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Evaluating Urban Bicycle Infrastructures through Intersubjectivity of Stress Sensations Derived from Physiological Measurements

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Abstract: A continued shift of human mobility towards sustainable and active mobility modes is a major concern for society in order to reduce the human contribution to climate change as well as to improve liveability and health in urban environments. For this change to succeed, non-motorized modes of transport need to become more attractive. Cycling can play a substantial role for short to medium distances, but perceived safety and stress levels are still major concerns for cyclists. Therefore, a quantitative assessment of cyclists' stress sensations constitutes a valuable input for urban planning and for optimized routing providing low-stress routes. This paper aims to investigate stress sensations of cyclists through quantifying physiological measurements and their spatial correlation as an intersubjective indicator for perceived bikeability. We developed an automated workflow for stress detection and aggregation, and validated it in a case study in the city of Salzburg, Austria. Our results show that measured stress generally matches reported stress perception and can thus be considered a valuable addition to mobility planning processes.

Keywords: active mobility; urban mobility; bikeability; stress sensation; infrastructure evaluation; electrodermal activity; wearable sensors

1. Introduction

The increase of traffic in urban areas has become a major challenge. The high share of motorized vehicles leads to traffic congestion, high greenhouse gas emission, traffic noise, and air pollution. All this causes negative impacts on the environment, society and even individual health; see [1–6]. To improve this situation and to accomplish better liveability in urban areas, a shift towards alternative forms of transport is needed. Especially for short to medium distances, walking and cycling are valuable alternatives to motorized modes. These forms of mobility not only help reduce the problems stated above, but additionally have a positive effect on individual health [7,8].

In the modal split of the city of Salzburg, Austria, bicycle traffic amounted to 19.6% of traffic in 2012, which is remarkably high. Still, the majority of 36.9% of traffic in Salzburg is motorized private transport [9]. Due to restrictive topographic conditions and the historic, densely built-up environment, the capacity for motorized private transport is severely limited. This continuously causes serious traffic problems, which raises new demands for political solutions [10]. Prototypical European bicycle cities like Copenhagen successfully demonstrate how a high share of bicycle traffic—here 29%—can improve the urban traffic situation in a sustainable way [11]. This example suggests that potential exists for significantly increasing the bicycle share in Salzburg if supporting framing conditions are created.

Quality and perceived safety of road and path infrastructure for walking and cycling are major criteria for route and mode choice [12–16]. This emphasizes the importance of identifying safety and quality issues within the existing infrastructure as valuable input for urban planning and possible applications in routing to reduce stressful situations.

In 2003, numerous approaches for quantifying an infrastructure quality measure termed "walkability" and "bikeability" already existed, but required further empirical validation [17]. As Winters, Teschke, Brauer, and Fuller showed in [18] for a more recently published bikeability measure named Bike Score®, higher bikeability of a city correlates with a higher modal share of bicycle traffic. Previous research has further shown that cyclists are willing to take detours summing up to 140% of shortest path distance to avoid main roads with high traffic volume [19]. When bike lanes were present, the total length of bicycle trips was advanced by 51% [20].

Previous approaches for deriving bikeability measures were mainly based on assumptions regarding the impact of the built environment on the perceived quality and safety of a route [12,15,21,22]. Many followed the assumption that low exposure to traffic stress leads to high bikeability [23,24]. Empirical validation was performed based on tracking of cyclists' route choices using GPS e.g., [20,25]; or based on surveys e.g., [26,27]. A common underlying approach was the use of route choice models. These models are defined based on a set of routes meeting the criteria (here bikeability), a set of alternative routes between the same origin and destination and a regression model representing assumptions on the influence of attributes assigned to all routes contributing to meet the main criteria. Examples for utilizing route choice models are found not only in bikeability research as in [19,20], but also in related fields like scenic route calculation e.g., as in Alivand et al. [28].

Following increased availability of portable sensor devices, this work aims to quantify stress sensations directly from physiological measurements. This approach implicitly takes into account any possible variable influencing subjective sensation of stress during cycling. It is thereby capable of offering a more holistic view on cyclists' stress perception under real-world traffic conditions.

Previous research has already proved successful in identifying stress hot-spots within cities based on physiological measurements, targeting different application fields: Investigation was done on stressful locations for walking [29], cycling stress [30–32], stress of car drivers [33,34], and the emotional reactions of tourists [35]. Existing research commonly utilized single stress locations or hot-spot analysis based on spatial proximity of individual stress locations.

Our research intends to go one step further by aggregating identified stress locations of multiple participants to an intersubjective stress index that is assigned to every path segment and intersection of the transport infrastructure. It allows new insights into the perception of the built environment based on infrastructure attributes and may serve as direct input to quality-based routing applications for promoting bicycle traffic.

The term "intersubjectivity", following the definitions in [36,37], is used in this work to clearly distinguish between the objective, physical properties of the built environment and subjective human perception and interpretation of these properties, and possible additional factors. Objective measurements of stress sensations amongst a group of cyclists still reflect individual perception and cognition. If these objective measurements show a common pattern amongst a group of people, they can be considered an intersubjective measure valid for this group. Other people, e.g., from a different cultural background, might perceive the same objective properties of the built environment in a different way. This is a general constraint to be considered when interpreting the results of this and other comparable studies.

Within this project, a case study was performed for a predefined set of routes in the city of Salzburg, Austria, using physiological measurements and an accompanying survey. The main research question was whether quantified stress perception among participants showed an intersubjective pattern and as a consequence could be used as valid proxy for human perception of infrastructure quality in bicycle traffic.

2. Materials and Methods

2.1. Case Study

The case study was carried out during Summer and Autumn 2018 in the city of Salzburg, Austria. The capital of the federal state of Salzburg with approximately 150,900 inhabitants [38] had a 19.6% modal share of bicycle traffic in 2012 [9]. Four routes connecting the Science City (one of the major hubs for employment) with the city centre (Residenzplatz) were defined, each with a length of approximately 4 to 6 km. For route selection, a major criterion was to include routes composed of different road types and linear bicycle infrastructure. The defined routes and selected statistics are shown in Figure 1. All four routes can be considered flat except for short sections at underpasses, where slope is noticeable. We considered this a further characteristic of the built infrastructure such as road type.

Figure 1. Overview of pre-defined routes for the case study. (**a**) Screenshot of web-map displaying all four routes connecting Science City (North) with the city centre (South); (**b**) Share of different bicycle infrastructure types per route; (**c**) Share of road categories involved in each route.

Route 1 mainly followed the river Salzach with 86% dedicated bicycle infrastructure or mixed ways, few road crossings and a high value for leisure activities. Of the second route, 60% offered no bike infrastructure, contained many road crossings and partly followed secondary roads. Routes 3 and 4 showed mixed bicycle suitability, partly followed bicycle ways along the river Salzach and used bicycle lanes on secondary and primary roads.

For communication to the public, especially to acquire participants for the case study, a website was launched with information about the participation process and detailed instructions. This included an interactive map for exploring the pre-defined routes as shown in Figure 1.

The website link was spread within the community of Geoinformatics students, employees at University of Salzburg's Interfaculty Department of Geoinformatics–Z_GIS, and their networks. Regarding the evaluation of intersubjectivity, this restricted group sample did not impose any issues as intersubjectivity per definition relies on social groups potentially sharing similar cultural background, education, or interests (again, see [36,37] for general definitions of the term "intersubjectivity"). This sample represented a group of experienced cyclists on these routes.

Each participant was asked to cycle at least routes 1 and 2 in each direction, resulting in a minimum of four trips. This decision was made in order to reduce the total time participants had to spend (only 2 out of 4 routes required) whilst obtaining a maximum amount of data for direct comparison between a route pair. All rides were performed with an Empatica (Empatica Inc., Cambridge, MA 02142, United States / Empatica Srl, 20144 Milano (MI), Italy) E4 sensor device [39] mounted to the left wrist and a mobile phone for storing measurements and tracking geolocation using GPS. The Empatica E4 records electrodermal activity (EDA) and skin temperature at a frequency of 4 Hz [39]. The device was previously shown to provide robust results for EDA [40,41].

2.1.1. Trip Survey

After completion of one trip (one route in one direction), the participants were asked to fill in a mobile-optimized online-survey regarding their sensation of stress and environmental conditions. This was to provide direct subjective data for comparison with measured moments of stress and information on external factors possibly influencing the data acquisition or subjective perception. Participants were asked about temperature, precipitation, sight impact, traffic volume of motorized vehicles, bicycles, and pedestrians as well as the intensity of overall stress and safety perception. An interactive web-map displaying the selected route was included in the survey where participants were able to mark remembered spots of high stress sensation. This is shown in Figure 2.

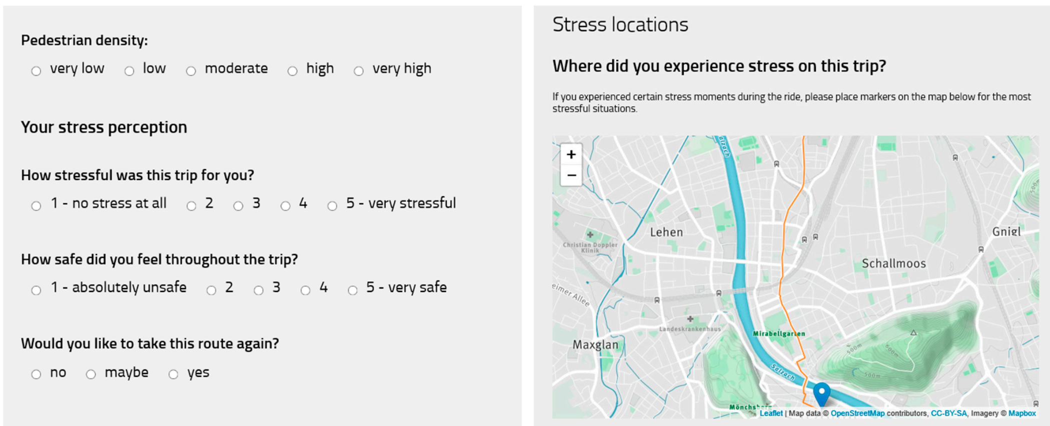


Figure 2. Excerpt of online trip-survey. An interactive web map was used to register individual stress locations that participants still remembered.

2.1.2. Final Survey

Participants were asked to fill in a final survey after the completion of all trips. This survey added information on demographics, cycling experience, and overall stress perception of each individual. It enabled the characterization of intersubjectivity groups and improved the understanding of factors influencing stress sensation. Regarding cycling behaviour, participants were asked about weekly distance and frequency of cycling and the type of bicycle used for the case study. Overall route preference of the case study was inquired as of favourite and most disliked routes, assigning for each an importance for possible influencing factors: Scenery, safety, distance, speed, and simplicity (easy to find?) using a 5-level rating scale. The last section asked for feedback regarding the case study process and user interfaces involved to facilitate future improvements.

2.1.3. Participants

Due to technical issues, only 17 out of 21 participants contributed valid data. In total, 9 female and 8 male participants were counted, each contributing at least four trips. In total, 100 valid trips were processed, where 76% of participants were in an age range from 20 to 29 years. 53% were employed, and 47% were students. Trekking bikes accounted for 41% of bikes used, 41% were city bikes and 18% other bikes. 82% used their bicycle at least two days per week, with 64% cycling at least 40 km per week. Only 41% used the bicycle for commuting, other frequent options were leisure activities, sports, and business purposes. This sample group may not have been representative of the whole population of Salzburg but served as a suitable example for a social group sharing common background as outlined in definitions on intersubjectivity. Please refer to the introduction of Section 2.1 for further details.

2.1.4. Privacy

In dealing with personal information and physiological measurements, special attention was paid to privacy aspects, in accordance with [42]. Physiological measurements and GPS tracks were stored locally, only survey data was collected and stored online in a secure database. No external processing or cloud storage services were used. For the evaluation of study results and publication, anonymized data were taken as input. The result dataset was based on aggregated moments of stress from all participants, thereby making it impossible to link back to individual participants. The use of predefined routes avoided privacy concerns by not tracking individual movement paths that could reveal information about daily life.

2.2. Data Processing

Data processing was split into four steps that are described in the subsequent paragraphs of this section. An overview is shown in Figure 3.

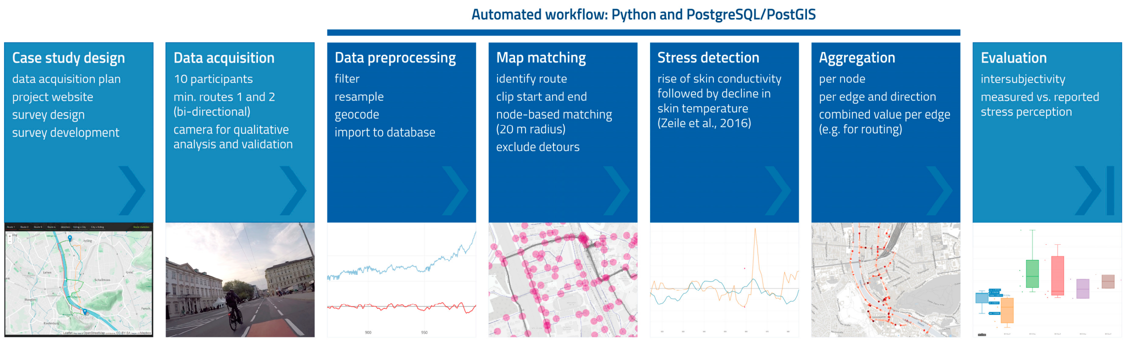


Figure 3. Summary of methods with automated workflow highlighted.

2.2.1. Preprocessing

Main purpose of the preprocessing step was to resample data to a common frequency, to geocode samples, and to filter data from the baseline signal. A few implementation-specific steps were undertaken to compensate for delays in data transmission via Bluetooth®between the sensor device and the recording application on a smartphone and to temporally re-align and crop signals. Linear interpolation of geocoordinates was used in geocoding to assign position information to each sensor sample based on its timestamp and known GPS sample positions.

As stress detection requires phasic skin conductance responses (SCR) as input instead of raw tonic skin conductance level (SCL) [43], a bandpass filter was applied to the raw SCL signal. Although advanced and more precise methods for decomposition exist, as proposed by Benedek and Kaernbach in [44], a bandpass filter provided appropriate quality for this purpose as this study only considered detecting distinct moments of stress without analysing duration or intensity. Additionally, uncertainty exists concerning the comparative accuracy of methods in non-laboratory conditions as in this field test with physical exercise. We discuss this issue further in Section 4. The bandpass filter of second order was applied with a low-cut of 0.02 Hz and a high-cut of 0.5 Hz. For skin temperature, a bandpass filter with low-cut of 0.02 Hz and high-cut of 0.3 Hz was used to compensate for baseline changes due to physical exercise and environment temperature. Decisions concerning filter selection and applied parameters were based on expert knowledge involving a biophysics scientist. Filtered signals were then decimated to 1 Hz frequency as input for stress detection and map matching. This parametrization aligned with the findings in [45].

2.2.2. Map Matching

With map matching, measurements were linked to corresponding network elements based on GPS position and temporal sequence. Numerous general-purpose methods exist for map matching such as those reviewed in [46], but these did not fit our purpose where we had additional knowledge about predefined routes and case study instructions. Therefore, a more specific method was applied that involved geometric and implicit topological analysis based on route definitions. The main concept was to detect node traversals and possible detours in trajectory data by computing the intersection between GPS samples and buffers around nodes. An example with similar context, where buffer intersection was used for map matching, can be found in [47]. A major difference is that we applied buffers around nodes instead of edges. With this and the knowledge about network edges participants were asked to pass, we avoided conflicts where parallel edges occur within high proximity, thereby improving the overall matching result. General-purpose methods in such a case might assign the wrong edge as they try to minimize overall distance between samples and matched edge. This is especially the case when GPS samples show a constant offset. The transport network data was derived from a public authority dataset representing a topologically cleaned, routable graph [21].

For determining an appropriate node buffer size, we analyzed the accuracy of GPS samples and applied exploratory analysis in a Geographic Information System (GIS) environment for the complete dataset. GPS sample accuracy (defined as radius of 68% confidence as provided by Android (developed by Google LLC, Mountain View, CA 94043, USA, and the Open Handset Alliance) SDK [48]) showed a mean of 6.89 m with a standard deviation of 4.55 m. Based on these results and exploratory GIS analysis of trajectories, we defined the node buffer radius to be 20 m.

In a first step, the according route and direction of each trip was determined by finding the route with minimum Hausdorff Distance to the trajectory between route origin and destination. With this approach, we could distinguish route association of samples even at sections where the routes overlapped.

Secondly, all nodes of the detected route were extracted and sampled GPS positions within node buffers were matched as node candidates. Iteratively for all subsequent matched node pairs of the route, samples temporarily between the node visits were considered belonging to the according edge linking the node pair. If no edge connecting the nodes was available (i.e., at least one node of the route had been omitted), the candidates were skipped and a potential derivation from the pre-defined route was recorded for this section. In case of node buffer overlap, samples were matched according to their proximity to each node.

As previously pointed out, this purpose-specific map matching approach ensured optimal results for this setting, as knowledge about target routes and case study instructions help resolve problematic situations e.g., where parallel edges of the network with close proximity occur. Common map matching algorithms are more versatile but cannot incorporate this knowledge.

2.2.3. Stress Detection

Stress detection was based on identifying a rise of skin conductance followed by a decline of skin temperature within a 3-second window as proposed by Zeile et al. in [32]. The original approach is sensitive to very small changes in amplitude. Therefore, a minimum threshold for change in amplitude and minimum duration of the rise in skin conductance was introduced.

Implementation involved applying a moving window searching for a rise in skin conductance lasting for at least 2 seconds followed by a decline in skin temperature within 5 seconds to cover for timing uncertainties introduced by wireless data transmission. A stress candidate was only considered if average skin conductance change was greater than 0.015 μS during the first 3 seconds. This threshold was defined based on comparative analysis of all datasets.

2.2.4. Aggregation

The aggregation of moments of stress produced datasets that included measured and reported stress per individual trip, stress range per participant, stress per route (and direction), and stress per route and participant. The final aggregation step was performed per network element and direction (route direction and graph element direction). It took into account the average of measured stress events per km for all trips.

3. Results

As a result of case study instructions, more data were available for routes 1 and 2 (30 trips for route 1 and 32 trips for route 2) than for routes 3 and 4 (8 trips for route 3 and 6 trips for route 4). Therefore, our intersubjectivity evaluation focused on results for routes 1 and 2.

As can be seen in Figure 4, the range of stress sensation per trip varied between participants. Participant 14 showed the lowest interval, ranging from 0.0 moments of stress (MOS) per km to 0.56 MOS per km. In contrast, MOS per km for Participant 2 ranged from 6.42 to 10.65. This led to the conclusion that general stress sensation is highly individual and might depend on various preconditions. As Participant 5 (with the highest number of trip contributions) showed a large range of MOS per km, the potential influence of external factors like traffic load or weather needs to be discussed, as outlined in Section 4.

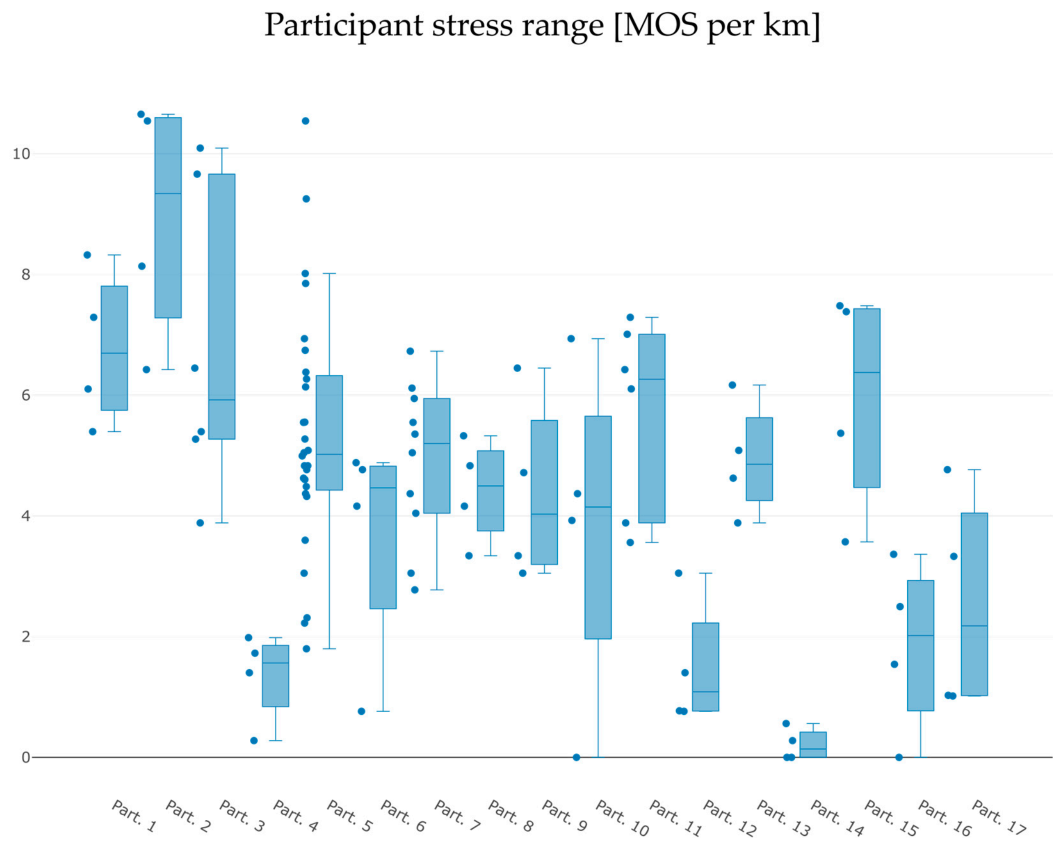


Figure 4. Moments of Stress (MOS) per km by participant—showing highly individual stress ranges.

From the map in Figure 5 we identified spatial patterns of MOS density per network edge. It clearly illustrates a non-random spatial distribution of measured subjective stress perception among participants. The measurements indicate that certain route elements were generally perceived as more stressful compared to others. Examples for high stress perception were found in Ignaz-Harrer-Str. (1) and in the city centre between Rudolfskai and Residenzplatz (2). Low stress perception was measured e.g., in route 1 along the Salzach river (3) and in some sections of Elisabethstr. (4).

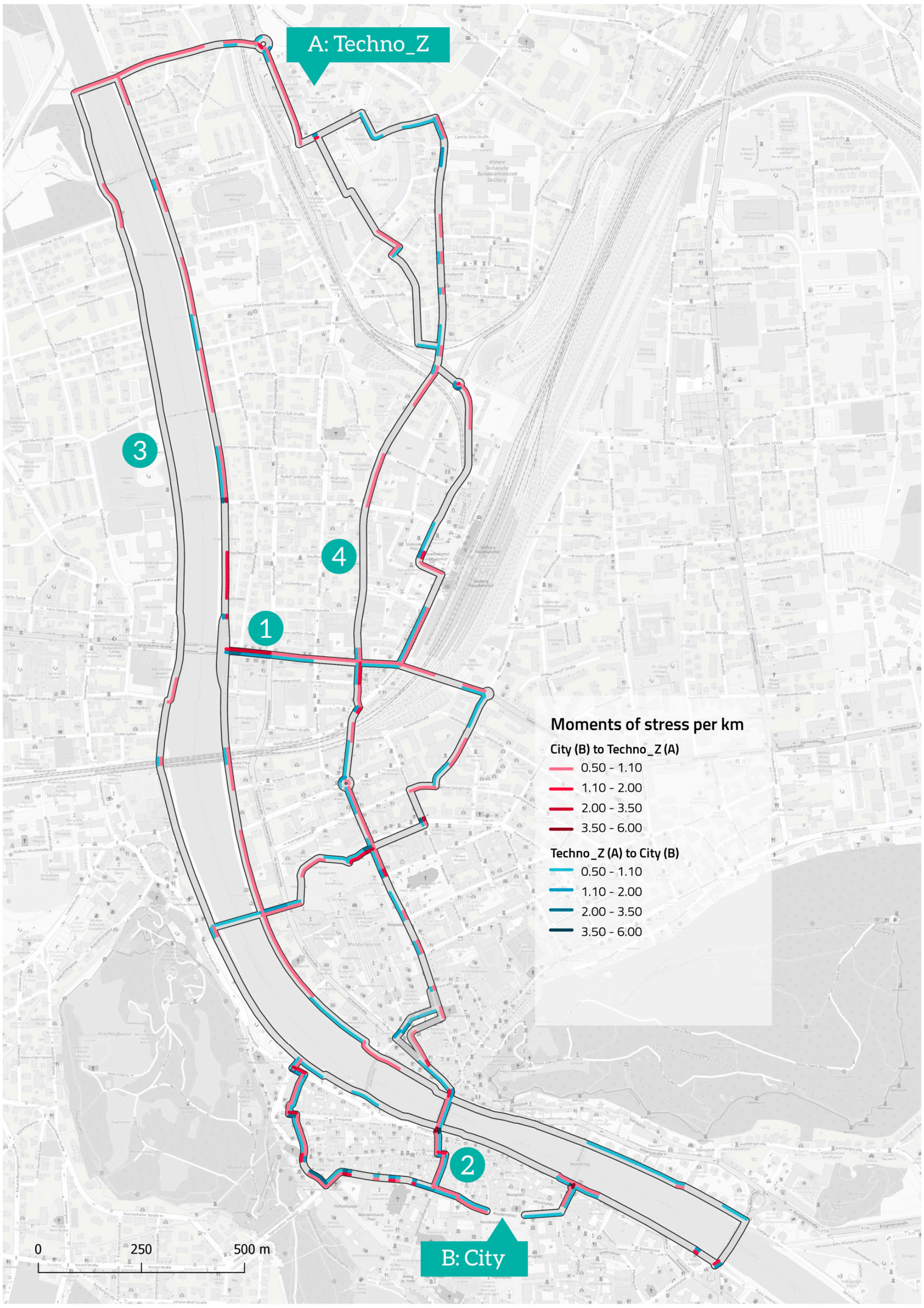
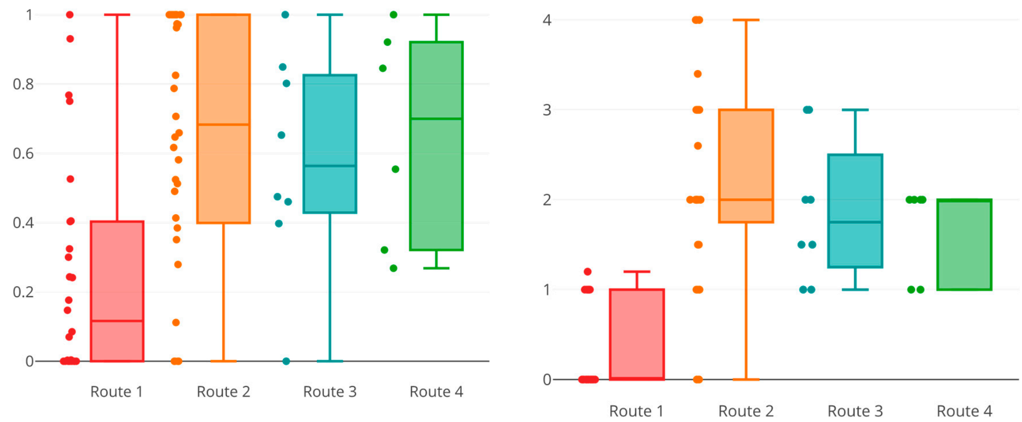


Figure 5. Map of aggregated MOS per edge by route direction. *Map data © OpenStreetMap contributors, www.openstreetmap.org*.

Mean absolute MOS per km ranged from 3.52 with a standard deviation (SD) of 2.51 for route 1 to 5.99 (SD 1.38) for route 4. Route 2 had a mean of 4.89 MOS per km (SD 2.61). The maximum MOS per km was 9.66 for route 1 and 10.65 for route 2. These absolute values, however, were not directly comparable as Figure 4 revealed high divergence of stress range between participants.

In Figure 6a, measured MOS per km were normalized by participant stress range in order to compensate for the effect of individual sensitivity to stress, as outlined before. This resulted in a linear mapping to a range between 0 and 1, where 0 represents the lowest MOS per km measured for any trip of this participant and 1 represents his or her highest measured value. Relative stress level per route was significantly lower for route 1 (median: 24% of maximum stress) compared to all other routes (56% to 70%). This finding generally corresponded to the distribution of reported stress perception revealed by trip surveys, see Figure 6b. Comparing mean values of normalized measured MOS per route with reported stress per route disclosed high conformity.



a. MOS per km by route (normalized by participant stress range)

b. Reported stress level by route

Figure 6. Comparison of measured and reported stress by route. (**a**) Measured moments of stress per km by route, normalized by participant stress range (1 = highest stress level for this person, 0 = lowest stress measured for this person); (**b**) reported stress level by route, based on web-based trip survey.

The difference between normalized measured stress and reported stress for each individual trip by route, as shown in Figure 7, revealed partly high divergence between measured and reported stress mainly for route 2. The highest difference equaled to –100%, meaning measured stress was lowest but reported stress was highest of all trips for this participant. The lower quantile for route 2 was at –49.3% and the upper quantile was at 0.3% with a median of –10.9%. For route 1, values ranged from 0 (perfect match) to 100%. The lower quantile was at 0%, the upper quantile at 33.6% with a median of 17.6%. This showed that route 1 was generally reported to be less stressful compared to actual measurements, whereas route 2 comprised more variation with a tendency to be reported more stressful than physiological measurements reveal. The high divergence, possible reasons, and implications are discussed in Section 4.

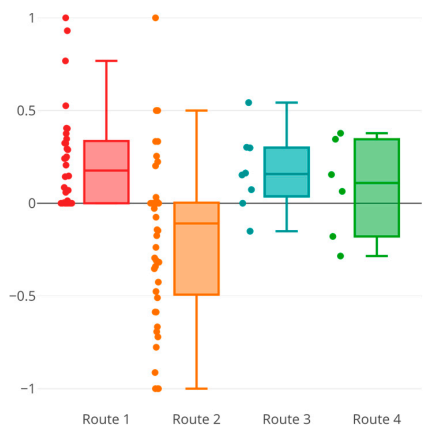


Figure 7. Difference between measured moments of stress and reported stress level [normalized].

Results of the final survey underlined the general route preference of participants—favoring route 1 over route 2—as stated in trip surveys. Safety and scenery were indicated by the participants as having highest influence on positive route perception, whereas safety concerns formed the strongest cause for disliking a route, followed by the lack of simplicity (difficult to find). Distance and speed were minor factors. Further conclusions based on demographic data or cycling-related experience were not possible due to the small sample size.

Although high divergence exists partly between measured and reported stress on the individual trip level, aggregated measured and reported stress per route showed clear correlation across participants. Non-random spatial distribution of MOS revealed a common sensation of stress hot-spots within the road network among participants. With these results, the main research question can be positively answered. It is shown that common spatial patterns exist in stress sensation derived from physiological measurements among a group of people. Therefore, the method shown can generally be used to quantify intersubjective stress sensation in bicycle traffic. Possible implications to consider and additional improvements are discussed in the next section.

4. Discussion

The stress detection method proposed by Zeile et al. in [32] was extended by adding threshold values for exclusion of minor fluctuations in skin conductivity and skin temperature signals. Furthermore, a high sensitivity of their method to pre-processing of the raw signal was revealed. Based on expert knowledge (cooperation with University Hospital Zurich), an optimal bandpass filter design for pre-processing was developed. Further testing and verification will be performed to validate general transferability of these parameters to other case study settings. In general, future work should investigate the accuracy of skin conductance decomposition into tonic and phasic signals under non-laboratory conditions, especially during physical exercise and on how MOS can be reliably detected under these circumstances. An interesting starting point can be the work by Posada-Quintero et al. [49], still utilising a controlled laboratory setting with constant temperature, humidity, and low risk of motion artefacts for analysis of the effects of physical exercise on EDA. The importance of considering these influences is underlined e.g., by the results of a study on stress monitoring in real life situations by Gjoreski et al. [50]. These aspects gain importance as more detailed analysis of moments of stress is performed involving amplitude, duration, or gradient of skin conductance signal. This detailed analysis should be focused on in future research, as the method outlined within this work considered every moment of stress to be of identical quality. Since the results revealed some divergence between measured and reported stress levels for several trips, one possible reason could be the effect of different intensity or quality of stress moments. Additional influencing factors might be subjective preferences in relation to external conditions not directly resulting in quantifiable stress such as the perception of scenic or air quality, but these are hard to quantify. Not only in this context, analysis of similarity in stress perception and contributing factors within and among different social groups may be a key for the better understanding of complex interaction between humans and the built environment. This is why we introduced the concept of intersubjectivity within this study. It will be the subject of future research to investigate these patterns for various social groups (e.g., children, the elderly, commuters, leisure cyclists, etc.). Finally, there are numerous potential errors in the qualitative survey caused by a variety of cognitive biases, memory errors, and others [51]. This is of particular importance because no reliable information exists for "ground-truthing" emotion measurements or sensations reported through qualitative surveys.

A general concern is the possible divergence in subjective stress affinity and short-term intrinsic or extrinsic parameters as an impact on baseline stress. This work tried to compensate for such effects by normalizing the per-trip stress level based on the range of stress levels this person showed during the experiment. Future research could be conducted to determine the importance of the individual baseline for deriving spatial conclusions and on how this baseline can be determined per individual trip. General situational influences such as weather, traffic load, sight impact, or cycling equipment quality might influence quantified stress level. Therefore, these aspects need to be considered as it was done in this case study using an additional survey. For this study, no significant correlation of stress measurements with any of these factors was found. Possible reasons could be potential errors introduced by cognitive biases, memory errors etc. as outlined before, the small sample size of a minimum of only four trips per person or a predominance of other factors e.g., directly related to the built environment. To enable more detailed analysis, future research may enquire these factors in a survey for subsections of routes instead of a global assessment per trip. Additionally, requesting annotating stress locations marked on the web map regarding triggers or further emotional classification might provide valuable insights, but appears to be hardly viable in practice. We encourage further analysis on these aspects in future research, especially with a larger sample.

One preliminary decision to be made for each implementation of this method is whether to include MOS during rest phases. These occur e.g., while participants wait at traffic lights. This decision may depend on the individual (applied) research question asked. For this work, all MOS were included, as an overall indication for spatial and route-based stress patterns was to be analysed. Following this main objective, we decided to base the aggregated stress index on distance instead of time. This allows for application e.g., in comfort-oriented routing, where stress during rest phases (waiting) might play a major role.

A logical next step is to perform more detailed analysis on spatial clustering of MOS and to investigate possible interrelations of these spatial patterns with local infrastructure characteristics.

As quantified intersubjective stress sensation can serve as a proxy for intersubjective perception of several attributes of the (built) environment, its value for urban planning or bicycle routing might be comparable to existing bikeability indices or could be used for validation of their underlying models. A potential advantage of using this value derived from physiological measurements is the missing human interpretation and possible relativization based on additional criteria, thereby providing a higher degree of objectivity. These aspects are promising further research directions.

5. Conclusions

Even if there exist numerous possible factors influencing individual stress sensation that cannot be controlled, this research showed the general utility of physiological measurements for quantification of perceived stress in bicycle traffic. Based on the case study in Salzburg, Austria, the general intersubjectivity of stress perception among a group of people was shown. When aggregated on network elements, moments of stress (MOS) can indicate deficits in bicycle infrastructure. Thereby, the method presented in this work may support urban planning for making better informed decisions to improve bikeability and safety of the street network. While it allows quantification and localisation of potential infrastructure issues, additional qualitative research might be necessary to determine underlying reasons and for finding appropriate solutions.

The main contribution of this work is to prove the general applicability of automated detection of moments of stress from physiological measurements for deriving intersubjective indication for perceived bicycle infrastructure quality. By offering analysis on the infrastructure network level, more detailed conclusions for urban planning can be drawn compared to general aggregation in heatmaps as presented in [32]. Aggregation on edge and node level enables analysis based on travel direction and can provide a measure relative to the number of visits instead of absolute stress count. The findings of this research are relevant for supporting better informed decision making in urban planning with new data-driven (near-) real-time applications in the context of smart cities in order to find sustainable solutions for various traffic-related urban issues.

Author Contributions: Conceptualization, Christian Werner, Martin Loidl and Bernd Resch; Data curation, Christian Werner; Formal analysis, Christian Werner; Funding acquisition, Bernd Resch; Investigation, Christian Werner; Methodology, Christian Werner, Martin Loidl and Bernd Resch; Project administration, Bernd Resch; Resources, Bernd Resch; Software, Christian Werner and Bernd Resch; Supervision, Bernd Resch and Martin Loidl; Validation, Christian Werner; Visualization, Christian Werner; Writing—original draft, Christian Werner; Writing—review & editing, Christian Werner, Martin Loidl and Bernd Resch.

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