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Virtual social networking increases the individual's economic predictability

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ABSTRACT

Forecasting economic choice is hard because today we still do not know enough about human motivation. A fundamental problem is the lack of knowledge about how the neural networks in the brain give rise to thinking and decision making. One way to address the issue has been to develop simplified economic experiments, in which participants need skills of little complexity and their minds employ cognitive mechanisms, already well understood by mathematical psychology and neuroscience. Here we take a neural model for rudimentary emotion generation and memorizing and use it as a guiding theory to understand decision making in an experimental oligopoly market. For the first time in that line of research, participants are put in a lab virtual social network serving to exchange opinions about deals with companies. On average, choices become significantly more predictable when people participate in the network, in contrast to working alone with expert information. Calibrating the model for each person, we find that some people are predicted with startling precision.

1. Introduction

Trying to predict people's actions is hard because not enough is known about the decision making mechanisms of the mind. Cognitive psychology has reached a consensus that the brain does not compute value or utility but conducts ad hoc and direct comparisons between the available options in the specific situation, circumstances, framing, and context (Rieskamp et al., 2006; Vlaev et al., 2011). Any choice forecasting effort, therefore, should humbly accept the prospect to accomplish very little. One approach could be statistical – gather data and use it to anticipate human behavior in the long run. In our time, machine learning with big data has done exactly that, with respectable success. Its main problem though, is that its key component – the artificial neural network – is a black box, not capable of discovering cognitive mechanisms and causal relationships. This lack of strictly scientific knowledge makes the method less effective with unknown data and new situations, posing an upper bound to its achievements.

One alternative is the bottom-up approach developed by mathematical neuroscience. It studies how neural circuits in the brain give rise to cognitive phenomena like emotion, memory, learning, etc. This endeavor has already identified the neural substrate of a variety of complex psychological processes. As the field matured, some researchers made pioneering attempts – initially at the conceptual level only – to envision what neurobiological structures in the human brain could be at work in some economic, consumer, and utility-based choices in general (Leven & Levine, 1996; Levine, 2006; Levine, 2012; Grossberg, 2018).

A parallel line of research conducted experiments with monkeys to identify brain areas and single neurons, believed to encode the usefulness of goods (Padoa-Schioppa & Assad, 2006; Padoa-Schioppa & Assad, 2008; Grabenhorst et al., 2012). These efforts, alongside the entire field of neuroeconomics, have successfully related economic concepts with brain regions in which they are processed. Yet never a serious attempt was made at forecasting economic decisions, obviously due to the huge theoretical gap between neural circuits and actual behavior (Carandini, 2012; Kriegeskorte & Douglas, 2018; Marr, 1982; Palmieri et al., 2017; Turner et al., 2017). Several ways to connect neural with behavioral data have been developed (Zhang et al., 2017; Forstmann et al., 2016; Hein et al., 2016; Schulte-Mecklenbeck et al., 2017; Wang, 2008; Klein et al., 2017; Meder et al., 2017) but no method for their integration has prevailed.

Finally, another forecast-aiming approach sought to bridge the neuron–behavior gap by designing lab economic experiments needing only that kind of cognitive processes, for which neurobiological theory is already available. One such study put participants in the role of consumers, choosing to retain or abandon a service provider resembling a mobile-phone operator (Mengov et al., 2008; Mengov & Nikolova, 2008). The authors applied an established neuroscience model of opposite emotions (Grossberg & Schmajuk, 1987; Grossberg &

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Gutowski, 1987) to interpret their data. Influenced by Levine's ideas about connecting brain neural circuits with consumer behavior (Leven & Levine, 1996; Levine, 2006), they made a step further by successfully fitting a complex model to empirical data of economic meaning. Following the Grossberg & Gutowski (1987) neurobiological interpretation of prospect theory by Kahneman and Tversky, these authors derived a neuroscientific analogue to the PT utility function and used it to explain a reference point shift in their data (Mengov & Nikolova, 2008; Mengov, 2015). A further economic experiment entailed a choice among offers from four companies in an oligopoly market and implemented a generalized version of the earlier model (Mengov, 2014). These studies were based on mathematical neuroscience that could reproduce and predict emotion-based decisions but not rule-based or strategic reasoning.

In the present paper we follow the above approach yet take it to another dimension by conducting a similar economic experiment in a lab virtual social network. In this way people are put in a more realistic environment as decisions in life are often made under the influence of others. Our network is designed to transmit messages about the participants' economic choice and their satisfaction with the outcome, which makes it more focused than any other virtual social network. We seek to enable a word-of-mouth effect whereby predefined company profiles would be more easily discovered by consumers than in the benchmark study (Mengov, 2014) where each person had worked alone.

To match this more complex situation, we use an augmented theoretical frame encompassing social communication via network. We implement a mathematical extension of the same neurobiological model of opposite emotions (Grossberg & Schmajuk, 1987; Mengov, 2014), to simulate decision-making not only with internally emerged feelings, but also with emotional influences from others who make the same kind of choices. On the other hand, the model can still not accommodate logical or rule-based reasoning but only rudimentary affect and its memorizing. What the model can do, therefore, is predict economic choices made without much mental effort. Psychology has established (e.g., Seamon & Kenrik 1992) that people choose that way when judging the problem to be of little importance or very easy.

Equipped theoretically and experimentally as explained, we seek to clarify if people working in a social network change their behavior and make more easy-going economic decisions, in contrast to work-alone conditions. That would imply people become more predictable from the standpoint of our neurobiological model. Just as interesting is the question, how does networking affect the quality of decisions as measured by economic achievement, again in relation to previous studies. It could be that people ignore the presence of others when it comes to economic matters and do not change their decision style and efficiency. To answer these questions, some experimental conditions are designed to provoke mostly the cognitive process, supported by the particular neural circuit, and explained by its theoretical model.

Unlike other studies, here the model equations are calibrated on a person-by-person basis using a participant's sequential records and are tested with subsequent records of the same person. As both data sets are small (10 ± 2 elements each), this may seem too ambitious and unrealistic. After all, the state-of-the-art artificial neural networks typically need thousands of records to produce meaningful results. The logic of scientific research, however, has always been different. Science has sought to integrate data with conceptual thinking and theory development to discover the mechanisms of phenomena. With reliable theory, few observations would do the job, while with no theory thousands may not. Often, the researcher's position is between these extremes and must deal with semi-empirical theories capturing only parts or aspects of the phenomena. This is exactly our case. The work of Grossberg and colleagues (Grossberg & Schmajuk, 1987; Grossberg & Gutowski, 1987) comprises a strong foundation for emotion- and experience-based learning and adapting to environmental demands. That theory belongs to mathematical psychology and is general enough to explain simple emotion-based economic choices. On the other hand, complex cognitive processes develop in the brain in parallel and have a huge influence on the data. What one can do is, carefully design the experiment aiming to provoke as much as possible those brain mechanisms that are explained by the concrete theory. When a computer model implementing that theory consistently succeeds in predicting somebody's economic choices using that person's previous data, this is evidence that the cognitive process is sufficiently well understood. Of course, here we mean only the process dominating one's thinking over a short period of time – those minutes in which the experiment took place. Lack of prediction success indicates inadequacy of the hypothesis about the theory's usefulness in the specific study. Therefore, in our experiment there exist two extremes in the potential results. Forecasting a series of somebody's choices with precision approaching or reaching a hundred percent would mean that the model – simple as it is – explains sufficiently well the decision making process, adopted by that person for the moment. Chance-level prediction, on the other hand, means that the hypothesized cognitive mechanism – intuitive-emotional decision making, had been either irrelevant or much obfuscated by other processes. In the latter case the research expectations had not been realistic.

Previous studies (Mengov et al., 2008; Mengov, 2014) have shown this method to be viable in the sense that it used just as few observations to demonstrate an earlier model's ability to predict human intuitive decisions. Here we conduct an experiment with a social network and hypothesize that intuitive-emotional choice will become more prominent. The new model is more general in the sense that it can take in and be influenced by other people's emotions. Because it can still not capture logical reasoning, we seek to establish only if it predicts networked people better than isolated workers. That is, the goal is to find significant difference between the two groups. The direction of the expected difference is clear, yet we always use two-sided statistical tests.

For the methodology to work, some simplifying assumptions are needed to deal with the layers of brain computation not accounted for by the theory and its model implementation. These are explained in detail in the following sections.

2. Materials and methods

2.1. Model and experiment overview

Originally introduced as the main element of a neural theory of reward, punishment, and opponent processing (Grossberg, 1972), the gated dipole model we use here was in time augmented to account for the neural dynamics of conditioned reflexes and cognitive-emotional interactions in decision making (Grossberg & Schmajuk, 1987; Grossberg & Gutowski, 1987; Grossberg & Levine, 1987). It was later adapted to fit the needs of computer-based experiments with economic content. That line of research is based on the assumption that the neural model is an adequate description of the microcircuit in the brain dealing with the particular economic situation. In (Mengov et al., 2008) two options have been available, and the choice has been between status quo and change. The study demonstrated the possibility to use a psychometric scale of the type "extremely satisfied – very satisfied – satisfied – …" to gather quantitative data, good enough to feed computer simulations of a neural circuit. These authors harnessed the classic psycholinguistic finding (Cliff, 1959) that such adverb-adjective compounds, which form the Likert scales, reliably measure the presence of a property – in that case the intensity of an emotion. They reported slightly better forecasting by their computer model than the classic econometric tools. A further economic experiment (Mengov, 2014) entailed a choice of one among four options and discovered that roughly 5% of the participants were very well predicted, about a third remained totally unpredictable, and all others were in-between. All of them worked autonomously.

In contrast to those studies, the present paper presents an experiment where everyone is connected and receives potentially useful information from everybody else. Again, assuming that we use an overall adequate model of the involved brain circuitry, we adapt it to accommodate not only choice by internal 'gut feelings', but also choice, influenced by the experienced satisfaction of others in the same situation. In practical terms that means generalizing mathematically some of the equations to enable receiving signals from more than one source.

The model used here is composed of neurons, synaptic connections, and memories (Fig. 1). Following the logic of the gated dipole neural circuit (Mengov et al., 2008; Grossberg & Schmajuk, 1987; Grossberg & Gutowski, 1987; Mengov, 2014; Grossberg, 1972; Grossberg & Levine, 1987), we relate a positive emotion – in our case satisfaction – with the output signal of neuron u_5, and a negative emotion of disappointment with u_6. Feedback loops involving neurons $u_1 \rightarrow u_7$ and $u_2 \rightarrow u_8$ are capturing the memory of already experienced opposite emotions, be they as primitive as anxiety and relief, or as sophisticated as disappointment and satisfaction. Inhibitory connections $u_3 \rightarrow u_6$ and $u_4 \rightarrow u_5$ implement opponent processing whereby the two loops suppress each other to achieve emotionally neutral state in the absence of stimuli from the environment – economic or any other. All neuron activities are described by special cases of the Hodgkin–Huxley equation (for which a Nobel Prize was given), used here in unitless form. For example, the satisfaction-generating neuron u_5 is represented as $\dot{u}_5 = -u_5 + (1 - u_5)u_3 - (u_5 + 1)u_4$. Memories w_{1k} and w_{2k} store emotional responses to incoming stimuli and are described by the Grossberg learning law. An example is $\dot{w}_{1k} = u_k(-h_1 w_{1k} + h_2[u_5]^+)$, where index k designates the sources feeding into the memory, and h_1, h_2 are positive constants. Synapses v_1 and v_2 are represented by equations of transmitter release such as $\dot{v}_1 = \beta_1(1 - v_1) - \gamma_1 u_1 v_1$, where β_1 and γ_1 are positive constants. In contrast with previous studies (Mengov et al., 2008; Mengov, 2014), our model incorporates not only incoming emotional signals $u_A, \ldots, u_D$ due to one's own choices ("I choose A", …, "I choose D"), but also signals informing how others felt due to their choices ("Participant at Computer 5 is disappointed by Supplier B"). It should be noted that Fig. 1 is not the only possible configuration. At least two other variations of the basic circuit, without the multiple-signal sources, exist (Grossberg & Schmajuk, 1987) and all three share essentially the same mathematical properties with another independently introduced model (Raymond et al., 1992). Thus, neurobiological knowledge about a neural circuit for the most basic emotional reactions is used to explain and predict behavior in an economic experiment.

As the computer screen shows (Fig. 1, upper part), in each round a participant must choose one among four offers for a fictitious good called 'omnium bonum' (a good for everyone, in Latin). The goal is to maximize the total amount received because at the end all are paid real money proportionate to their achievements. A supplier may deliver more or less than promised. Then the participant reports on a Likert scale their satisfaction or disappointment with the outcome. This game is played for 20 rounds, a figure unknown to the players. Each person receives data on all the other people's emotional reactions in the form of posts (short messages similar to tweets as in the example above) popping up in the screen field to the right. Suppliers who deliver more on average do so with higher variability, which implements the idea of a risk–return tradeoff.

In half of the treatments task-relevant information is provided in the form of two 'macroeconomic indicators' or 'aggregates': (1) total production of omnium bonum in the entire 'economic system' in the last round and (2) an unbiased forecast for the current round's production growth. The aggregates' function is to provoke logical reasoning at the expense of emotional reaction and therefore to act in the opposite direction of the virtual social network.

In the present study, we have other people's messages incorporated in the neural model dynamics. Conducting pretests, we established that submitting to the screen a message from somebody else every two seconds is quite comfortable. To attract the participant's attention, the new message is highlight initially in a red frame for 400 ms (see Fig. 1), which is more than the 300 ms needed by the brain to comprehend a new event of that kind (Banquet & Grossberg, 1987). With these design features the player presumably spends 1/5th of the time paying attention to what other people do and has enough opportunity to balance one's own judgment with what others communicate.

Further, we assume that the more omnium bonum is offered, the greater the satisfaction during the initial period of offer examination. This is common sense and corresponds to the foundations of utility analysis ever since Daniel Bernoulli. Next, the model flexibly accommodates a bored or irritated participant who no longer perceives the most promising bid as attractive but sees it as the least unattractive. In the equations, this is cast as transmitter release in the negative emotion loop $u_2 \rightarrow u_8$ due to depleted positive loop. The weakest offer is used as reference point for the other three and is put rescaled as I_b in the u_1 and u_2 equations, shown in Section 3. When a supplier delivers more omnium bonum than promised this positive difference is modelled by term $I_{\Delta+}$ added to the positive loop. That does not always prompt satisfaction – a gratuity too small may provoke model dynamics of disappointment, just as in real life. Similar considerations apply to the negative difference.

We plug recorded response times in the model, rather than have it figure them out for itself. This implementation feature is due to the occurrence of a variety of decisions in each game round and their different cognitive mechanisms. First, the participant chooses a supplier with a mouse click; then the delivery is comprehended, which ends with another click; next, satisfaction/ disappointment must be self-reported; a final click ends the round. The neural circuit (Fig. 1) has no capability to account for all of that and it was not feasible to augment it with, for example, a multiple-choice drift-diffusion model (Forstmann et al., 2016) or an adaptive resonance theory mechanism (Grossberg, 2020). Instead, an algebraic decision function is computed for the u_7 and u_8 values at moments, corresponding to the participant's choice moments. Similarly, satisfaction and disappointment are accounted for by taking the computed u_5 and u_6 at the self-report moments (Supplementary Information, section How the Model Makes a Choice).

2.2. Experimental design

The experimental design implemented different supplier profiles. Their parameters were chosen so as to meet the following requirements:

(1) To make choice prediction possible, each of the four suppliers had to offer distinctly different choices. One way to achieve this was to implement a risk-return tradeoff as discussed in Section 2.1. (See also Supplementary Information, Fig. S2).
(2) Each supplier had to be attractive enough during the game, otherwise it would drop and reduce the number of competitors. For the same reason, no supplier ought to be so attractive as to become a monopolist.
(3) The game had to last a sufficient number of rounds so that the suppliers could become recognizable. But the experience ought not be too long to make choices routine, or cause boredom.

The experimental design is outlined in detail in the Supplementary Information.

2.3. Participants

Excluding pretests with 80 people who received no payment, 257 students from Sofia University St Kliment Ohridski took part in the experiment. Of them 19.8% majored in Economics, 61.5% majored in Business Administration, and 18.7% majored in Public Administration. Their average age was 20.75 years (s.d. = 2.64). They were 154 women and 103 men. All of them gave consent to participate by voluntary registering. At the end of the procedure, which lasted about half an hour in total, all participants were paid in proportion to achievement, typically the equivalent of EUR 5–9/ GBP 4–8/ USD 6–10. No participant was allowed to take part in the study more than once. All of them were naïve to the experiment and were told that its goal was to study how

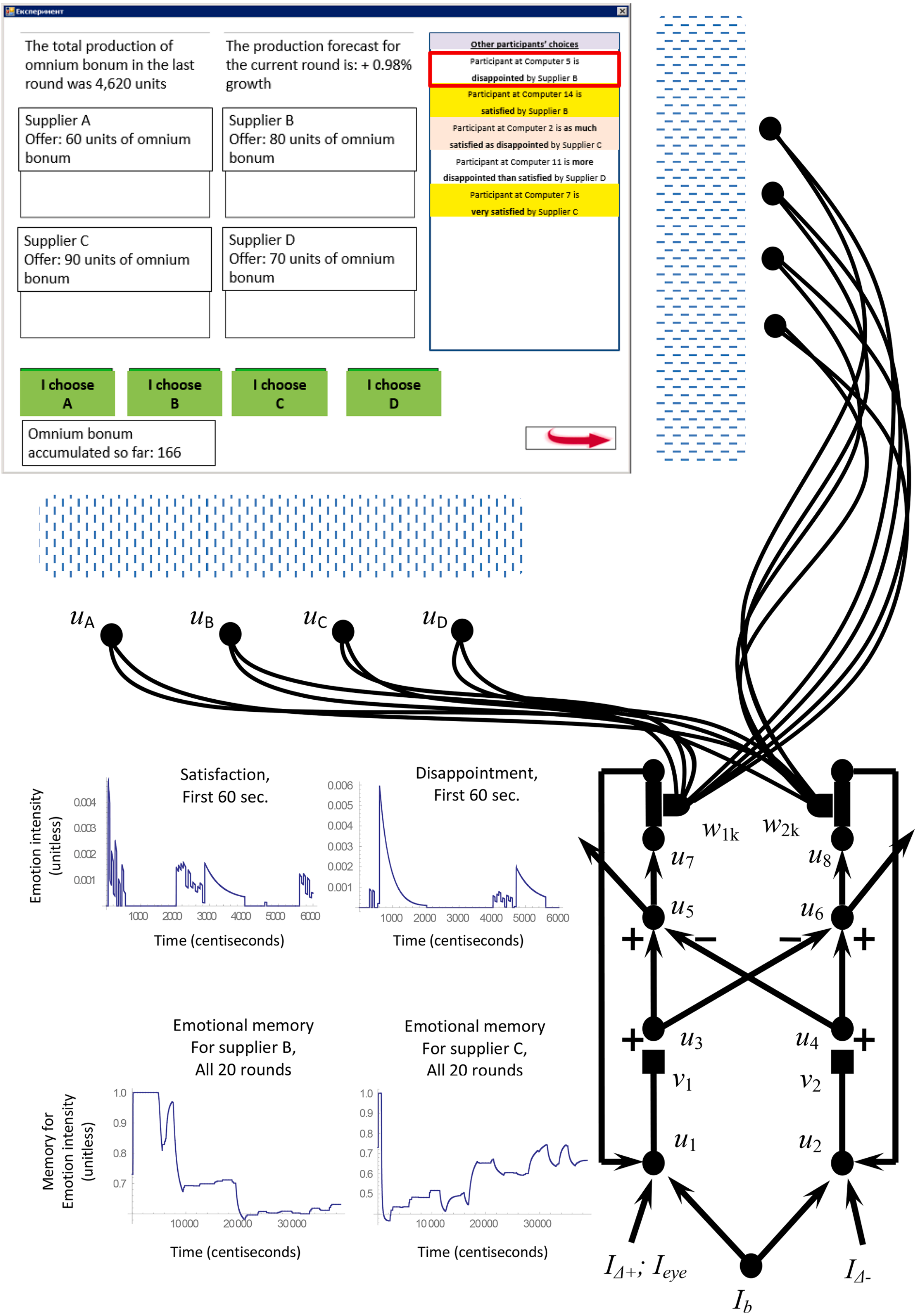

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Fig. 1. A neural circuit model explains and predicts individual actions in an economic experiment. At the top is the computer screen as seen by a participant. Four suppliers offer and deliver a fictitious good 'omnium bonum'. In each round only one offer may be chosen. Previous round total production and a production forecast are given above the offers. Other participants' reactions to supplier behavior are posted every two seconds in the field to the right. In another screen (see Supplementary Information Fig. S1) each participant reports one's satisfaction or disappointment. In the social network conditions these self-reports are sent automatically to every other participant. Horizontal and vertical striped areas signify the theoretical gap (bridged by simplifying assumptions) between the empirical data from choices and the neural circuit model at the bottom-right. Fig. 1. **Inset.** ***A computer simulation mimics the individual's choices and emotions. Top two plots***: A participant eyeballs the screen and feels satisfaction (initial jagged diminishing signal in 'Satisfaction, First 60 s.'). Then the participant chooses a supplier, which underperforms causing a peak signal ('Disappointment, First 60 s.'). A new round begins with eyeballing the offers (indented satisfaction signal) immediately followed by a peak of satisfaction (around 3000 centisec.) due to a lucky choice, supplier B. ***Bottom plots***: Emotional memory dynamics over the entire game for the most popular suppliers, B and C.

people make decisions. No ethical concerns are involved in this research other than preserving the anonymity of the participants.

A feature of the study design was that it can be described as $2 \times 2 \times 2$ in the following sense. About half of the people ($N = 126$) were put in front of a computer screen with a virtual social network (Fig. 1, upper part, left field), while another 131 saw no network, had to work alone, and served as control group. No participant was informed about the variations of the experimental design. In an orthogonal dichotomy, approximately half ($N = 125$) faced conditions without economic aggregates. About half ($N = 128$) experienced ever-growing market while the others were subjected to growth, followed by economic slump.

2.4. Experimental procedure

At the start, participants listened to an Instruction (the text is in Supplementary Information) and had the opportunity to ask questions for clarification. Soon after each person started the game with a mouse click, postings from other players began arriving on the screen (Supplementary Information, Fig. S1). Messaging was automatic and participants had no control over it other than giving (dis)honest answers to the satisfaction/ disappointment question. Filling a post-hoc electronic questionnaire, 93% of them declared they had given honest answers. Postings sent by others entered a queue and were shown in order of arrival at a rate of two seconds as explained above. Each participant saw between 51 and 300 such messages.

3. Theory and calculation

This section summarizes how the classic neural circuit model (Grossberg & Schmajuk, 1987; Grossberg & Gutowski, 1987) is adapted to the experiment. Information about the omnium bonum offers is submitted to neurons u_1 and u_2 (See Fig. 1). The former neuron serves as the entry to the 'positive' loop (dealing with positive events and emotions) and is described by its activation as follows:

$$\dot{u}_1 = -u_1 + I_b + \delta_1 I_{\Delta+} + \delta_2 I_{eye}^{(k)} + M u_7. \tag{1}$$

Quantities δ_1, δ_2, M are constants. In Eq. (1), signal I_b is related to the most modest offer. The idea is that examining the four offers, a participant is likely to view the weakest among them as a reference point for comparing the attractiveness of the other three. In particular, $I_b = \min\{I_{eye}^{(k)}\}_k$.

Index $k = A, B, C, D$ refers to that supplier of omnium bonum, to which the participant is paying attention at the moment. Signal $I_{eye}^{(k)}$ implements the commonsense assumption that examining the four options ends with a choice when they have been well understood, possibly after several glances at each. Here we follow the design in Mengov (2014), postulating that facing a new set of bids, a player randomly casts three glances at each for equal time. That may not always happen yet is a psychologically realistic simplification.

We denote with ξ_k the amount of omnium bonum offered by Supplier k. When a supplier delivers more than promised, the difference $\Delta\xi_k$ is put in the positive emotion loop in the form of signal $I_{\Delta+}$ in Eq. (1) above. A negative difference is put in the negative loop $u_2 \rightarrow u_8$ and is accounted for as $I_{\Delta-}$ in a similar way:

$$\dot{u}_2 = -u_2 + I_b + \delta_1 I_{\Delta-} + M u_8.$$

In this case $I_{\Delta-}$ is proportional to a negative $\Delta\xi_k$. The signal transfer among neurons is modulated by neurotransmitter release as follows:

$$\dot{v}_1 = \beta_1(1 - v_1) - \gamma_1 u_1 v_1$$

$$\dot{v}_2 = \beta_2(1 - v_2) - \gamma_2 u_2 v_2.$$

A detailed discussion on neurotransmitter signaling is available in Grossberg & Schmajuk, 1987; Grossberg & Gutowski, 1987; Grossberg, 1972). Further, Eqs. (2)–((5) are special cases of the Hodgkin–Huxley equation in dimensionless form and describe neuron activities:

$$\dot{u}_3 = -u_3 + u_1 v_1 \tag{2}$$

$$\dot{u}_4 = -u_4 + u_2 v_2 \tag{3}$$

$$\dot{u}_5 = -u_5 + (1 - u_5)u_3 - (u_5 + 1)u_4 \tag{4}$$

$$\dot{u}_6 = -u_6 + (1 - u_6)u_4 - (u_6 + 1)u_3. \tag{5}$$

Eqs. (4) and (5) show how the two channels suppress each other by exchanging inhibitory input signals. The neural circuit model generates a pair of opposite emotions by its neurons u_5 and u_6:

$$\phi_1 = [u_5]^+ \tag{6}$$

$$\phi_2 = [u_6]^+, \tag{7}$$

where $[\varsigma]^+ = \max(\varsigma, 0)$. Eqs. (4)–(7) mean that a person can feel either satisfaction or disappointment but not at the very same moment.

Eqs. (8) and (9) describe neurons whose behavior is driven by two factors – the ad hoc emotion and the effect of emotional memories:

$$\dot{u}_7 = -u_7 + G[u_5]^+ + L\sum_{k=A}^{D} u_k w_{1k} \tag{8}$$

$$\dot{u}_8 = -u_8 + G[u_6]^+ + L\sum_{k=A}^{D} u_k w_{2k}. \tag{9}$$

Neuron u_7 receives as input the person's satisfaction $[u_5]^+$ in response to examining supplier offers, or due to a particular omnium bonum delivery. The sum $\sum_{k=A}^{D} u_k w_{1k}$ represents the emotional memory with each of the four suppliers. Because only one of them, say, Supplier B, can receive attention at a given moment, only for it $u_B = 1$. For all other ks is true $u_k = 0$. Essentially, emotional memory w_{1k} is the product of all positive memories the participant has had with the kth supplier in their interactions. Similarly, w_{2k} in Eq. (9) accounts for all the negative experiences. Thus, memories w_{1k} and w_{2k} taken together form something like a supplier reputation in the eyes of a particular customer. G and L are constants.

In the experimental conditions with virtual social network, other people's satisfactions and disappointments also influence a supplier's reputation in the mind of a participant. This fact is modelled in Eqs. (10) and (11) by introducing terms $\widetilde{\phi}_{1k}$ and $\widetilde{\phi}_{2k}$ for the positive and negative emotions, communicated by others:

$$\dot{w}_{1k} = u_k(-h_1 w_{1k} + y_k h_2 \phi_1 + \bar{y}_k h_2 \widetilde{\phi}_{1k}) \tag{10}$$

$$\dot{w}_{2k} = u_k(-h_1 w_{2k} + y_k h_2 \phi_2 + \bar{y}_k h_2 \widetilde{\phi}_{2k}). \tag{11}$$

At the heart of this experiment is the idea that internal and external sources of emotion mix together in the decision. Making up one's mind is a complex process. It is assumed, however, that during any 10 ms interval – the time-step of the computer model – one can pay attention either to one of the four offers, or to the emotional messages from other people. This is realistic both psychologically and neurobiologically.

Previous studies Mengov et al., 2008; Mengov, 2014) used simpler equations as they dealt with only one source of emotion – one's own interaction with suppliers. To model the new situation with incoming data from others, now in Eqs. (10) and ((11) we introduce Boolean variable y_k, which is equal to 1 when the satisfaction or disappointment with supplier k comes after one's own choice and is zero otherwise. In the latter case the negation $\bar{y}_k$ is switched on, $\bar{y}_k = 1$. That is how the emotional memory is updated by other participants' postings.

The model makes prediction based on three factors. The first, $\mathbf{\Phi}_1$ is the momentary emotional reaction to the four offers as captured by neuron activities u_7 and u_8. The second, $\mathbf{\Phi}_2$, is the experience with each supplier, accounted for by memories w_{1k} and w_{2k}. And the third factor $\mathbf{\Phi}_3$ is emotional memory, storing the satisfaction/ disappointment after the last interaction with a supplier. The model's "choice" is a weighted sum of the three:

$$\Lambda = \delta_3 \mathbf{\Phi}_1 + \delta_4 \mathbf{\Phi}_2 + \delta_5 \mathbf{\Phi}_3.$$

Here Λ is a vector of four scalars, each representing the current attractiveness of a supplier. The one with the largest number wins. Parameters $\delta_3, \delta_4, \delta_5$ are real positive numbers adding up to 1.

To enhance the model's forecasting ability, it is calibrated not only with a sequence of the person's previous decisions, but also with the self-reported satisfactions and disappointments immediately following each

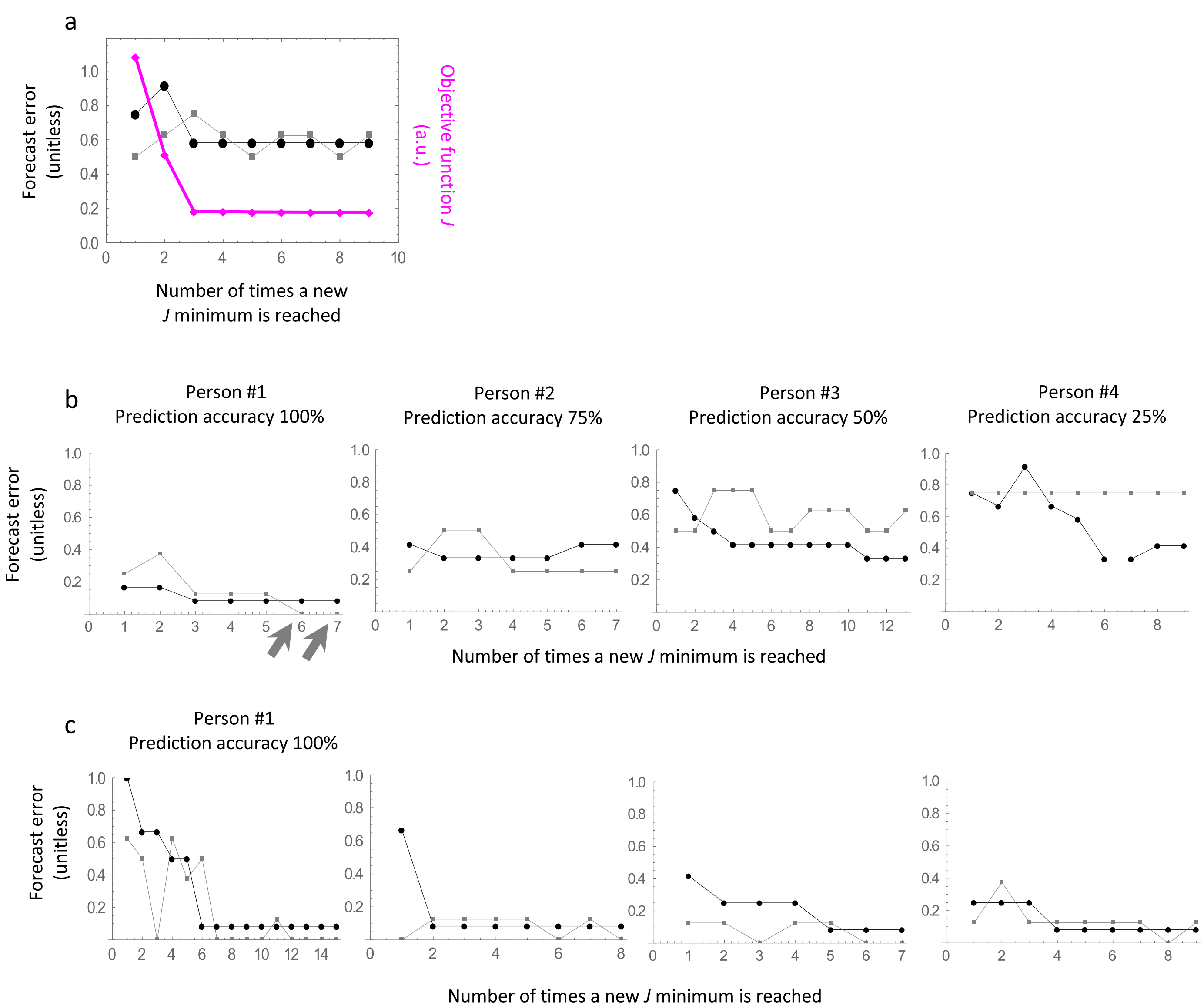

Fig. 2. Prediction error during stochastic optimization. (a) ***Errors and objective function.*** For each person, forecast error in a sequence of game rounds is the ratio of successfully predicted supplier choices to the total number of choices. Errors are plotted as black dots connected by black lines for the calibration sequence (first 12 rounds), and grey dots with grey lines for the test sequence (last 8 rounds). Objective function J is minimized by simulated annealing. (See main text for details.) Notation a.u. means arbitrary units. (**b**) ***Error minima for four participants.*** Arrows indicate prediction accuracy reaching 100% for Person #1 in the test sequence, meaning correctly forecast all 8 choices. In contrast, for others (Person #4) only 25% accuracy is achieved, equal to guessing. (**c**) ***Person #1 – other realizations.*** Additional stochastic optimization runs for the same Person #1 show that the model consistently reaches error of 0% for the test sequence.

of them. Term $R(\boldsymbol{\psi}, \phi)$ is the correlation between true emotions $\boldsymbol{\psi}$ in the calibration subsample, and their model-generated counterparts ϕ. These vectors are: $\boldsymbol{\psi} = [\psi(t_{DS}^{(1)}), \ldots, \psi(t_{DS}^{(m)})]^{T}$ and $\phi = [\phi_l(t_{DS}^{(1)}), \ldots, \phi_l(t_{DS}^{(m)})]^{T}$, where $l = 1, 2$ accounts for satisfaction or disappointment; $t_{DS}^{(i)}$ is the moment of mouse click conveying the self-reported emotion in the i-th round; and $m = 12$ is the size of the calibration subsample. When two different solutions yield identical choice predictions in the calibration rounds, the one with higher correlation $R(\boldsymbol{\psi}, \phi)$ is preferred as it accounts better for the participant's emotions.

To calibrate the model equations means to find optimal values for 11 constants like h_1, h_2 etc. Fig. 2 shows that indistinguishable forecasting results can occur through different sets of parameter values, a well-known effect in mathematical biology (Marder & Taylor, 2011; Prinz et al., 2004). In our case, an objective function J must be optimized in a simulated annealing procedure. In particular, $J \propto f(\sum_{i=1}^{m_1} \zeta_i + \theta \sum_{i=1}^{m_2} \zeta_{m_1+i} + R(\boldsymbol{\psi}, \phi))$, where ζ_i is indicator equal to 1 if in round i the model chose exactly as the participant, and 0 otherwise. Function J puts more weight on the final four calibration rounds ($\theta > 1; m_2 = 4$) to

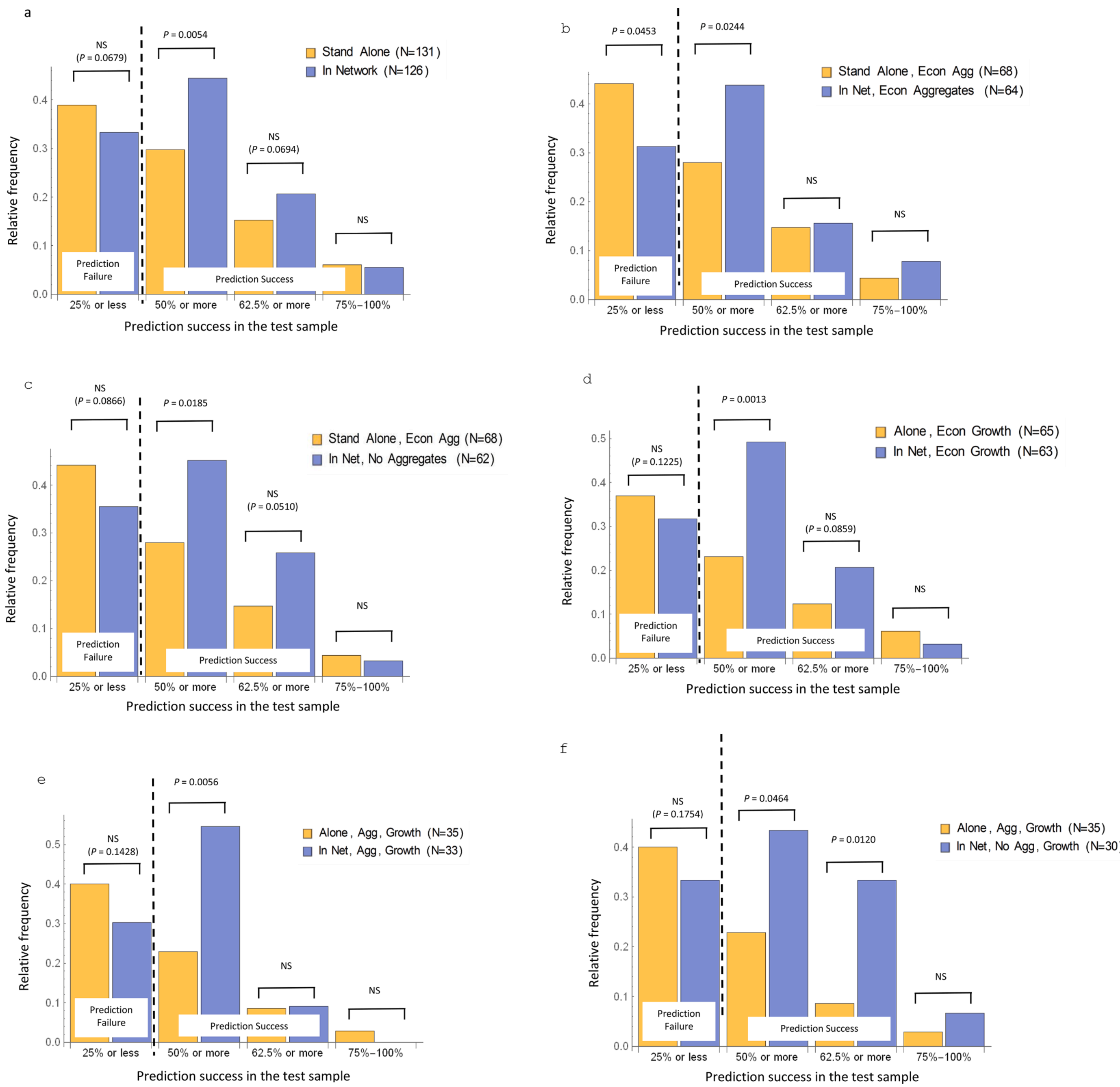

Fig. 3. Model forecasting. Forecasting by the model is superior in the network condition than in the work-alone condition, both as fewer failures and as more successes. The vertical dotted line separates model failure (inability to guess correctly more than 25% of the choices when four options are available) from substantial success (loosely defined as at least 50% correct prediction). Data for moderately successful prediction (above 25% but less than 50%) are not shown. P values are calculated by Fisher's exact test of association. (**a**) In Network vs. Stand Alone, total samples. (**b**) Subsamples for In Network and Stand Alone conditions with data on economic aggregates available to the participant. (**c**) Contrasting Stand Alone with available aggregates, against In Network without aggregates. (**d**) Comparing subsamples In Network and Stand Alone only under the condition of economic growth. (**e and f**) Prediction difference is often statistically significant even with subsamples as small as 30–35 participants.

address the possible evolution of the human decision process as the game unfolds. Consequently, a J with fewer correct choice predictions in the last four calibration rounds may be better than J with more guesses, but mostly happening in the earlier eight rounds ($m_1 = 8$). For this reason, the error function (Fig. 2a) is nonmonotonic while J is. Among thousands of simulated annealing iterations only a few produce new J minima. For each person, the model may reach the same error minimum several times, always with a smaller J and different parameters, as Fig. 2b shows.

4. Results and discussion

In the previous section we explained how the neural model is connected with the experimental data's components – participant choices, self-reported satisfactions, and different kinds of response times in a game round. As stated, the model was calibrated with a sequence of the initial 12 game rounds and tested with the remaining subsequence of last 8 rounds. All findings, reported here, are over these eight-element subsamples in the different experimental conditions.

Overall, the neural model predicts better people's decisions in the virtual social network than those made when working alone (Kruskal-Wallis Test Value = 3.99, $P = 0.0457$; Mann-Whitney Test Value = 9416.5; $P = 0.0496$; Kolmogorov-Smirnov Test Value = 1.1759, $P = 0.0332$). At first sight these numbers seem only borderline convincing, however one should remember that a 2 × 2 × 2 design loads the two samples with mixtures of opposing factors. Therefore, stronger statistical significance should be expected comparing subsamples from separate conditions and from divisions by different levels of successful prediction. Exactly that story is told by the six panels of Fig. 3, as follows.

Technically, any statistically significant forecasting above the chance level of 25% (due to four suppliers) can count as successful. It is more convincing though, to define as such double that figure, i.e., 50%. That is what Fig. 3a shows – predicting 'In Network' decisions is significantly better than 'Work Alone'. Subsamples half the size show the network effect to be stronger than the economic aggregates' influence (Fig. 3b). As one might expect, the strongest difference occurs between the most extremely-opposite conditions: 'In Network without aggregates' and 'Stand Alone with aggregates'. These two are put together in Fig. 3c. Further, it is remarkable that the significant difference stays there with subsamples as small as 30 to 35 elements, as Fig. 3e and f. show. The complete data on the model's predictive success as well as on all statistical comparisons can be found in Supplementary Information, Tables S3–S13. Not a single case of superior forecasting in a 'Work Alone' condition is identified.

In the entire sample of 257 people, a few are predicted with startling precision. It is worth discussing Fig. 2b (Person #1) and Fig. 2c, which show somebody for whom 100% accuracy is achieved, meaning correctly guessed all eight supplier choices in the test sequence. This finding was consistently repeated over a large number of independent simulated annealing runs. Only two people in the total sample are predicted at that level. Further, at least 75% accuracy is reached for 15 participants (5.84% of the sample). With accuracy of 62.5% or more are predicted 46 people (17.9%). For almost 2/3 of all participants the achievement is substantially above the success-by-chance value of 25%. As expected from the benchmark study (Mengov, 2014) the method fails with about a third of all players in the present experiment. In particular, now these are 93 people, 36.19%.

Because we simulate a neural circuit for inciting and memorizing primitive emotion only, the systematically repeated forecasting success with a few participants supports the adopted theory and its computer implementation. Apparently, this tiny faction of people have considered the game too easy or unimportant to deserve more than an easy-going attitude. Seeing no necessity for a strategy or even simple logic, they have acted intuitively and have become transparent to the model.

Such a forecasting result is evidence also for another kind of achievement. It looks like the implemented simplifying assumptions efficiently bridge the gap between higher levels of cognition and a rudimentary neural circuit somewhere in the prefrontal cortex (Levine, 2012; Grossberg, 2018). This is important because potentially more complex neural models dealing with sophisticated psychological processes could in the future help explain and predict human behavior in economic experiments resembling yet closer the real economic activity.

As we saw, people's choices become significantly more predictable when communicating in a network as opposed to working alone. Further support that in a group one acts less thoughtfully offer the behavioral data in Fig. 4a. Comparisons between paired response times show that deliveries of goods are comprehended faster, and less time is needed to self-assess satisfaction or disappointment, though the decision task in the net is cognitively more complex and as expected, takes longer to do.

Answering a post-hoc questionnaire, all participants claimed the others' messages to be helpful or very helpful for maximizing their own economic achievement. Objectively, no such effect is found (Fig. 4b), meaning that information exchange about supplier behavior has either not been effective, or has not served its purpose. It is likely that receiving dozens of messages about how a company treats its customers has been fairly helpful in creating a reputation. Yet, linking that with a pending decision concerning that company appears to be more ambivalent and depending on the participant's approach to the game. Answering another set of questions after the experiment, people described a variety of different strategies. It seems that the stream of postings about others' choices and satisfactions has created only an illusory sense of being better equipped for a decision than one really is. Here we have an intriguing example that to be informed and to be competent are not the same things.

Some of our hypotheses received no support, while other findings should be treated with caution. We expected that experiencing delivery slump would make participants think more rationally and reduce the model's capabilities, but no such effect was found (Supplementary Information, Tables S4, S6, and S7). One possible explanation is that the slump happened in the last 1/4th of the game and lasted for only 5 rounds, which may not have been enough to detect a pronounced effect.

Another finding is that economic gains are linked only to the task-relevant aggregates (Fig. 4b and c). Its statistical significance may be the result of concrete design features.

In addition, the average satisfaction reported round-by-round is higher when working alone (Kruskal-Wallis Test Value = 7.12, $P = 0.0076$, Table S23), suggesting that people in the network could not but indulge in social comparisons. That the latter have a sinking effect on subjective wellbeing is a well-known fact in behavioral economics. The interesting thing here is that it manages to show up in a cooperation-nudging experiment where stakes are not high. On the other hand, it is understandable to feel a tiny bit more miserable when a company has disappointed you the very moment it has acted generously toward somebody else.

5. Conclusion

A relevant question is, to what extent our findings from a lab virtual social network carry over to the billion-people networks on the Internet. We believe that a lot of what we established would still be valid. To begin with the obvious, it is hardly doubtful that working alone with expert information would make one adopt a more thoughtful approach, compared with someone less informed and better connected. Ceteris paribus, exchanging opinions with others will inevitably provoke some emotion. Depending on education and expertise, in some individuals that emotion could instigate creative thinking with unpredictable results, but that is not guaranteed. What is certain is that at population level people would become a bit more predictable by neuroscience models like ours.

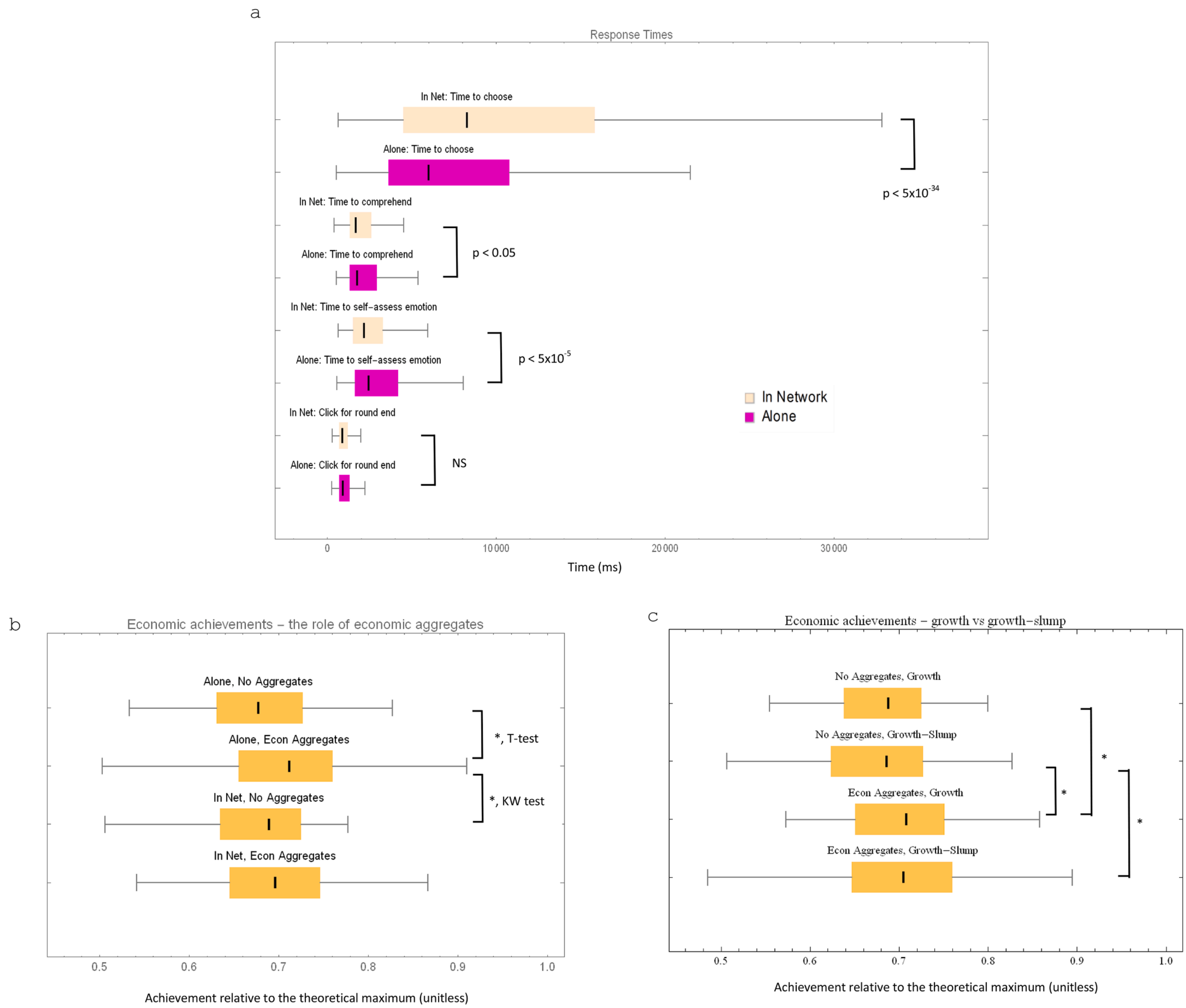

Fig. 4. Behavioral data. (a) ***Response times in rounds 4 to 20***. Participants in the network condition take more time to choose a supplier due to heavier cognitive load but comprehend economic outcomes faster. Also, in the network they need less time to assess the level of own satisfaction or disappointment. The first three rounds are excluded due to learning effects, but do not change the general picture (See Tables S21 and S22 in Supplementary Information.). *P* values are calculated by the Kruskal-Wallis test. Vertical bar is median. Outliers are not shown in the picture but are used in all computations. **(b)** ***Effect of expert information on economic achievement***. Availability of economic indicators (aggregates) significantly improves people's achievements when working alone. The effect does not show in the network conditions. $^*P < 0.05$, *T*-test and Kruskal-Wallis test. Vertical bar is median. Only significant differences are indicated. **(c)** ***Availability of expert information enhances achievement in both growth and growth-slump conditions***. $^*P < 0.05$, *T*-test. Vertical bar is mean. Only significant differences are indicated.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.socec.2022.101944.

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