Travel Experience in Public Transport: A Geospatial Analysis by Experience Mapping

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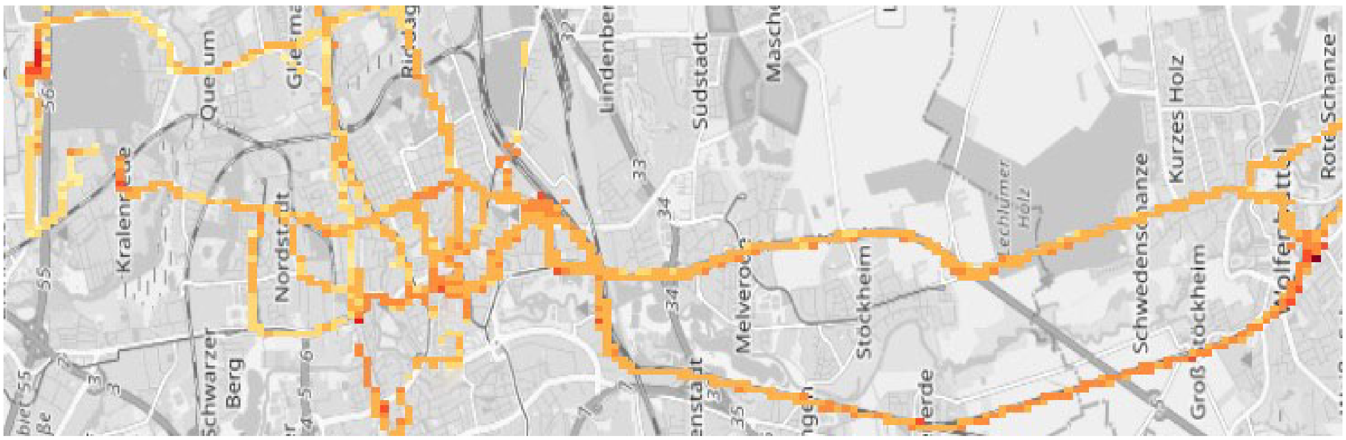

Figure 1: Complete experience map of all travelers' heart rates.

ABSTRACT

A change towards sustainability is crucial also in the transportation sector. However, humans' need for mobility is increasing. Therefore, a shift towards sustainable transportation is necessary. Besides changes in reliability and availability, transportation can be made more attractive by better understanding travelers' needs. This paper presents first results of a study with 23 participants that traveled by public transport. We continuously recorded travel satisfaction, stress, event, and cardiological data. We plotted the collected data averaged in 0.0008 degree squares over the traveled map to detect points of collective positive or negative travel experience in public transport. Preliminary results show that bothersome people are a major cause for negative experience at a busy changing point. This adds to existing research, as most previous studies have concentrated on time- and cost aspects of public transport. Our method is a powerful tool to analyze points at which a transportation system needs to change to take the traveler's needs into account.

CCS CONCEPTS

• **Human-centered computing** → **Visualization techniques**; • **Applied computing** → Psychology; • **Information systems** → *Geographic information systems.*

KEYWORDS

travel experience, public transport, geospatial data, cardiological data, affective computing

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1 INTRODUCTION

An essential step towards reducing greenhouse gas emissions in the mobility sector is to nudge travelers towards shared, often intermodal transport. However, shared and intermodal travel leads to negative experiences more often than individual transport. These arise due to unmet needs, such as safety, comfort, accessibility, efficiency, reliability, or information (e.g., [4, 21]). Because of these unmet needs, travelers choose private motorized transport over public transport ([9]). Reasons for negative travel experiences vary individually and can arise due to intrinsic (e.g., number of luggage pieces to carry) and extrinsic (e.g., delays, weather conditions) factors. It is therefore difficult to meet these needs with general solutions. Furthermore, real-time information on travel experience is unavailable, rendering situation-adapted reactions impossible.

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Therefore, methods are needed to visualize travel experience concerning the current travel location.

We define travel experience as the subjective experience of events experienced during a journey by a traveler. These events can entail, for example, the use of services and vehicles or the interaction with the interfaces to the traveler (e.g., hubs, displays, apps) (cf. [21]). As travel experience is highly related to affect and emotions, it can only be assessed successfully based on multimodal measures of the traveler's state and knowledge about the context [2, 20]. Hence, for assessing travel experience during intermodal trips, a combination of subjective and physiological data (e.g., heart rate and heart rate variability) together with context information is desirable (e.g., [1]). Especially when aggregated over several journeys and travelers, subjective and cardiological data can inform us about points in which travelers frequently experience positive or negative affect. When contextualized with location information, such points of positive or negative experience can help to identify reasons for the experience peaks. Such knowledge can help mobility providers improve travel experience at negative 'pain points', and possibly increase the likelihood of positive reported events.

One intuitive way to visualize dynamic location-based data is map representations (e.g., Google Traffic Layer). Previously, map representation has been used to compare experienced emotions between regions (e.g., [11]) or to understand how citizens experience specific routes as well as parts or quarters of cities (e.g., [5, 18]. Interestingly, some work regarding this was published as early as 1977 [8]). The advantage of using this map representation over a post-hoc questionnaire is its ecological validity: moments of positive and negative travel experience are reported in the immediate moment they happen, which enables the researcher to get highly accurate data that is not skewed in amount and intensity as much as a report from memory would be. Recently, the method of emotion mapping was started to be used in the area of mobility, for example, in the automotive sector [7, 10], in a study surrounding pedestrians and cyclists ([16]) or in a case study from public transport [6]. However, to our knowledge, no approaches have been published for mapping the travel experiences of many travelers in intermodal public transport. Therefore, we present work-in-progress research on developing pertinent map representations for visualizing travel experiences during intermodal travel in an easy-to-understand way. In the future, the vision for this method is to recognize moments of negative travel experience in real-time based on physiological data. When aggregated, this experience map can indicate points where changes in the transportation system are necessary [13].

2 METHODS

In our ongoing study, so far, 23 participants experienced three to five in- and outbound journeys on a predefined route. We continuously measured their electrocardiogram. Every 3.5 minutes participants were prompted to report their travel satisfaction, stress level and any events affecting travel experience. Each journey included at least two changes in the mode of transportation.

2.1 Participants

Twenty-three participants (8 male, 15 female) that were, on average, 23.7 years old (standard deviation 2.8 years) participated in the study. They were acquired over our institute's participant pool and received 60€-100€ (depending on the number of journeys taken) as financial reimbursement for participation. Before starting the study, participants were informed about the study's procedure and the handling of personal data (in line with the General Data Protection Regulation of the EU). The study's procedure was reviewed by the institution's ethical committee (reference no. 07/22).

2.2 Measurements

Subjective measures: The participants rated their current satisfaction with the journey and their stress level on a Likert scale from 1 (low stress/low satisfaction) to 10 (high stress/high satisfaction) every 3.5 minutes on a smartphone using the movisensXS App (Movisens GmbH, Karlsruhe, Germany). Participants also reported any events that happened at any time during the journey. The frequency of 3.5 minutes was chosen based on an unpublished pre-study in which participants tried different questionnaire request frequencies. Based on the same prestudy, the event categories *delay*, *bothersome people*, *style of driving*, *infrastructure*, *positive interaction*, *entertainment*, *on time*, *discomfort*, *comfort*, *pleasant surroundings* (in the following abbreviated with *surrounding*), *errands* and *report a different category* could be chosen. First results of the experienced events during travel can be found in [17]. **Cardiological measures:** Their heart rate and heart rate variability as measured in root mean square error (RMSSD) calculated over a 30-second window was measured every second by the ecgMove4 sensor by Movisens GmbH during all journeys. Heart rate measures were transformed by median absolute deviation per person. Only data where participants were sitting for more than 60 seconds was considered in our analyses. This was done to prevent confounding effects of cardiological changes due to walking activity. Participants indicated every change in the mode of transport. **Context data:** The location and travel mode were continuously logged while traveling using the movisensXS App. Following a requirement from our institute's data protection committee, participants were instructed to switch on the study cell phone's GPS data only when entering the first large street after starting their journey to ensure anonymity.

2.3 Procedure

Participants arrived at our institute and were informed about our study's procedure and aim. They were equipped with a cell phone and an ECG belt. Subsequently, they traveled from a German city with roughly 250,000 inhabitants to a city with roughly 50,000 inhabitants by public transport (distance of roughly 15 km). They were instructed to travel from home via a central tram station to the central train station to the second city and back. They were free to choose how to get from home to the central tram station, took a tram to the main station, and changed between taking the train and bus to the second city. The same instructions were given for the way back. Every participant traveled this in- and outbound journey three to five times (depending on their time and availability) during a freely chosen time of the day. Participants had a mean familiarity rating of 2.69 on a scale from 1 (unfamiliar) and 5 (familiar) with the route before the study.

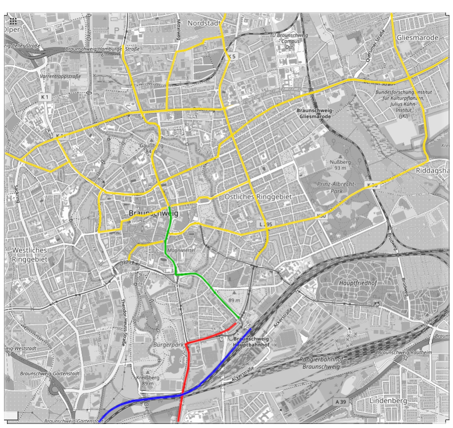
(a) mean stress ratings.

(b) mean satisfaction ratings.

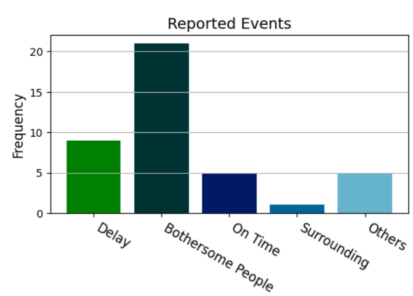
(c) mean z-transformed heart rate.

(d) mean RMSSD values.

Figure 2: Experience maps showing the average a) stress rating, b) satisfaction rating, c) heart rate and d) heart rate variability of all 23 participants.



(a) Transportation modes used in the zoomed-in map of the busiest and most dense area of our data. Blue: bus, red: train, green: tram, yellow: free mode selection from or to the starting point



(b) Events reported at the point of interest chosen based on the experience map data.

2.4 Experience Map

The mean of all participants' data (stress, satisfaction, heart rate, and heart rate variability) was calculated over 0.0008 degrees (90m) squares and plotted on a map using the raster package of R. In a first explorative analysis, we chose a point of interest as evident by changes in subjective and cardiological data by visual inspection and identified which events participants reported in that area. We chose this point out of the area that all participants traveled (see green, red, and blue paths in Figure 3a) to ensure that all 23 participants contributed data to the point of interest.

3 RESULTS

Figure 2 depicts four zoomed-in experience maps of the busiest and most dense area of our data. Figure 3a shows the modes of transportation that participants took in that area. Each map shows a different measure of experience, assessed using self-report (stress and travel satisfaction) and cardiological data (heart rate and heart rate variability). As a point of interest for deeper investigation, a location with increased stress and satisfaction ratings, as well as increased heart rate and decreased heart rate variability, was chosen (circled on maps in Figure 2). Participants changed their transportation mode from 'free to choose' (coming from home) to 'tram' at this location. As it is close to the city hall, it is a busy place in the inner city and a highly frequented changing point for several trams and buses. Forty-one events were reported in this area, of which nine belonged to the category *delay*, 21 to *bothersome people*, 5 to *on time*, 1 to *pleasant surroundings*, and 5 to *report a different category*, see Figure 3b. It is the only change point at which the category *bothersome people* was reported.

4 LIMITATIONS AND FUTURE WORK

Besides collecting further participants, we aim to develop a rule-based extraction of 'pain points' in the next steps of this research. We also plan to expand on the calculated variables per square to include measures of variance between participants in the subjective ratings. With more participants, it might be possible to identify subgroups of travelers based on their subjective, physiological or physical characteristics. One limitation of our study is that we excluded data points where participants walked or stood due to the changes in physiological arousal connected to it. For its inclusion, further research on how to disentangle physiological arousal due to emotion versus due to physical activity is necessary.

5 DISCUSSION AND CONCLUSION

In this paper, we present the first results of a study that aims to detect points of frequent positive or negative traveling experiences in public transport. Subjective and cardiological data were collected from 23 participants. Plotting this information on a map enables us to see at which points participants collectively experience changes in these data. As one concrete example, we chose an area showing collective changes in subjective and cardiological data. Interestingly, this was the area where the most occurrences of the event category 'bothersome people' occurred. This aligns with previous research that found, through affective mapping, that high arousal primarily occurs at intersections and crowded sites in pedestrians [12]. Furthermore, it first seems counter-intuitive that stress and satisfaction ratings are high in the chosen area. However, when considering that also 'on time' and 'nice surroundings' are reported, these opposing subjective ratings likely stem from different participants that made different experiences. Regarding public transport, previous research has mainly concentrated on time- and cost aspects of public transport ([19]). This glimpse into possible results of experience mapping in public transport hints towards promising new insights into reasons for positive and negative experiences, such as frustration [3] or cognitive workload [14, 15]. When collected on a larger scale, such an experience map can inform urban planners, public transport operators, and politicians about points where changes in public transport are necessary. When collecting data on specific user groups, such as elderly or people with disabilities, experience maps can further deepen our understanding of where and how these subgroups of users can be supported in using public transportation. In the long term, this knowledge can be utilized to decrease the pain points of public transport and increase its attractiveness as a viable alternative to individual motorized transportation.

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