A naturalistic experiment on individual activity, mobility and emotional patterns

C. Lima Azevedo[1,*], M. Conceição[2], S. Haustein[1], P. Morgado[3], and B. Miranda[2]

[1]Department of Technology, Management and Economics, Technical University of Denmark, Denmark
[2]Lisbon School of Medicine, University of Lisbon, Portugal
[3]Institute of Geography and Spatial Planning, University of Lisbon, Portugal
[*]Corresponding author

Extended abstract for presentation at the 12th Triennial Symposium on Transportation Analysis conference (TRISTAN XII)
June 22-27, 2025, Okinawa, Japan

Keywords: emotions, activity patterns, travel patterns, well-being, bio-sensing, surveys

1 INTRODUCTION

The impact of travel and urban feature exposure on emotional well-being has long been examined through epidemiological studies, controlled experiments and surveys (Conceição *et al.*, 2023). While the use of physiological measurements to infer travel and urban space experience has been studied for over 20 years, mostly in driving and cycling task experiments, applications looking at the exposure to selected urban features (Tost *et al.*, 2019), public transport (Barría *et al.*, 2023) and commuting trip attributes (Zhang & Ma, 2024) have been proposed recently. Beyond traditional statistical models, these measurements have started to be included as extensions of classical choice modelling formulations (Castro *et al.*, 2020, Hancock & Choudhury, 2023). Yet, finding such empirical evidence under the real-world complexity of diverse emotional stimuli calls for more comprehensive data collection (Palmberg *et al.*, 2021). In the medical field, the growing availability of wearable sensors has led to increased research towards continuous, patient ambulatory monitoring of stress or cardiovascular health within the medical community (Krittanawong *et al.*, 2021), even reaching large-scale studies (Smets *et al.*, 2018). Such empirical findings have already motivated behavioural interventions, targeting directly the relationship between daily activity patterns and lifestyle and selected health outcomes (Ledderer *et al.*, 2020).

For supporting both future health policies in mobility and the understanding of the dynamics between the joint time-space evolution of activity and mobility choices with emotions, data from real-life conditions is essential. Yet, such empirical evidence is still absent, possibly waiting for a bridge between the methods from real-life biomedical experiments and travel behaviour.

2 METHODOLOGY

We propose eMOTIONAL Daily Patterns, an experimental framework using a wearable device and a smartphone framework to collect detailed data on self-reported emotions, psychophysiological markers, activities, travel and related contextual information on their daily lives. The framework includes three stages described below (Fig. 1).

2.1 Screening and Pre-Survey

In the screening survey, we ensure that the participants are suitable for the study (checking for relevant health conditions and smartphone availability) and balance the diversity of the sample by collecting and monitoring information on gender, age, residential area and primary

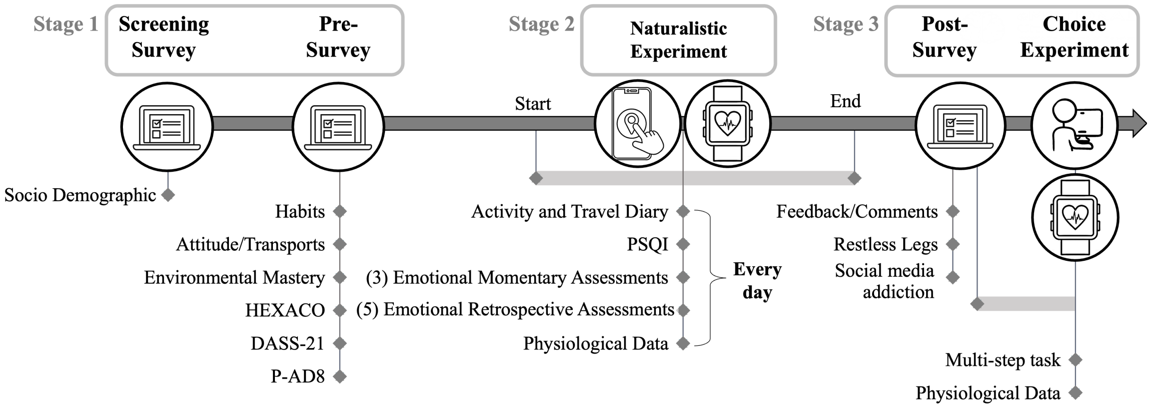

Figure 1 – *eMOTIONAL Daily Patterns' Data collection framework*

occupation. The pre-survey is computer-based and allows for the collection of relevant factors that may influence emotions beyond demographics, namely: **(1) Habits** as regular physical activity and coffee, alcohol and tobacco intake; **(2) Attitudes** toward transport modes and mobility; **(3) Environmental mastery** as one aspect of Psychological Well-being particularly related to stress; **(4) Personality factors**, namely the "honesty-humility" domain and the facets "prudence", and "anxiety" of the HEXACO inventory; **(5) Mild Cognitive Impairment** using the P-AD8 questions; **(6) Mental State** from a self-report on depression, anxiety, and stress (DASS-21); and **(7) other** relevant questions on participants' height, weight, medication intake (that can affect the physiological markers) and perceived problems with their physical health.

2.2 Naturalistic Experiment

Participants carried the Empatica E4 medical wristband and a personalized version of the mobile sensing app X-ing[1] in their daily lives for approximately 2 weeks. The app logs space-time trajectories, infers transportation modes and categorizes stops as activities (home, work, shopping, social, etc.), allowing the participant to review, validate and provide additional information on the trip's or activity's attributes (travel party, when the activity was planned, etc.). We extended the app capabilities by sampling subjective emotional states using the Short Mood Scale (Wilhelm & Schoebi, 2007) as random Ecological Momentary and (end-of-day) Retrospective Assessments (EMA and ERA, respectively). EMAs and ERAs were paired with questions on the impact of surrounding environments or other emotional stimuli. Also, the daily self-reported Pittsburgh Sleep Quality Index (PSQI) is obtained through the app. Simultaneously, the E4 continuously gathers physiological metrics during wakefulness: blood volume pulse, electrodermal activity, skin temperature, and acceleration.

2.3 Post-survey and Choice experiment

The post-survey collects feedback on the study protocol and assesses the impact of major events on participants' stress levels during the Naturalistic experiment stage. It also performed a set of standard questions on selected factors with potential impact on the overall emotional state of the participants, namely a rapid screening of the restless legs syndrome and the Bergen Social Media Addiction Scale questionnaire. Finally, a classical choice experiment was realized, where participants performed a standard two-stage Markov decision task in the field of reinforcement learning (RL) and decision-making psychology (Daw *et al.*, 2011), which is designed to differentiate model-based and model-free learning strategies by analyzing how second-stage rewards influenced subsequent first-stage choices. Inferring on how each individual resorts to these two processes helps understand immediate rewards accounting and longer-term goals, which has implications in various contexts, from habits to learning and adaptability in future nudging.

[1]https://www.empatica.com/en-gb/research/e4/, https://www.mobilemarketmonitor.com/

3 RESULTS

We deployed the eMOTIONAL Daily Patterns framework in a trial in the greater Copenhagen area (GCPH), Denmark. It included 119 participants (53 men, 65 women and one non disclosed), with an average age of 49.9 ± 16.9 years, recruited through panels from the GCPH. Participants received a 500Dkk gift card compensation. The experiment included in-person single Pre- and Post-Survey sessions and an observed average of 13.2 ± 2.4 days of user-validated app data and 12.1 ± 2.9 daily hours of physiological measurements. The data collection spanned from November 2024 to July 2025 due to the limited number of wristbands available.

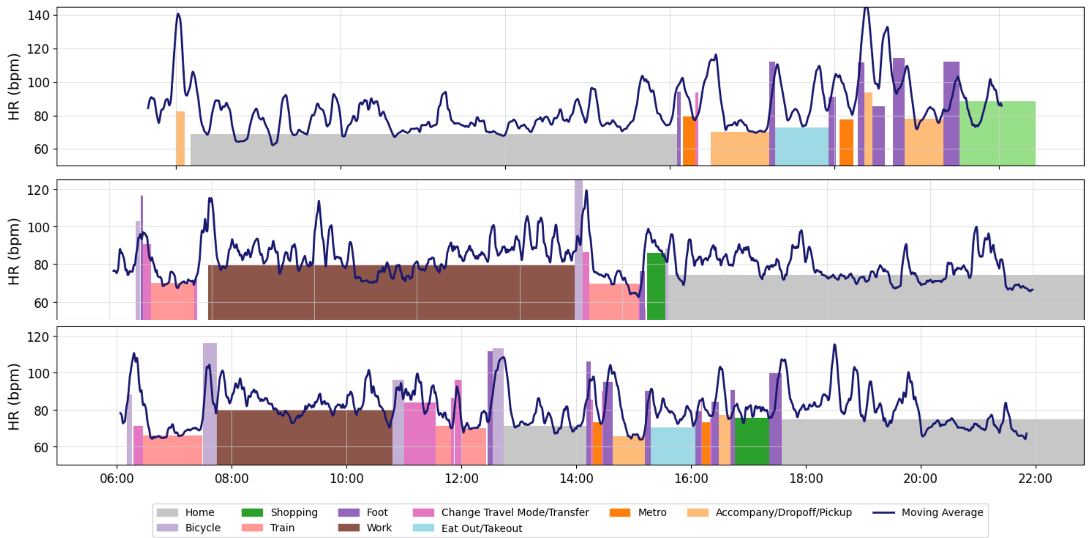

Figure 2 – *Heart Rate and Activity pattern for three different days of the same participant*

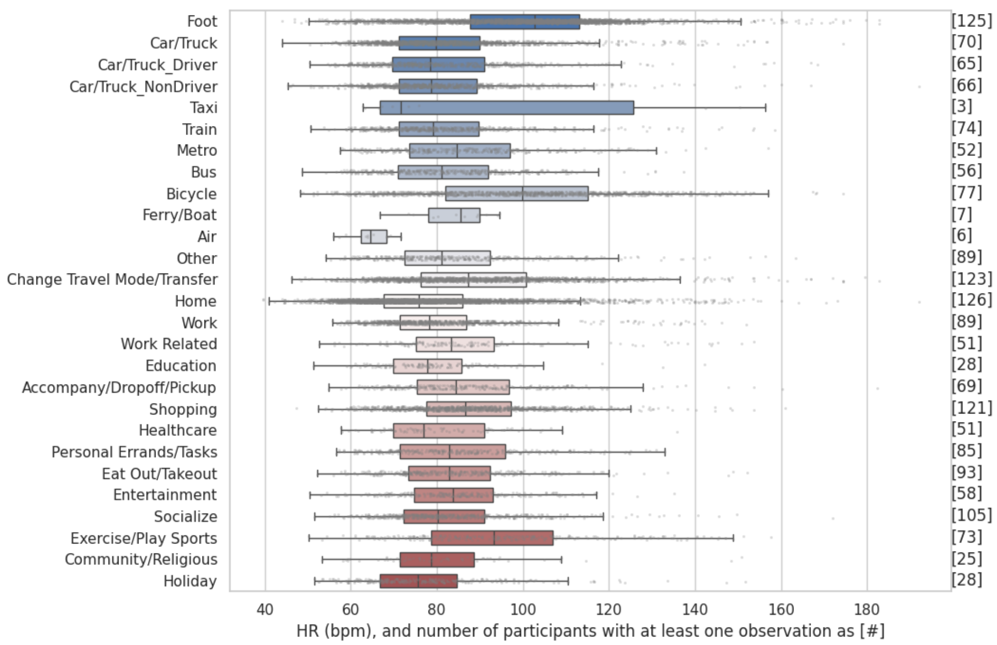

Figure 3 – *Average Heart Rate by activity type for the full sample population*

Figures 2 and 3 showcase the variability of the collected physiological signals (in this case, simple heart rate for straightforward understanding) within and across individuals. The first underscores the need for personalized models for emotion recognition while the second showcase the potential of naturalistic datasets for better understanding how decisions and its features may affect emotions. Indeed, our early statistical results sustain the link between different daily mobility and activity features and emotions. Significant statistical evidence was observed in several dimensions of this relationship, supporting existing laboratory findings: a greater heart rate variability (measured as RMSSD, often used as a proxy of relaxation and recovery process) for driving compared to bus use (Wilcoxon rank-sum $p < 0.001$); a greater average EDA recovery time (an indicator of autonomic regulation and resilience to stress) during social than healthcare-related activities; a greater overall median valence of individuals aged 50-year-old or more (Mann-Whitney U-test $p < 0.001$); a lower subjective valence of all sampled activities for individuals with moderate or higher ranking of chronic stress (DASS specific questions, Mann-Whitney U-test $p = 0.002$). These are just some examples of our initial results, which also allowed for the early identification of limitations of our experiment (e.g.: in-home activities can be very diverse, and so can their emotional response).

4 DISCUSSION

This study lays the groundwork for large-scale naturalistic experiments for monitoring emotional well-being through multi-sensor data integration. Early findings open the door to emotion detection and exploring the daily factors affecting it, promising a new path for policy design for better well-being. Our ongoing analysis includes advanced modeling of complex relationships in daily activity, mobility and emotional patterns and exploring the collected data on sleep, emotional stimuli inference from open-text responses, and extracted location-based urban features.

Acknowledgements: This study was funded by the EU H2020 project eMOTIONAL Cities (945307) and benefited from contributions to experiment design and implementation by M. Pires, M. Monteiro, A. Dubois, N. Holst, L. Sørensen, A. Chamadia, and P. Manousaridou.

References

Barría, C., Guevara, A., Jimenez-Molina, A., & Seriani, S. 2023. Relating emotions, psychophysiological indicators and context in public transport trips: Case study and a joint framework for data collection and analysis. *Transportation Res. Part F: Traffic Psychology and Behaviour*, **95**, 418–431.

Castro, M., Guevara, A., & Jimenez-Molina, A. 2020. A methodological framework to incorporate psychophysiological indicators into transportation modeling. *Transportation Res. Part C: Emerging Technologies*, **118**, 102712.

Conceição, M., Moraes Monteiro, M., Kasraian, D., van den Berg, P., Haustein, S., Alves, I., Lima Azevedo, C., & Miranda, B. 2023. The effect of transport infrastructure, congestion and reliability on mental wellbeing: systematic review of empirical studies. *Transport Reviews*, **43**(2), 264–302.

Daw, N. D., Gershman, S. J., Seymour, B., Dayan, P., & Dolan, R. J. 2011. Model-based influences on humans' choices and striatal prediction errors. *Neuron*, **69**(6), 1204–1215.

Hancock, T., & Choudhury, C. 2023. Utilising physiological data for augmenting travel choice models: methodological frameworks and directions of future research. *Transport Reviews*, **43**(5), 838–866.

Krittanawong, C., Rogers, A., Johnson, K., Wang, Z., Turakhia, M., Halperin, J., & Narayan, S. 2021. Integration of novel monitoring devices with machine learning technology for scalable cardiovascular management. *Nature Reviews Cardiology*, **18**(2), 75–91.

Ledderer, L., Kjær, M., Madsen, E., Busch, J., & Fage-Butler, A. 2020. Nudging in public health lifestyle interventions: systematic literature review and metasynthesis. *Health Education & Behavior*, **47**(5).

Palmberg, R., Susilo, Y. O., Gidófalvi, G., & Naqavi, F. 2021. Built Environment Characteristics, Daily Travel, and Biometric Readings: Creation of an Experimental Tool Based on a Smartwatch Platform. *Sustainability*, **13**(17), 9993.

Smets, E., Rios Velazquez, E., Schiavone, G., Chakroun, I., D'Hondt, E., De Raedt, W., Cornelis, J., Janssens, O., Van Hoecke, S., Claes, S., Van Diest, I., & Van Hoof, C. 2018. Large-scale wearable data reveal digital phenotypes for daily-life stress detection. *NPJ digital medicine*, **1**(1), 67.

Tost, H., Reichert, M., Braun, U., Reinhard, I., Peters, R., Lautenbach, S., Hoell, A., Schwarz, E., Ebner-Priemer, U., Zipf, A., & Meyer-Lindenberg, A. 2019. Neural correlates of individual differences in affective benefit of real-life urban green space exposure. *Nature neuroscience*, **22**(9), 1389–1393.

Wilhelm, P., & Schoebi, D. 2007. Assessing mood in daily life. *Euro. J. of Psychological Assess.*, **23**(4).

Zhang, X., & Ma, L. 2024. Impact of commuting on mental well-being: Using time-stamped subjective and objective data. *Transportation Res. Part F: Traffic Psychology and Behaviour*, **107**, 395–412.