A METHODOLOGICAL FRAMEWORK TO INCORPORATE PSYCHOPHYSIOLOGICAL INDICATORS INTO TRANSPORTATION MODELING[1]

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ABSTRACT

Reporting and hypothetical biases are inherent to canonical methods of transportation data collection and had implied that analysis in this field has often neglected aspects that are strong behavioral drivers, such as uncertainty, physical effort or stress. Granular information on these aspects would allow measuring their valuation and/or addressing a pervasive source of endogeneity. Recent advances in miniaturization and data processing, as well as evidence that indicators from biosensors correlate with psychophysiological states and emotions, suggest that there is an opportunity to close this gap by collecting a new type of data from transportation users. This research works on leveraging this opportunity by putting forward, illustrating and testing a methodological framework to incorporate psychophysiological indicators gathered from biosensors into transportation choice behavioral modeling. The proposed framework adapts the integrated choice and latent variable approach by incorporating the psychophysiological responses as additional indicators of a latent psychophysiological state that enters the utility. For the practical implementation of the proposed framework we also consider a specific form of aggregation of the indicators across time to avoid the curse of dimensionality arising from the unmanageably large number of folds for integration. The proposed framework is illustrated and validated using Monte Carlo simulations. Besides, a prototype field experiment was designed and performed to confirm the validity of three crucial components of the proposed framework: i) the relation between transportation markers and emotions; ii) the possibility of measuring those emotions trough biosensors installed on travelers, iii) and the validity of the proposed aggregation needed for practicality. In the experiment, a public transport user travelled wearing a bracelet with a Printed Circuit Board that integrated tiny biosensors to capture electrodermal activity, heart rate variation, temperature and acceleration. Results confirm the hypotheses, enabling future massive data collection efforts to take full advantage of the proposed framework.

Key words: Public transportation, discrete choice, travel behavior, psychophysiological indicators, tracking technologies

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1. Introduction

Reporting and hypothetical biases are inherent to canonical methods of transportation data collection and had implied that analysis in this field has often neglected aspects that are strong behavioral drivers, such as uncertainty, physical effort or stress. Granular information on these aspects would allow measuring their valuation and/or addressing a pervasive source of endogeneity (Guevara, 2015). Recent advances in miniaturization and data processing, as well as evidence that indicators from biosensors correlate with psychophysiological states and emotions, suggest that there is an opportunity to close this gap by collecting a new type of data from transportation users.

This research works on leveraging this opportunity by putting forward, illustrating and testing a methodological framework to incorporate psychophysiological indicators gathered from biosensors into transportation choice behavioral modeling. The proposed framework adapts the integrated choice and latent variable (ICLV) (Walker, 2001) approach by incorporating the psychophysiological responses as additional indicators of a latent psychophysiological state that enters the utility.

2. Theoretical Framework

The proposed theoretical framework to incorporate psychophysiological indicators is summarized in Figure 1. Figure 1a shows the classical Random Utility Maximization (RUM) model in which individual n chooses alternative i considering a mix of attributes and characteristics, synthetized by the vector X_{in}, plus some exogenous disturbances ε_{in} that conform the indirect utilities U_{in}, which are latent to the researcher. Besides, the indirect utility is divided into a systematic part V_{in} that depends on the observed variables X_{in} and the random part, formed by the disturbances ε_{in}. Then, assuming rationality, it is considered that the individual chooses the alternative with the largest utility among those in the choice-set C_n, election that is observed by the researcher through the indicator y_{in}, which takes value 1 if alternative i is chosen by individual n and zero otherwise.

Consider now that, using biosensors, it is possible to collect psychophysiological indicators that are directly related to psychophysiological states and emotions (PPSE) and perceived by the transport user. Having this type of data, the choice framework can be enriched as shown in Figure 1b, where G_{int} corresponds to a vector of granular events g_{inst} experienced by individual n at time t on alternative i, and PP_{int} corresponds to the respective vector of psychophysiological indicators. PP_{int} is assumed to be observed by the researcher, but G_{int} may or may not be fully observed and it is thus represented by a rectangle with dashed borders.

Consider first relations (i_a) and (i_b) in Figure 1b. These links represent the fact that psychophysiological states and emotions PPSE λ_{int}, perceived by an individual n while traveling on alternative i at time t, depend both on the vector G_{int} granular events g_{inst} occurring at time t and the attributes and characteristics X_{in}. All the disturbances in Figure 1b are assumed to be exogenous and are not the same of Figure 1a.

Besides, relation (i_c) corresponds to a measurement of λ_{int} through the psychophysiological indicators PP_{int}. Relations (i_a), (i_b) and (i_c) can be synthetized as shown in Eq.(1), where δ_{int} represents, e.g., a measurement error of the psychophysiological indicator, which is assumed to be exogenous.

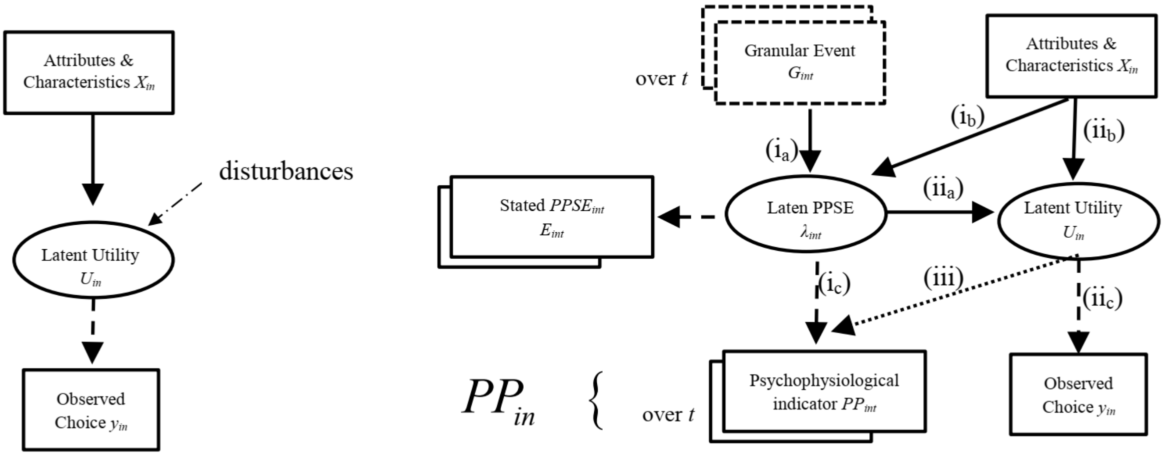

Fig. 1a: Canonical framework   Fig. 1b: Framework for incorporating psychophysiological indicators

Figure 1. Discrete Choice Modeling Framework

$$PP_{int} = \lambda_{int}\left(G_{int}, X_{in}\right) + \delta_{int} = \alpha_{in} + \tilde{\lambda}_{int}\left(G_{int}\right) + \delta_{int} \tag{1}$$

Note that, despite PP_{int} depends both on G_{int} and X_{in}, since the latter does not depend on time, it can be argued that only G_{int} will truly remain as an independent variable in Eq. (1), while the effect of X_{in} is being reduced to a constant α_{in} that depends on the individual and the alternative, as shown at the right of Eq. (1). Furthermore, since psychophysiological indicators are often analyzed after subtracting their mean over time to account for a baseline (Burt and Obradović, 2013), even the effect of the constant may vanish from Eq. (1). This effect will potentially wipe out the impact of relations (i_b) shown in Figure 1b, or at least reducing them to a constant by alternative i, α_i.

Consider now relations (ii_a) and (ii_b) in Figure 1b. Without loss of generality, it can be considered that effect of the granular and budgetary attributes in the indirect utility U_{in} can be respectively separated in the systematic utility V_{in} into two terms, as shown in Eq. (2).

$$U_{in} = V_{in}\left\{V_{in}^{G}\left(G_{in}\right), V_{in}^{B}\left(X_{in}\right)\right\} + \varepsilon_{in} \tag{2}$$

V_{in}^{B} corresponds to the traditional systematic part of the utility, which is often considered to be linear in the budgetary attributes X_{in}, capturing relation (ii_b) in Figure 1b. In turn, V_{in}^{G} corresponds to some function of the granular events G_{int}, transformed through the psychophysiological states and emotions PPSE and integrated over t across the whole trip, capturing relation (ii_a) shown in Figure 1b.

Besides, relation (ii_c) corresponds to a measurement of U_{in} through the observed choice y_{in}. Assuming rationality, relations (ii_a), (ii_b) and (ii_c) can be synthesized as shown in Eq. (3).

$$y_{in} = 1\left[U_{in} \geq U_{jn} \forall j \in C_n\right] \tag{3}$$

Finally, consider relation (*iii*) in Figure 1b, which represents a correlation between the psychophysiological indicators PP_{int} and the utility U_{in}. Different from relations of types (*i*) and (*ii*), relation type (*iii*) is not causal, is not a link that comes from the behavior of the individual, but is a mere correlation implied by the way in which the data is generated. To remark its incidental nature, relation (*iii*) is depicted with dashed arrow in Figure 1b.

Despite PP_{int} may in principle correlate with the whole utility U_{in}, since budgetary attributes X_{in} can be assumed to remain unchanged during the trip, PP_{int} would only be accounting for the granular attributes or events G_{int}. Under this setting, any mean effect ignored by such a treatment of the psychophysiological indicators would be captured by a unique additive alternative specific constant of the systematic utility, shared with V_{in}^{B}. In general, this constant would then have to be heterogeneous in the sample, but that may not be needed if the baseline is subtracted from PP_{int}. Furthermore, under this setting, the vector of psychophysiological indicators PP_{in}, somehow integrated over t, can be a function of V_{in}^{G}, as shown at the left bottom of Figure 1b, and in in Eq. (4), where ξ_{in} is an exogenous error term.

$$PP_{in} \approx f\left(V_{in}^{G}\left(G_{in}\right)\right) + \xi_{in} \tag{4}$$

For the practical implementation of the proposed framework we also consider a specific form of aggregation of the indicators across time to avoid the curse of dimensionality arising from the unmanageably large number of folds for integration.

3. Monte Carlo Simulation Analysis

The proposed framework was also illustrated and validated using Monte Carlo simulations. The exercises undertaken in this section have two objectives. First, by generating simulated data sets with known underlying model parameters, examine the ability of the proposed aggregated function of the psychophysiological indicators to recover parameters from finite samples in a model. Second, to quantify the effect of omitting granular events from the utility function when these events are correlated with the observed attributes and are perceived by individuals and condition their choices. The latter objective also considers the analysis of the feasibility of correcting such an effect with the proposed method.

The results are summarized in Figure 2. The figure is divided in two sections: the left one provides the results for the uncorrelated datasets, where the granular events are generated independently from the explanatory variables, while the right section presents the results for endogenous variables. Additionally, Figure 2 shows the results both for the proposed model ("EV model") and an ordinary MNL that does not account for the granular events perceived by the individuals ("MNL model"). For each model, the table displays the true ratio of the coefficients (dashed horizontal line), and a box plot of the estimated coefficients obtained from 100 repetitions. Results show that in the uncorrelated data case, both the EV model and the MNL model correctly estimate the parameter´s quotient, while in the correlated data case the MNL model provides a large bias.

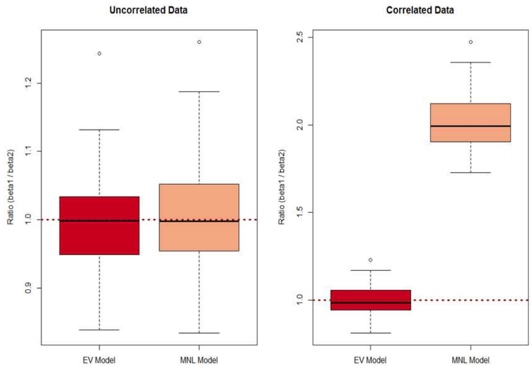

Figure 2: Boxplot of Ratio β_1 / β_2 for Simulated Data (N=5000).

4. Prototype Experiment

Besides, a prototype field experiment was designed and performed to confirm the validity of three crucial components of the proposed framework: i) the relation between transportation markers and emotions; ii) the possibility of measuring those emotions trough biosensors installed on travelers, iii) and the validity of the proposed aggregation needed for practicality. In the experiment, a public transport user travelled wearing a bracelet with a Printed Circuit Board that integrated tiny biosensors to capture electrodermal activity, heart rate variation, temperature and acceleration.

To elicit the participant's emotions during the journey (***E_{int}* in Figure 1**), in our experiment a simplified version of the circumplex model was used. The circumplex model of affect, proposed by Russell (1980), is one of various models for the measurement of emotions have been developed, and it states that emotions are generated primarily as a combination of two dimensions: valence and arousal. As shown in Figure 3a, the vertical axis corresponds to the state of arousal where a high arousal is associated with activation and a low one to deactivation. In the same way, on the horizontal axis a positive valence is associated with pleasant states and the contrary with a negative one (Posner et al., 2005). For example, emotions of happiness and excitement are found in the quadrant with positive valence and high arousal, euphoria being a greater value of arousal. On the other hand, in the quadrant of negative valence and high arousal are emotions such as stress or nervousness. In the quadrant of negative valence and low arousal are the emotions of sadness and boredom, negative and more passive emotions. Finally, in the positive valence and low arousal quadrant we find emotions such as calm and serene.

The simplified circumplex model was applied through an ad-hoc mobile app, which captures the self-reported participant's emotions in random timestamps, as shown in Figure 3b, depicting a selection of only three emotions by quadrant. On average, emotions were measured every 5.1 minutes.

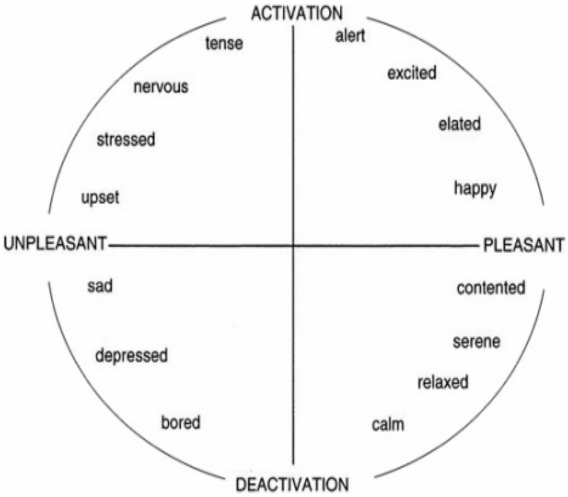

Fig. 3a: Original Circumplex Model. (Posner Et Al., 2005).

Fig. 3b: Mobile Application with Simplified Circumplex Model

Figure 3: Graphical Representation of the Circumplex Model

For data acquisition (***PPint* in Figure 1**), the following signals were used: EDA, photoplethysmography (PPG), and ST. To measure the EDA and HR signals, the Shimmer GSR+ unit sensor was used with a sampling frequency of 120 Hz. The position of the electrodes for measuring the EDA was the palm area of the proximal phalanx of the index and ring fingers of the left hand (Villarejo et al., 2012). The optical sensor that functions as a photoplethysmograph was attached to the lobe of the right ear (Ye et al., 2017). The Shimmer Bridge Amplifier + unit sensor with a sampling frequency of 50 Hz was used to measure ST. The sensor was applied under the right armpit. This sensor was synchronized with the EDA and pulse sensors using a base provided by Shimmer together with the Consensys software.

The experimental procedure consisted of various stages. As soon the participant arrived in the experimental room, the experiment was explained to him, and he was asked to read and sign the informed consent, as well as a questionnaire to obtain his basic anonymous information. The participant was seated in front of a screen, and the sensors were connected in the following order: ST, EDA, and PPG.

Prior to the experiment in the outdoor environment, the user underwent a relaxation session consisting of the visualization of three four-minute videos of landscapes with background instrumental music. Then, the participant was asked to take deep breaths for one minute with his eyes closed and with soft background instrumental music. This procedure aimed to eliminate the Hawthorne effect—modification in the behavior of the subjects due to their awareness of being studied—and physiological effects similar to the "white coat" effect in measured signals (Parsons, 1974).

The chosen trip route includes a segment by bus and another by metro, both supervised by the experimenter. As soon as the baseline condition signals were captured, the participant walks two hundred meters towards the bus stop, where he waits for 5 minutes. The participant rides a bus route with 13 bus stops. Then the passenger transfers to the nearest metro station, a walk that takes about 6 minutes. This stage includes a wait for the metro, and a trip through four stations, at which point the participant undertakes the same trip in the opposite direction. To measure different conditions, the participant is instructed to travel both seated and standing on both modes. During the journey, the participant received automatic, random notifications in the mobile application to record his emotional state, choosing one among five options. Each notification was randomly generated within 1 to 10 minutes from the previous notification. In addition, the experimenter recorded notable events that happened during the trip, such as the appearance of vendors or public transport inspectors, among others.

Finally, the experimenter recorded the timestamps (**G_{int} in Figure 1**) of the participant's actions, such as getting on or off the bus, sitting or standing on the seat and, walking to the bus stop or metro station. The entire experiment lasts almost 2 hours.

The sample characteristics are presented in Table 2. A short name was defined for the categorical variables presented at the top of the table. It should be noted that the samples share do not vary across the 5 and 10-seconds windows dataset, as they are constructed from the same original data. Regarding the Circumplex emotions, stressed, sad and relaxed have basically the same sample share, while neutral and happy are more uncommon emotions during the trip. The trip stages were grouped in four unique stages: walking to the bus stop / metro station, waiting for the bus/metro, riding the bus and at the metro (riding the metro or walking within the underground station). The statistics on the table show that in most pseudo-choice occasions, the individual is riding the bus. The main difference among datasets is the standardized EDA, which is higher for the 10-seconds window (EDA was measured, on average, every 0.12 seconds). Figure 4 summarizes the estimation sample.

Table 2. Sample Characteristics

Variable	Variable name	5-seconds window		10-seconds window	
		Observations	Share	Observations	Share
Circumplex Emotions					
Neutral	Neutral	184	13.4%	92	13.4%
Alert, excited, elated, happy	Happy	86	6.2%	43	6.2%
Tense, nervous, stressed, upset	Stressed	382	27.7%	190	27.6%
Sad, depressed, bored	Sad	387	28.1%	194	28.2%
Contented, serene, relaxed, calm	Relaxed	339	24.6%	170	24.7%
Trip Stages					
Walking to the bus stop / metro station	Walk	294	21.3%	148	21.5%
Waiting for the bus/metro	Wait	242	17.6%	121	17.6%
Riding the bus	Bus	633	45.9%	316	45.9%
At the metro	Metro	209	15.2%	104	15.1%

Descriptive statistics

Variable	Statistic	5-seconds window	10-seconds window
Standarized Electrodermal Activity (EDA)	Mean	3.69	4.39
	Std. Dev.	1.00	1.00
	Minimum	0.49	1.19
	Maximum	5.58	6.19

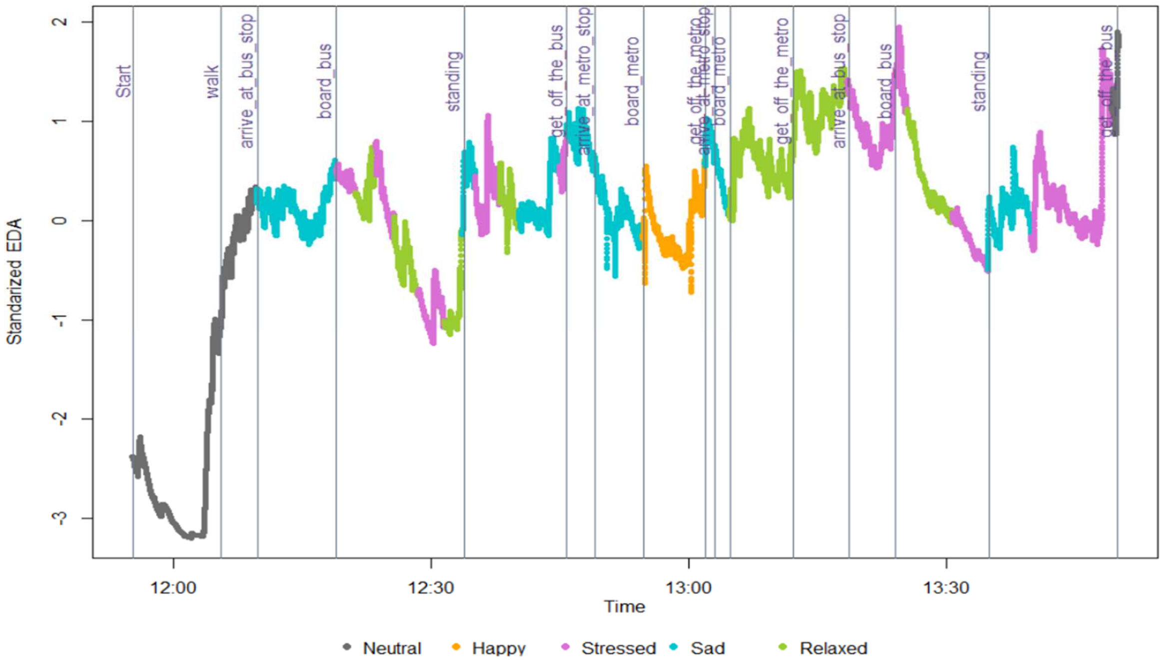

Figure 4. Relationship between Emotions, EDA and Trip Stages over Time.

The modeling hypothesis in this case is that analyzing psychophysiological indicators can lead to understand traveler's emotions; that is, relationship (i_c) in Figure 1b. It should be noted that even if this relationship exists, emotions could be associated with events unrelated to the trip (such as an annoying phone call or a pleasant conversation), though relationship (i_a) in Figure 1b . Then, the results are limited in linking trip characteristics with emotions.

To classify the emotional states during the journey based on the psychophysiological signals, a random forest model was used. The characteristics extracted for its execution correspond to the mean and the standard deviation of EDA, EDA phasic component, PPG, HR and ST.

To evaluate the model's fit, we conducted a cross validation exercise using the K-fold method, where the original sample is randomly partitioned into k equal sized subsamples. For each k, the model is estimated using $k-1$ subsamples; the last subsample is used for out-of-sample validation.

Table 4. Performance Measurements for Out-Of-Sample Validation

Sample	Model	Precision	Recall	F1 Score
5-seconds window	Random forest	77.4%	74.2%	75.5%
	Only constant	26.2%	20.0%	40.2%
	EV model	**51.5%**	**50.1%**	**60.5%**
10-seconds window	Random forest	71.8%	61.7%	64.1%
	Only constant	25.4%	19.9%	39.8%
	EV model	**53.7%**	**50.0%**	**59.9%**

Table 4 presents three performance measurements (precision, recall and the F1 score) for the K-fold method, with $k=10$. The performance measurements of the proposed approach are compared to those of the random forest model. It should be noted that, given the nature of the random forest model, the performance measurements obtained for that model are the highest possible measurements attainable. For the proposed model, the results is Table 4 show a lower fit than the random forest model, but the fit is considered relatively high, validating the proposed approach.

5. Conclusion

The planning, evaluation and management of transport services have been based almost exclusively on measures of travel time and cost, ignoring various relevant aspects because they are hard to measure with traditional methods of transport data collection. These data collection tools are also limited by a reporting and hypothetical bias. This research works toward closing this gap using indicators gathered from psycho-physiological sensors, given that empirical evidence has shown that they covariate among each other, and correlate with psycho-physiological states such as stress, cognitive load, various emotions, fatigue, among others.

With that goal in mind, this article conveys the development of a framework for modeling the modal utility by incorporating psychophysiological data extending the conceptual framework for modeling integrated choices, including the psychophysiological responses as additional indicators.

The proposed approach was assessed, enhanced and validated using first Monte Carlo. Results show that the proposed methodological framework is feasible for the incorporation of psychophysiological indicators to the modeling of transportation choices, potentially enriching the understanding of the phenomena and the forecasting capabilities.

A prototype field experiment was designed that makes use of a Printed Circuit Board that integrates tiny psycho-physiological sensors to capture electrodermal activity, heart rate, heart rate variation, temperature and acceleration. Although the purpose of this experiment is limited and the results cannot be generalized, it opens new possibilities in terms of data collection and modeling, as it serves to validate some critical components of the proposed framework. Future research can build upon the prototype experiment increasing sample size and/or studying other discrete outcomes, such as modal choice or route choice.

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