, reached between occasions of emotional stimuli, and sharp increases immediately after the onset of a stimulus. The remaining tonic signal changes over a course of minutes or hours in response to physical activity and environmental conditions. After deconvolution into these two components, we retained the phasic component as a continuous, time-indexed metric of emotional arousal, which became the dependent variable in our statistical models (R Core Team, 2017). We z-standardized the phasic signal to reduce differences between participants in the average amplitude of skin conductance responses, as discussed by Braithwaite et al. (2013).

As mentioned earlier, the physiological data were georeferenced through a time-based synchronization of the SCR data with GPS location data. To preserve the higher frequency of physiological measurements, the SCR data were assigned to the closest GPS location collected at 1 Hz frequency. To further enhance the precision of the location associated with each physiological measurement, the GPS locations can also be interpolated to match the 4 Hz frequency. The entire data set, consisting of over 180,000 georeferenced physiological measurements, was then re-projected to the local coordinate reference system (Amersfoort, EPSG: 28992) to facilitate integration with the geospatial data sets and analysis.

3.4. Static geospatial data

To develop a digital surface model (DSM) and a land use map, we used three geospatial data sets. These included orthoimagery, airborne lidar point cloud, and vectorized buildings, roads, and other land use features downloaded from the official open data repositories[1]. See Fig. 1 for an overview of the processed geospatial data used as input for the analysis, and the Appendix[2] for the full Jupyter notebook environment containing all used data and detailing cloud-executable code of the employed analyses.

3.4.1. Elevation

We used lidar point cloud to generate a detailed model of the environment. Several studies have demonstrated that high resolution lidar-derived DSM improved accuracy of visibility calculations compared to lower resolution (Klouček et al., 2015) and bare ground surfaces (Vukomanovic, Singh, Petrasova, & Vogler, 2018). Thus, DSM was interpolated from first-return lidar points at 0.5 m resolution to provide input for computation of viewsheds along the cyclists path while capturing the impact of buildings and other structures (Fig. 3). We used a regularized spline with tension algorithm implemented in GRASS GIS to balance the smoothness and approximation accuracy of the interpolated elevation surface (*v.surf.rst*[3] module; Mitasova, Mitas, & Harmon, 2005).

3.4.2. Land use

Visual perception of environmental features often has a significant impact on how cyclists value their environment and the trips themselves. Within the current context, environmental features were obtained using the data set 'Bestand Bodemgebruik' (BBG), or 'Resistant Land Use', maintained by Statistics Netherlands (CBS, 2018). Based on previous research in the Netherlands using similar data (Jansen, Ettema, Kamphuis, Pierik, & Dijst, 2017), these extensive land classification data were categorized into seven overarching land use groups: 1) developed, 2) natural, 3) recreation, 4) water, 5) business, 6) agriculture, and 7) forest. Developed areas were classified as either built or semi-built up land. Built land contained residential areas, retail areas, and public facility areas, for example. Semi-built land included cemeteries, dumping grounds, and junkyards. Natural areas in the vicinity of the cycle highway were constituted by open terrain, consisting of either dry or mixed vegetation. Recreation contained places frequented for leisure like sports areas, and amusement parks. Any area described as containing a body of water such as rivers, was also defined. Agricultural areas contained greenhouses, or land used for general agricultural purposes. The polygon-based land use layer was then converted to 0.5 M resolution raster representation.

The chosen categorization of land cover types is a simplified yet necessary perspective on the visual stimuli offered by this landscape to a cyclist in motion. We felt that seven land cover types offered a reasonable compromise among 1) representing visual stimuli as realistically as possible, 2) creating a statistical model of emotional arousal based on sufficiently few parameters that it can be readily estimated and interpreted, and 3) grouping the visual stimuli experienced along this particular cycle path in sufficiently few types so that each type comprises a substantial number of data points.

4. Analysis

4.1. Distance to roads

Since our analyses were interested in potential dependence between distance from environmental features and associated skin conductance values, we used *v.distance*[4], a GRASS GIS (Neteler & Mitasova, 2008) module to map the distances between each cyclist's location point and the closest roads. These were stored for later statistical analyses to determine possible relationships between how far away cyclists were from roads and observed levels of emotional arousal.

4.2. Viewsheds

Viewsheds, the portions of a landscape visible from a given point or set of points (Wilson, Lindsey, & Liu, 2008), are computed on a DSM

Fig. 3. High resolution digital surface model (DSM) in Tillburg, with two tall buildings and a segment of the studied route. Orthophotography is draped over the DSM.

based on a line-of-sight method. To perform this analysis, we used the GRASS GIS *r.viewshed*[5] module, which employs a computationally efficient algorithm (line-sweeping method) suitable for deriving viewsheds on a high-resolution DSM (Haverkort, Toma, & Zhuang, 2009).

The viewsheds were computed for 1739 viewpoints evenly distributed along the cycling highway at 20 m intervals. These points were used twice, as required to derive viewsheds for each riding direction, resulting in a total of 3478 data points for statistical modeling. Considering the marginal increase in a person's height when riding a bike, the viewsheds were computed on the 0.5 m resolution DSM slightly above eye-level–1.75 m–to simulate a typical viewpoint while riding a bicycle. Cyclists' maximum range of visibility was set at 1000 m. The static cut-off distance of 1000 m was selected after careful evaluation of line of sight in this flat terrain. Our preliminary computation of viewsheds indicated that the range of views is within 1 km, and often times, was much less as buildings and vegetation limited views along the bike route. Additionally, we limited cyclists' horizontal viewing angle to 180°. The viewing angles were computed based on the directions participants were traveling along the cycle highway, and were set in degrees counterclockwise (East is 0°), between 0° and 360° (Fig. 4b).

Viewshed maps were then intersected with land cover data and zonal statistics were applied to extract proportional contributions of each visible land cover class (e.g., buildings, forest) within the total visible area, creating 'visible land cover maps'. These maps are high-resolution visualizations of participants' environmental interaction as it unfolds over time, within both natural and built conditions (Fig. 4d). By coupling these with associated *Z*-transformed SCR data (phasic z), we can then statistically associate variations in the cyclists' perceptual and related mental states as they experience their environment.

4.3. Statistical modeling & visualization

Because the data were nested within participants, we took a within-participants multilevel modeling approach using the *lmer()* (Bates, Mächler, Bolker, & Walker, 2015) function in R. The specific modeling approach used—within-participant random intercept models—models unique variance in a time-variant outcome as a function of time-variant predictors for an average participant, while controlling for baseline (intercept) differences between participants in the outcome variable. The data resolution was limited by the resolution of the calculated viewsheds to one data point per 20 m. This was the maximum possible resolution given computational limitations. The distribution of points translates to a temporal resolution of 0.278 Hz, or once per 3.67 s. Because our central question was to determine the effects of environmental stimuli on experience, we used variables representing stimuli—extent of viewable area in different land cover types, direction, distance to road, and speed—as predictors. We used a variable representing the level of emotional arousal experienced, quantified as phasic skin conductance responses, as the outcome. We compared this model using an F-test to a model with no predictors to establish its overall predictive value, before applying the Satterthwaite approximation of T-value to determine the statistical significance of each parameter. Thus, each parameter in the model represents the statistical relationship between the visible extent of a particular type of landcover and emotional arousal within the experience of the average participant.

We took a hierarchical approach to making the model more complex

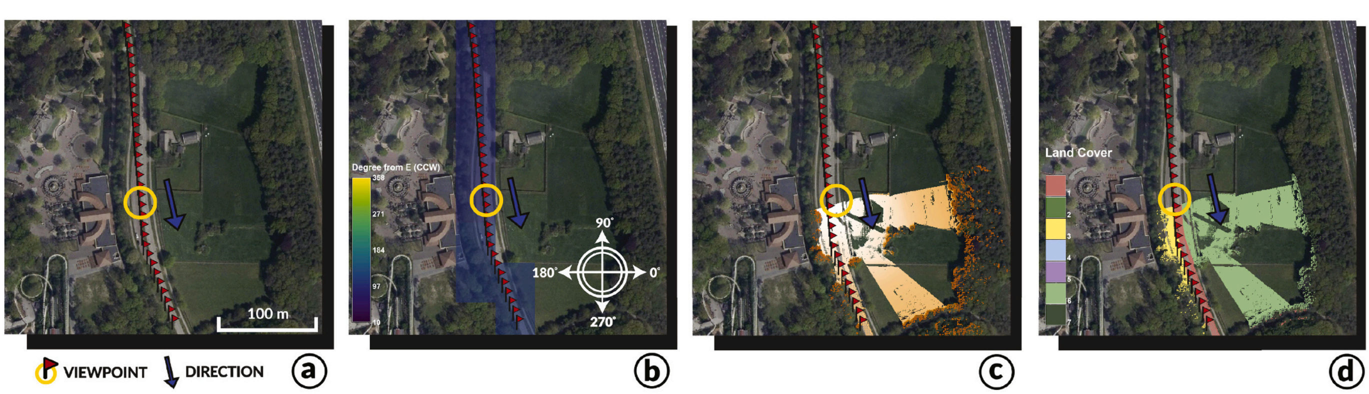

Fig. 4. Procedure for computing viewshed for a single viewpoint: (a) viewpoints were set along the cycling highway at 20 m evenly distributed intervals; (b) riding direction angle was established with line direction in degrees counter-clockwise from east; (c) binary viewsheds were generated on the DSM, horizontally limited to 180°; (d) viewshed maps were then intersected with land cover data layer to extract visible land cover classes.

as a way of addressing the second part of our research question. As previous research based on the same participants emphasized the importance of turns during navigation to the overall experience, we added a measure of directional change to the model, once again using the F-test to determine if this constituted an improvement in model fit. The added parameter, directional change, represents the relationship between how much participants were turning in a given moment based on temporally proximal data and their emotional arousal, while holding visible land cover constant.

Finally, to move beyond an aggregated consideration of space and time, we have developed a dynamic, interactive web-based mapping system capable of: 1) registering linkages at individual and grouped levels, 2) visualizing high-resolution spatiotemporal, geographically contextualized, interpretable data, and 3) allowing researchers to investigate various aspects of environmental exposure and experience simultaneously.

5. Results

5.1. Descriptive statistics

To summarize and graphically represent descriptive statistical results from the measured data, we used a hexagonal binning process–a technique for synthesizing geographical data which groups pairs of locations based on their distance from one another across a spatial grid. The hexagonal grids were generated using *v.mkgrid*[6], which creates a vector map representation of a regular coordinate grid. Then, *v.vect.stats*[7] was used to compute and display spatial distributions of the phasic skin conductance and speed variables along the cycling route, grouped by their respective average and standard deviations. Fig. 5 shows the resulting gridded hexagons, generated at 300 m resolution. These spatially distributed summary metrics indicate prevailing lower values of phasic skin conductance in urban areas, while higher phasic skin conductance values are seen midway along the route in more rural settings (Fig. 5).

5.2. Multilevel models

Our initial model (Table 2) examined the relationships between visible area extent of seven different landcover types and emotional arousal while controlling for ride direction, speed, and proximity to

Table 2
Mixed-effects linear models of the connections among viewable land cover, speed, direction, distance to roads, direction changes, and emotional arousal.

Predictor(s)	Fixed effect CE	SE	T	Model AIC
Model 1				
Developed in view	−0.000002	0.0000002	−10.203***	
Natural in view	−0.000023	0.000025	−0.903	
Recreation in view	0.0000068	0.0000016	4.221***	
Water in view	0.0000023	0.0000037	0.643	
Business in view	−0.0000022	0.0000006	−3.418***	356399.8
Agriculture in view	0.0000014	0.0000002	5.172***	
Forest in view	0.0000378	0.0000017	22.171***	
Speed (km/h)	−0.0145064	0.0003125	−46.416***	
Direction	−0.2884326	0.2334752	−1.235	
Distance to road	0.0098596	0.0003992	24.693***	
Model 2				
Developed in View	−0.0000016	0.0000002	−6.229***	
Natural in View	−0.0000299	0.0000256	−1.170	
Recreation in View	0.00000634	0.00000161	3.921***	
Water in View	−0.00000002	0.00000368	−0.004	
Business in View	0.00000077	0.00000065	1.182	
Agriculture in View	0.00000070	0.00000028	2.531*	355591.9
Forest in View	0.00003474	0.00000171	20.361***	
Speed	−0.01495816	0.00031218	−47.916***	
Direction	−0.28314307	0.23396383	−1.210	
Distance to Road	0.00871448	0.00040035	21.767***	
Direction Change	−0.00075514	0.00002650	−28.494***	

Note: Signif. codes: 0′***’ 0.001′**’ 0.01′*’ 0.05′.’ 0.1″ 1.

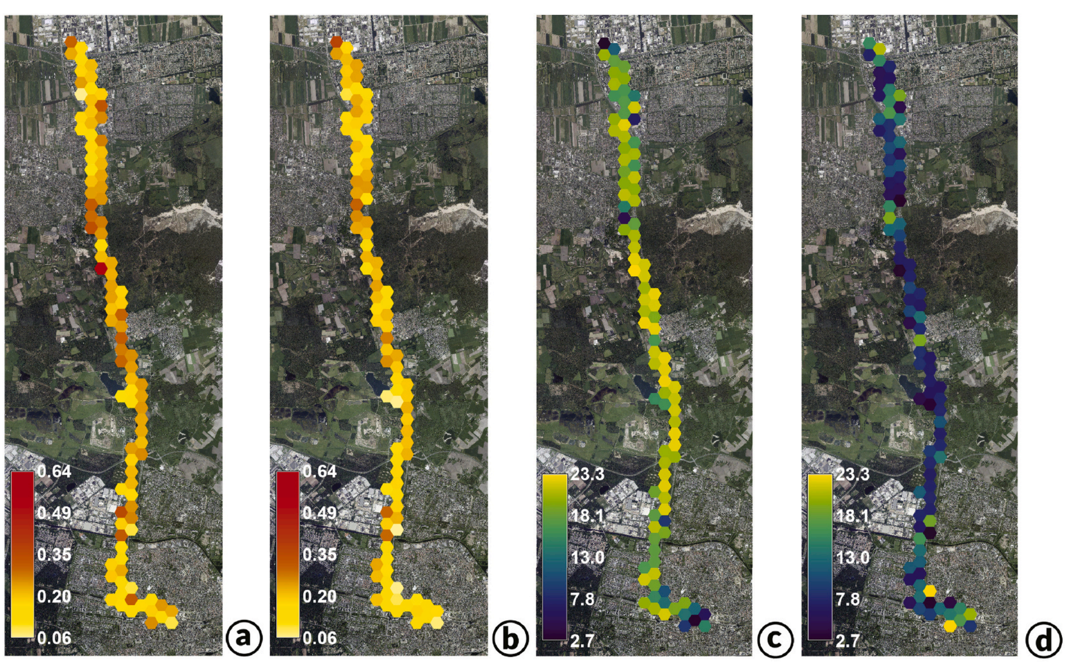

Fig. 5. Result of the hexagonal binning process at 300 m resolution. These maps represent the spatial distributions of the (a) averages and (b) standard deviations of phasic skin conductance [μS] and the (c) averages and (d) standard deviations of the smoothed speed variable in [*km*/*h*]. Both maps are overlaid on the orthophotography.

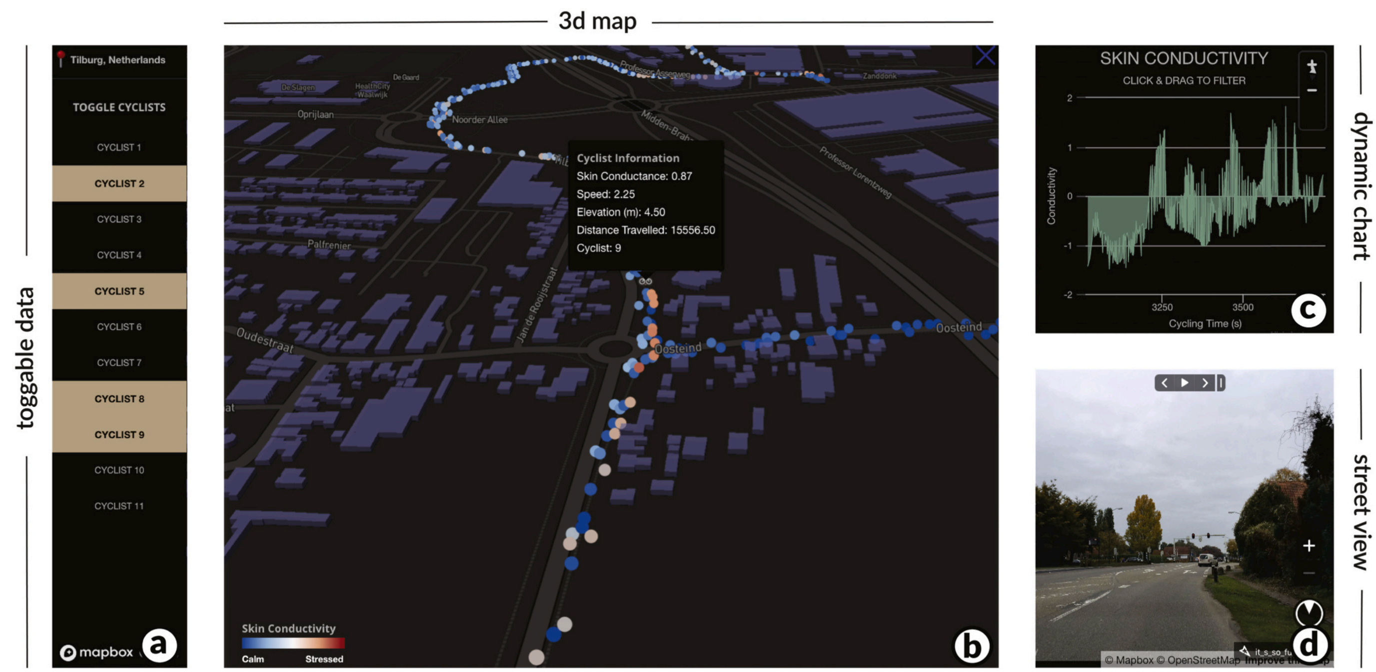

Fig. 6. Web-based dynamic visualization of georeferenced physiological data: `gcmillar.github.io/e-motion/`.

roads. This model was significantly better than a null model (*AIC* = 356,400; *LL* = −178,187; *Chi-square* = 4143.1; $p < 0.001$). Of the control variables, distance to roads was positively related to emotional arousal, while speed was negatively related to emotional arousal. In other words, within the average participant, the most intensely emotional moments were relatively further from roads and at lower cycling speeds, holding visible area extent of different landcover types constant. Direction, namely whether participants cycled from Tilburg to Waalwijk or vice versa, was unrelated to emotional arousal. The visible extent of five landcover types had a significant effect on emotional arousal. The extents of viewable recreation, agriculture, and forest areas were positively related to emotional arousal, while the extents of developed and business areas were negatively related to emotional arousal (all p's < 0.001). Thus, while holding distance to roads, speed, and direction constant, participants became more emotional in large viewable areas managed for natural resource uses. They became relatively less emotional in large viewable human-built areas.

We then entered the variable of directional change into the model, which captures the extent to which participants were turning rather than riding straight in a given moment. This addition resulted in a better fitting model (*AIC* = 355,592; *LL* = −177,782; *Chi-square* = 809.93; $p < 0.001$). The effects of control variables on emotional arousal did not change in direction or significance. The effects of visible extent of landcover types also did not change in direction or significance, except the effect of business landcover became non-significant ($p = 0.24$). The variable of interest in this analysis, extent to which participants were turning, was negatively related to emotional arousal ($p < 0.001$). In other words, the more steeply participants were turning, the less emotionally aroused they were, holding direction, speed, proximity to roads, and extent of viewable landcover type areas constant.

5.3. Dynamic visualization

The main view of the dynamic visualization system and its user interface is shown in Fig. 6. Its components, key views, and interactive features are described below. The implementation is mainly based on Mapbox GL JS, a JavaScript library that uses WebGL to render interactive maps.

Toggable Data: With toggable data (Fig. 6a), we can seamlessly switch back and forth between different cyclists. This is important to explore variability in skin conductance across multiple participants.

3D Map: The 3D map view (Fig. 6b) provides an overview of the cyclists' physiological responses within the spatial context, including the effects of buildings. It allows us to display data as a 2D map or zoom-in and explore details in a 3D perspective view. The 3D view facilitates visual assessment of data location accuracy in relation to the buildings and transportation infrastructure, queries all attributes associated with each point, and visually analyzes spatial patterns of attribute values using colored point symbols. The 3D mapping platform thus serves as a valuable feature for exploration, analysis, and interpretation of complex human physiology data across urban landscapes.

Dynamic Graph: The dynamic graph (Fig. 6c) shows the temporal distributions of cyclists' collective (or individual when only one cyclist has been selected) physiological patterns. This chart dynamically displays all data that is currently loaded into the map frame. As we zoom in and out and pan around in the map, the chart automatically updates with a spatiotemporal overview of complex, highly dynamic human physiological data.

Automatic Street View: Using Mapillary[8], a crowd-sourced alternative of street-level photographs to Google Street View, the automatic street view (Fig. 6d) allows us to more naturally and realistically inspect areas and their surrounding environmental features at a given time and thus, provides more realistic insight into the complexities of moving through and directly experiencing 3D space. With this capability, our application derives information that is not visible on aerial imagery, for example type of traffic sign, or to map features that would require in-person exploration through field surveys (Juhász & Hochmair, 2016). While a researcher did observe and collect video recordings of the participants' journey along the cycle highway, we opted for a more automated approach using Mapillary. This was done to ensure the application's reproducibility and applicability to a wide variety of use cases. Specifically, if researchers or users did not collect videos or similar imagery during their research efforts, they can still adopt the application for their research needs. Yet, Mapillary is a community-led service which fully relies on the street-level photos captured and uploaded by its users, and thus, is prone to containing improperly captured street-views. For example, we encountered street-level views impeded by passing traffic, for example. Thus, we intend on supplementing Mapillary's preexisting database with high-resolution video recordings, as collected by GoPros used in our study. Overall, the 3D viewer visualization and user interaction components enabled us to explore multiple data sources and related spatiotemporal details of fine-grained dynamics of human physiology. It was essential for informing the development of workflows for data processing and for interpretation of the results.

6. Discussion

The principal aim of the present study was to determine how the visible environment affects individuals' experiences of an inter-urban cycling highway. Twelve participants cycled the cycle highway between Tilburg and Waalwijk while their location and skin conductance were recorded. We used a multilevel model to determine the relationships between extents of different types of viewable land cover and emotional arousal, operationalized as phasic skin conductance, while controlling for speed, direction, and distance to roads. We subsequently added a measure of directional change to the model, which significantly improved its fit. This definitive model suggested that ride segments containing relatively less developed and more recreational, agricultural, and forest land cover in view, were more emotionally arousing for participants. Conversely, segments which were more developed and less covered in visible recreational, agricultural, and forest land cover were less arousing. These patterns occurred over and above the positive effect of distance from roads and negative effect of speed, as well as the negative effect of turning, on emotional arousal. Thus, in locations of similar land cover, slower, straighter segments which were further from roads were experienced by participants as more emotionally arousing.

Several studies have shown that emotional arousal is elevated with cities, usually being seen as exciting and stimulating places. This was seen in Zeile et al. (2009, Zeile et al., 2016), which deemed less-busy streets as more calming. However, these studies relied heavily on aggregate techniques for assessing spatial-emotional interactions at the individual level. Our model, in contrast, nested both external visual stimuli and movement variables such as speed and turning within the experience of the average participant. In so doing, along with holding confounds to emotional arousal constant, it is possible that the enjoyment of large, open, green views may instead involve elevated emotional arousal, not cities. This is reasonable to assume when considering the relatively functional experience navigating urban areas entails, such as Tilburg and Waalwijk. It is also important to remember that many Dutch cities, including Tilburg and Waalwijk, have a culturally-rich central core surrounded by large, more open commercial and industrial areas. Thus, these larger developed views may have been perceived as boring, and thus relatively low in emotional arousal. It is more likely, however, that emotional arousal as we measured it—according to phasic skin conductance, which spikes whenever an individual feels any emotional arousal, positive or negative—did not reflect a single (positive or negative) direction of emotional valence. In this way, our findings echo the caution of i Agust'ı et al. (2019) to combine physiological findings with various self-report data, as simply mapping physiological signals across space does not do justice to the complexity of emotion. Uncorrelated emotion measures, as i Agust'ı et al. (2019) has found, are not necessarily inaccurate, but rather represent independent components of emotion experience (Mauss and Robinson, 2009).

It is important to interpret the present results with a significant measurement limitation in mind, namely, that physiological measures of emotion have so far been validated to only measure arousal, not valence. Valence refers to the extent to which an emotion is positive (pleasant) or negative (unpleasant). The consensus in emotion psychology is that valence and arousal are independent dimensions and thus require separate measures (Mauss and Robinson, 2009). A large synthesis of emotion psychophysiology studies shows consistent links between some measures, such as skin conductance, and emotion arousal, but few consistent links between physiology and valence (Kreibig, 2010). The valence of emotions in the cycling experience is crucial for urban planning decisions, however, and must be obtained in future research using other, most likely self-report based methods. These include questionnaires, as well the use of physiological data to elicit qualitative explanations and interpretations from participants, a method pioneered by Nold et al. (2009).

According to Brakus, Schmitt, and Zarantonello (2009), all perceptions start with the eye. That is, human sight is the main driver behind human perception (Brakus et al., 2009) and consequent experience (Kalat, 2015). Past research has relied on qualitative assessments to establish aesthetic judgments of urban and nature-based locations (Kirillova et al., 2014; Kirillova & Lehto, 2015; Kirillova, Lehto, & Cai, 2017). Walking in urban locations has also been studied using methods similar to ours, namely a combination of location tracking and physiological measures of emotion, first by Nold et al. (2009), and more recently by i Agust'ı et al. (2019), Shoval et al. (2018), Birenboim et al. (2019b), and others. We extend this research in several ways. First, we bring the approach of combining location and physiological measurement to cycling. Doing so allowed us to demonstrate that wearable measurement of emotional arousal is possible during cycling, affirming the promising findings of Zeile et al. (2016) and Schmidkunz et al. (2019). Furthermore, we show that such data can form a foundation for maps, statistical models, and interactive 3D visualizations of the (inter) urban cycling experience. Second, we model the relationship between these variables using a multilevel statistical model. This model revealed that in the present study context, relatively natural interurban visual stimuli were relatively more emotionally arousing for e-bike cycle highway users. Third, this model uses visual stimuli derived from location information using viewsheds, rather than merely location or proximity, as a predictor. Thus, we incorporated the perceptual variable of sight to explore relationships between environmental interaction and resulting physiological responses. Simple spatial proximity to an environmental feature does not imply true environmental interaction and experience. Specifically, one can be cycling past an amusement park with yet a low ability to view it due to surrounding tree coverage, speaking to the true value of viewsheds for establishing more accurate environment interaction metrics. This claim is made with caution however, as people still remain capable of developing experiences from multiple sensory inputs. For example, smell, sight, and sound, even when transmitted from long distances, can be simultaneously received, processed, and integrated for immediate experiential development (Blauert, 1997; Dalton, Doolittle, Nagata, & Breslin, 2000; Wickens, 2008; Wolfe et al., 2006).

In contrast to other studies linking location with physiological measurement of emotion, we measured an experience that included both urban and rural settings. Of these, rural land cover area were predictive of higher emotional arousal, whereas land cover area associated with urban settings, especially industrial areas on the urban fringe, predicted lower emotional arousal. This contrasts somewhat with the portrayal of urban areas being necessarily exciting compared to rural settings that is occasionally mentioned in the literature (Shoval et al., 2018; Zeile et al., 2009, Zeile et al., 2013, Zeile et al., 2015, Zeile et al., 2016). Thus, this finding in particular deserves further exploration using self-report methods which can also capture emotional valence.

Ellard (2015) stressed that urban planning decisions should be made based on evidence collected from actual urban residents, and that wearable psychophysiological methods represent a breakthrough for gathering such evidence. Using physiological data on experiences offers numerous opportunities to inform urban planning processes with not only evidence of a difficult-to-measure construct—experience—but also to involve residents in the gathering and interpretation of such data. Such an approach was pioneered by Nold et al. (2009) and can be further facilitated with contemporary visualization methods, such as our 3D visualizer (Fig. 6). A future step would be to automate statistical modeling of data, so a model such as the one we have derived would be continuously updated with resident-driven data collection, as Zeile et al. (2016) suggested.

7. Limitations & future directions

This study has several important limitations, mostly stemming from the technical complexity of measuring emotional experiences as they unfold over space and time. While the wearable technology we used to measure skin conductance is increasingly accessible, it is still expensive. Thus, we were limited to a convenience sample of 12 participants, which excludes any possibility of analyzing between-participant differences, some of which strongly affect experiences. Even if budgets do not allow purchasing more wearable devices, it is possible in future research to build up larger sample sizes from using groups of participants to record data in ‘shifts’. With such samples, it would be possible to examine differences in how urban spaces are experienced based on individuals’ gender, age, demographic status, and even personality traits.

Similar resource limitations were encountered due to computing power required to calculate and generate analyzable viewsheds from the high resolution DSM with over 500 million grid cells. While skin conductance was measured at 4 Hz, location was only measured at 1 Hz, whereas viewshed area and accompanying composition metrics were sampled and analyzed at a reduced spatial resolution, every 20 m, which was roughly equivalent to temporal resolution of about three and a half seconds, depending on speed. If more powerful devices would be available to record GPS location data at the same 4 Hz frequency in which skin conductance is sampled, with calculations of viewsheds matching this frequency as well, presented analyses would be more precise. Alternatively in the future work, the location data can be interpolated to 4 Hz along the road using the 1 Hz GPS data and parallelized version of the viewshed calculation would make the more precise analysis feasible. However, a thorough analytical investigation and optimization of spatial and temporal resolution should be performed to assess possible effects of varying data resolutions on statistical power and computational complexity. It must also be noted that angle and extent cutoff values for viewsheds were constant and based on a smaller sample of line of sight range analysis specific to our study area. To apply this technique to environmental regions with more variable topography, more computationally optimal and adaptive viewshed techniques must be developed, which stand capable of better accounting for the multi-scaled dynamics of environmental interaction and resulting experiences.

Finally, it must be admitted that our statistical model was limited in complexity to including speed, direction, direction changes, distance to roads, and extent of viewable area across various land cover types as predictors of emotional arousal. Interaction effects between these predictors, as well as other within-individual predictors such as weather changes were excluded for the sake of interpretability of the model. Models, including statistical models, are by definition simplifications of reality which allow realistic interpretation of phenomena. Extremely complex models of the present data would, thus, be self-defeating.

8. Conclusions

Our model incorporated multiple levels of environmental exposure, interaction, and experience into a single analysis. Our approach is novel in holding environmental and human elements of speed, distance to roads, and turns constant, more adequately modeling environmental exposure at both individual and ecological levels. Furthermore, we demonstrated how accounting for a wider range of perceptual variables, specifically cyclists’ line-of-sight, results in surprising links between environment and experience.

More generally, our study demonstrated the possibility, potential, and utility in continuously monitoring cyclists with wearable sensors. This approach can be adopted to better understand the human experience as it unfolds over space and time, in its appropriate environmental context. This approach represents a step toward supplying urban planners with accurate, concrete, educated, and actionable insight which can be used to make just-in-time decisions and investments, decisions and investments aimed toward making our environment not only a more beautiful place to be visited and traveled through, but one that functionally contributes to emotional and physical well-being.

Declaration of Competing Interest

None.

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