MODELLING EXPERIENCE-BASED CHOICES AND IDENTIFYING INSTANT UTILITY (LATENT EMOTIONS) USING PSYCHOPHYSIOLOGICAL INDICATORS

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ABSTRACT

We propose the Experience-Based Choice Model, a novel approach capable of: (1) revealing triggers of instant utility (latent emotions), (2) using psychophysiological indicators (PPIs) to identify instant utility, and (3) estimating choices based on experiences. This framework combines static and normative views with cyclical decisions influenced by hedonic memories. We formulate the model and show (1) and (2) it in a travel experiment, finding that instant utilities are affected by factors like travel mode, velocity, crowding, brightness, temperature, and humidity. We discuss methodological implications and potential applications in travel satisfaction assessment, demand estimation, and policy evaluation.

1. INTRODUCTION

Kahneman et al. (1997), revisiting Bentham (1789), proposed a framework that relaxes the classical rationality argument of Random Utility Models (RUM, McFadden (1974)) and latent variables (ICLV, Ben-Akiva et al. (2002)). He 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. These outcomes trigger hedonic emotions (*instant utilities*) at each time point, which influences future decisions. We will refer to this framework as the Experienced Utility Framework (EUF). This framework has been discussed in travel literature (Gärling, 2020; De Vos et al., 2016) but has not been incorporated into a discrete choice modelling framework.

The canonical models are better suited for one-shot decisions, rather than for repeated decisions, as is the case of commuting choices within a transport system where the experience, hedonic memories, and learning processes may influence the decision-making. In this sense, McFadden (2014) claims that economic consumer theory is changelled to use measurements and experimental methods from other fields (cognitive psychology, social sciences and neurosciences) to create a new behavioural science of pleasure, which inherits the quantitative, predictive characteristics of neoclassical theory, and the capacities to explain the individual sensation of well-being. In McFadden's view, such a theory should better predict the impact of novel economic policies on consumer well-being.

The integration of EUF with ICLV could give a solid theoretical framework to model the interaction of experiences, exogenous information, and latent variables (i.e. perceptions, attitudes, etc.), which is consistent with the literature from psychology and neurosciences. Nevertheless, the measurement of *instant utilities* is one of the main difficulties in adopting the EUF. Fortunately, affective computing methods allow utilizing peripheral physiological data and contextual information to identify multimodal characteristics to explain in an unbiased way individuals' psychological states. PPIs have been used in travel context (Castro et al., 2020; Hancock & Choudhury, 2023; Conceição et al., 2022) but most are correlational studies carried out in controlled laboratory environments.

Then, **the first research question of this article is if it is possible to integrate the canonical discrete-choice models with the experienced utility framework** (Kahneman et al., 1997). For this, we propose the Experience Based Choice Model (EBCM), which is capable of (1) revealing the triggers of instant utility, (2) measuring instant utility using PPIs and (3) estimating choices based on experiences. **The second research question is if it is possible to estimate instant utilities using PPIs**. For this, in a case study, we focus on components (1) and (2) of EBCM using data from a travel experiment reported in Barría et al. (2023). After answering those questions, we show the environmental and travel variables that influence instant utility; how PPIs variate with instant utility; the benefit from incorporating PPIs as indicators of instant utility; and we explored how individuals keep biased memories of their experiences. We also show how this methodology can be used to detect geographical zones that cause higher or lower satisfaction. 25 years after Kahneman et al.'s (1997) article, we are capable of measuring instant utilities as a latent variable measured by PPIs and stated emotions in a real-life travel experiment. The framework proposed here may be straightforwardly applied in several other fields.

The remainder of this article is divided into three sections. Section 2 details the proposed discrete choice-modeling framework. Section 3 describes the case study and its results, and Section 4 exposes the main conclusions of this work.

2. EBCM MODEL FRAMEWORK

The first aim of this research is to combine the EUF proposed by Kahneman et al. (1997) with the integrated choice and latent variables (ICLV) framework (Ben-Akiva et al., 2002). As mentioned earlier, we call the integrated model EBCM, which comprises two parts: the ICLV part and the experience model part (Figure 1). The top left of the figure depicts the ICLV part, while the rest corresponds to the experience model (adaptation from the EUF). We argue, that decision-making is a cyclical process, where the individual learns from his/her experience and also considers exogenous information, and latent variables as perceptions or attitudes for making a choice.

Let us first describe the ICLV part. Since the model assumes a cyclical process, each iteration (a specific choice-task followed by an experience) is denoted by the index k. In a given choice-task, the individual n faces a set of alternatives C_n^k of size J. Then:

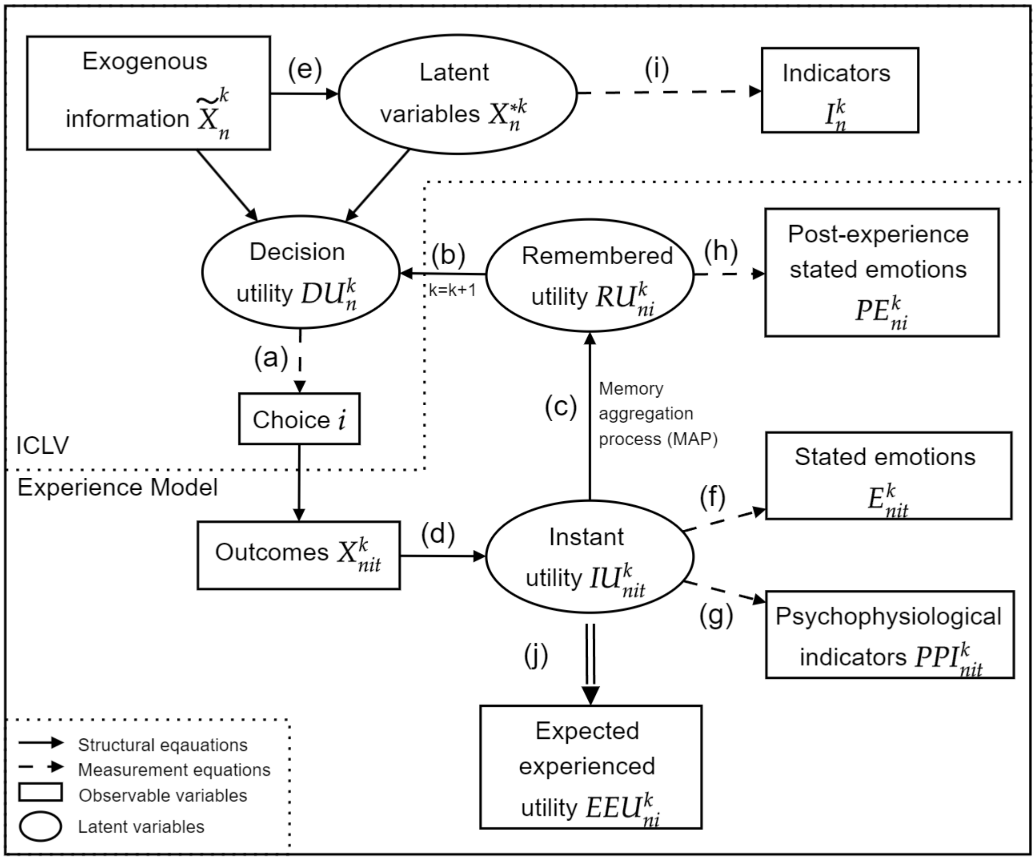

Figure 1: The Experience-Based Choice Model (EBCM).

- The individual computes the **decision utility** (DU_n^k) for the alternatives from a set of size J (DU_n^k is a vector of length J), as usual in any RUM model. The decision utility of each alternative is explained by exogenous information of the M attributes ($\tilde{X}_n^k$, matrix $M \times J$) and latent variables, e.g., perceptions or attitudes, $\tilde{X}_n^{*k}$.
- The Decision utility of the alternative j at choice-task k is also explained by the remembered utility (RU) associated to that alternative in previous experiences. We will later detail how it is RU generated.
- Then, the subject chooses an alternative i based on the vector of decision utility DU_n^k. In the absence of previous experience, it can be assumed that the decision utility depends just on exogenous information and latent variables (attitudes, beliefs, perceptions, etc.).

Once the alternative is chosen, the individual begins a temporally extended experience with limited duration. The time of the experience is discretized, denoting every time instant $t \in \{1, ..., T^k\}$, where T^k is the duration of the experience. Then:

- In every time instant, the subject is exposed to a set of **outcomes** (X_{nit}^k, a matrix with T^k rows and as many columns as outcomes).

- The outcomes (stimuli) trigger **instant utilities** (IU^k_{nit}) on each instant of the experience, which shall be interpreted as the latent emotions or the perceived level of pleasure or displeasure. Instant utilities explain the variation of psychophysiological indicators (PPI^k_{nit}), and also underlay stated emotions (E^k_{nit}) (Castro et al., 2020; Hancock & Choudhury, 2023; Kahneman et al., 1997).

- At the end of the experience, the subject aggregates, through a process we call *Memory Aggregation Process* (MAP), all the instant utilities into a memory. This memory is called the **remembered utility** (RU^k_{ni}), and is a remembered level of satisfaction with the experience, biased by the bounded mental capacities of the subject. For the aggregation of instant utilities into remembered utility, Kahneman proposed the *peak-end rule*, a heuristic that basically gives more importance to more salient and more recent memories. However, many other functional forms could be adopted.

- The integral of instant utilities over time, and is called the **experienced utility** (Theorem 1, Kahneman et al. (1997)), This is as a free-of-memory-bias measure of the experience. Note that, conditional on IU, the **expected experienced utility** (EEU^k_{ni}) can be estimated. This measure has the potential of being used to assess public policy or welfare-seeking projects, as proposed in Kahneman & Sugden (2005). The information obtained from the experienced utility is much more valuable than the information that can be obtained from ex-post questionnaires, since any subject is prone to keep biased memories of an experience. We call "memory bias" (ρ^k_{ni}) the difference between the remembered and the experienced utility.

2.1. General specification

In this general formulation, we will not specify functional forms nor error term distributions. This formulation is based on the formulation of ICLV (Ben-Akiva et al., 2002). This section is ordered following the order of the relations in Figure 1 (indexes "a" to "j").

Relation (a): First, it is necessary to define criteria for the decision model. For instance, we can suppose utility maximisation:

$$y^k_{ni} = \begin{cases} 1 & i = argmax_j(DU^k_{nj}), j \in C^k_n \\ 0 & \text{other case} \end{cases} \tag{1}$$

Where C^k_n is the set of alternatives for subject n in experience k. Now we detail the structural and measurement equations. In the scheme (Figures 1), structural equations are represented with solid lines while measurement equations with dashed lines.

Structural equations

Relation (b): Now, we need to suppose a known distribution of decision utilities $f_1(DU|RU, \beta, \tilde{X}, X^*, \Sigma_\eta)$, then we pose that decision utility of every alternative is reinforced by the remembered utility of the experiences. In absence of previous experiences, decision utility depends just on exogenous information and the latent attitudes or beliefs X^*:

$$DU_{nj}^{k} = \begin{cases} DV\left(RU_{nj}^{z}, \beta, \tilde{X}_{nj}^{k}, X_{nj}^{*k}\right) + \eta_{nj}^{k} & H_{nj}^{k} \neq \emptyset \\ DV\left(\beta, \tilde{X}_{nj}^{k}, X_{nj}^{*k}\right) + \eta_{nj}^{k} & \text{other case} \end{cases} \tag{2}$$

Where $z \in H_{nj}^{k}$ and $\eta \sim G(0, \Sigma_\eta)$, Σ_η is a variance-covariance matrix and G is a generic distribution function. DV is a generic function that the represents the systematic part of the decision utility.

Relation (c): Assuming the distribution $f_2(RU|IU, \Sigma_\varepsilon)$, the remembered utility associated to the alternative i chosen in experience is given by: $RU_{ni}^{k} = f\left(IU_{nit}^{k}\right) + \varepsilon_{ni}^{k}$, where $\varepsilon \sim G(0, \Sigma_\varepsilon)$. As said before, different functions f can be defined to aggregate the instant utilities into a remembered utility (e.g., see the *peak-end rule*[1] Kahneman et al. (1997)). We call this process the *Memory Aggregation Process* (MAP).

Relation (d): Assuming instant utilities have a distribution $f_3(IU|X, \gamma, \Sigma_\nu)$, relation (d) can be expressed as $IU_{nit}^{k} = IV(X_{nit}^{k}, \gamma) + \nu_{nit}^{k}$, where $t \in [0, T^k]$, with T^k the total duration of experience k, and $\nu \sim G(0, \Sigma_\nu)$. We here assume, as usual, that instant utility can be separated into a systematic part ($IV(X_{nit}^{k}, \gamma)$) and a disturbance ν.

Relation (e): The last relation corresponds to the latent variables from ICLV part. Let $f_4(X^*|\tilde{X}, \theta, \Sigma_s)$ be the distribution of the latent variables X^*. Then, with $s \sim G(0, \Sigma_s)$, the latent variables can be written as: $X_n^{*k} = g(\tilde{X}_n^k, \theta) + s_n^k$.

Measurement equations
For estimating instant utilities and remembered utilities, we need the distribution of the indicators. There are three sets of indicators for the latent experience model: the real-time stated emotions, the psychophysiological indicators and the post-experience stated emotions.

Relation (f): Let us suppose that stated emotions have a distribution $f_5(E|IU, \alpha_E, \Sigma_\xi)$, then we can express an emotion E as: $E_{nit}^{k} = h(IU_{nit}^{k}, \alpha_E) + \xi_{nit}^{k}$, with $\xi \sim G(0, \Sigma_\xi)$, which applies for each stated emotion used as an indicator.

Relation (g): Similarly, if PPIs have a distribution $f_6(PPI|IU, \alpha_{PPI}, \Sigma_{\xi'})$, a measurement equation of a PPI can be expressed, for example, as $PPI_{nit}^{k} = l(IU_{nit}^{k}, \alpha_{PPI}) + {\xi'}_{nit}^{k}$. With $\xi' \sim G(0, \Sigma_{\xi'})$. This applies for each measured psychophysiological indicator.

Relation (h): On the other hand, the post-experience stated emotions depend on the remembered utility and are supossed to have a distribution $f_6(PE|RU, \omega, \Sigma_\zeta)$. It can be expressed as $PE_{ni}^{k} = q(RU_{ni}^{k}, \omega) + \zeta_{ni}^{k}$. With $\zeta \sim G(0, \Sigma_\zeta)$.

Relation (i): Then, if each indicator I of the latent variables of beliefs and attitudes of each subject follow a distribution $f_8(I|X, X^*, \lambda, \Sigma_\psi)$ and $\psi \sim G(0, \Sigma_\psi)$, it can be written as: $I_n^k = d(\tilde{X}_n^k, X_n^{*k}, \lambda) + \psi_n^k$

[1] The peak-end rule essentially proposes that the human mind gives more importance to salient and most recent events

Relation (j): Finally, the non-biased aggregated measure of instant utilities is called *experienced utility*, and is obtained by integrating the systematic part of instant utility:

$$EU_{ni}^{k} = \int_{0}^{T_j^k} IV_{nit}^{k} dt \tag{3}$$

Which is different from remembered utility due to the "memory bias" (ρ_{ni}^{k}), wich can be expressed as $\rho_{ni}^{k} = RU_{ni}^{k} - EU_{ni}^{k}$. Then, the expected experienced utility (EEU_{ni}^{k}) is:

$$EEU_{ni}^{k} = \int EU_{ni}^{k} d\nu \tag{4}$$

Recall that EEU is a measure of high value, which potential applications in policy evaluation must be further explored.

Likelihood: For estimating the model with likelihood maximization, we need to construct the probability distribution function $L = P(y, E, PPI, PE, I|\tilde{X}, X, \beta, \alpha, \gamma, \theta, \omega, \lambda, \Sigma_\eta, \Sigma_\varepsilon, \Sigma_\nu, \Sigma_\xi)$:

$$\begin{aligned} L = \int & P(y|\tilde{X}, X, X^*, RU, \beta, \Sigma_\eta) f_4(X^*|X, \theta, \Sigma_s) f_8(I|X, X^*, \lambda, \Sigma_\eta) \\ & f_2(RU|IU, \rho, \Sigma_\varepsilon) f_3(IU|X, \gamma, \Sigma_\nu) f_5(E|IU, \alpha, \Sigma_\eta) f_6(PPI|IU, \theta, \Sigma_\nu) \\ & f_7(PE|RU, \omega, \Sigma_\zeta) dX^* dIU dRU \end{aligned} \tag{5}$$

Potential applications

EBCM can be used to predict behaviour and to estimate a level of satisfaction with an experience, in any field where subjects are exposed to discrete choice tasks followed by temporally extended experiences. Psychophysiological indicators have been claimed to serve for experience assessment for different authors, but no concrete methodology has been proposed.

Once the model is estimated, expected instant utilities can be estimated without psychophysiological indicators or stated emotions. It is just necessary to measure the outputs (stimuli of the experience) and know how they influence the instant utility. In a transportation context, that would allow the detection (even in real-time) of areas or modes that cause higher or lower satisfaction on users, and based on that, making policy decisions. In the following case study, we show how this methodology can be used to detect zones that cause higher or lower satisfaction.

Furthermore, the experienced utility can be used for public policy or project evaluation (Kahneman & Sugden, 2005), since it can be translated into money by finding out the marginal variation of instant utility with income (how much happier is someone when increasing the income). Then, when evaluating a project portfolio, the decision-maker would know how much happier would be the population with each project, and make welfare-oriented investments.

3. CASE STUDY

The data were collected in the experiment reported by Barría et al. (2023), but, to make this article self-contained, a brief description of the experiment follows. The experiment sought to capture part of the participants' public transport trip experience by recording PPIs; environmental indicators; and stated emotions. 44 participants were recruited through a publication on the university's institutional web forum. All the participants were students from the Faculty of Physical and Mathematical Sciences at the University of Chile. They received a payment of approximately 15 USD.

Transport variables were recorded using an application for smartphones called PsycoTrans. In addition, ambient indicators are recorded by a device called ContextINO, which was developed by WeSST Lab at University of Chile. The stated emotions are captured using a smartphone application, in which participants were asked to declare their emotional state at regular intervals of time. Lastly, a specially designed wristband captured at a frequency of 100 Hz [2], the heart rate (HR); heart rate variability (HRV); electrodermal activity (EDA); and skin temperature (SKT) (Jimenez-Molina et al., 2018). PPIs were first recorded during a baseline period of 3.5 minutes. At the end of the experiment, participants were asked to state how they remember to have felt along the trip, but due to time constraints, just half of the participants answered this question.

The stated emotions were characterized according to the circumplex model of affect. It establishes that affective states are made up of sensations that arise from the activity of two basic neurophysiological systems: Valence and Activation (Posner et al., 2005; Russell, 1980). The first of these systems corresponds to a continuum between pleasure and disgust. In contrast, the second system corresponds to a continuum between low and high excitement or exaltation. The linear combination of both dimensions results in four affective quadrants. The participants were asked to choose one of those quadrants every 4 minutes (on average). Then, for example, if a participant stated to be stressed (second quadrant), that emotion was discomposed into negative valence (valence=0) and high activation (activation=1).

The participants were instructed to make specific routes using different modes. All the routes have in common the use of bus (high and low-standard), metro (Line 4, low-standard in terms of indoor comfort), and walking. However, some routes had additional sections: Autonomous vehicle (an experimental autonomous vehicle that was being tested) and metro lines 3 and 6 (high-standard wagons). The autonomous vehicle observations were discarded since participants just stated "happy" emotions (valence=1, activation=1).

Since we are interested in studying the variations in PPIs induced by the travel experience, we analysed the variation of PPIs concerning the baseline period. Additionally, we aggregated the PPIs and the environmental indicators in a time window of 6 seconds prior to the statement of the emotions. In order to do that, as proposed by Castro et al. (2020), it was used the logsum of the records in every instant in that time window for each participant. Furthermore, we standardised the indicators to avoid scale differences that affect the analysis.

[2]All recorded indicators have different frequencies, but were resampled to 100 Hz. See Barría et al. (2023) for more details

3.1. Specification

In this case study, we partially modelled the Experience-Based Choice Model. Specifically, the relations (d) to (g) from Section 2, as seen in Figure 2. The instant utility is assumed to vary linearly with the environmental and travel attributes. Seven environmental variables were considered: Carbon dioxide concentration, brightness, noise level, noise variation, temperature, humidity, and the interaction of temperature and humidity. On the other hand, six travel variables were considered: mode, crowding level, position (sit or not), travel time, velocity, and waiting. Velocity was considered an indicator of congestion by taking velocities below the average (12 [km/h]) as a sign of slow traffic. We also considered the sex of the participants. Instant utility also explains the latent valence or activation of the underlaying emotion, which is measured by the valence or activation of the stated emotion. On the right-hand side of the figure, IU linearly explains the PPIs (EDA, SKT, HR, and HRV). Below, the structural and measurement equations are detailed.

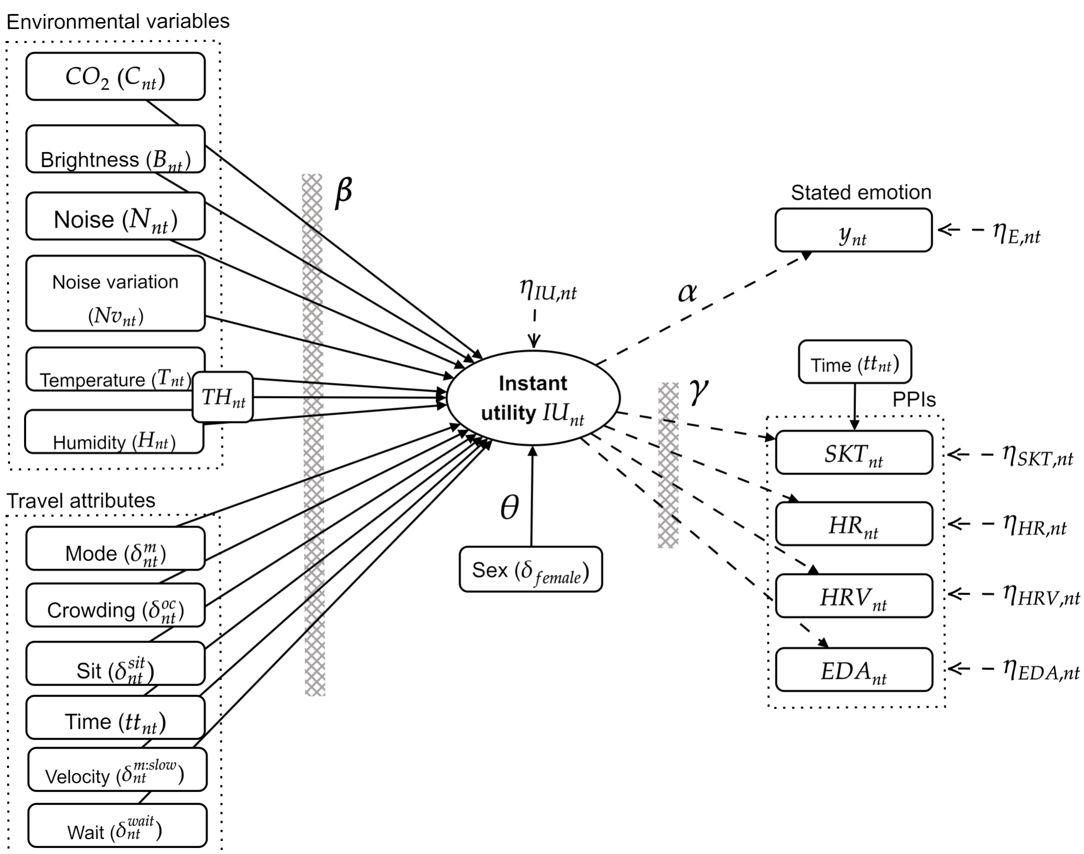

Figure 2: Instant utility modelling framework. In this case study, valence and activation are modelled separately. Model MV considers y_{nt} as the valence of the stated emotion, while model MA considers y_{nt} as the activation of the stated emotion.

Structural equations

The instant utility (IU_{nt}) was modelled as function of the vector of outcomes of the travel experience perceived by the subject n in each instant t (X_{nt}), a dummy δ_{female} (1 for females, 0 in other case), the parameters β_0, β, θ, where β_0 is a constant, β is a vector of length equal to the number of outputs. We included just the stated gender as variable due to the homogeneity of the sample. Future studies should consider samples with higher heterogeneity. X_{nt} represents the environmental variables and travel attributes in each instant. The environmental variables were measured with a frequency of 100Hz, but we used as indicator an aggregated measured indicator in a window of time previous to the emotion statement. Most environmental indicators were aggregated with the logsum, just in the case of noise it was considered the standard deviation observed in the window of time [3]. The structural equation of instant utility is described below.

$$IU_{nt} = \beta_0 + X'_{nt}\beta + \theta\delta_{female} + \eta_{IU,nt} \tag{6}$$

Where $\eta_{IU,nt}$ is an error term with inter-subjects normal distribution with mean 0 and variance σ^2_{IU}. Because of identification issues, it was necessary to make the normalisation $\sigma_{IU} = 1$.

Measurement equations

First, it is shown how the modelling of the binary choice of a stated emotion. Recall that the stated emotions were discomposed into valence and activation. If a subject stated a "stressed" emotion, it was discomposed as valence=0 (low) and activation=1 (high). The term E_{nt} denotes the measurement of the stated emotion y_{nt}. It can be formulated as a linear function of the instant utility in time t (equation 7).

$$E_{nt} = \alpha_0 + \alpha_{IU} IU_{nt} + \eta_{E,nt} \tag{7}$$

The distribution of the error term $\eta_{E,nt}$ is supposed to be EVI with scale 1. To define E_{nt} in the same units of the emotion (higher IU implies a higher latent valence or activation), we decided to normalise dividing equation 7 by α_{IU}. The response y_{nt} could be understood as multiple alternatives (e.g. a set of emotions or the quadrants of the circumplex) or in a dichotomous way. In this case of study y_{nt} is dichotomous, i.e. it is either the valence or the activation of the stated emotion by subject n in time t. This was modelled independently; MV model use the valence, while MA uses the activation. Here, it is assumed that the subject states a high valence/activation emotion, if $E_{nt} > 0$, in other case, she states $y_{nt} = 0$. In other words, we define $y_{nt} = 1[E_{nt} \geq 0]$. Then, the probability of stating an emotion with high valence or high activation is denoted by $P(y_{nt} = 1|\alpha, IU)$, and can be estimated as follows:

$$P(y_{nt} = 1|\alpha, IU) = P(E_{nt} > 0|\alpha, IU) \tag{8}$$

$$P(y_{nt} = 1|\alpha, IU) = \frac{exp(\alpha_0 + \alpha_{IU} IU_{nt})}{1 + exp(\alpha_0 + \alpha_{IU} IU_{nt})} \tag{9}$$

On the other hand, the measurement equations of the psychophysiological indicators (SKT, HR, HRV and EDA) are linear relations in function of the instant utility. Here, each indicator represents the logsum of the measured physiological indicator in a window of time before the stated emotion[4]. For example, EDA_{nt} is the logsum of the electrodermal activity (measured with a frequency of 100Hz), in 6s previous to the response. The error term of each indicator is supposed to be normal. The PPIs' measurement equations are formulated as follows:

$$EDA_{nt} = \gamma_{0,EDA} + \gamma_{EDA} IU_{nt} + \eta_{EDA,nt} \tag{10}$$

[3]To define this, we conducted a factorial analysis with different aggregation measures for each environmental indicator

[4]To define this, we conducted a factorial analysis with different aggregation measures for each PPI

$$HR_{nt} = \gamma_{0,HR} + \gamma_{HR} IU_{nt} + \eta_{HR,nt} \quad (11)$$

$$SKT_{nt} = \gamma_{0,SKT} + \gamma_{SKT} IU_{nt} + \gamma_{tt} tt_{nt} + \eta_{SKT,nt} \quad (12)$$

$$HRV_{nt} = \gamma_{0,HR} + \gamma_{HR} IU_{nt} + \eta_{HRV,nt} \quad (13)$$

The slopes of the PPIs equations (γ_{EDA}, γ_{HR}, γ_{SKT} and γ_{HRV}) have inter-subjects variations. It was necessary to add travel time (tt_{nt}) in the SKT measurement equation, due to the correlation of SKT variation with the elapsed time. The model was estimated by utilizing the maximum simulated log-likelihood method (Train, 2003). Because of extension constraints, a detailed explanation of this method is omitted. We developed two models: MV and MA, which explain the valence and activation of stated emotions, respectively. In addition, we tested the effect of removing the PPIs (models MV-NoP and MA-NoP). The estimation was carried out using *Apollo*, a freeware package for R (Hess & Palma, 2019), in R 4.2.2 on an octa core AMD Ryzen 7 4800H with 16 GB RAM. The estimation of each model took about 40 hours.

3.2. Results

The model MV (explaining PPIs and valence) was estimated with 25000 Halton draws (it was stable between 20000 and 25000 draws) and model MA (explaining PPIs and activation) was estimated with 15000 draws (it was stable between 10000 and 15000 draws). Each model comprises 36 parameters. For the sake of simplicity, we summarize in Figure 3 the impact of the parameters on the valence and on the activation. This impact was calculated relative to the travel time parameter (β_{tt}) to avoid scale differences. Just the statistically significant parameters are shown ($p - value < 0.1$). Showing the results this way eases the interpretation of the results of both models.

Travelling on BHS (when velocity is above the average) causes more happiness than any of the other variables. It performs even better than the use of the Metro, which could be a priori considered a preferred mode. Travelling on BLS (when velocity is above the average) triggers more sadness than any other considered variables. When velocity is below the average, the BLS improves its impact and is similar to walking. We suggest this is due to an unsafe feeling, higher displeasure caused by vibrations and route accelerations when riding BLS. Crowding levels from 1 to 3 trigger stressful emotions. Environmental humidity triggers more stressful emotions. It is also worth commenting, that women had higher probability to state emotions with high activation.

On the other hand, in order to verify the value of gathering the PPIs, we conducted a similar latent variable model, but without these indicators. In this case, no environmental variables, and almost no travel variables, turned out to be statistically significant. Then, we verify that incorporating psychophysiological indicators increase the efficiency of the estimation, adding high value to the results.

3.3. Posterior parameter distribution

As mentioned in the section of EBCM's potential applications, it is interesting to explore if the expected variation of the PPIs in function of instant utility is similar for every subject. If that is the

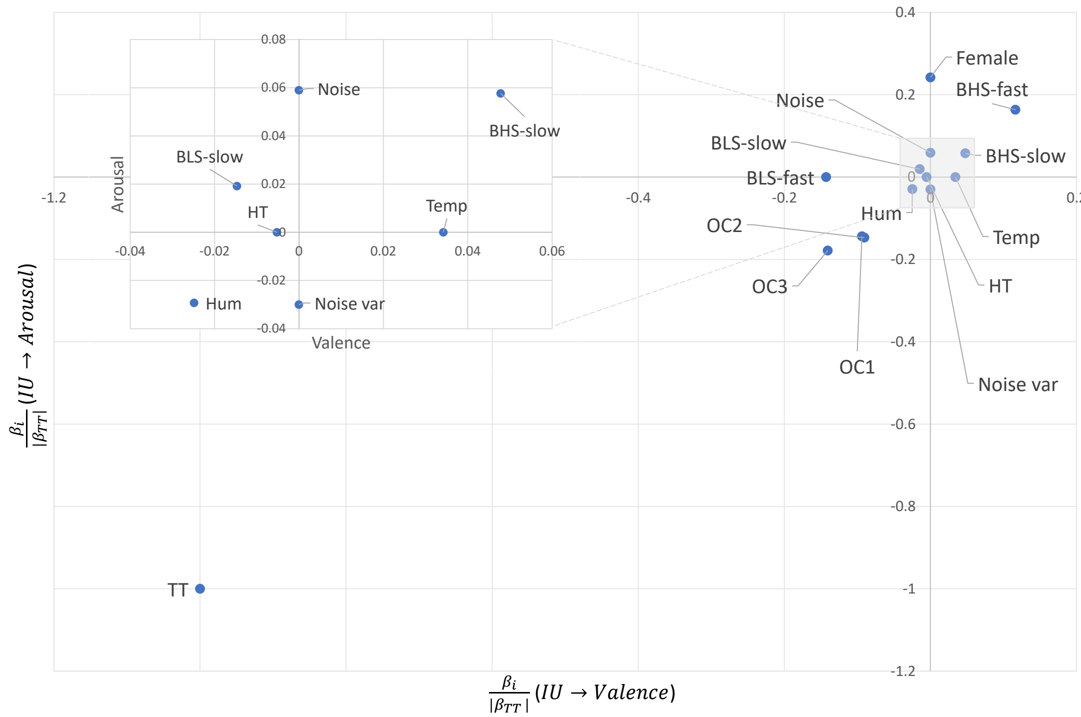

Figure 3: Marginal instant utility of environmental and travel variables relative to travel time absolute marginal instant utility (β_{TT}). Y axis corresponds to instant utility explaining activation, and X axis explaining valence. The different quadrants indicate a higher probability of stating a "happier", "sadder", "more stresful" or "more relaxed" emotion, respectively.

case, the mean marginal PPI variation caused by instant utility variation could be used inversely to infer instant utility from PPIs. If that is not the case, that application would not be possible.

For answering that, we estimated the posterior model parameter distributions using the function *apollo_conditionals* of the Apollo package. Table 3.3 shows a summary with the expected values from the posterior distributions, the standard deviation, t-test and p-values. The posterior distribution of EDA's parameter from MV model shows that, for most of the participants, instant utility increased the EDA, with a significantly different from zero expected value. In the case of SKT, most of the participants experienced diminishing skin temperature when instant utility increased, and the expected value across individual is significantly lower than zero. In contrast, from MV model, it was found that HR and HRV suffer no significant expected variations when instant utility changes. On the other hand, from MA model, it could be seen that, when related to activation, instant utility causes significant variations on all the PPIs but SKT. EDA's posterior distribution, shows a multi-modal distribution. These results should not be directly compared with studies that analyse emotional changes with isolated stimuli. However, when analysing the results of both models (MV and MA), it can be seen that they broadly agree with the literature.

Table 1: Expected PPIs variation with IU: mean, standard deviation, t-test against zero and p-value

	Mean	sd	t-test	p-value
Model MV				
EDA	0.69	0.21	3.27	0.002
HR	0.07	0.16	0.44	0.32
SKT	-0.74	0.20	-3.72	<0.001
HRV	0.09	0.06	1.55	0.13
Model MA				
EDA	0.45	0.21	2.11	0.04
HR	0.36	0.12	2.94	0.005
SKT	-0.15	0.22	-0.66	0.51
HRV	-0.19	0.05	-3.43	0.001

3.4. Instant utility profiles

Kahneman et al. (1997) analysed temporal profiles of instant utilities. With the proposed methodology, it is also possible to analyze spatial and temporal distributions of the probability of stating high-valence and high-activation emotions, As mentioned in the potential applications of EBCM section, this kind of analysis can be used to detect zones that cause higher or lower travel satisfaction. From the above estimations of models MV and MA, spatial and temporal profiles were constructed for all participants, showing the probability of sating a high valence (Figure 4)[5].

In the Figure, higher probability of stating a high-valence emotion are represented with blue dots. Red dots indicate low probability. It can be seen that, trip section H-D is the worst, in particular between I and D, which is a highly congested zone. Participants went by high-standard bus from B to D, showing high-probability of stating high-valence emotions. But they went from D to B at the end of the experiment, and experienced more stressful emotions due to the elapsed time. The section from D to E is provided with a bus corridor, which caused participants, riding high-standard bus, to experience the highest probability of stating happier emotions (higher valence and higher activation). Metro sections, i.e. E-G and C-F (just a few participants used metro from I to D), have similar probabilities of stating high-valence or high-activation emotions than walking sections (G-H and A-B). From temporal profiles, it can be observed that both valence and activation decreased with time, but some participants experienced isolated peaks. Temporal profiles compliment the spatial profiles, since the later show information without the time component.

4. CONCLUSIONS

Random utility models (RUM) have a static and normative view of human thinking, ignoring the impact of emotions and experience on decisions. In contrast, Kahneman proposed an experienced utility framework (EUF) that considers how instant utilities (hedonic feelings or latent emotions)

[5] The geolocalization of observations inside the metro was estimated by taking a mean velocity of 32 [km/h], since the gps signal was lost in that mode

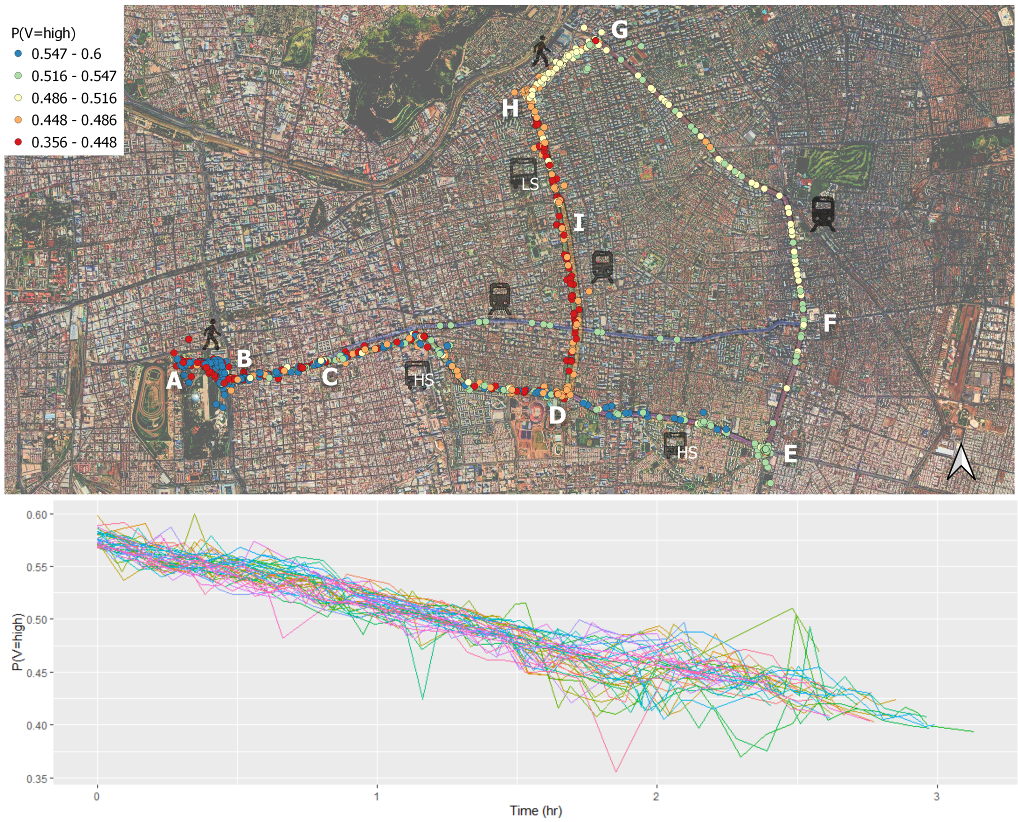

Figure 4: Spatial (top figure) and temporal (bottom figure) profiles of the probability of stating high-valence emotions (MV model). In the spatial profile, blue and red dots indicate higher and lower valence emotions respectively. In the temporal profile, each line corresponds to a participant. Transfer points are indicated with letters from A to I.

influence future choices. However, EUF lacks integration with latent variables and the interaction of exogenous information. The proposed EBCM joins both frameworks, and allows to measure instant utility with psychophysiological indicators. This article is a step toward relaxing the rationality assumptions in travel behaviour. EBCM contributes to the incorporation of psychological factors that influence behaviour, in a framework that maintains the quantitative and predictive characteristics of neoclassical theory. Moreover, the analysis of experienced utility has the potential of being used for policy evaluation.

The presented case study showed, with data from a travel experiment, how the incorporation of PPIs on-board measured with a wristband, increases the efficiency of the estimated parameters and brings to light how environmental and travel variables influence instant utility. Travel time, travel mode, velocity, humidity, temperature, and noise turned out to significantly explain instant utility variations. Also, we showed how the estimation of instant utilities can be used to detect geographical zones or time periods that cause higher or lower satisfaction with travel by plotting temporal and spatial profiles of the probability of stating high activation or high valence emotions. From the posterior parameter distribution, it was shown that at a higher probability of stating a high valence emotion, EDA was significantly higher and SKT was lower. On the other hand, at higher activation, EDA and HR were higher while HRV was lower.

This paper bridges the gap between the canonical models and the experience utility framework (Kahneman et al., 1997) and contributes to what McFadden (2014) calls the new behavioural science of pleasure. The case study model should be replicated with a higher and more heterogeneous sample. Once the model's parameters are estimated using the PPI and stated emotions of the sample respondents, it would be possible to estimate a level of instant utility at each bus and metro wagon of the network, if they were equipped with environmental sensors such as the ContextINO. This periodic (or even in real-time) estimation of travel satisfaction has a great potential to work as a level of service indicator and guide policy design.

However, we note that this work has just started new lines of research. Further work is necessary to test different functional forms in the model; estimate and predict choices based on experience measured with PPIs; predict instant utilities with exogenous information and infer instant utilities from PPIs; estimate the effect of income and other demographic characteristics on experience utility; use experience utility for public projects evaluation; and test this framework in other areas.

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