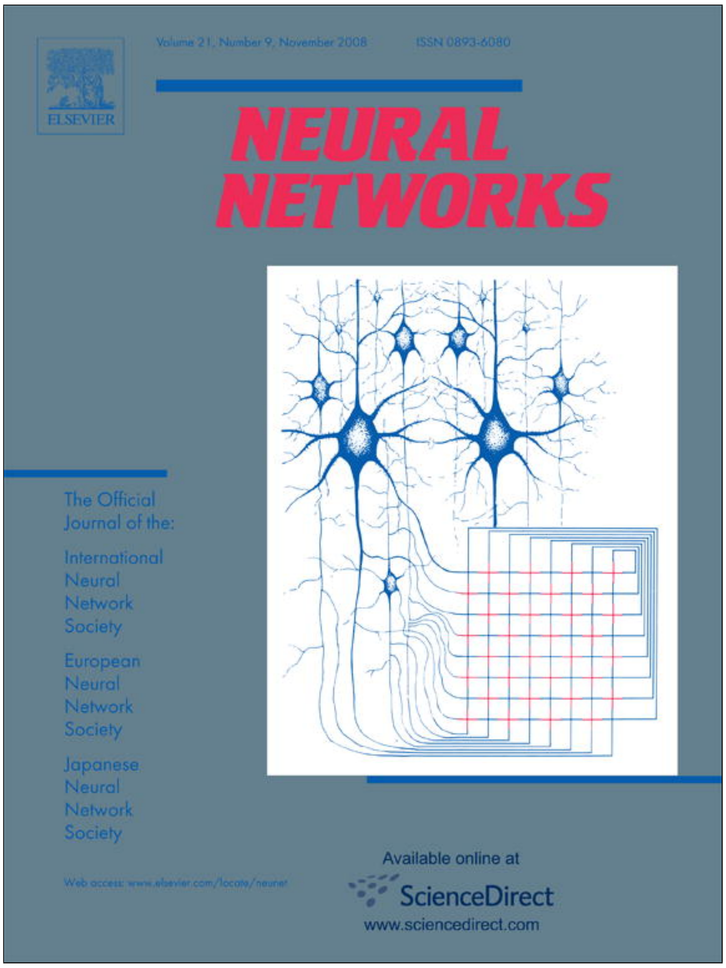
ELSEVIER
Volume 21, Number 9, November 2008
ISSN 0893-6080
NEURAL NETWORKS
The Official Journal of the:
International Neural Network Society
European Neural Network Society
Japanese Neural Network Society
Web access: www.elsevier.com/locate/neunet
Available online at
ScienceDirect
www.sciencedirect.com

Neural Networks 21 (2008) 1213–1219

Contents lists available at ScienceDirect

Neural Networks

journal homepage: www.elsevier.com/locate/neunet

Neural networks letter

Emotional balances in experimental consumer choices

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ARTICLE INFO

Article history:
Received 6 January 2008
Received in revised form
21 August 2008
Accepted 29 August 2008

Keywords:
Consumer behaviour
Decision making
Gated dipole
READ
Satisfaction treadmill

ABSTRACT

This paper presents an experiment, which builds a bridge over the gap between neuroscience and the analysis of economic behaviour. We apply the mathematical theory of Pavlovian conditioning, known as Recurrent Associative Gated Dipole (READ), to analyse consumer choices in a computer-based experiment. Supplier reputations, consumer satisfaction, and customer reactions are operationally defined and, together with prices, related to READ's neural dynamics. We recorded our participants' decisions with their timing, and then mapped those decisions on a sequence of events generated by the READ model. To achieve this, all constants in the differential equations were determined using simulated annealing with data from 129 people. READ predicted correctly 96% of all consumer choices in a calibration sample ($n = 1290$), and 87% in a test sample ($n = 903$), thus outperforming logit models. The rank correlations between self-assessed and dipole-generated consumer satisfactions were 89% in the calibration sample and 78% in the test sample, surpassing by a wide margin the best linear regression model.

1. Introduction

John Watson, founder of behaviourism, is quoted to have said in 1922, "The consumer is to the manufacturer, the department stores and the advertising agencies, what the green frog is to the physiologist" (DiClemente & Hantula, 2003). Many decades later, we cannot but agree with this provocative insight, although we know a lot more about consumer behaviour, its conditioning, and economic psychology in general. Today fMRI methods help us discover how brain systems interact when we think about economic decisions (see for example Camerer, Loewenstein, and Prelec (2005)). Yet, these studies still try to locate regions in the cortex involved in forming emotions, judgments, and decision making (cf. Winkielman, Knutson, Paulus, and Trujillo (2007)). It might be advantageous to complement such an observational approach, or even step aside from it for a while, by using more extensively the available theoretical models.

In this paper, we present experimental evidence that the mathematical theory of Pavlovian conditioning, known as Recurrent Associative Gated Dipole (READ) (Grossberg & Schmajuk, 1987) is able to capture essential features of consumer behaviour. A computer based experiment showed how a supplier of a fictitious service provoked satisfaction and disappointment, and gradually built its own reputation in the minds of participants as consumers. Accommodated by READ, these factors turned out to be strong predictors of customers' decisions to retain or abandon their current supplier. Our work borrows ideas from affective balance theory (Grossberg & Gutowski, 1987) and the Leven and Levine (1996) neural model of a consumer.

2. Experiment

This experiment investigates the links between (1) monetary outcome and momentary affect, (2) previous emotional experience and supplier reputation, and (3) provoked emotions and consumer decisions to retain or abandon the current supplier. It was conducted in May 2007 and involved 129 students of economics from Sofia University. Its content bears resemblance to the Bulgarian market of mobile phone services where two leading providers offered indistinguishable quality and prices at the time of the study. However, similarities with other markets in other countries would have been just as useful.

In each of 17 rounds the participant sees on a computer screen an advertised price (P_a) offered by the current supplier, which serves as orientation about what final price (P_f) might be expected (Fig. 1). No payments with real money are made. Prices P_a were adjusted to fluctuate slightly around an average monthly bill obtained in a survey among another 40 students. Thus, P_a varied within 40 ± 5 Bulgarian leva, and 1 lev is 0.5 euros.

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doi:10.1016/j.neunet.2008.08.006

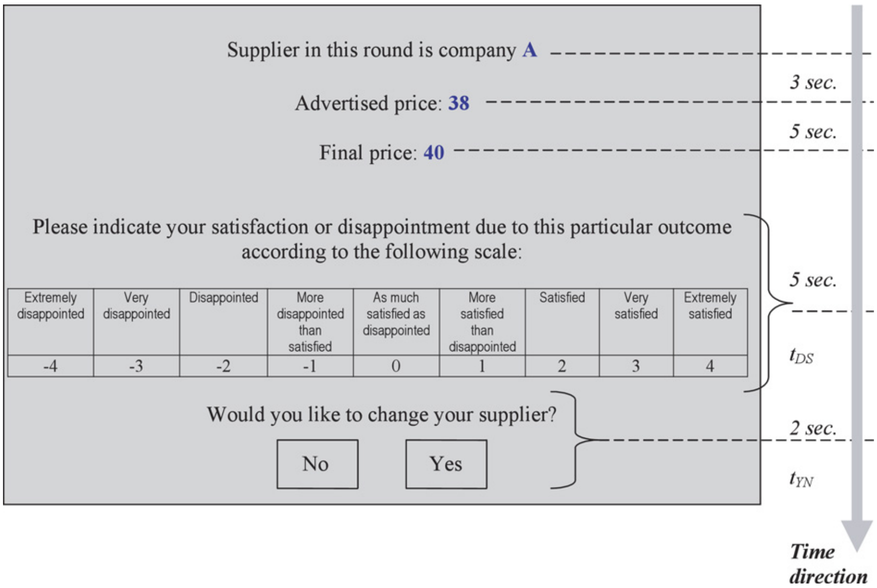

Fig. 1. Experimental screen of the software application. The downward arrow indicates how events unfold in time during one round. All periods have fixed duration except the time t_{DS} needed by the participant for self-assessment of satisfaction or disappointment, and time t_{YN} needed to choose next supplier. We imposed no time constraints on these decisions. Once a No or Yes is chosen, a new round starts with a blank screen. Immediately the new supplier name is shown.

The final price is shown on the screen a few seconds after the advertised and both never coincide. When the difference $(P_a - P_f)$ is positive (denoted ΔP^+), the customer is effectively offered a discount, otherwise one is asked to pay more (ΔP^-). Then the participant has to assess his (her) disappointment or satisfaction (DS) on a nine-point scale. Its adverb–adjective compounds were created for us by the Bulgarian psycholinguist Encho Gerganov, in such a way as to make the segments between neighbouring points equidistant in line with Cliff's (1959) multiplicative rule. In the Bulgarian language this is an interval scale with semantically exact opposites at the ends (Gerganov, 2007), although this may not necessarily be so for its English translation in Fig. 1. The numerical scale $(-4, -3, \ldots, 4)$ beneath only reinforces the idea of equidistance in the participant's mind.

Just seconds after the emotion question, one has to choose between suppliers A and B for the next round. Changing the current supplier incurs no costs. That decision taken, the round ends, and a new one begins with a blank screen. The first round always starts with supplier A. Note that the 'No' button indicating decision not to change the supplier is placed below the 'disappointment' part of the scale. Thus, we avoided that a mere convenience in navigating the mouse between the areas of disappointment and abandoning could cause an additional correlation between the answers to these two questions.

We fixed most of the time intervals and recorded all human reaction times (Fig. 1). This information was needed for calibrating the READ differential equations.

Each participant finds themselves in one of four experimental treatments (Fig. 2). In treatment A the price differences vary slightly, unlike D, where they fluctuate substantially. The other treatments are homogeneous in the sense that only discounts are offered (B), or more money is asked for (C). As all cases bear some resemblance to real life circumstances, we call them 'Saturated', 'Favourable', 'Hostile', and 'Fluctuating' markets.

One feature of our design is that the prices and price differences shown on the screen are predetermined and do not depend on the participant's decisions. Should he (she) choose for example to change supplier A with supplier B, in the next round he (she) would receive exactly the same offer (Fig. 1) as if supplier A had been retained. With this experimental design, each participant generates a sequence of unique ordering of both suppliers.

Treatments B and C create expectations in only one direction and thus provoke diminishing emotional responses like in a hedonic or satisfaction treadmill (Kahneman, 1999). It may happen that a financial discount could cause disappointment because a larger amount had been anticipated. Similarly, a mild satisfaction could be observed when less money is lost than expected. Our experimental evidence is that in about five hundred observations in each treatment, in A and D such 'paradoxical' answers were less than ten percent, as compared to 18% in B and 26% in C. Standard analytic tools like linear regression would ignore such effects and would always associate discount with satisfaction and loss with disappointment. Their explanation by Kahneman and Tversky's prospect theory would invoke a shifting reference point and would be purely phenomenological. In contrast, the gated dipole dynamics with neurotransmitter release and replenishment offers a natural way to understand such emotional reactions (Grossberg & Gutowski, 1987).

3. Connecting the READ neural model with the empirical data

Transferring information from empirical data to the differential equations of READ comprised a computational experiment in its own right. Essentially, in it we mapped each person's record of events, and their timing, on a sequence of events generated by the numerical solution of the READ system of equations (Fig. 3). We present now the model as we use it and explain how we connected it with the data. Its adapted equations are:

$$\frac{dx_1}{dt} = -A.x_1 + P_a + \delta.\Delta P^+ + M.x_7 \tag{1a}$$

$$\frac{dx_2}{dt} = -A.x_2 + P_a + \delta.\Delta P^- + M.x_8 \tag{1b}$$

$$\frac{dy_1}{dt} = B_1(1 - y_1) - C_1 x_1 y_1 \tag{2a}$$

$$\frac{dy_2}{dt} = B_2(1 - y_2) - C_2 x_2 y_2 \tag{2b}$$

$$\frac{dx_3}{dt} = -A.x_3 + D.x_1 y_1 \tag{3a}$$

$$\frac{dx_4}{dt} = -A.x_4 + D.x_2 y_2 \tag{3b}$$

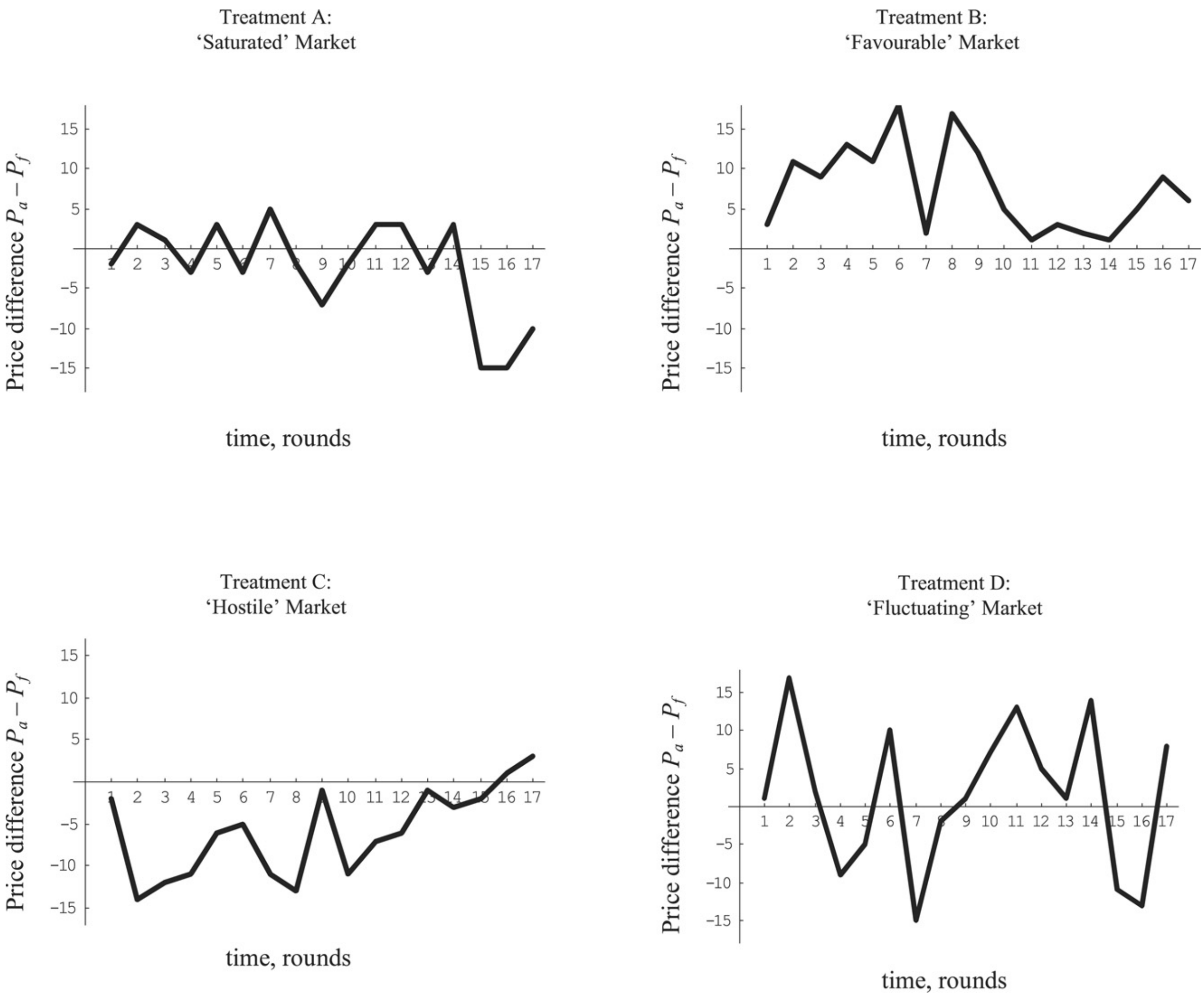

Fig. 2. Four experimental treatments.

$$\frac{dx_5}{dt} = -A.x_5 + (E - x_5)x_3 - (x_5 + E)x_4 \tag{4a}$$

$$\frac{dx_6}{dt} = -A.x_6 + (E - x_6)x_4 - (x_6 + E)x_3 \tag{4b}$$

$$\frac{dx_7}{dt} = -A.x_7 + G[x_5]^+ + L(S_A.z_{7A} + S_B.z_{7B}) \tag{5a}$$

$$\frac{dx_8}{dt} = -A.x_8 + G[x_6]^+ + L(S_A.z_{8A} + S_B.z_{8B}) \tag{5b}$$

$$\frac{dz_{7A}}{dt} = S_A(-K.z_{7A} + H[x_5]^+) \tag{6a}$$

$$\frac{dz_{7B}}{dt} = S_B(-K.z_{7B} + H[x_5]^+) \tag{6b}$$

$$\frac{dz_{8A}}{dt} = S_A(-K.z_{8A} + H[x_6]^+) \tag{6c}$$

$$\frac{dz_{8B}}{dt} = S_B(-K.z_{8B} + H[x_6]^+). \tag{6d}$$

$$o_1 = [x_5]^+ \tag{7a}$$

$$o_2 = [x_6]^+. \tag{7b}$$

Here we can afford only a brief discussion on these equations and refer to the original works of Grossberg and Schmajuk (1987) and Grossberg, Levine, and Schmajuk (1988) for more detail. The $x_1, \ldots, x_8$ variables are neuron activities, and y_1 and y_2 are neurotransmitters. The four $z_{7A}, \ldots, z_{8B}$ are memories. Signal S_A in Eqs. (5a), (5b) and (6a) and (6c) is equal to one during the rounds in which supplier A is active, and is zero otherwise. Signal S_B is the opposite. The operator $[.]^+$ denotes rectification $[\xi]^+ = \max\{\xi, 0\}$. We discuss all equation constants in Section 3.1.

We postulate that the dipole's tonic signal should be the advertised price P_a, subsuming any other tonic signal. Here it is constant during a round, but is updated three seconds into each new round to match the appearance of P_a on the screen in front of the participant (Fig. 1). This approach is justified because an advertised price is shown most of the time, and it is reasonable to assume that in the first three seconds a participant is still under the impression of the previous one. Whenever the price difference $\Delta P = P_a - P_f$ is positive, it is submitted to x_1 (see Eq. (1a)) eight seconds after the round starts, and is switched off exactly when the round finishes (with Yes or No click), to match the unfolding of events with the participant. The same is done with a negative price difference and x_2. Because the experimental consumer's attention focuses on the price difference relatively independently from attending P_a and P_f separately, we introduce constant δ in Eqs. (1a) and (1b).

Next, we postulate that the value of o_1 in Eq. (7a) and o_2 in Eq. (7b) can represent a participant's self-assessed emotion (DS). Let us denote by $t_{DS}^{(i)}$ the recorded time moment in round i when

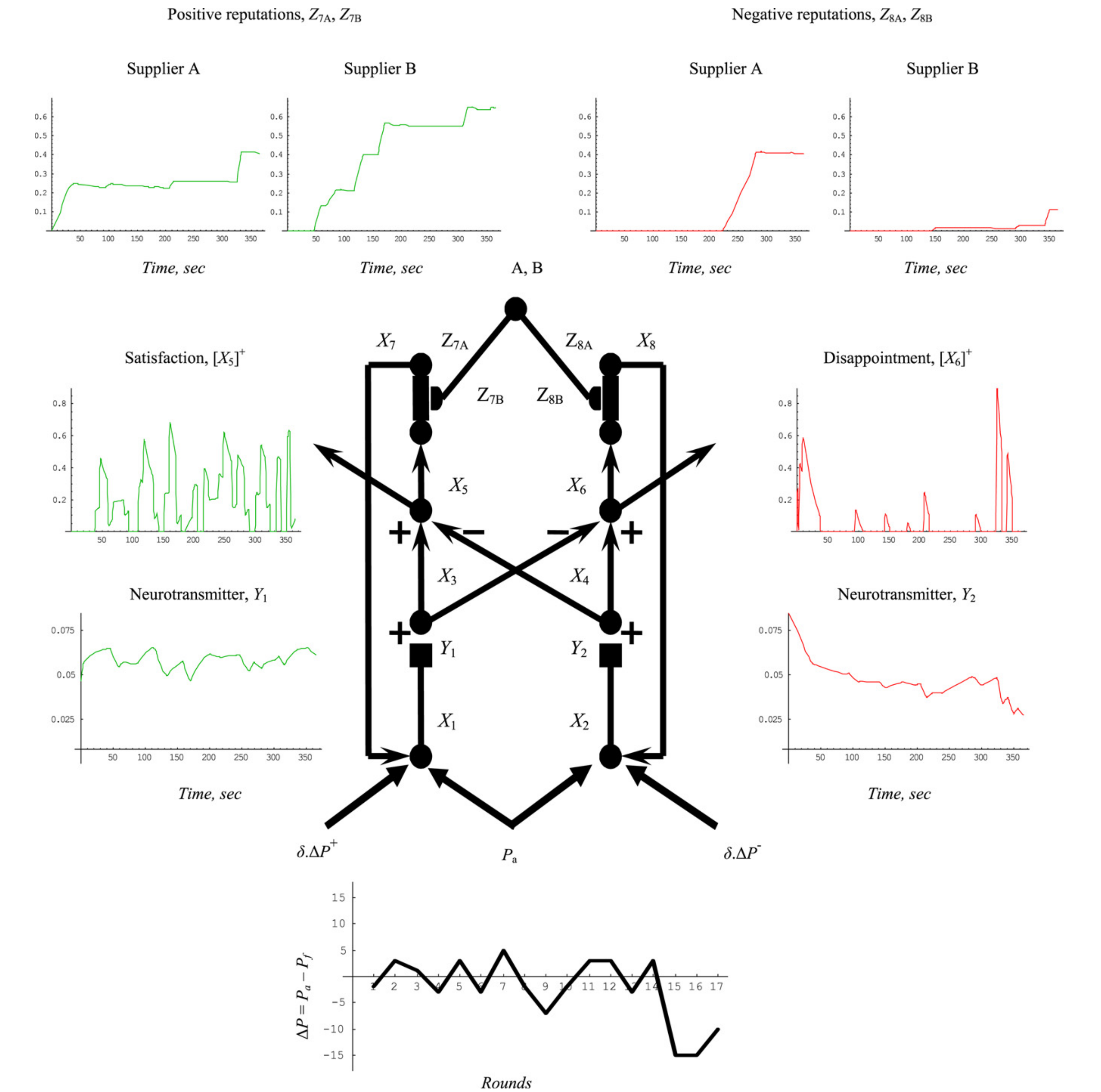

Fig. 3. Relating a participant's data to the READ model. Market is 'Saturated'. All plots show variables computed with that person's best set of constants obtained with simulated annealing. Note the Y_2 neurotransmitter release and increased disappointment in the last rounds due to larger unfavourable price differences ΔP. In addition, because the participant switched from Supplier A to B at the end of the first round, A's positive reputation did not change much for a while, while B's increased over the next couple of rounds.

the participant clicked on his chosen DS level (Fig. 1). Satisfaction is represented by o_1 and disappointment by o_2. The numerical experiment's objective is to make $o_j(t_{DS}^{(i)})$, $j = 1, 2$ as close as possible to $DS(t_{DS}^{(i)})$.

A further postulate is that the memories $z_{7A}, \ldots, z_{8B}$ store emotional experiences a participant is acquiring over the rounds. They form the supplier's reputation with its positive and negative aspects. We give the following operational definition to positive (negative) reputation: this is the memory of past satisfaction (disappointment) caused by a supplier, and is stored in z_{7i} (or z_{8i}), $i = A, B$ according to Eqs. (6a)–(6d). Note that here the emotional responses, not the price differences, determine the image of a supplier. A financial discount judged to be disappointingly small would still harm the reputation.

Our final postulate is about how the consumer choices should relate to READ. Factors such as prices P_a, P_f, their difference, provoked emotions and their current neurotransmitter balance, as well as suppliers' reputations should be accounted for. We notice that all of them more or less directly influence the activities of neurons x_7 and x_8. Let $t_{YN}^{(i)}$ be the recorded moment of clicking the Yes or No button in round i. We postulate that the choice made in the human brain should be mapped onto the relation between neural signals x_7 and x_8 at moment $t_{YN}^{(i)}$. Thus, in round i one chooses to continue with one's current supplier iff:

$$x_7(t_{YN}^{(i)}) \geq x_8(t_{YN}^{(i)}). \quad (8)$$

Eq. (8) means that, with all factors on the balance, the positives outweigh the negatives and the deal is renewed. A supplier who has just caused disappointment, i.e., $o_2(t_{DS}^{(i)}) > 0$, may still be retained, but only on the grounds of a very positive previous reputation. If the inequality in Eq. (8) does not hold, this is interpreted as decision to change the supplier. Formally, we can define a variable CS_i, which has value 1 if a change was made and 0 otherwise. An alternative solution could be to introduce a threshold in Eq. (8), but such a complication was not really needed.

3.1. Stochastic calibration

Calibrating the READ model in our case meant to make it emulate the human behaviour in the experiment. We would like in each round to have $o_1(t_{DS}^{(i)})$, $o_2(t_{DS}^{(i)})$, $x_7(t_{YN}^{(i)})$, and $x_8(t_{YN}^{(i)})$ resemble the participant answers as close as possible. We achieved this by selecting suitable values for the constants A, δ, M, B_1, B_2, C_1, C_2, D, E, G, L, K, and H in Eqs. (1a)–(6d). Their meaning except δ (explained in the previous section) is exactly as in Grossberg and Schmajuk (1987) and Grossberg et al. (1988). Because there was no obvious way for selecting their values, we implemented simulated annealing. We defined an objective function, optimized with respect to both emotional self-assessments and supplier choices. One possibility was to have a sum of the two criteria with equal weights.

Let $\mathbf{DS}(\mathbf{t}_{DS}) = \left[DS(t_{DS}^{(1)}), \ldots, DS(t_{DS}^{(N)})\right]^{\mathrm{T}}$ be the vector of a participant's answers to the emotion question, and $\mathbf{o}(\mathbf{t}_{DS}) = \left[o_j(t_{DS}^{(1)}), \ldots, o_j(t_{DS}^{(N)})\right]^{\mathrm{T}}$, $j = 1, 2$ the computed values of o_1 in Eq. (7a) and o_2 in Eq. (7b). Here N is the number of sequential rounds taken as calibration sample. Note that the actual emotion DS varies from -4 to $+4$ while READ can have only positive outcomes o_1 or o_2. Therefore, to relate the empirical and computed scales one must take all o_2 values (representing disappointment) with negative signs in $\mathbf{o}(\mathbf{t}_{DS})$.

We needed a way to put $\mathbf{DS}(\mathbf{t}_{DS})$ and $\mathbf{o}(\mathbf{t}_{DS})$ in the objective function. A good choice was to maximize their Spearman rank correlation $r_N\,(\mathbf{DS}(\mathbf{t}_{DS}), \mathbf{o}(\mathbf{t}_{DS}))$, and in particular, its variant with corrections for ties in the data. Other suitable measures of association could be the simple Spearman rank correlation, the Kendall rank correlation and, as long as both $\mathbf{DS}(\mathbf{t}_{DS})$ and $\mathbf{o}(\mathbf{t}_{DS})$ are quantitative, classical correlation could do too.

The second term in the objective function should account for the number of correct choices READ makes. Let $I_i(t_{YN}^{(i)})$ be indicator equal to 1 if in round i the READ model has chosen a supplier in the sense of Eq. (8) exactly as the participant, and 0 otherwise. Then the objective function to be maximised was:

$$J = r_N\,(\mathbf{DS}(\mathbf{t}_{DS}), \mathbf{o}(\mathbf{t}_{DS})) + \frac{1}{N}\sum_{i=1}^{N} I_i(t_{YN}^{(i)}). \quad (9)$$

In Eq. (9) the first term varies within $[-1, 1]$, and the second within $[0, 1]$. As simulated annealing proceeds, J increases, seeking to reach its maximum of 2 and thereby both terms have equal contribution. The READ Eqs. (1a)–(7b) were numerically solved by a Runge-Kutta-Felberg 4–5 method whose implementation by Gammel (2004) offered a suitable trade-off between quality and speed needed for the many solutions. Of the four million times we solved the READ system several thousand did not finish successfully, but due to the stochastic nature of the optimization process this did not matter.

Each participant's data of 17 rounds were divided into calibration sample of the first 10, and validation sample of the last 7. The former were used to fit Eqs. (1a)–(7b) in an annealing process with 6000 solutions. We repeated this computation three times and now report the best results with respect to the validation sample. An alternative division of 5 calibration and 12 validation rounds achieved slightly lower correlations and predictions for both samples. In another numerical experiment, only the second term in Eq. (9) was used for two runs of 6000 solutions for each participant. Its results were a bit less good, indicating that indeed, emotions should be taken into consideration.

4. Results and discussion

We wanted to know what emotion as valence and intensity would READ predict for each person in the i-th round, provided it had received all records for that person from previous rounds, as well as this round's P_a, P_f, and the actual timing of self-assessment $t_{DS}^{(i)}$. Further, we were interested in READ's decision as per Eq. (8) about the next supplier at moment $t_{YN}^{(i)}$. Thus we base our conclusions on sampled values of o_1, o_2, x_7 and x_8 at key moments of participant reactions. It must be stressed, therefore, that our prediction method heavily depends on availability of information about the timing of events.

Table 1 compares the prediction rate of next supplier choices by READ and two logit models. The latter were calibrated on the entire sample of 129 participants, and are the end results of logistic regression excluding numerous insignificant variables one at a time. Logit Model 1 was specified without the DS scale. That variable was added only for Logit Model 2, and it was remarkable how it ousted all the rest.

Taking the validation sample, the difference between READ's 0.8682 and Logit Model 1's 0.8283 was statistically significant, $F(1, 1804) = 5.60$, $p = 0.018$. READ performed better than its rivals; however, its lead over the DS-containing model was insignificant. It is interesting that both logit models did better on the unknown data in the last seven rounds than on the calibration data. We believe that a learning effect has occurred as participants have managed to adjust themselves to the course of events in our not so complex experimental design.

The other important question was how the emotion, in this case, customer satisfaction, could be predicted in each round. We compared the performance of READ and a linear regression model (Table 2), obtained by excluding insignificant variables from a large initial set. This time the neural model's lead amounted to 8% on the validation sample (Table 2, column 'All 129'). Interestingly, both models performed equally on test data from markets offering mixtures of discounts and losses—Treatments A and D. However, READ's emotion prediction was better by 13 percentage points in the 'Favourable' market B and by 16 p.p. in the 'Hostile' C.

Let us discuss the meaning of these findings. First, the affect caused by price differences in our experiment unfolds on the time scale of minutes rather than seconds. It took our participants 20–25 s on average to finish a round. The linear model (Table 2) shows that the emotion in round i depended not only on the current price difference, but also on variables going two rounds back.

That conclusion is reinforced by the nature of the advantage READ had over the regression model. The former did much better in homogeneous markets B and C where satisfaction treadmills occurred. In Section 2 we mentioned the large number of 'paradoxical' instances of disappointment and satisfaction in these two treatments. A READ framework offers natural interpretation to this phenomenon. It can be argued that here we have indirect evidence for lasting depletion of neurotransmitter in one of the channels of a gated dipole. Sustained habituation, in other words – hedonic or satisfaction treadmill, occurs exactly as described

Table 1
Correct prediction rate of next supplier choices

	READ Neural model	Logit model 1 $\tilde{CS_i} = [1 + \exp[-(\beta_0 + \beta_1 \Delta P_i + \beta_2 CS_{i-1})]]^{-1}$	Logit model 2 $\tilde{CS_i} = [1 + \exp[-(\beta_0 + \beta_1 DS_i)]]^{-1}$
Calibration sample of first 10 rounds	0.9574 ($n = 1290$)	0.7580 ($n = 1161$)	0.8031 ($n = 1290$)
Validation sample of last 7 rounds	0.8682 ($n = 903$)	0.8284 ($n = 903$)	0.8549 ($n = 903$)

In the logit models $\tilde{CS_i}$, CS_{i-1}, ΔP_i and DS_i are, respectively: Predicted supplier change (to be rounded to 0 or 1), actual supplier change in the preceding round, price difference, and disappointment–satisfaction self-assessment. Betas are regression coefficients. In parentheses, we give the number of observations.

Table 2
Rank correlations between actual (DS_i) and predicted ($\hat{DS_i}$) satisfactions by READ and a regression model

Model	Condition	All ($s = 129$)	Treatment A ($s = 31$)	Treatment B ($s = 34$)	Treatment C ($s = 36$)	Treatment D ($s = 28$)
$\hat{DS_i} = \beta_0 + \beta_1 \Delta P_i + \beta_2 \Delta P_{i-1} + \beta_3 \Delta P_{i-2} + \beta_4 DS_{i-1} + \beta_5 DS_{i-2}$	First 10 rounds for calibration	0.7077 (0.027)	0.6867 (0.049)	0.6609 (0.065)	0.6552 (0.046)	0.8487 (0.045)
	Last 7 rounds for validation	0.7065 (0.030)	0.8228 (0.053)	0.5196 (0.067)	0.6655 (0.055)	0.8584 (0.044)
DS_i predicted by READ	First 10 rounds for calibration	0.8930 (0.010)	0.9068 (0.012)	0.8753 (0.021)	0.8759 (0.018)	0.9229 (0.025)
	Last 7 rounds for validation	0.7846 (0.019)	0.8238 (0.038)	0.6529 (0.044)	0.8213 (0.025)	0.8575 (0.027)

With 's' we denote the number of participants. Numbers in parentheses are the standard error of the sample mean.

in (Grossberg & Gutowski, 1987), and eventually makes a lesser discount provoke disappointment, and a minor loss – satisfaction.

Yet, as Table 2 shows, READ's achievement with Treatment B's validation sample was only 65%, much less than the 82%–85% of the other experimental conditions. The reason lies in the structure of that particular market, combined with the way its data was divided for calibration and validation. A closer look at Fig. 2 reveals that the first ten rounds contain mostly big discounts, and sharp turns. It is this type of knowledge that READ accumulated in the training phase. However, the validation sample offers mostly small discounts, gradually changing from round to round. The process altered exactly at the end of the calibration sample, leaving the model relatively ill equipped for what would follow. In this line of thought, it is noteworthy that such a thing did not happen in Treatment C, which is also nonstationary. Its calibration part, however, had offered gradually diminishing surplus charges (rounds 2 – 6), which had been apparently enough to prepare READ for the test sample's similar part. In addition, the discounts in rounds 16 – 17 have triggered a change from nonzero ΔP^- to ΔP^+ in Eqs. (1a) and (1b). Thus, the dipole's internal mechanism and adequate training have contributed to its fine performance in condition C.

Perhaps a less obvious reason for READ's overall success lies in some features of our experimental design. It was simple enough, yet the unfolding of events turned out to be interesting for the participants throughout the entire session. However, they needed no prior training for it—the first one or two rounds served that purpose quite well. Naturally, they took much more time to finish (Table 3) but this variability was very useful for calibrating the READ differential equations. The information-processing load during the last 15 rounds remained constant. After Round #2, people needed two seconds on average to take a decision on the supplier, and twice longer to assess their own satisfaction. As seen from Table 3, all standard deviations are quite large, which is due to the variability across subjects.

We checked for systematic differences in information-processing effort, as manifested in the reaction times, across the four treatment groups. Apparently, it made sense to examine only the last 15 rounds. There are a number of ways to perform this analysis. One is, to take the average reaction time for each person in those rounds, and use that data to form groups for each market condition, then to look for differences among the four groups' means. However, this procedure would, all else being equal, treat a person who took more time to do the experiment than another person did, as someone who spent more mental effort. Of course, this need not be the case, as some people are simply slower than others are. Therefore, a better proxy for the effort would be the mean-to-standard-deviation ratio over the 15 rounds, rather than the mean per se. We did ANOVA on both types of measure. No significant differences were found between groups for any of the two reaction times t_{DS}, t_{YN}. In particular, for t_{DS}, simple means, we obtained $F(3, 125) = 0.85$, $p = 0.46$, and for the mean-to-standard-deviation ratios, $F(3, 125) = 1.09$, $p = 0.36$. For t_{YN} the results were similar: for the simple means, $F(3, 125) = 1.33$, $p = 0.27$, and for the mean-to-standard-deviation ratios, $F(3, 125) = 0.33$, $p = 0.81$.

We were also able to gain some insight into the reasoning of our participants in post hoc interviews. It was interesting why some of them demonstrated excessive loyalty to their supplier regardless of the incurred costs and self-reported disappointment. After the experiment, they told us they had expected their loyalty to be somehow rewarded, which had motivated their choices to a degree. Analyzing this effect is outside the scope of the present paper. Another interesting case was presented by a male participant, who explained how after the first couple of rounds he had decided to abandon his supplier each time its advertised price exceeded 40 (a remarkable coincidence with the average P_a). To account for such instances of strategic thinking, the READ model of Pavlovian conditioning should be augmented with new functionality, as discussed below.

Another feature of our design was the presence of only two competing suppliers. Because of that, we were able to frame the choice between them as a choice between the status quo and a change, and map it onto Eq. (8). However, the case of more than two suppliers, or more than two alternatives generally, would have required a lot more complex neural functionality. Alternatives would have to be represented in long-term memory outside the dipole, and a mechanism for selection among them would be needed. A theoretical outline of such a neural circuit has been proposed (Grossberg et al., 1988; Grossberg & Schmajuk, 1987), and it involves an adaptive resonance theory neural network, to account for remembering the different choices with their attributes, and a READ circuit, to incorporate Pavlovian learning and the motivation to select one option from a set. Leven and

Table 3
Response times t_{DS} and t_{YN}

	Round #1	Round #2	Average on the last 15 rounds
t_{DS}, seconds	20.60 (13.76)	7.37 (5.99)	4.27 (2.99)
t_{YN}, seconds	5.14 (4.55)	3.18 (2.83)	2.02 (1.50)

Numbers in parentheses are the standard deviation.

Levine (1996) further developed and specified these ideas by effectively introducing the key elements of a neuroscientific theory of customer motivation encompassing personal needs and goals, past experiences with goods or services, brand loyalty, relevant attributes of competing goods etc. These authors have also discussed in detail an illustrative example with the consumer of Coca Cola, and touched upon some other examples. That work has been very helpful for researchers to realise how many conceptual and technical issues remain to be resolved before neuroscience gains understanding of the decision making process. Our own experiment, with its design of medium complexity, has been only a step in that direction.

5. Conclusion

We attempted to understand key elements of customer behaviour in an experiment, by applying the READ theory of Pavlovian conditioning.[1] We suggested a way to relate prices, discounts, satisfaction and disappointment, supplier reputations, and consumer choices to neural circuit elements like memories, neurotransmitters, neurons, and neural dynamics. A separate computational experiment calibrated the differential equations, making them emulate features of human performance. In our ‘reading’, READ was able to predict correctly 87% of the experimental choices in a validation sample, and 96% in a calibration sample (Table 1). Its predictions of emotions like customer satisfaction and disappointment were also highly correlated (65%–86%) with people's self-assessments. In view of these results, affective balance theory as augmented with functionality for conditioning stands out as a convincing explanation of essential aspects of consumer behaviour.

Experimental work such as ours, and the theories in which it is grounded, occupy a distinct place in the general context of decision making research. After decades dedicated to studies of utility maximization and rational choice, came behavioural economics and economic psychology, which established that the agent was not always rational but was often emotional. In our time, neuroeconomics investigates how brain systems consume oxygen when we make judgements and choices. It would take computational neuroscience, though, with its theories and modeling, to chart the middle ground between the more traditional psychological and economic studies on one side, and brain activity observation on the other, before we could gain full understanding of our decision processes.

Acknowledgements

We thank Trifon Trifonov for helping us with part of the computational experiment, Encho Gerganov for his advice on the psychometric scale, the Action editor Daniel Levine and an anonymous reviewer for improving the quality of the paper.

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[1] At http://debian.fmi.uni-sofia.bg/~stranxter/dipole/ we provide the psychological experiment software, the empirical data, and an illustrative Mathematica file with constants obtained from simulated annealing.