



The neuroeconomics of shopping-related decision-making

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Abstract: Neuroeconomic modeling has been proposed as a predictive and explanatory formalization of human decision-making. We used the measure of the entropy of the EEG activity correlation to study shopping-related decision-making, and economic modeling to formalize our experimental results. The model involves both an *emotional component* and a *cognitive factor* in the estimation of the *expected utility* of products or processes. The conflict established between competing products or processes is assumed to be a major component determining the decision-making probabilities. The agreement between the experimental and the theoretical decision-making time distribution seems to validate the proposed model and to make an important argument in favor of neuroeconomic modeling of decision-making.

Keywords: neuroeconomics, neuromarketing, decision-making, EEG, modeling.



Daniel Bernoulli proposed that people's evaluation of potential outcomes is based on a subjective value and differs from the simple mathematical product of probability and outcome magnitude ^{1,2}. In his model, decision makers choose the option with the highest expected utility $e(x_i)$:

$$e(x_i) = \sum_{i=1}^n u(x_i) p_i \quad (1)$$

where $u(x_i)$ represents the utility of obtaining outcome x_i . The psychological function underlying the evaluation of $u(x_i)$ was proposed to be concave in the gain domain because the difference between \$200 and \$400 is evaluated as larger than the difference between \$1200 and \$1400; whereas the function in the loss domain is convex because losing \$400 versus \$200 is more aversive than losing \$1400 versus \$1200. Empirical results have shown that our brain tends to compress the representation of large numbers, such that the accuracy and speed with which calculations can be performed necessarily decreases as the numbers get larger ^{3,4}. Perhaps this fact, and not different evaluating functions, could explain the above preferences. One of the goals of neuroeconomics is to investigate the brain mechanisms devoted to decision-making in order to get a better understanding of how economic decisions are taken.

The introduction of a competing alternative increases the delay to make a decision, because it introduces conflict. Rocha et al ⁵ used the measure of the entropy ($h(r_i)$) of the correlation r_i of the EEG activity recorded at each recording site s_i to study decision making in moral judgment, and economic modeling to calculate the expected utility $e(P_i)$ of conflicting dilemma propositions P_i with different emotional (β_i) and cognitive (δ_i) loads as

$$e(P_i) = \beta_i^{1/k_t} \delta_i^{n_t} \quad (2)$$

The conflict was proposed to be dependent on $e(P_i)$ entropy and to be one of the major components determining the decision-making probability of choosing P_i . Conflict is important in decision-making not only on complex matters, but even in daily life events. For example, people are less likely to buy a t-shirt, even if its on sale, when at the same time another t-shirt is on sale, which creates a conflict, relative to the non-conflicting situation when only one t-shirt is on sale².

Products and processes P_i are developed for defined purposes and their utilities are dependent both on the efficiency of attaining such a purpose as well as on the emotional responses they trigger upon the user. Marketing scholars^{6,7,8,9} have stated the importance to study emotions evoked by marketing stimuli, products and brands on shopping decision making. For instance, cars have the specific purpose of transporting people and all (or at least most) of them are efficient on this task. But individually we experience different emotions concerning each car, depending on our appraisal of their beauty, power, etc. While some P_i trigger an emotional

positive valence (e.g., pleasure), some others may be associated with a negative emotional evaluation (e.g., distaste, disgust, etc.)^{7,8,9,10,11,12,13}. For example, different chemical products to kill or repel bugs (Fig. 1) may elicit different concerns about people's health, which may depend on user's sensory perception (odor in the specific case) of their chemical properties. Therefore, $e(\mathbf{P}_i)$ estimation of products and processes \mathbf{P}_i is also dependent on both emotional (β_i) and cognitive (δ_i) factors computed by different neural^{10,11,12,13}.

Rocha et al⁵ showed that $h(\mathbf{r}_i)$ for distinct recording sites \mathbf{s}_i were positively or negatively correlated to either the decision time \mathbf{DT} or the **yes/no** decision in dilemma judgment. They assumed that these results were due to the activation of different neural systems involved in emotional and cognitive processing, and used them to estimate the emotional (β_i) and cognitive (δ_i) factors involved in $e(\mathbf{P}_i)$ calculation in order to estimate the theoretical \mathbf{DT} distribution. The agreement between the theoretical and experimental \mathbf{DT} distributions validated the proposed decision-making formalization. We decided to use the same approach to investigate decision-making about the use of chemical products or mechanical processes to kill or repel domestic bugs in order to estimate the generality of this formatization¹⁴ as a model for decision-making.

Volunteers (10 males and 10 females) played a decision-making game (e.g., fig. 1) about the use of chemical products or mechanical methods (e.g., smashing, , etc.) \mathbf{P}_i to kill or repel bugs in different house environments while having their EEG recorded¹⁵. The game consisted in deciding about using one of two \mathbf{P}_i s in a given environment to kill a bug. Two chemical products (spray or plug-in repellent), two mechanical methods (smashing or repel) four environments (parents bedroom, children bedroom, kitchen or dinning room) and three bugs (mosquito, cockroach or flea) were combined to propose 36 decision-makings for each volunteer. The correlation $r_{i,j}$ between the EEG activity recorded at recording site $\mathbf{s}_i, \mathbf{s}_j$ was calculated for all the 20 electrodes of the 10/20 system and for the EEG epoch before the volunteer decided for a \mathbf{P}_i . At the end of the experiment, the volunteers were asked to associate a valence v to each \mathbf{P}_i by choosing a word from a list of negative and positive terms^{6,15}. They were also requested to rank the \mathbf{P}_i s according to their estimation of \mathbf{P}_i efficiency ξ and emotional valence v using one of the following qualifiers: **very low, low, medium, high and very high**. These words were then translated into the ranks 10, 20, 30, 40 and 50, respectively, for statistical calculation purposes. The entropy $h(\mathbf{r}_i)$ of $r_{i,j}$ obtained for each electrode \mathbf{s}_i was used to measure how much the activity recorded at \mathbf{s}_i was related with ξ, v and \mathbf{DT} ^{4,16} (Fig. 2). These data were used to estimate β_i and δ_i in order to calculate the corresponding $e(\mathbf{P}_i)$ of the selected products/methods \mathbf{P}_i and the theoretical \mathbf{DT} distribution.

The majority of the volunteers assigned a negative estimation of v to all \mathbf{P}_i ; associated high v and ξ values to chemical products and smashing a cockroach (which was considered the most disgusting solution) and low v and ξ values to the other mechanical methods (Fig. 1). The probability of selecting a given \mathbf{P}_i

correlated negatively with ξ ($R=-0.7$, $p< 0.05$) and positively with v ($R=0.9$, $p< 0.03$). The corresponding angular coefficients b_ξ or b_v are shown in Fig. 2. Also, ξ was negatively correlated with v ($R=-0.69$, $p< 0.00001$). Therefore, those P_i with low emotional negative valence and low efficiency were preferred to those P_i that were considered to be life threatening or disgusting¹⁷.

Regression analysis showed a complex correlation between $h(r_i)$ and ξ , v and **DT** (Fig. 2). The linear correlation between $h(r_i)$ and ξ ($r = 0.48$, $p<0.016$) and v ($r = 0.34$, $p<0.05$) disclosed three types of electrode activity:

- P_1 electrodes (red areas in Fig. 2A) for which the angular coefficient b was greater than 0 ($p<0.05$) meaning that the increasing of $h(r_i)$ favored a high ξ or v ;
- P_2 (or **not- P_1**) electrodes (green areas in Fig 2A) for which $b<0$ ($p<0.05$), that is the increasing of $h(r_i)$ favored a low ξ or v ; and finally
- N** (or neutral – black areas in Fig. 2A) electrodes for which b was not statistically different from zero.

The summation B_2 of the computed b_ξ or b_v for the P_2 electrodes was almost twice as large as the summation B_1 of b_ξ or b_v for the P_1 electrodes (Fig.2A)¹⁸.

The volunteer had always to decide about two products P_1, P_2 having different estimated ξ, v . Because of this, we assumed that two different $e(P_1)$, $e(P_2)$ were evaluated by the volunteer in order to make a decision. In this condition, the theoretical **DT** distribution should be calculated as in Rocha et al⁵ depending on the conflict generated by $e(P_1)$ vs $e(P_2)$. Therefore, we assumed that B_2^v/B_1^v could be an estimate of β_2/β_1 and that B_1^ξ/B_2^ξ could be an estimate of δ_2/δ_1 to be used to calculate $e(P_1)$, $e(P_2)$.

DT linearly increased with both ξ, v ($R= 0.37$, $p< 0.00001$)¹⁹. The regression analysis between $h(r_i)$ and **DT** ($r = 0.53$ to 0.60 , $p<0.01$) also disclosed three types of electrode activity:

- DT**⁺ electrodes for which the increase of $h(r_i)$ was associated with the increase of **DT** ($b>0$, $p<0.05$ - red areas in Fig 2B);
- DT**⁻ electrodes for which the increase of $h(r_i)$ was associated with the reduction of **DT** ($b<0$, $p<0.05$ - green areas in Fig 2B), and
- N** electrodes (black areas in Fig.2C) for which b was not statistically different from zero.

The summation B_1 of the computed b^- for the **DT**⁻ electrodes was around 64% of that of the summation B_2 of b^+ for the **DT**⁺ electrodes (Fig.2B). As in Rocha et al⁵ we assumed that B_1/B_2 , the mean values B_1^m , B_2^m of the angular coefficients b^- , b^+ , and the experimental **DT** distribution could be used to estimate the other theoretical parameters of the model used to calculate the theoretical **DT** distribution (Fig. 2B). The agreement between the theoretical and experimental **DT** distributions (Fig. 2C) validates, once again, the model proposed by Rocha et al⁵

and represents an important argument in favor of neuroeconomic modeling of decision-making as broadly predictive and explanatory.

Our results are similar to those by Agarwal and Malhotra⁷, who demonstrated the importance of emotional marketing although by using a different theoretical approach. They are also compatible with the findings reported by Allen et al⁸ showing that emotion explains around 40% and cognition accounts for 30% of the variance of consumer's attitude. Also, Zaltman²⁰ warns, "most emotions and cognitive functions which guide thought and behavior occur without awareness". Notwithstanding, the present results showed that conflict solution in decision-making involved complex interactions between a large number of widely distributed neurons which, as we proposed elsewhere^{4,21}, requires quantum computing which in turn gives rise to awareness.



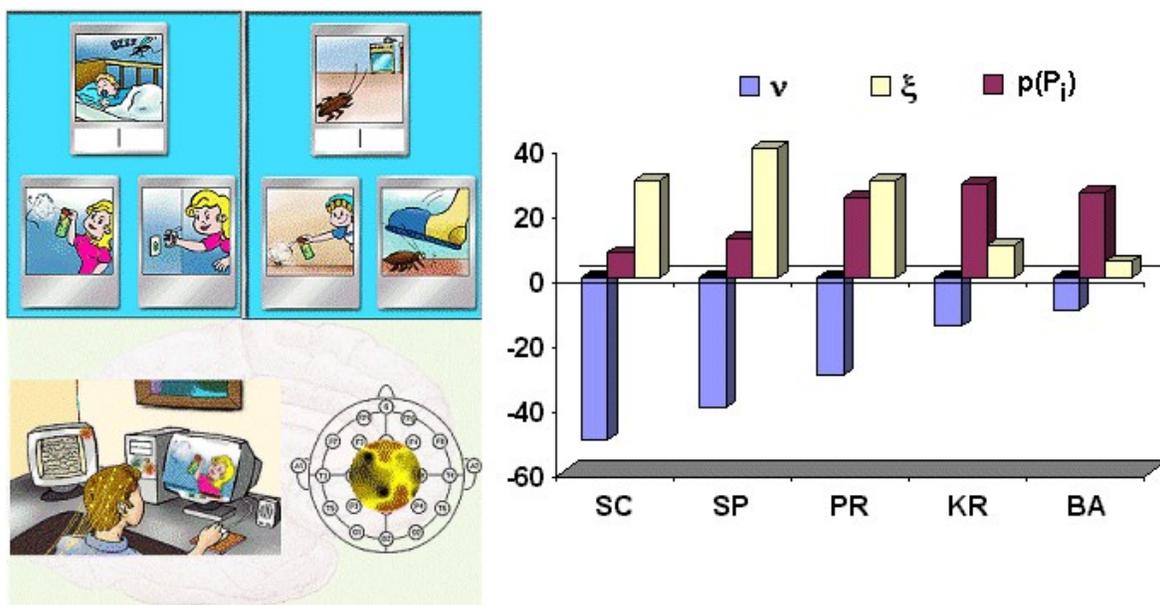


Fig. 1 – The decision-making game about chemical products or mechanical insecticide processes

The game consisted in deciding about using one of two products or processes P_i s to kill a bug. Two chemical products - spray (**SP**) or plug-in repellent (**PR**); two mechanical processes - smashing (**SC**) or repel (**KR** – killing a mosquito or flea with a rag or **BA** – brushing a cockroach away); four environments (parents bedroom, children bedroom, kitchen or dining room) and three kinds of bugs (mosquito, cockroach or flea) were combined to propose 36 decision-makings for each volunteer while his/her EEG was recorded. At the end of the experiment, the volunteers were asked to associate a valence v to each P_i by choosing a word from a list of negative and positive terms¹⁵. They were also requested to rank the P_i s according to their estimation of P_i efficiency ξ and emotional valence v using one of the following qualifiers: **very low, low, medium, high and very high**. These words were then translated into the ranks 10, 20, 30, 40 and 50, respectively, for statistical calculation purposes. The choice probability $p(P_i)$ of a given P_i was linearly correlated to the efficiency ξ and emotional valence v assigned to P_i .

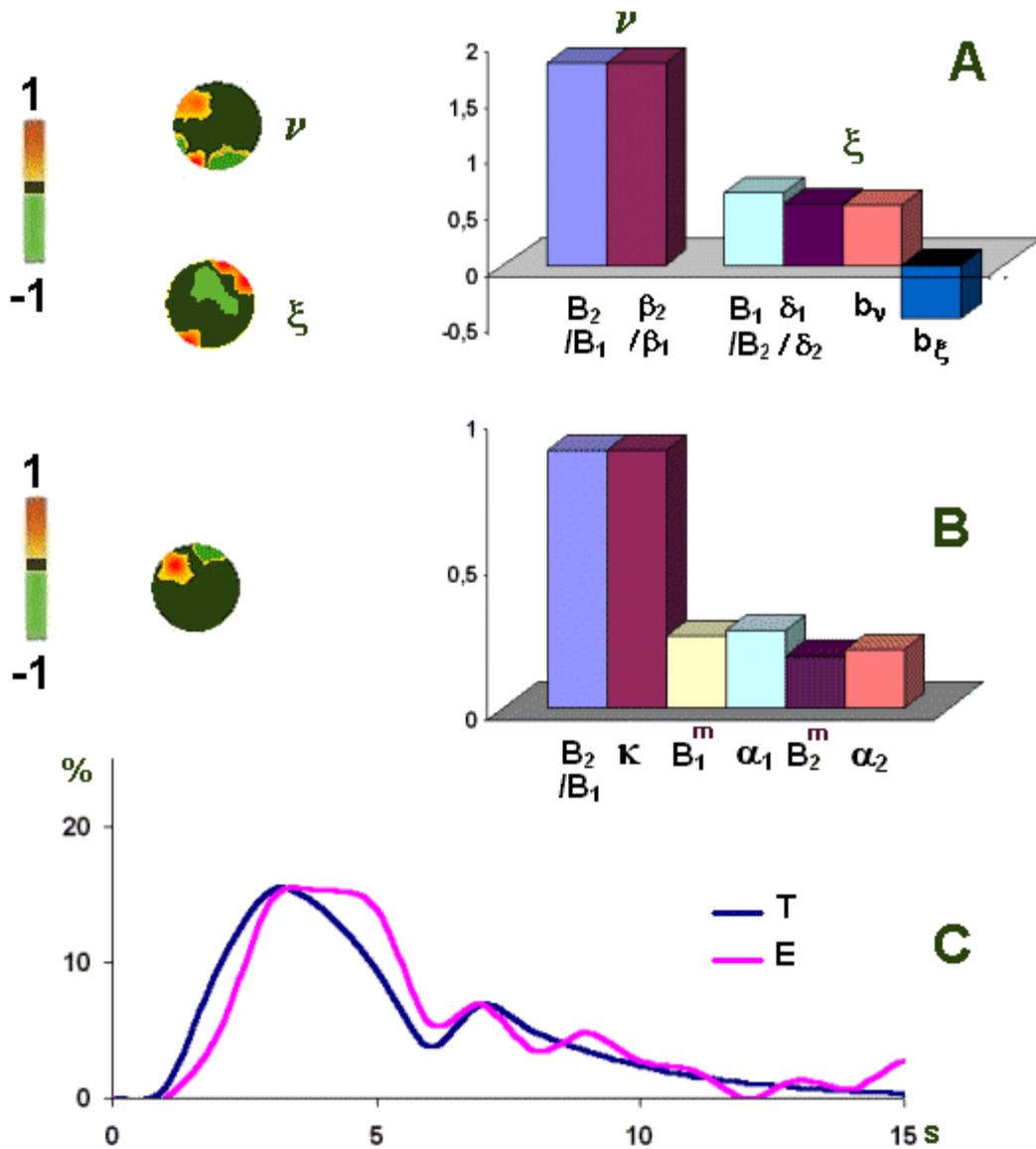


Fig. 2 – Experimental and theoretical results

A: correlation between $h(r_i)$ and ν or ξ is shown in red (P_1 electrodes) if the increase of $h(r_i)$ increases ν or ξ and in green (P_2 electrodes) the increase of $h(r_i)$ decreases of ν or ξ . The summation B_2 of the computed b_ξ or b_ν for the P_2 electrodes was almost twice as large as the summation B_1 of b_ξ or b_ν for the P_1 electrodes. β_2/β_1 and δ_2/δ_1 are the ratio between the emotional and cognitive theoretical parameters used to calculate the theoretical DT distribution¹⁵.

B: correlation between $h(r_i)$ and **DT** is shown in red (P_1 electrodes) if the increase of $h(r_i)$ increases **DT** and in green (P_2 electrodes) the increase of $h(r_i)$ decreases of **DT**. B_2/B_1 is the ratio between the summation B_2 of the computed b for P_2 and P_1 electrodes, respectively. B_1^m and B_2^m are the average of of the computed b for P_2 and P_1 electrodes, respectively. α_1 and α_2 are theoretical parameters used to calculate the theoretical **DT** distribution¹⁵.

C: the theoretical (**T**) and experimental (**E**) **DT** distributions.



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14) These products were chosen because in a previous survey their use was pointed as having an important emotional component. This is a desirable quality in the present experiment, because as far as we know, it is the first attempt to study the brain activity associated with shopping decision.

15) to be available on Science on line

16) Foz et al, *Pediatric Neurology* 26: 106-115 (2002); Rocha et al, *Cognitive Brain Research* 22: 359-372 (2004)

17) Emotion and efficiency influenced P_i selection in opposite ways, suggesting that conflict in decision making was mainly dependent on aversion vs efficiency of the competing P_i s.

18) Although EEG spatial power discrimination may be always asked in question, the results clearly demonstrated that different neural systems were in charge of the estimation of the emotional and cognitive $e(P_i)$ components. Also, different circuits had distinct roles in emotion and efficiency estimation.

19) We interpret this finding as a consequence from the conflict between emotion and efficiency. Thus, it seems that DT increased as the conflict between ξ , v augmented.

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