Identifying instant utility (latent emotion) triggers using psychophysiological indicators with an Experience-Based Choice Model in a travel experiment

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Short summary

We propose the Experience-Based Choice Model (EBCM), a novel approach capable of: (1) revealing the triggers of instant utility (emotions) in a transportation context, (2) measuring instant utility using psychophysiological indicators, and (3) estimating choices based on experiences. This framework combines the canonical discrete choice modelling, with the cyclical idea of decisions influenced by hedonic measures of experiences. In this article, we apply the components (1) and (2) of EBCM with data from a real-life travel experiment, in which skin temperature (SKT), heart rate (HR), heart rate variation (HRV), and electrodermal activity (EDA) were measured with a specially designed wristband. Using a latent variable approach, the main results show that instant utilities are sensible, to the travel mode; speed; crowding; brightness; and noise. In addition, it is shown that the participants kept a biased memory of the emotions and that EDA and SKT are meaningful indicators of instant utilities.
Keywords: EBCM; instant utility; psychophysiological indicators; travel experiment; emotions.

1 Introduction

The traditional models used to predict travel behaviour and discrete choice, in general, are based on the classic assumption that people are able to perfectly predict the utility they will perceive once they choose any alternative (Becker, 1996). This rationality argument, which is questionable in various fields including transportation, may be relaxed by introducing the ideas of experienced and instant utility proposed by Kahneman et al. (1997).

Kahneman proposed that when an individual chooses a specific alternative from a set, that alternative is afterwards experienced, causing a set of outcomes in every instant of that experience. The outcomes trigger hedonic feelings at each time point, which are called *instant utilities.* At the end of the experience, the individual has experimented a total utility (or *experienced utility*) which is the area beneath the curve of instant utilities. However, the individual may associate with that experience a biased level of utility due to memory limitations or any other bias source. This is called the *remembered utility* and is a function of the experienced instant utilities.

In the practical implementation of his framework Kahneman et al. (1997) measured instant utility directly from questionnaires of stated emotions, while fantasising with future methods that may instead incorporate *physiological indices of stress and of hedonic states.* Such is the goal of the present paper. After 25 years, we are capable of measuring instant utilities using PPIs in a real-life experiment. For this we adapted Kahneman et al. (1997)'s framework and propose the Experience-Based Choice Model (EBCM), which is capable of (1) revealing the triggers of instant utility, (2) measuring instant utility using psychophysiological indicators (PPIs) and (3) estimating choices based on past experiences. **In this framework, we understand *instant utility* as a latent variable that gives account of the psychophysiological states and emotions triggered by an experience in a specific time point**.

For this purpose, we use a transportation context, plagued with situations where this framework occurs naturally, but the methodology may be straightforwardly applied in several other fields.

Castro et al. (2020) and Hancock & Choudhury (2023) proposed the use of PPIs to correct endogeneity of hybrid models (Walker & Ben-Akiva, 2002) and to measure latent variables. But, no previous studies have used PPIs as indicators of latent variables. However, PPIs have been used in travel context in correlational studies, to predict choices based on stress levels in driving simulators (see Hancock & Choudhury (2023) for a review) and to model stated emotions with logistic

regressions (Barria et al., 2022). To the best of our knowledge, none of them bring to discussion framework of Kahneman et al. (1997).
In this article, we focus on estimating the components (1) and (2) of EBCM. The results show the triggers of instant utility; how PPIs variate with instant utility and the benefit from incorporating PPIs as indicators of instant utility. We also explored how individuals keep biased memories of their experiences.
The data used in this study is retrieved from the experiment reported in Barria et al. (2022). They collected physiological indicators, environmental and travel variables from 44 participants travelling in different modes. The field experiment design is based on the methodological framework proposed and validated by Castro et al. (2020).
The remainder of this article is divided into 4 sections. Section 2 overviews the EBCM. Section 3 shows the methods, Section 4 the main results and Section 5 exposes the main conclusions of this work.

2 The Experience-Based Choice Model

We propose an extended Experience-Based Choice Model (EBCM) that integrates Kahneman's theory with the canonical discrete choice framework. Figure 1 shows a schematic view of the model. We argue, that decision-making is a cyclical process, where the individual learns from his/her experience and also considers exogenous information for making a choice. In this framework, an experience is composed by a mapping of outcomes to instant utilities, which are latent hedonic measures of the outcomes of the decision and can also be understood as latent emotions. Instant utilities are aggregated as a memory into a *remembered utility*. We call this process the *Memory Aggregation Process* (MAP), which could adopt different functional forms (e.g. the mean or the logsum of instant utilities). Instant utility is a latent variable that can be measured with statements of emotions and PPIs, while the remembered utility can be measured with post-experience stated emotions. Remembered utility is a biassed measure of the experience, in contrast to experience utility which is the area beneath the curve of instant utilities. When facing the same decision in the future, the decision utility will be a function of exogenous information and the remembered utility from previous experiences with each alternative. In the absence of previous experience, it could be assumed that decision depends just on exogenous information.
Both frameworks complement each other, since Kahneman's framework did not consider the exogenous information and did not consider instant and remembered utilities as latent variables that can be measured. On the other hand, the canonical decision making framework neglects the weigh of experience on decisions. EBCM is capable of (1) revealing the triggers of instant utility, (2) measuring instant utility using psychophysiological indicators (PPIs) and (3) estimating choices based on past experiences.
When an experience is remembered worse than what it actually was, i.e., negative memory bias exists, the subject is less likely to choose it in the future, despite the actual level of experienced utility (the opposite follows directly). This is the main reason why observed choices should not be used to infer satisfaction with the alternatives but only a biased notion of satisfaction.
In this article, we focus on modelling the relations outside the canonical framework in Figure 1 (relations 4, 5, 6, and 8) in order to: (1) prove the feasibility of measuring instant utility with PPI plus real-time and PPI plus post-trip stated emotions; (2) identify the triggers of emotions; and (4) identify which PPIs are best suited to measure latent emotions. Future efforts should be made to model the complete EBCM.

3 Methods

In this study we used the data collected in the experiment reported by Barria et al. (2022) to partially model the EBCM. To measure the PPIs, a wristlab called Biomonitor 2.0 was used, which was developed by WeSST Lab at Universidad de Chile (Jimenez-Molina et al., 2018). It can measure electrodermal activity (EDA), heart rate (HR), heart rate variation (HRV), skin temperature (SKT), and acceleration. In addition, an observer collected environmental data using device of sensors called ContextINO, and recorded punctual events that occurred during each trip using a mobile application called PsychoTrans. Specifically, the relations outside the canonical framework were modelled in Figure 1. We estimated the following models:

1. MV: instant utility measured by valence of emotions and PPIs (Figure 2)

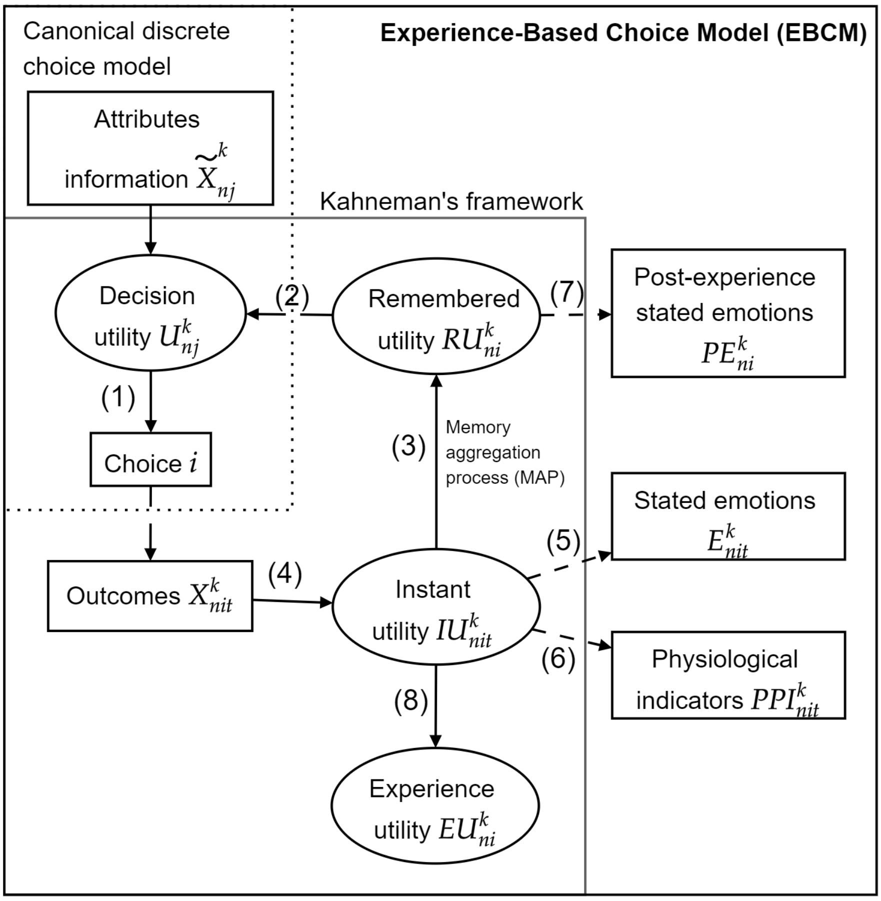

Figure 1: Experience-Based Choice Model (EBCM)

2. MA: instant utility measured by arousal of emotions and PPIs (Figure 2)
3. MV-NoP: MV without PPIs
4. MA-NoP: MA without PPIs
5. MV-NoT: MV without travel data
6. MA-NoT: MA without travel data

The estimation was carried out using *Apollo*, a freeware package for R (Hess & Palma, 2019). After model estimation, we estimated the posterior model parameter distributions using the function *apollo_ conditionals* of the Apollo package. In addition, onboard stated emotions were compared with ex-post stated emotions.
Then, spatial and temporal profiles of instant utility are generated using the estimated parameters. These profiles allow visualising how did participant's instant utility vary in the different sections of the trip.

4 Results

The results shown are obtained using 5000 Halton draws (N(0,1)) for the likelihood simulation. It was verified that estimates are stable between 4000 and 5000 draws. We display in Figure 3 the impact on the valence and on the arousal of the different triggers studied. Since only the ratio of the coefficients can be identified in discrete choice models, the analysis is presented relative to (β_{tt}), which showed the largest nominal value. Just the statistically significant, and those that were slightly above the significance limit in at least one of the models, are shown.
It was observed that:

- Travelling on BHS (when velocity is above the average) causes more happiness than any of the other variables.

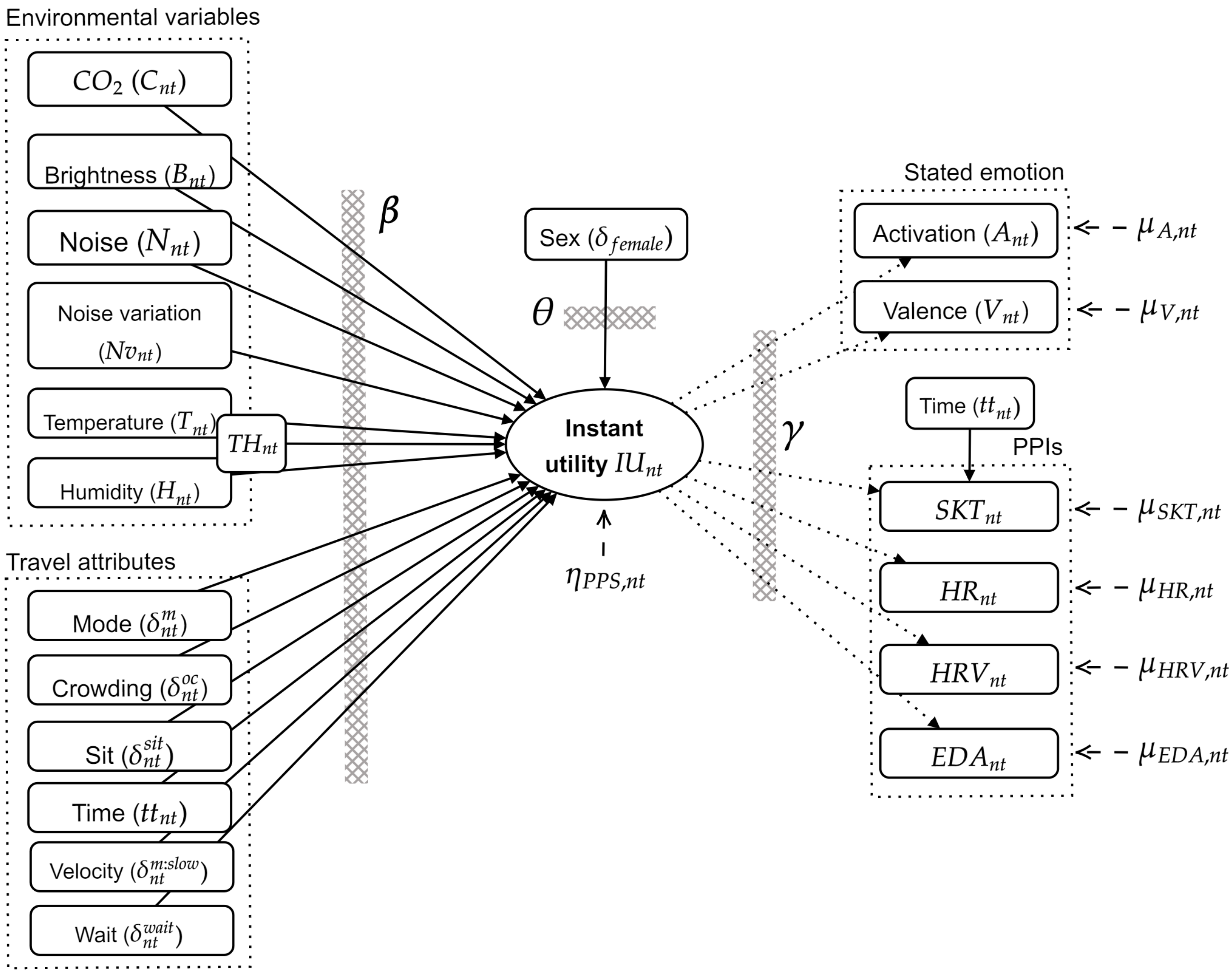

Figure 2: Model diagram of MV and MA

- Travelling on BLS (when velocity is below average) triggers more sadness than any other considered variables.
- When velocity is above the average, the impact of BLS on emotions is similar to walking. This may appear contradictory, but we suggest this is due to an unsafe feeling when riding BLS and higher displeasure caused by vibrations and route accelerations.
- Crowings levels 2 and 1 reduce the arousal.
- Better-illuminated places positively affect emotions.
- Higher humidity and higher noise variation increase the feeling of sadness.

We conducted a similar latent variable model but neglecting PPIs (MV-NoP and MA-NoP). It was found no environmental variables turned statistically significant. Some travel variable are significant.
From the estimation of the parameters of the measurement equations, some relations are derived:
At higher valence:

- Higher EDA
- Lower SKT, HR

At higher arousal:

- Higher EDA, HR
- Lower HRV

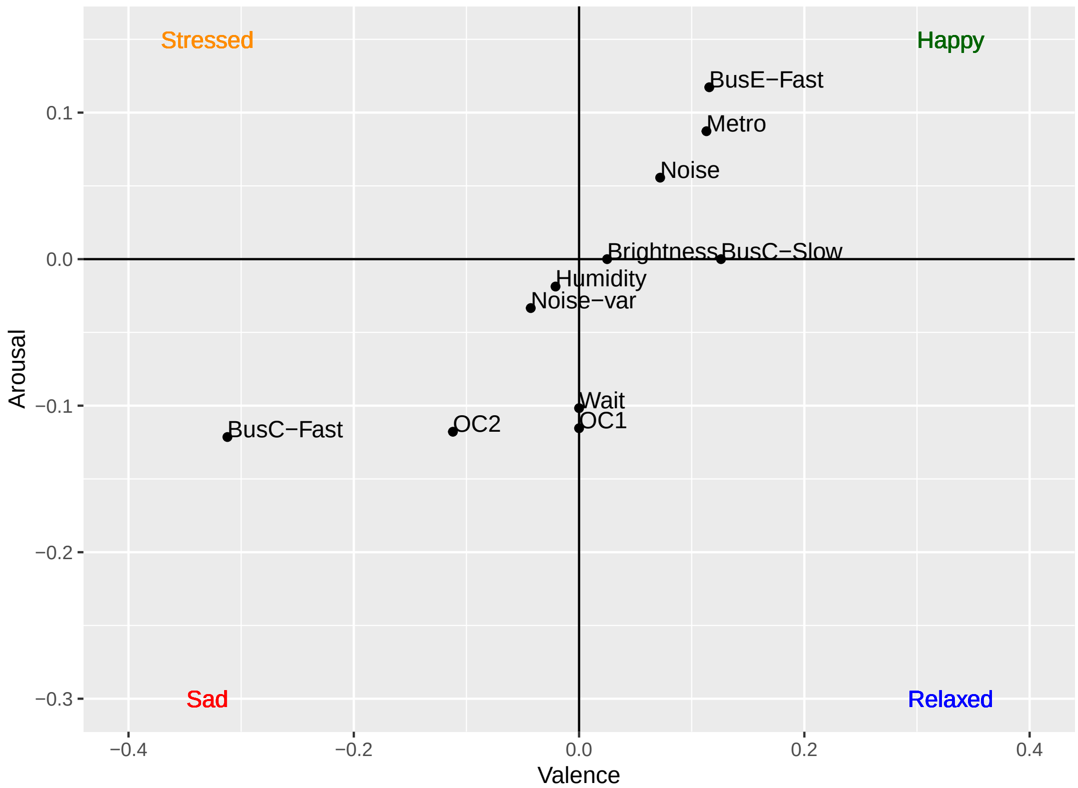

Figure 3: Relative marginal contribution to Valence and Activation

Posterior parameter distribution
This section seeks to answer whether the relations found between instantaneous utility and PPI can be extrapolated to the individual level. Figure 4 and Figure 5 show, for MV and MA models, respectively, the density function of both the population distribution (no filled area) and the density of the expected value of each parameter across individuals (filled area). The mean population distribution of the parameter is shown with a vertical dashed line, while the mean expected value across individuals is shown with a vertical solid line. Under each density plot, a box-plot shows the distribution of the expected parameters for each individual.
Tables 4 and 4 show the analysis of the mean expected value of the valence-PPI and arousal-PPI effects. It can be observed that, on average, higher valence is expected to increase EDA, while it is expected to decrease SKT (-0.75, $p < 0.001$). Higher arousal significantly increases the EDA (0.56, $p = 0.01$) and HR (0.37, $p = 0.02$) while it decreases HRV (-0.17, $p = 0.01$).

Table 1: Individuals' expected valence-PPI relation: mean, standard deviation, t-test against zero and p-value

	Mean	sd	t-test	p-value
EDA	0.65	0.21	3.12	<0.001
HR	0.19	0.14	1.33	0.19
SKT	-0.75	0.17	-4.55	<0.001
HRV	0.06	0.05	1.41	0.17

Instant utility profile
Figures 6 and 7 show the spatial instant utility profiles. In both figures, higher values of instant utility indicate a higher probability of experiencing a positive valence or arousal, respectively.
Also, it was estimated the mean instant utilities and the mean valence and arousal direct from the stated emotions. On the contrary, the comparison between the remembered mean arousal and the mean onboard stated arousal shows a negative bias (-4.447%, $p = 0.0923$). The same way, the mean remembered valence was 5.848% lower than the mean onboard stated valence ($p = 0.0267$). This means that participants, after the experiment, associate to the travel sadder feelings than what they actually experienced.

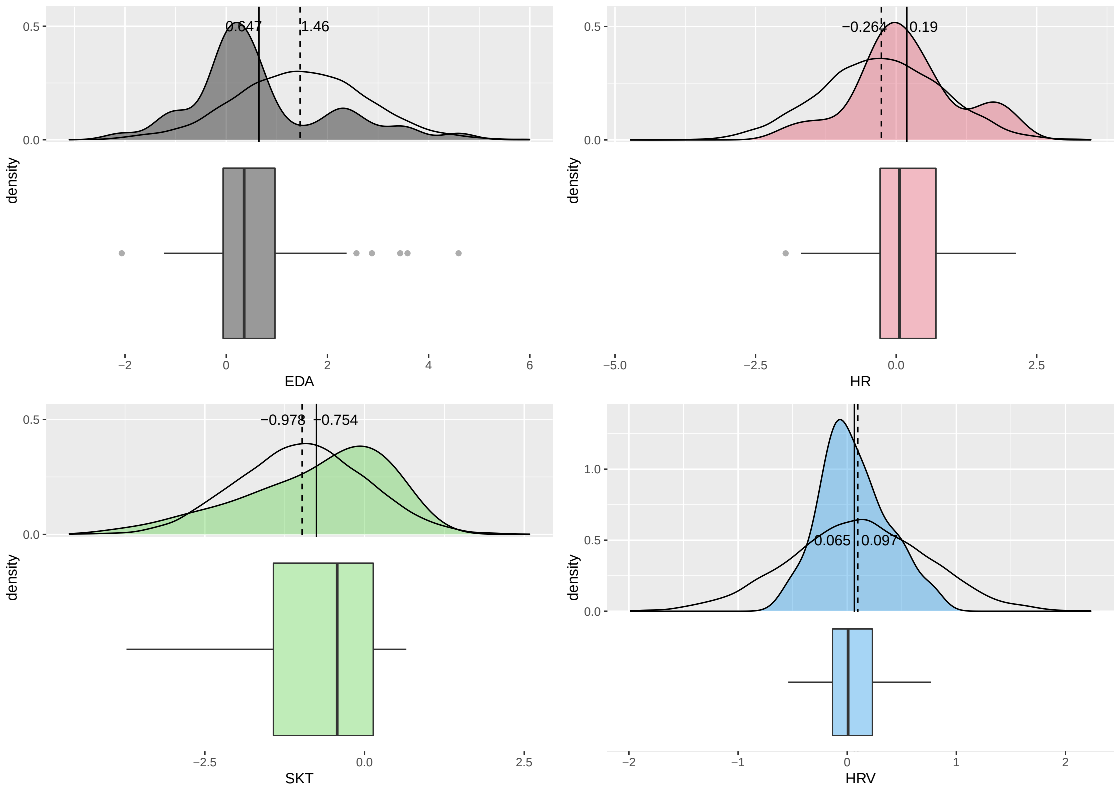

Figure 4: Distribution of the relation valence-PPI for the population (no filled density plot) and distribution of the expected parameters for each individual (filled density and boxplot)

Table 2: Individuals' expected Arousal-PPI relation: mean, standard deviation, t-test against zero and p-value

	Mean	**sd**	**t-test**	**p-value**
EDA	0.56	0.21	2.63	0.01
HR	0.37	0.15	2.49	0.02
SKT	-0.19	0.23	-0.81	0.42
HRV	-0.17	0.06	-2.88	0.01

5 Conclusions

A novel methodology was implemented to estimate the latent psychophysiological state of 44 participants in an on-road travel experiment. A novel approach to discrete choice is proposed: the Experience-Based Choice Model (EBCM). This model is partially estimated incorporating environmental, travel, and physiological variables.

It was shown that the participants' emotions were sensible environmental and travel variables. The low-standard bus has, better effects on emotions when velocities are slow, which can be associated with insecurity or discomfort feelings.

Also, it was shown statiscally significant mean effects of instant utility physiological indicators, despite that for different individuals this effect may be in opposite directions. It was also shown that the estimation of the instant utilities without the physiological indicators is futile due to the loss of statistical efficiency.

In addition, it was shown that the participants hold biased memories of what they actually experienced on the public transport trip. In fact, the bias on valence was negative and significant, which we suggest may be due to an over-weighting of past experiences or to a social tendency to negatively evaluate the use of public transport.

Policy-makers should consider the potential benefit of psychological well-being associated with less stressful travel conditions. Future research should consider including more heterogeneity in the sample and assess more interactions between variables. Also, the instant utility discussion opens

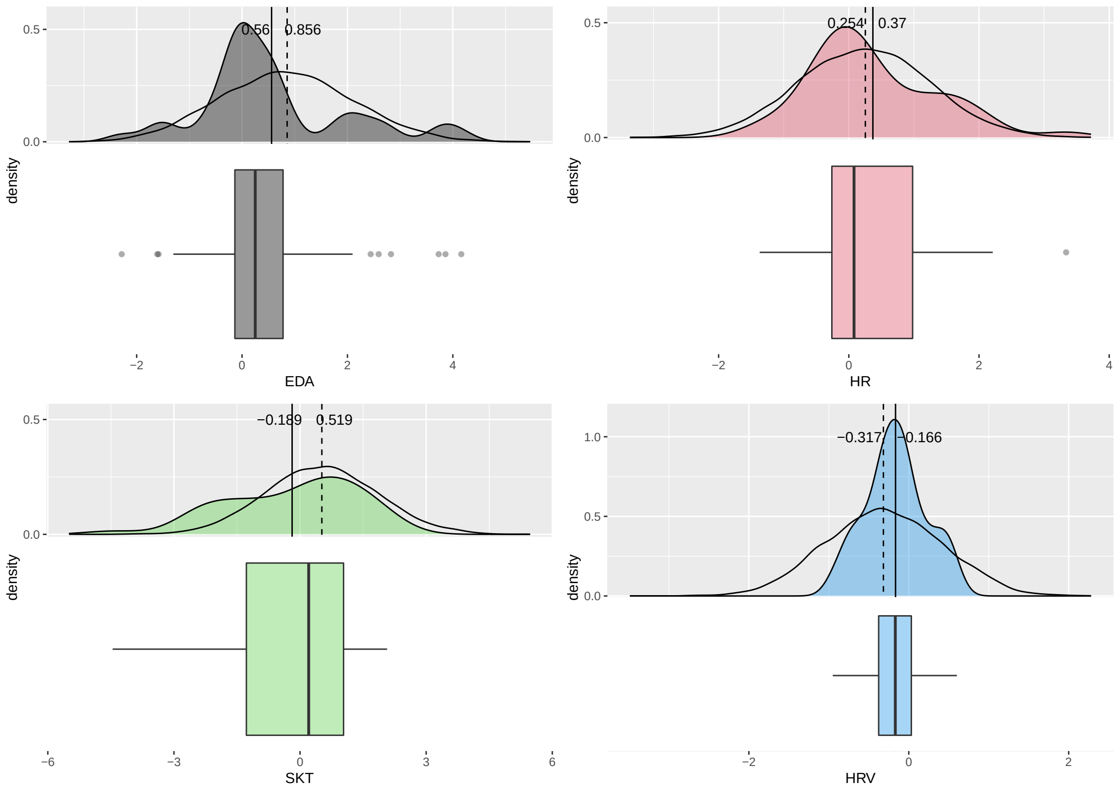

Figure 5: Distribution of the relation aroussal-PPI for the population (no filled density plot) and distribution of the expected parameters for each individual (filled density and boxplot)

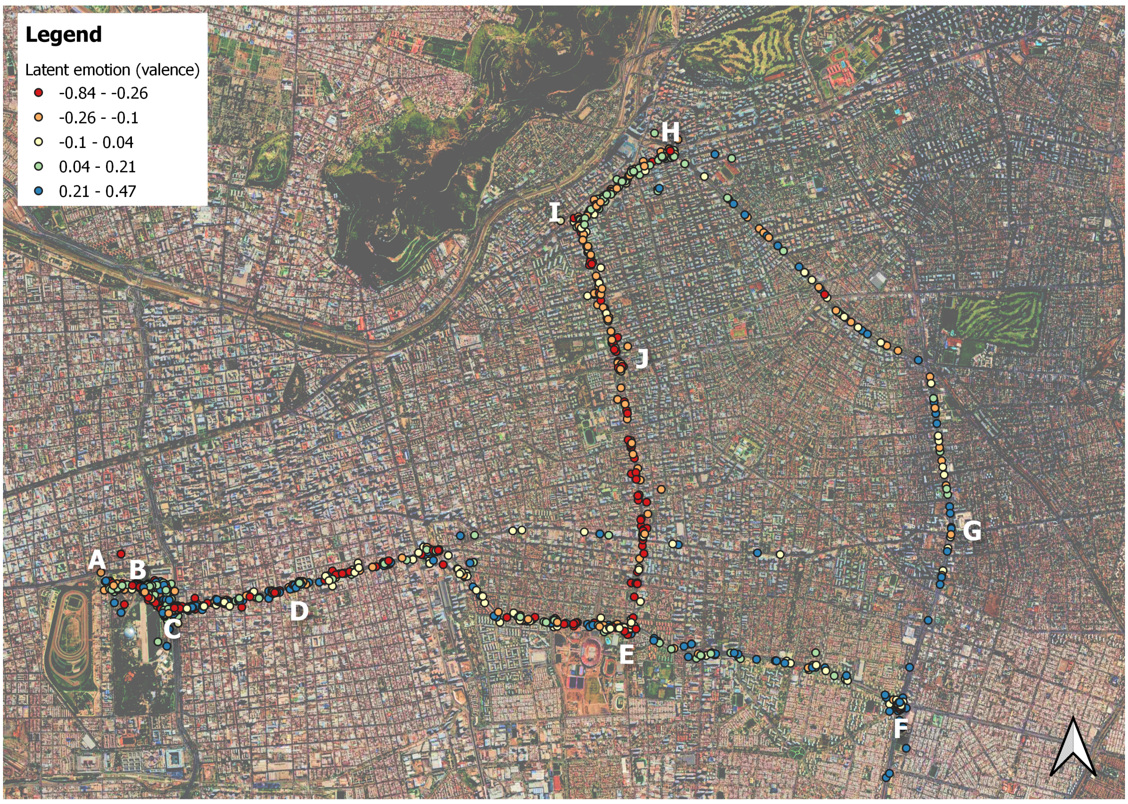

Figure 6: Spatial latent emotion profile estimated from model MV results

at least two research lines, namely: to explore whether memory bias influences modal choice and

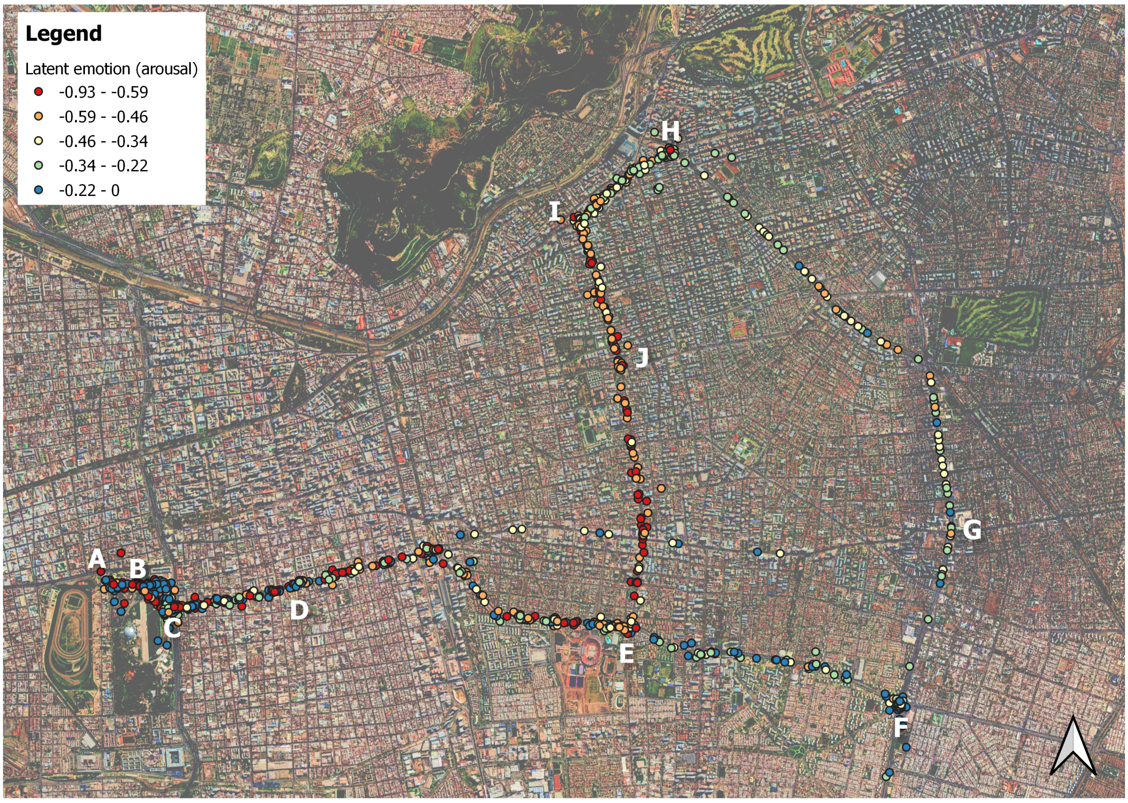

Figure 7: Spatial latent emotion profile estimated from model MA results

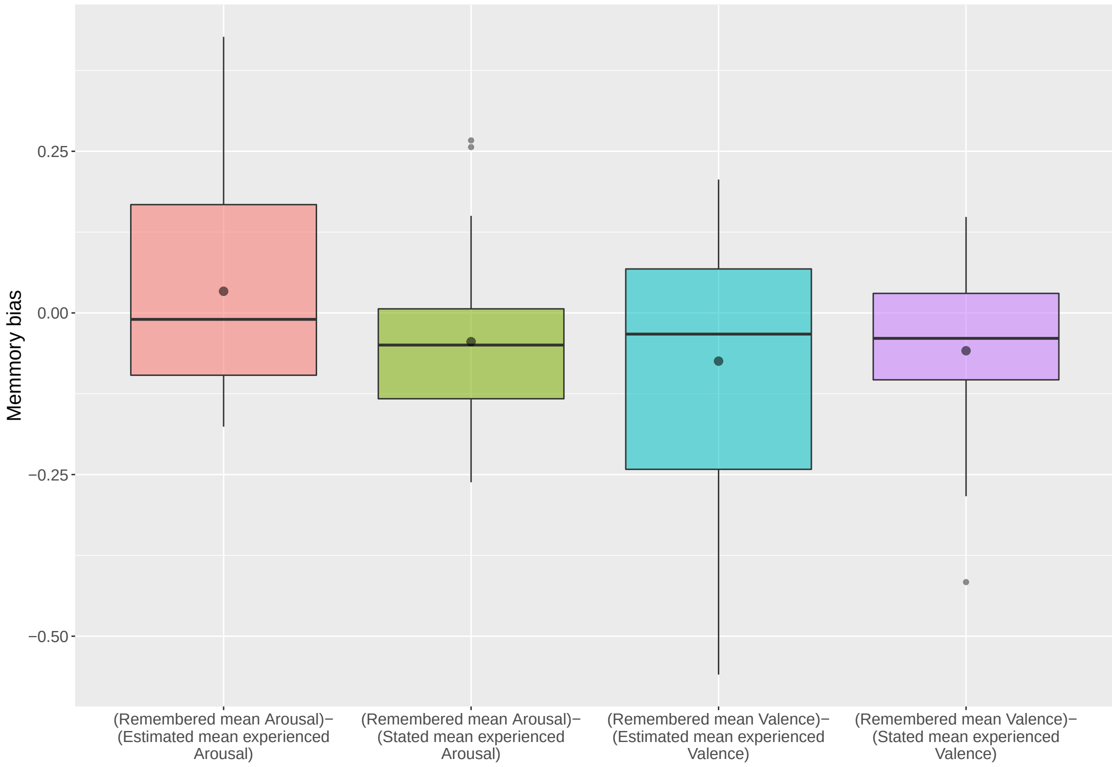

Figure 8: Estimated memory bias as the difference of the mean arousal and valence stated at the end of the trip (remembered valence and arousal) and the estimated or the stated valence during the trip

to explore whether this bias holds when travelling by other modes and if it is necessary to design public policies that tackle a possible loss of (biassed) public transport users.

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