



Strategic sophistication and attention in games: An eye-tracking study



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ABSTRACT

We used eye-tracking to measure the dynamic patterns of visual information acquisition in two-player normal-form games. Participants played one-shot games in which either, neither, or only one of the players had a dominant strategy. First, we performed a mixture models cluster analysis to group participants into types according to the pattern of visual information acquisition observed in a single class of games. Then, we predicted agents' choices in different classes of games and observed that patterns of visual information acquisition were game invariant. Our method allowed us to predict whether the decision process would lead to equilibrium choices or not, and to attribute out-of-equilibrium responses to limited cognitive capacities or social motives. Our results suggest the existence of individually heterogeneous-but-stable patterns of visual information acquisition based on subjective levels of strategic sophistication and social preferences.

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1. Introduction

While traditional game theory assumes agents to be fully rational and self-interested, recent research in behavioral and experimental economics has attempted to relax both of these assumptions, drawing increasing attention towards the idea that there are different types of players, both with regards to cognition and to motivation (Camerer et al., 2011).

For instance, Level- k (Crawford, 2003; Nagel, 1995; Stahl and Wilson, 1994, 1995) and Cognitive Hierarchy (Camerer et al., 2004; Ho et al., 1998) models relax the assumption of full rationality and explain out-of-equilibrium outcomes assuming individuals being boundedly rational and performing different and limited levels of iterative strategic thinking due to limited cognitive capacities.

On the other hand, relaxing the notion of self-interest, theories of social preferences account for the fact that individuals often have positive or negative attitudes towards others, and may go out of their way – thus out of equilibrium – to harm or benefit them. Under such assumptions, agents may differ in their motives towards altruism, reciprocity, and inequity (Bolton

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and Ockenfels, 2000; Charness and Rabin, 2002; Cox et al., 2008; Fehr and Camerer, 2007; Fehr and Schmidt, 1999), rather than envy or competition (Coricelli and Rustichini, 2010; Kirchsteiger, 1994; Maccheroni et al., 2012).

So far, the two streams of research investigating cognitive and motivational aspects have been developed mostly separately, though it is likely that both aspects co-exist and interact. A promising way to evaluate different theories of strategic choice comes from methods that allow investigating the processes underlying choice. The aforementioned research mostly focused on choice data, however, methods like mouse-tracking (Brocas et al., 2010; Costa-Gomes et al., 2001; Johnson et al., 2002), eye-tracking (Arieli et al., 2011; Krajbich et al., 2010; Reutskaja et al., 2011), and fMRI (Bhatt and Camerer, 2005; Coricelli and Nagel, 2009) allow observation of how decisions are developed, permitting researchers to compare and test multiple theories, and exploring alternative explanations more efficiently (Camerer and Johnson, 2004).

In the present study, we analyze eye-tracking data to test the contributions of both motivation and cognition in strategic decision-making. Starting from both theories of social preferences and limited cognition, we make specific predictions as to which patterns of visual analysis would be observed by different player types. For instance, a player motivated by fairness would observe the payoffs of the other player, regardless of whether these payoffs are strategically relevant (as with a strictly dominant strategy). Conversely, theories of limited thinking, such as level- k theories, predict that agents may not play in equilibrium because they fail to process relevant information (Camerer and Johnson, 2004; Johnson et al., 2002; Rubinstein, 1999). The relationship between information search patterns and strategic behavior has been studied in different settings, and attentional data have been used to classify agents into different strategic types. Costa-Gomes et al. (2001) used mouse-tracking to investigate the information search process in normal form games with different strategic structures. They identify nine strategic types, and observe that most of their participants exhibit look-ups and decisions consistent with level- k models. Devetag et al. (2015) manipulate game features (such as presence of focal points and strategy riskiness) in 3×3 normal form games and use eye movements to test how those features impact not only subjects' behavior, but also their information search patterns. They observe stability in information search both across games and despite features manipulation, but they report adaptation in subjects' strategic behavior. Chen et al. (2009) use eye movements to identify participants' level of strategic sophistication in a spatial beauty contest. Their results show that lookups-based types are better models than choice-based types. Funaki et al. (2011) observe a strong correspondence between participants' eye movements and choices in simple three-person distribution experiments, suggesting that subjects' social preferences can be inferred from the type of analysis of the game that they perform. Hristova and Grinberg (2004) show that, when playing prisoner's dilemmas, agents with different strategic behavior analyze the game markedly differently; while in Fiedler et al. (2013), differences in information search turn out to be correlated with the individual Social Value Orientation.

While it is now well established that there is a strict correlation between information search patterns and strategic behavior, there have been no final results that tell us clearly how to exploit eye movements to identify players' types and predict their behavior in different interactive situations. The aforementioned articles either focus on single types of games or fit data (both choice data and information search data) across games, without predicting them. In this paper, we will instead use a subset of our information search data – collected in a specific class of games – to predict subjects' strategic behavior in different classes of games. The method we develop for clustering participants based on their patterns of visual analysis allow us to make cognition visible and to identify, with a high level of precision, the decision rule adopted.

We will also answer some open questions concerning the relation between cognition and strategic behavior. For example: is the individual pattern of information acquisition constant across different classes of games? Is it possible to identify, independently by the game type, a well-defined temporal pattern of information acquisition that leads to equilibrium (or leads to a certain equilibrium in games with multiple equilibria)? Is it the pattern of information search adopted that determines the decision strategy (bottom-up hypothesis) or, vice-versa, the information search pattern that is determined by the player's type (top-down hypothesis)? In this paper we will try to answer to these questions by linking basic attentional processes to the underlying cognitive and motivational drivers.

The games we use to test the role of motivation and cognition are two-by-two one-shot normal form games. To test the level of thinking reached by the agents, we introduce games having different level of strategic complexity, in which either, neither, or only one of the two players has a strictly dominant strategy. To test the role of motivation (cooperation as well as competition) we introduce in all our games both a cell with symmetric payoffs that also maximized the sum of the two players' payoffs (cooperation), and a cell in which the difference between player's own payoff and the payoff of the counterpart was maximal, at the player's own advantage (competition).

We hypothesize that people's behavior in one-shot games is guided by their social motives and by the ability to perform iterative steps of reasoning. In those situations where there is no opportunity to learn, social preferences as well as cognitive abilities can be considered as relatively stable traits within individuals. Therefore, we hypothesize that different behaviors (in one-shot games) are determined, possibly with error, by different decision rules or types, with each type of player that remains constant across games (as in Costa-Gomes et al., 2001).

To identify the decision rules adopted by the players, we employ an eye-tracking technique (see Method section), which allows for accurately measuring fixation times and saccades (eye-movements from one target to another) with the same level of precision used in psychophysiological studies on perception and attention.

Using a mixture models cluster analysis, we associate each player with a specific decision rule on the basis of the pattern of visual analysis exhibited in a specific class of games (games with a strictly dominant strategy for the other player). Then for each type, we predict agents' choices in different games having unique (e.g., prisoner dilemmas) or multiple equilibria (e.g., stag hunt). We also observe that patterns of information acquisition are stable across different classes of games. Our

method provides detailed information and allows us to predict whether the decision process will lead to equilibrium choices or not; moreover, it allows us to attribute out-of-equilibrium responses to different aspects, like bounded rationality or the willingness to compete or cooperate.

We introduce the concept of *Visual pattern of Information Acquisition* (henceforth VIA pattern), as the sequence of eye movements (saccades) and fixations, needed to extract specific information about the payoff structure of the game, and therefore characteristic of a specific strategic behavior.

Our analysis is structured in five parts: We first group participants according to the VIA pattern exhibited when faced with a specific class of dominance-solvable games. Second, we test the hypothesis that the typical VIA pattern of each group does not change across different classes of games. Third, we associate each group of players with a decision rule, characterized by level of thinking or social motives. Fourth, we predict players' choices depending on the group players belong to. Fifth, we trained a second pool of participants to adopt specific strategies in order to evaluate further the accuracy of our classification method.

Our findings strongly support the hypothesis that agents facing one-shot games apply different and stable decision rules that can be correctly detected by analyzing the VIA pattern that they adopt. For example, we identify a specific temporal pattern of Visual Information Acquisition that leads to equilibrium independently of the class of games. Our data show that is possible to predict players' choices just by observing the pattern of visual analysis that they exhibited in a single class of games. Finally, our results strongly support the role of both social motives and level of strategic thinking in determining players' behavior in one-shot games.

2. Experimental procedure

2.1. Participants

Participants were 90 undergraduate students from the University of Trento, Italy (41 males, 49 females, mean age 21.2, SD 2.46). The study was approved by the local ethics committee and all participants gave informed consent. Eye-tracking data from four of the participants were excluded due to poor calibration.

Participants took part in the experiment individually (as in: [Bhatt and Camerer, 2005](#); [Knoepfle et al., 2009](#)). After entering the lab, each participant was randomly assigned to the “eye-tracking group” (60 participants) or to the “non-eye-tracking group” (30 participants), and then to the role of “row player” or “column player”. Participants were equally split between the two roles. Participants were instructed in the procedure and the rules of the experiment. Control questions were administered before the experiment started to verify that rules and procedures of payment were understood. When participants failed to answer control questions, instructions were repeated. It was made clear that the numbers in the matrices represented payoffs in euro and that participants would be paid according to the outcome of one randomly chosen game plus a show-up fee. Participants played 32 games divided into four blocks of 8 trials each (with two games from each class, as described below). We kept the order of the blocks fixed but randomized the games within each block. In each round, players selected their choice by typing the corresponding key number on the keyboard. Before starting the experiment, participants played four practice games. As we were interested in initial behavior only, no feedback was provided, and each game was played only once. Participants came back for the payments two weeks after the end of the experiment. A game and a counterpart were randomly selected, and participants were paid according to their choice and that of the selected counterpart. Participants earned between 1 euro and 9 euros in addition to the 5 euros show-up fees.

2.2. The games

We selected four classes of games with different equilibrium structures, and created eight two-by-two-games for each class, varying the size of the payoffs but keeping constant the difference among them.

The four classes of games (presented in [Fig. 1](#), from the perspective of a row player) were: (1) dominance solvable “self” games (DSS), in which only the eye-tracked participant had a strictly dominant strategy; (2) dominance solvable “other” games (DSO), in which only the non-eye-tracked participant had a strictly dominant strategy; (3) “prisoner’s dilemma” games (PD), in which both players had a strictly dominant strategy; (4) “stag hunt” games (SH), a coordination game in which there were no dominant strategies and both players could choose between a safe-low return choice and a high-risk high-return one. The dominance-solvable games had a unique Nash equilibrium in pure strategies, whereas the coordination game had two pure strategies Nash equilibria (one of which is Pareto-efficient) and one equilibrium in mixed strategies.

To reach the equilibrium in DSS and PD games, only one step of iterated elimination of dominated strategies is required, while in DSO games two steps are required (i.e., first the elimination of the dominated strategy of the counterpart, then the elimination of own dominated strategy).

2.3. Eye-tracking procedure

Participants in the “eye-tracking group” were seated in a chair with a soft head restraint to ensure a viewing distance of 60 cm from the monitor. Presentation of the stimuli was performed using a custom made program implemented using the Matlab Psychophysical toolbox. Eye movements were monitored and recorded using an Eyelink II system (SR. Research

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Fig. 1. The games used in the experiment, grouped by class (from the perspective of a row player). When the participants were assigned to the role of column player, the matrices were transposed. Nash equilibrium in pure strategies is highlighted in grey. D indicates the actions consistent with dominance; PE, the Pareto-efficient equilibrium; RD, the risk dominant equilibrium.

Ontario Canada) with a sampling rate of 500 Hz. A fixation was defined as an interval in which gaze was focused within 1° of visual angle for at least 100 ms (Manor and Gordon, 2003). A nine-point calibration was performed at the beginning of each block. The calibration phase was repeated until the difference between the positions of the points on the screen and the corresponding eye locations was less than 1° . After the calibration phase, a nine-point validation phase was performed (similar to the calibration phase) to make sure that the calibration was accurate. Recalibrations were performed if necessary, and eye-tracking interrupted if these were unsuccessful. Before the beginning of each trial a drift correction was performed

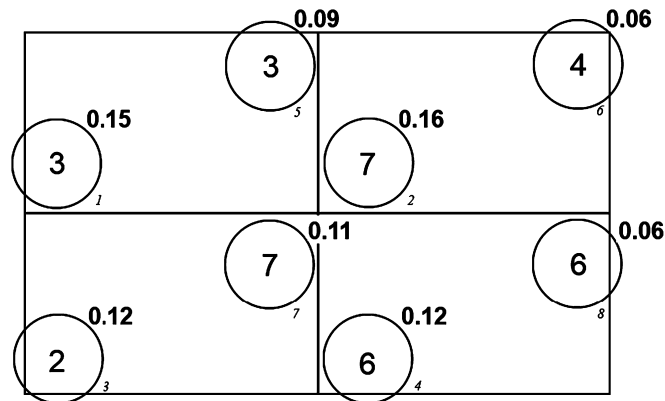


Fig. 2. A screenshot showing how the matrix was presented to the participants. Row player's payoffs are located at the bottom-left of each cell, while column's on the top-right. The circles (not visible to the participants) represent the AOIs, while the numbers in italic the corresponding labels. In bold, the proportion of fixation time of each AOI, averaged among participants.

(except for the first trial of each block). After the drift correction, a fixation point was presented, located outside the area covered by the matrix and between the two possible choices, to minimize biases related to the starting fixation point. The game matrix was presented after the fixation point was fixated for 300 milliseconds and remained on the screen until a response was made. Eye movements were recorded during the game matrix display. To minimize noise, information displayed on the monitor was limited to payoffs and participant's strategy labels. In addition, the payoffs were positioned at an optimal distance from each other (calibrated in a pilot study) to distinguish fixations and saccades between them, with row and column player payoffs at different latitudes and in different colors.

In order to analyze the eye-movements data, we defined 8 areas of interest (AOIs), centered in the payoffs. All the AOIs had a circular shape with a size of 36 000 pixels (Fig. 2). The AOIs covered only 23% of the game matrix area and never overlapped. All the fixations that were not located inside the AOIs were discarded. However, although a large part of the matrix was not included in any AOI, the large majority of fixations (85%) fell inside the AOIs.

Four types of variables were recorded by the eye-tracker in each round for each participant: (1) the time spent looking within an AOI (fixation time), (2) the number of times a participant looked inside an AOI (fixation count), (3) the number of times a participant returned to look at the same area of interest during a trial (number of runs), and (4) the number and type of saccades (defined as the eye movements from one AOI to the next). Since the first three variables (fixation time, fixation count, and number of runs) are strongly correlated, in our analysis we will mostly refer to the first variable (fixation time).

3. Results

We will first present an overview of choice and response time data, and then analyze data on eye movements.

3.1. Behavioral data

We used a Kolmogorov–Smirnov test to evaluate possible effects due to the use of the eye-tracking apparatus or to the role of the player. Even if payoffs in the two roles are slightly different, we did not find any significant difference between the two groups (“eye-tracking group” vs. “non-eye-tracking group”) on the proportion of equilibrium responses in dominance-solvable games ($D = 0.112$, $p = .97$, Kolmogorov–Smirnov two-sample test). The same analysis was performed to test possible differences in response times, but again no difference was found between the two groups ($D = 0.147$, $p = .36$, Kolmogorov–Smirnov two-sample test). Based on these results, we focus our analysis on the “eye-tracking group” only.

We performed a Kolmogorov–Smirnov test to analyze a possible “display effect” (whether the games were presented from the perspective of row or of column player) on the proportion of equilibrium responses and on response times in the “eye-tracking group”. No differences were found in both equilibrium response rates ($D = 0.133$, $p = .95$, Kolmogorov–Smirnov two-sample test) and response times ($D = 0.267$, $p = .24$, Kolmogorov–Smirnov two-sample test). Given these results, we merged the data.

We used a Friedman test to evaluate for possible effects of the class of games (DSS, DSO, and PD) on the proportion of equilibrium responses. Results showed a significant effect of the class of games ($\chi^2 = 48.03$, $p < .001$). Subsequent post-hoc Wilcoxon paired test (using Holm's correction) revealed a lower rate of equilibrium responses for DSO games compared to DSS games ($p < .001$), and PD games ($p < .001$). No significant differences were observed between DSS and PD games ($p = .105$). We did not test for differences in equilibrium response rates with the SH games since, in this type of game, both actions represent an equilibrium play. A Friedman test showed a marginally significant effect of the class of games on response time ($\chi^2 = 6.54$, $p = .09$). The average proportion of equilibrium responses and the response times are reported in Table 1.

Table 1

Proportion of equilibrium responses (Pareto equilibrium in stag hunt games) and average response times in the four classes of games (standard deviation in parenthesis).

	DSS	DSO	PD	SH
Equilibrium responses	0.70	0.35	0.68	0.45
(S.D.)	(0.35)	(0.34)	(0.39)	(0.37)
Response times	8765 ms	8565 ms	8353 ms	7679 ms
(S.D.)	(7736 ms)	(6638 ms)	(7285 ms)	(6167 ms)

Dividing the analysis of each experimental session in four blocks (of 8 trials each), we could exclude a learning effect by performing a Friedman test with the null hypothesis that the number of equilibrium responses in games with unique equilibrium is the same in each block of games ($\chi^2 = 3.16$, $p = .37$). Moreover, the mean response time did not decrease across the four blocks ($\chi^2 = 2.78$, $p = .42$).

In addition, we evaluated the correlations in the proportion of equilibrium responses in the four classes of games. The correlations between DSO–DSS and DSO–PD games were both positive and significant (DSO–DSS: Pearson's $r = .42$, $p < .001$; DSO–PD: Pearson's $r = .43$, $p < .001$). Conversely, the proportion of equilibrium responses in DSS, PD, and DSO games were significantly negatively correlated with the proportion of Pareto-equilibrium responses in SH games (DSS–SH: Pearson's $r = -.68$, $p < .001$; PD–SH: $r = -.69$, $p < .001$; DSO–SH: $r = -.46$, $p < .001$). Lastly, there was a positive correlation between DSS and PD games (Pearson's $r = .91$, $p < .001$).

The number of equilibrium responses and the correlations across subjects suggest that strategic behaviors in the various classes of games are strongly related and mostly consistent. In the following analysis of the eye-tracking data we will evaluate whether different choices within each class of games are related to different attentional patterns of visual information acquisition.

3.2. Analysis of fixations

Only fixations longer than 100 milliseconds were considered for the analysis, since this duration has been shown to be an accurate threshold to discriminate between fixations and other ocular activities (Manor and Gordon, 2003). The proportion of time spent by players looking at each AOI is reported in Fig. 2. We evaluate possible statistical differences in the mean percentage of time spent by participants towards their own and their counterpart's payoffs by using a Wilcoxon paired test. Results show that players spent significantly more time fixating their own payoffs compared to the payoffs of the counterpart (Wilcoxon paired test, $V = 2071$, $p = .003$). These results are in accordance with those obtained in previous studies that have used mouse-tracking and eye-tracking techniques (Costa-Gomes et al., 2001; Devetag et al., 2015; Wang et al., 2010). The level of attention toward each AOI was also influenced by the spatial location of the payoffs on the screen (see online Appendix F), however, equilibrium and focal cells were both evenly distributed across the four cells of the matrix (top-left, top-right, bottom-left, bottom-right) among games. Therefore, the tendency to fixate more those payoffs located closer to the center of the screen should not have affected the results.

Most of the participants started directing their attention from the fixation point to the top left corner of the matrix, showing a natural tendency to process visual stimuli with eye movements going from left to right and from top to bottom, a well-known bias associated with the western writing convention (Abed, 1991; Chua et al., 2005; Ishii et al., 2011).

3.3. Dynamic patterns of information acquisition: analysis of the saccades

Saccades are movements from one fixation to another. We included in our analysis only those saccades that occurred between fixations lasting longer than 100 ms.

Our main objective when analyzing the saccades was to identify which algorithms of visual analysis players used to acquire information about the structure of the games when facing the two-by-two matrices. In total, considering that each pair of areas of interest can be connected by two saccades (i.e., from "AOI_1" to "AOI_2" and from "AOI_2" to "AOI_1"), there are 56 possible saccades that could be observed for each game. However, we considered as relevant only those saccades useful for capturing pieces of information that are necessary to: (1) identify the presence of dominant strategies for the player; (2) identify the presence of dominant strategies for the counterpart; (3) identify the strategy with the highest average payoff among those of the player; (4) identify the strategy with the highest average payoff among those of the counterpart; (5) compare the payoffs of both players within the same cell.

We identified 24 saccades that meet the conditions listed above. However, our interest concerns the type of information that can be obtained by each type of saccade, regardless of their starting spatial location and direction. Therefore, we reduced the sample to twelve saccades by considering as equivalent all those connecting the same two AOIs (Fig. 3, Panel A).

We showed that there is no effect of the role in players' choices (whether they act as row or column player). Here, we tested whether the patterns of saccades were also unaffected by the role. A chi-square test revealed no significant effect of the role on the rate of the five classes of saccades (Pearson's Chi-square test, 3.73, $p = 0.444$).

The next step is to determine if some of these informative saccades might be grouped as part of the same *Visual Pattern of Information Acquisition* (VIA pattern). We defined VIA pattern as the sequence of saccades (and consequently fixations)

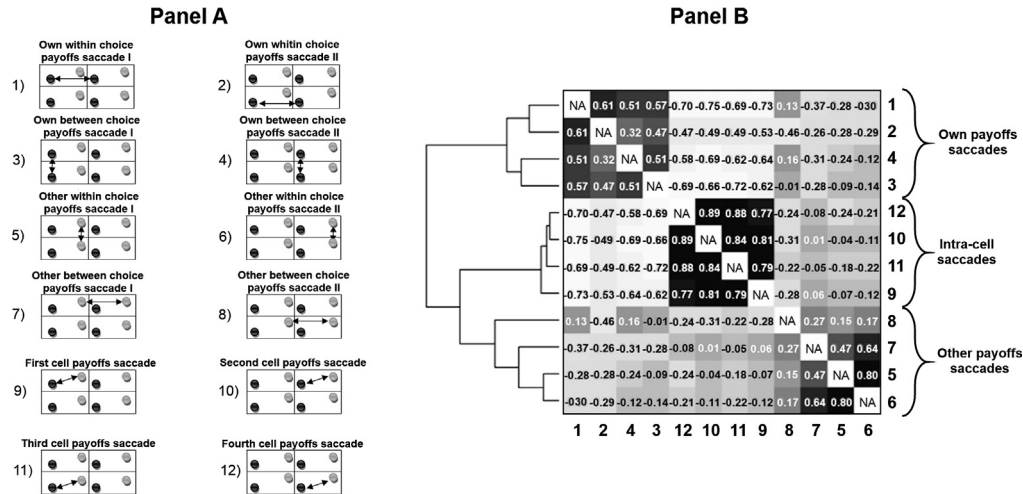


Fig. 3. Panel A) Classification of the 12 relevant saccades for row players. Black circles indicate row-player payoffs, and grey circles indicate column-player payoffs. Arrows indicate saccades. Panel B) Divisive clustering tree (on the left) and correlation map for the 12 saccades (on the right). Different shades indicate different levels of correlation, from white (−1) to black (1).

needed to extract specific information about the payoff structure of the game. We assumed that, to be considered as part of the same VIA pattern, two saccades had to satisfy the following conditions:

- i. *Co-occurrence*: for a given player in a given game, the number of times that they occurred had to be highly and positively correlated.
- ii. *Sequentiality*¹: for a given player in a given game, they must have a high probability of being performed sequentially.

In order to establish which saccades satisfied co-occurrence we used a seriation method, which is an exploratory combinatorial data analysis technique that produces a formal arrangement of units. The seriation method is used to reorder objects into a sequence along a one-dimensional continuum so that it best reveals regularity and patterns among the whole series (Liiv, 2010; Marquardt, 1978; O'Brien and Lyman, 1999). First, we determined for each pair of saccades the number of times that they occurred for a given game in a given trial. Then, we applied the seriation method to reorder the 12 types of saccades according to their level of correlation. The greater the positive correlation between two saccades, the higher the probability they co-occurred. Conversely, the greater the negative correlation, the lower the probability that saccades co-occurred². As Fig. 3 (Panel B) shows, the seriation method assigned the 12 saccades into three groups of four saccades each. Saccades were positively correlated within each group (dark shaded cells) and mostly negatively correlated between groups (fair cells). The three sub-groups are:

- i. *own payoffs saccades*: saccades between a player's own payoffs;
- ii. *other payoffs saccades*: saccades between the counterpart's payoffs;
- iii. *intra-cell saccades*: saccades between the payoffs of the two players, within the same cell.

Own payoffs saccades included saccades that were necessary to identify the presence of own dominant choices, and own strategies with the highest average payoff. *Other payoffs saccades* included saccades that were necessary to identify the counterpart's dominant strategy and strategies with the highest average payoff. *Intra-cell saccades* included saccades that were necessary to compare the two players' payoffs within a specific cell.

However, in order to be considered as part of the same VIA pattern, visual saccades of the same group also had to be executed sequentially.

¹ To create complex information structures (e.g. identify a dominant strategy), multiple elements (payoffs) have to be considered and integrated among them. This integration process requires that all elements of necessary information be collected sequentially; therefore we assumed that, to be part of the same VIA pattern, saccades have to be executed in a sequential order with a high probability.

² Seriation method is closely related to clustering method. Both methods include a clustering with optimal leaf ordering; however seriation method does not identify cluster boundaries but simply provides an optimal ordering and rearrangement of the objects (for an extensive review of the method see Liiv, 2010). In our case, the objects were the 12 different types of relevant saccades. The number of times that each type of saccade occurred in a given trial was calculated and the correlation for all pairs of saccades computed. The seriation method simply re-ordered the 12 saccades, putting together those saccades having a higher positive correlation and dividing those saccades having negative correlation.

Table 2

Probability for each of the 12 saccades to be followed by a saccade classified as “own payoffs”, “other payoffs”, or “intra-cell” saccade. The stars refer to the level of significance: one star <0.05 , two stars <0.01 and three stars <0.001 .

	Own payoffs saccades	Other payoffs saccades	Intra-cell saccades
1. Own within choice payoffs saccade I	0.74***	0.04	0.22
2. Own within choice payoffs saccade II	0.72***	0.07	0.21
3. Own between choice payoffs saccade I	0.66***	0.08	0.26
4. Own between choice payoffs saccade II	0.64***	0.08	0.28
5. Other within choice payoffs saccade I	0.07	0.54***	0.38
6. Other within choice payoffs saccade II	0.13	0.48**	0.39
7. Other between choice payoffs saccade I	0.12	0.56***	0.32
8. Other between choice payoffs saccade II	0.13	0.53***	0.33
9. First cell payoffs saccade	0.23	0.18	0.58***
10. Second cell payoffs saccade	0.27	0.19	0.53**
11. Third cell payoffs saccade	0.23	0.17	0.59***
12. Fourth cell payoffs saccade	0.26	0.19	0.54**

Table 3

Generalized linear mixed models. Dependent variable: equilibrium choice (or Pareto equilibrium in SH games) = 1; independent variables: number of own payoffs, other payoffs, and intra-cell saccades. Regressions were performed separately for the four classes of games.

Games	Predictor variables	Estimates	Z value	p-Value
DSS	Own payoffs saccades	0.219	3.603	$p < 0.001$
	Other payoffs saccades	0.078	1.105	$p = 0.269$
	Intra-cell saccades	−0.169	−2.961	$p = 0.003$
	AIC = 343	BIC = 368		$\log L = -166$
DSO	Own payoffs saccades	−0.080	−1.766	$p = 0.077$
	Other payoffs saccades	0.366	5.228	$p < 0.001$
	Intra-cell saccades	0.018	0.510	$p = 0.610$
	AIC = 418	BIC = 443		$\log L = -203$
PD	Own payoffs saccades	0.332	3.300	$p < 0.001$
	Other payoffs saccades	0.153	1.621	$p = 0.105$
	Intra-cell saccades	−0.166	−2.480	$p = 0.013$
	AIC = 300	BIC = 325		$\log L = -144$
SH	Own payoffs saccades	−0.227	−3.700	$p < 0.001$
	Other payoffs saccades	−0.076	−1.152	$p = 0.249$
	Intra-cell saccades	0.085	1.887	$p = 0.059$
	AIC = 430	BIC = 454		$\log L = -208$

Thus, we determined the probability for each saccade to be followed by a saccade of the same group. According to a one-tailed binomial test (Siegel and Castellan, 1988), the probability that each saccade was followed by another saccade of the same group was always significantly larger than what would have been predicted by chance, i.e. 0.33 (Table 2).

Based on these results, we maintained the classification obtained with the seriation method, treating each of the 12 visual saccades as part of one of the three identified VIA patterns.

We expected the analysis of the VIA patterns to give us important insights about the actual level of strategic reasoning underpinning players' behavior. Thus, we tested the relationship between the previously defined VIA patterns and players' choices in the four classes of games using a generalized linear mixed model (GLMM). We assumed a binomial family distribution where the dependent variable was equal to one if the strategy chosen was an equilibrium one (Pareto-efficient equilibrium in SH games) and zero otherwise (Risk-dominant equilibrium in SH games). The independent variables were the number of own payoffs, other payoffs, and intra-cell saccades. Participants and trials were treated as random effects.

We ran a separate regression for each of the four games to evaluate the hypothesis that different VIA patterns promote different choices depending on the structure of the game. For example, equilibrium choices in DSO games should be linked to the level of attention to the other player's payoffs. Conversely, equilibrium choices in DSS games should be sensitive to the level of attention toward the player's own payoffs.

Table 3 reports the results for the four classes of games. The equilibrium responses in both DSS and PD games – in which the players had a dominant strategy – were positively correlated with the number of saccades among players' own payoffs, and negatively correlated with the number of intra-cell saccades ($p < .001$ and $p = .003$ for DSS games; $p < .001$ and $p = .013$ for PD games). In DSO games, equilibrium choices were positively correlated with the number of saccades between other players' payoffs ($p < .001$), and marginally negatively correlated with the number of saccades between the player's own payoffs ($p = .077$). In SH games, the choices corresponding to the Pareto-efficient equilibrium were negatively correlated with the number of saccades between player's own payoffs ($p < .001$) and marginally positively correlated with the number of intra-cell saccades ($p = .059$).

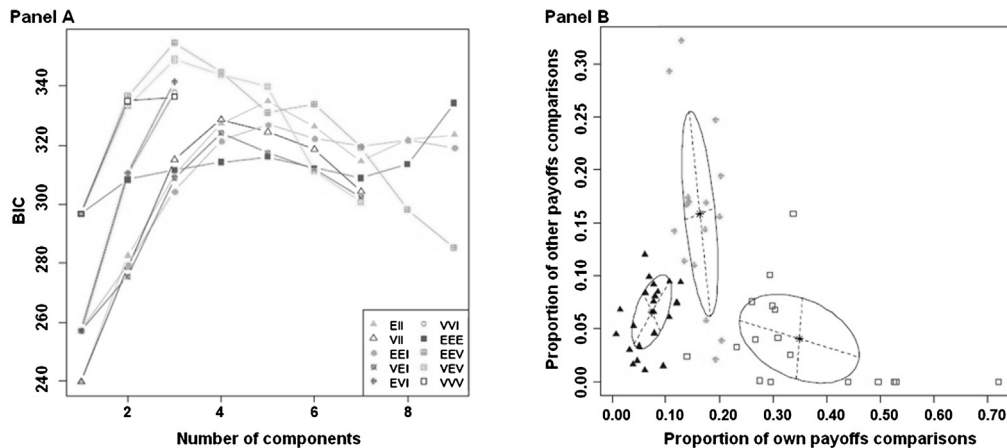


Fig. 4. Panel A) Bayesian information criterion of the 10 models. Panel B) Distribution of the three clusters.

Overall, the regressions showed that equilibrium and out-of-equilibrium responses were strictly related to the level of attention to different types of information. However, we cannot say much yet about the algorithms of visual analysis used by the players; in particular, we do not know if the behavior is determined, as we hypothesized, by different decision rules or types and if players behaved consistently across different games.

3.4. Cluster analysis based on saccades

In this section, we sought to answer to two questions: (1) Do players apply similar algorithms of visual analysis when acquiring information within a specific class of games – or, alternatively, is there heterogeneity in the algorithms that they use – and (2) do the algorithms of visual analysis used by players remain the same when they play different classes of games?

To answer the first question, we classified players based on their VIA patterns. Specifically, we clustered players based on their proportion of own payoffs, other payoffs, and intra-cell saccades over the total of saccades in DSO games (i.e., including also the non-classified saccades in any of these three classes). We chose DSO games because this class of games required participants to focus on the payoffs of the other player, and to perform iterative thinking to detect equilibrium play.

To identify the clusters, we adopted the mixture models cluster analysis used by Brocas et al. (2010) and proposed by Fraley and Raftery (2002, 2006). The advantage of using this clustering method is that the number of clusters and the clustering criterion are not determined a priori, rather they are optimized by the method itself. In this way, we can test the hypothesis of the heterogeneity of players' behavior by evaluating the number and characteristics of the clusters resulting from the clustering procedure.

Mixture models consider each cluster like a component probability distribution; then a Bayesian statistical approach is used to choose between different numbers of clusters and different statistical methods. As in Brocas et al. (2010), we considered a maximum of nine clusters for up to 10 different models, choosing the combination that maximizes the Bayesian Information Criterion (BIC). For our data, the Bayesian Information Criterion was maximized at 355 by an ellipsoidal model with equal volume and shape, yielding three clusters (Fig. 4, Panels A–B).

The three clusters represent players who analyzed the games in similar ways. The first cluster consists of 23 players who made more than 60% of intra-cell saccades, and roughly 20% of own and 20% of other payoffs saccades. The second cluster counts 17 players who made more than 80% of own payoffs saccades. The third cluster consists of 16 players who have their attention equally distributed among the three types of saccades; they used on average 37% of own payoffs, 36% other payoffs, and 27% of intra-cell saccades.

Fig. 5 (Panel A) summarizes the algorithm of visual analysis used the most by each cluster, while Panel B shows an example of the observed patterns for each cluster. These results are consistent with the hypothesis of individual heterogeneity in players' behavior and give us a picture of the different models built by players to represent this specific class of games. It is remarkable to note that more than two-thirds of the players (cluster 1 and cluster 2) focused their attention on a single type of information (intra-cell saccade for cluster 1, and own payoffs saccade for cluster 2), neglecting other pieces of information that were relevant to best respond to the other player's strategy. We labeled the clusters after the saccade that the players used the most: players *focused on intra-cell comparisons* (cluster 1), players *focused on own payoffs* (cluster 2) and players with *distributed attention* (cluster 3).

We then tested whether players maintained the same type of analysis when dealing with games having different strategic structures. Fig. 6 reports the normalized distribution of own payoffs, other payoffs, and intra-cell saccades for the three clusters in the four games and shows that the distributions of the three saccade types remained fixed within clusters across games. *Own focused* players mainly made saccades between their own payoffs, while *intra-cell* players made saccades within

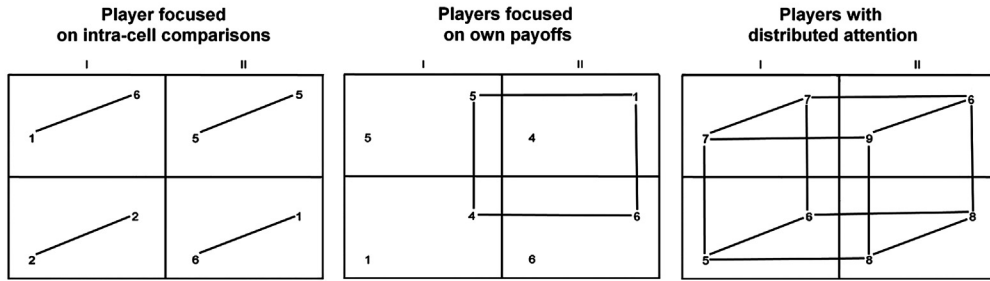
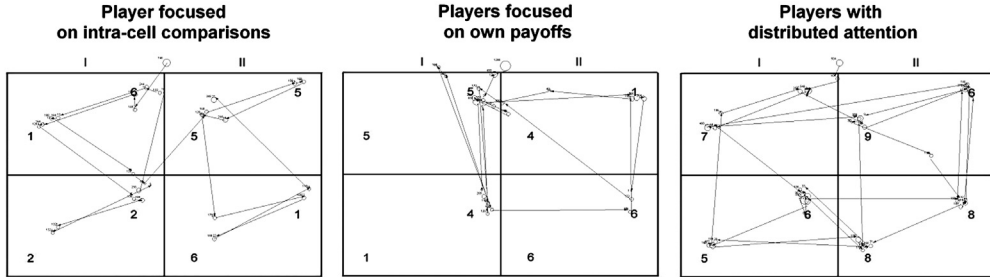
Panel A**Panel B**

Fig. 5. Panel A) Preferred algorithms of visual analysis for the three clusters (from the perspective of a column player). Panel B) Examples of analysis performed by three column players classified as *players focused on intra-cell saccades*, *players focused on own payoffs* and *players with distributed attention*. Lines indicate the saccades; circles, the fixation location.

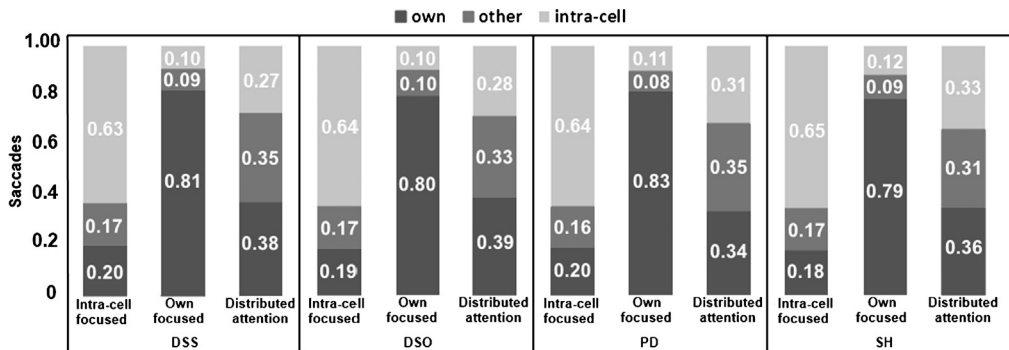


Fig. 6. Proportion of each type of saccade for the three clusters in the four classes of games.

the four cells. Lastly, players with *distributed attention* always took into account the other player's payoffs, even in those games where this was not necessary to determine the dominant choice.

From these results, we can conclude that players did not adapt their information search pattern to different classes of games.

3.5. Temporal patterns of visual information acquisition

To better understand the algorithms of visual analysis resulting from the clustering, we analyzed the individual VIA patterns over time, for each cluster. Specifically, we evaluated how the proportion of own, other, and intra-cell saccades evolves through time. Instead of arbitrarily choosing a fixed time span for our analysis, we decided to calibrate it on players' behavior. For each cluster, we computed the number of saccades needed by 75% of the participants to reach a decision, and used that number as cluster-specific time span.

Fig. 7 shows the temporal distribution of own, other, and intra-cell saccades for the three clusters in the four game classes. It is interesting to note that, for all the three clusters, the temporal pattern of visual analysis remained constant regardless of the game type.

Players in the *distributed attention* cluster exploited all the saccades types within the decision time. In addition, the pattern they followed was the same in all classes of games: i.e., they started by considering their own payoffs; after four or five saccades (depending on the class of game), the proportion of other payoffs saccades increased up to exceeding the proportion of own payoffs saccades. Lastly, and before making a decision, own payoffs saccades always returned to be more

frequent than other payoffs saccades. Players belonging to the *own focused* cluster used mainly saccades connecting their own payoffs, hardly looking at the counterpart's payoffs. Players in the *intra-cell focus* cluster used mainly intra-cell saccades.

These results support the hypothesis of the existence of individually heterogeneous attentional patterns of visual information processing, independent and unaffected by the strategic structure of the game. Our next step is to associate each cluster with a decision rule, defined in terms of level of thinking and social motives.

3.6. Characterization of types

The CH model (Camerer et al., 2004) assumes players have different level of sophistication and use iterative decision rules. Sophistication in interactive game playing reflects the extent to which players' take the game structure and other players' incentives into account. The iterative process starts with level-0 players that simply randomize over the action space. Level-1 players, believe that all other players are level-0 thinkers and best respond to random play. Players that make 2 steps of thinking believe to play against a combination of step-0 and step-1 players. In general, level- k players best respond to a population distributed from 0 to $k - 1$ steps. Formally, the CH assumes a frequency distribution of steps (a Poisson distribution) that characterizes the distribution of players belonging to each level. The distribution is described by only one parameter (τ), corresponding to the mean and the variance.

According to CH theory, players should adopt iterative decision rules that are based on a step-by-step reasoning procedure. Bhatt and Camerer (2005) define the information required by players exhibiting different levels of thinking, when playing normal form games. As argued by the authors, players that perform 1-step of thinking believe they are facing 0-steps players, therefore, "they do not need to look at the other player's payoffs at all since they do not use this information to refine their guess about what others will do" (page 426). Conversely, players who perform two-steps of thinking believe they are playing a mixture of 0 and 1-step players. Level-2 players "work harder at forming a belief, look at other players' payoffs, and use their belief to pick an optimal choice" (page 426).

Considering our data, players classified as having *distributed attention* could be associated with level-2 players. In fact, they took into account the counterpart's payoffs, and exhibited a temporal pattern of visual analysis that was in accordance with an iterative step-by-step procedure (i.e. they looked first at their own payoffs, then at the payoffs of the counterpart, then again at their own). Therefore, we expected for this cluster a parameter τ close to 2. Players who were *focused on own payoffs* could be associated with level-1 thinkers, because they hardly looked at the counterpart's payoffs, and their temporal pattern of visual analysis stopped after considering their own payoffs. For them, the parameter should be close to 1. The temporal pattern of visual analysis exhibited by players *focused on intra-cell transitions* did not reflect any iterative decision rule and could not be associated with any specific k -step of thinking. Then, we could not predict which value of τ could capture the data.

We estimated the value of the parameter τ for each of our clusters (*distributed attention*, *own payoffs focused* and *intra-cell focused*) in all games together. The parameters estimated were $\tau = 1.7$ for participants in the *distributed attention* cluster, and $\tau = 0.82$ for participants in the *own payoff cluster*. In both cases, the values of the parameters were consistent with our interpretations of players' behavior.

The τ estimated for participants who *focused on intra-cell saccades* was equal to 0, indicating that according to the model these players were assumed to choose randomly. However, considering the systematic and consistent VIA pattern observed by these participants, they can hardly be considered level-0 players. In what follows we will interpret the VIA pattern exhibited by players *focused on intra-cell saccades* in terms of other regarding preferences.

A player motivated by fairness or competition may look at the payoffs of the counterpart, regardless of whether these payoffs are strategically relevant or not (Johnson and Camerer, 2004, 2004b). On the one hand cooperative players aim to maximize the sum of their own and their partners' payoffs. On the other, competitive players intend to maximize the difference between their own and their opponent's gain³ (Van Lange, 1999). In order to do so, both player types need to compare their own payoffs with those of their counterpart, for each possible game outcome (cell). Both of these strategies are consistent with the VIA pattern exhibited by players *focused on intra-cell saccades*.

In all our games there was a cell with symmetric payoffs that also maximized the sum of the two players' payoffs. We assume cooperative players as the ones focusing on that cell. Conversely, competitive players should have focused more on the cell in which the difference between player's own payoff and the payoff of the counterpart was maximal, at the player's own advantage. We called these cells: "cooperative cell" and "competitive cell", respectively.

For each player focused on intra-cell saccades we calculated the Search Index (henceforth SI. Glöckner and Betsch, 2008; Norman and Schulte-Mecklendeck, 2010), obtained by subtracting the time ratio spent looking at the AOs located in correspondence with the competitive cell from the time ratio spent looking at AOs located in correspondence with the cooperative cell, and dividing this difference by the sum of them. SI ranges from -1 to $+1$; negative values indicate more time spent looking at the payoffs located in the competitive cell, while positive indicate more time spent looking at the payoffs located in the cooperative cell.

Players with a parameter value greater than zero were classified as cooperative (17 players) and those with a parameter value smaller than zero as competitive (6 players).

³ Competitive players assume that their counterpart is choosing each action with equal probability, therefore this model imposes no rationality on the opponent decisions.

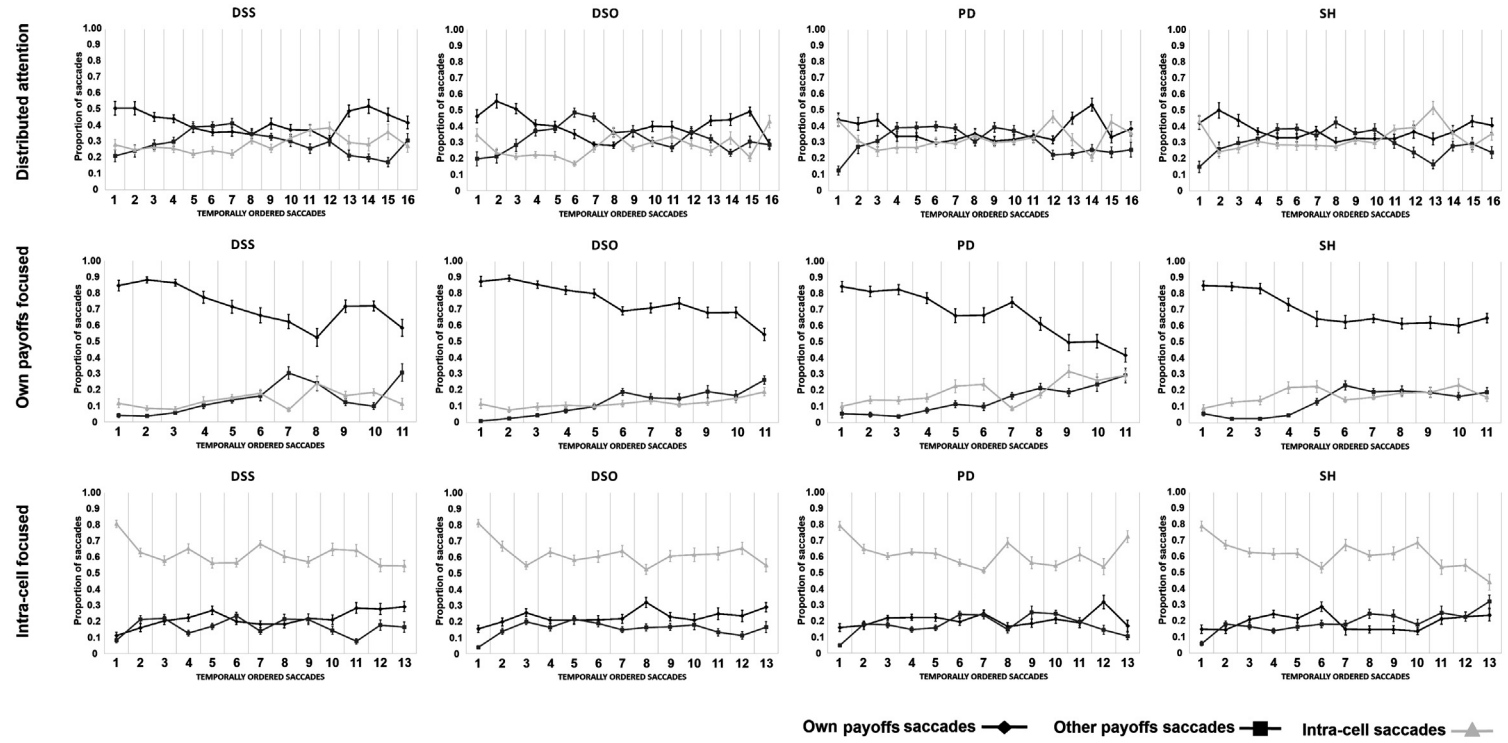


Fig. 7. Proportion of own payoffs, other payoffs, and intra-cell saccades (mean and standard error) over time, divided by cluster and games.

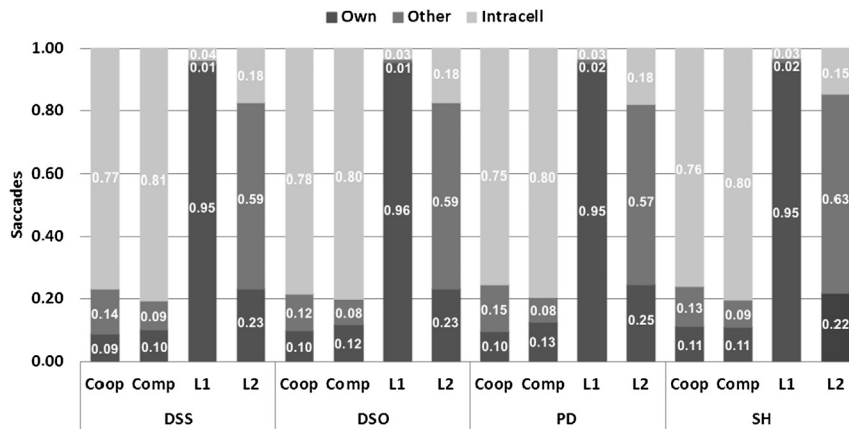


Fig. 8. Proportion of each type of saccades made by trained participants when applying the four decision rules (Cooperative, Competitive, L1 and L2), in the four classes of games.

To summarize, we associated players with *distributed attention* to level-2 thinkers (16 players), players *focused on their own payoffs* to level-1 thinkers (17 players), and players *focused on intra-cell saccades* were divided in cooperative (17 players) and competitive (6 players) types based on their search index.

3.7. Patterns of visual information acquisition adopted by trained participants

While the VIA patterns observed in our clusters (see Fig. 6) appear consistent with the types we identify (albeit noisy), one might wonder how closed they are to those we would observe if participants were trained to look for specific strategies. Following Funaki et al. (2011), we run a separate experiment where participants were trained to look for four strategies (one at a time), when playing the games presented in Fig. 1.

32 additional subjects participated in this experiment. Participants were asked to apply each of the four strategies to the 32 games for a total of 128 trials per subject⁴. We collected participants' saccades for each strategy and built the clusters accordingly. The four strategies participants were trained on were: 1) level-1 (L1): in which participants were asked to choose the option with the highest average payoff; 2) level-2 (L2): in which participants were asked to best respond to a player who chooses the option with the highest average payoff; 3) Cooperative: in which participants were asked to coordinate their actions with those of the counterpart on the outcome that maximize the join payoff; 4) Competitive: in which participants were asked to choose the option that maximizes the difference between their own payoff and the payoff of the counterpart, assuming that the counterpart was choosing randomly.

Fig. 8 reports the proportion of each type of saccade for trained participants. In Fig. 6 and 8, distributions of saccades in the three clusters (Intra-cell focused, Own focused, Distributed attention) are very close, although obviously slightly noisier in the clusters obtained with untrained participants.⁵ To further test the accuracy of our classification, we compared the analysis⁶ adopted by each untrained participant (in DSO games) with those of trained participants (again in the DSO games) and associate each subject to a decision rule based on the minimum Euclidean distance. Results show that only 5 of 56 participants (8.9%) would be classified differently. This is a first evidence that our clusters (obtained with untrained participants) reflect not only subjects' preference for a specific VIA pattern, but also their preference for a specific strategic behavior. Even more, this evidence supports the top-down hypothesis, i.e. that VIA patterns are the product of the search for a specific strategic solution of the game, not vice versa. In the next section, we will predict the behavior of the players based on our categorization.

4. Forecasting agents' behavior

Our final step is to predict the choices of players in the four classes of games, simply using our definition of types as proxy of players' strategic behavior. We remind that clusters and Search Index were both determined only using data on saccades in DSO games. Table 4 reports the expected and observed proportion of equilibrium responses (Pareto equilibrium in stag hunt games) for the four types in the four classes of games.

⁴ Further details on the experimental method can be found in online Appendix E.

⁵ In the clusters with trained participants noise is minimized since we only use the trials in which subjects correctly selected the strategy we asked them to, excluding those trials in which their answer was wrong. The clusters with untrained subjects were instead built exclusively based on saccades, without considering subjects' actual choice.

⁶ Defined in terms of proportion of own, other and intra-cell saccades.

Table 4

Proportion of expected and observed equilibrium responses (Pareto equilibrium in stag hunt games) for the four types in the four classes of games (standard deviation in parenthesis).

		Game			
		DSS	DSO	PD	SH
Own focused	Exp.	1.00	0.00	1.00	0.00
	Obs.	0.91 (0.19)	0.13 (0.20)	0.90 (0.22)	0.28 (0.30)
Distributed attention	Exp.	1.00	1.00	1.00	0.00
	Obs.	0.93 (0.12)	0.65 (0.25)	0.92 (0.17)	0.23 (0.27)
Cooperative	Exp.	0.00	0.00	0.00	1.00
	Obs.	0.27 (0.25)	0.16 (0.21)	0.19 (0.22)	0.83 (0.17)
Competitive	Exp.	1.00	1.00	1.00	0.00
	Obs.	0.88 (0.25)	0.85 (0.24)	0.88 (0.31)	0.31 (0.44)

Table 5

Average choice distribution in the coordination games (SH) among the three possible outcomes divided by type of player.

	Level-2			Level-1			Cooperative			Competitive		
	Coord.		Miscoord.	Coord.		Miscoord.	Coord.		Miscoord.	Coord.		Miscoord.
	Risk dom.	Pareto		Risk dom.	Pareto		Risk dom.	Pareto		Risk dom.	Pareto	
Level-2	0.59	0.04	0.36	0.55	0.07	0.38	0.13	0.19	0.68	0.53	0.07	0.40
Level-1				0.50	0.07	0.43	0.12	0.24	0.64	0.49	0.09	0.42
Cooperative							0.02	0.70	0.28	0.11	0.26	0.63
Competitive										0.43	0.06	0.51

Based on our definition of types, *own payoffs* participants should behave as level-1 players and play equilibrium in DSS and PD games only. In the remaining games, they should best respond to a counterpart playing randomly, therefore they should choose the strategy giving the highest expected payoff (the non-equilibrium strategy in DSO and the Risk Dominant in SH). Participants classified as *distributed attention* should behave as level-2 players and play equilibrium in all the dominant solvable games, while chasing the Risk Dominant equilibrium in the stag hunt. *Intra-cell* participants with *cooperative* attitude should not play equilibrium in dominance solvable games, since the cell maximizing the sum of the players' payoffs lies always in the non-equilibrium strategy; they should also be attracted to the Pareto-efficient equilibrium in SH games. Lastly, *intra-cell competitive* players should play always equilibrium due to the fact that the cell with relative higher payoffs for them lies always in the equilibrium strategy in dominant solvable games, and in the risk dominant strategy in the SH games.

In dominance solvable games (DSS, DSO, PD) players' choices were correctly predicted 84% of the time by our definition of types, while only 59% of the choices were consistent with the Nash equilibrium. In coordination games (SH), our definition of types explained 77% of the choices. A comparatively lower predictive power (65%) was found for DSO games for players categorized as *distributed attention*. We tried to explain this lack of predictability by comparing the temporal pattern of visual analysis in equilibrium and out of equilibrium responses. As shown in Fig. 9 when players categorized as *distributed attention* chose according to the equilibrium (Panel A), they started looking at their own payoffs, then they evaluated the payoffs of their counterpart, and finally, they chose their best response re-evaluating their own payoffs. Conversely, it was not possible to identify a well-defined temporal pattern of visual analysis (Panel B) when they did not choose in accordance with the equilibrium. Thus showing a distinctive and well-characterized pattern for equilibrium play.

Finally, we used our classification of types to predict whether, and in which equilibrium, there will be coordination in the stag hunt games. We matched participants' actual choices in all SH games (8 games), calculated each participant's average outcome distribution among the three possible outcomes (coordination in the risk-dominant equilibrium, coordination in the Pareto equilibrium, miscoordination), then averaged the distributions by type. As expected, participants classified using eye-tracking data as level-2, level-1 and competitive players coordinate mostly on the Risk Dominant equilibrium, and miscoordinate when matched with cooperative players (Table 5). Cooperative players coordinate on the Pareto Equilibrium, but only when matched with another cooperative player; they miscoordinate otherwise.

5. Concluding remarks

In this paper we study strategic interaction in normal form games, testing the hypothesis that players' behavior is based on different decision rules or types, and that these types can be inferred by observing how agents acquire information.

Monitoring eye movement, we could identify three types of players in terms of visual patterns of information acquisition (VIA): players focusing on their own payoffs, players with distributed attention, and players that analyzed payoffs within cell.

Players categorized as *own payoffs* systematically neglected the payoffs of the other player; moreover, the eye-movements were consistent with those of a person looking for her dominant strategy or the strategy giving her the highest average payoff. They acquired partial information and they purposely played equilibrium only in DDS and PD games, therefore only

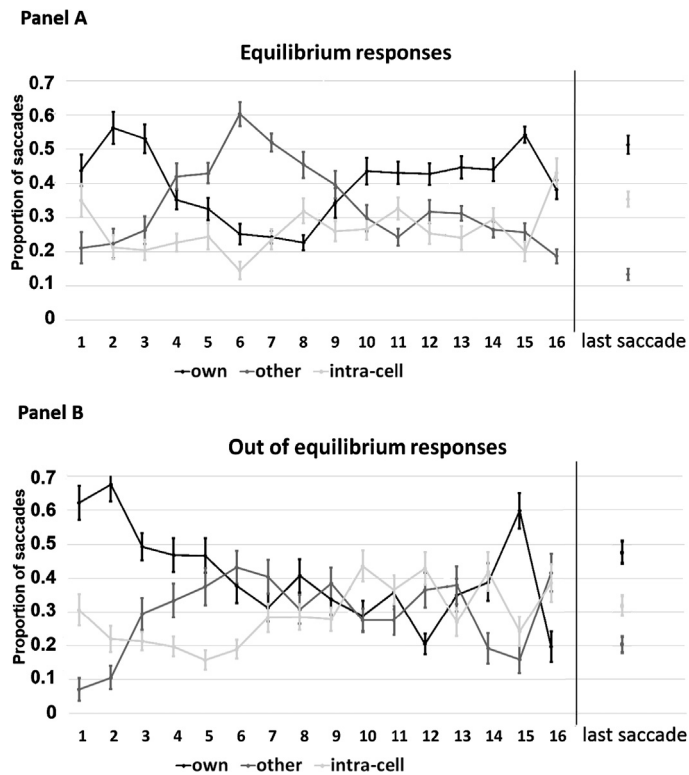


Fig. 9. First 16 saccades (mean and standard error) in DSO games, for players clustered as *distributed attention* (level 2), divided by equilibrium responses (Panel A) and out of equilibrium responses (Panel B). On the right side of each Panel we reported the proportion of own, other and intra-cell saccades at the time of choice (last saccade).

when they themselves had a dominant strategy. They performed only one step of iteration and they based their choices on their own rationality, ignoring the rationality of the other player. The presence of players of this type demonstrates non-attendance of relevant strategic information and how non-attendance leads to out-of equilibrium behavior.

Players categorized as *distributed attention* acquired all the available information, thus they performed saccades and fixations over own and other player's payoffs. Their VIA pattern shows that they performed two steps of iteration, thus taking into consideration their own and other player's rationality. They played the unique equilibrium in the three dominance solvable games and they played risk dominant equilibrium in the stag hunt. Interestingly, they performed a systematic and consistent dynamic pattern of information acquisition when playing equilibrium. Thus they sequentially looked at (i) their own payoffs, (ii) the payoffs of the other player, (iii) they integrated the two, and (iv) finally looked at their own payoffs prior to their response (i.e. the equilibrium choice). Deviation from this specific VIA pattern leads to out-of equilibrium choices. This suggests that the pattern of visual attention is strictly correlated with the final choice. Also, this result indicates that, for this type of players, deviation from equilibrium is not due to non-attendance of available information: the trials in which *distributed attention* participants deviate from equilibrium are the trials in which they looked mainly at their own payoffs. Thus, their out of equilibrium behavior is characterized by a self-referential bias.

Also players *focused on intra-cell saccades* acquired complete information. Their VIA was characterized by intra cell saccades between own and other player's payoffs. The VIA patterns of the *intra-cell* players reflected two types of social preferences: cooperative players search for the cell that minimizes the difference in relative payoffs, while competitive players look for the cell that maximizes the difference between own and other player's payoffs. This classification was determined using a Search Index on the eye-tracking data, thus showing how our method provides a measure of social preferences. Following this VIA pattern, they never played equilibrium in the dominance solvable games and they played payoffs dominant equilibrium in the stag hunt game. The evidence from this type of players shows again that full attention is not a sufficient condition to play equilibrium. Thus players focused on *intra-cell saccades* were non-strategic even though they acquired all the available information.

Strategic deliberation requires the player to acquire information about own and other player's payoffs following a specific order, such as the order of information processing adopted by the *distributed attention* players. Taken together, the specifications of types suggest that VIA patterns (directly measured with eye-tracking) is a set of information processing mechanisms associated with social preferences and strategic sophistication.

The results obtained in our study strongly support the hypothesis that participants in one-shot games apply different decision rules that can be accurately detected by analyzing the *Visual Pattern of Information Acquisition* that they adopted. These

decision rules can be easily described in terms of interaction between social motives and level of strategic sophistication. We also observed that players do not change their attentional pattern of visual information acquisition when dealing with games having different structures.

We believe that the algorithms of visual analysis adopted by our participants are actually the result of higher-level processes based on the interaction between motivational and cognitive aspects. Thus, preferences and cognition may characterize the visual attention pattern through preferential looking.

Our results indicate that the agents have a predetermined and stable way to acquire information (i.e. represent contexts) in interactive games, and that this pattern of visual attention is strictly related to both their preferences and their ability to reason strategically. Comparing patterns of information acquisition in our clusters with those of trained subjects suggests that VIA patterns are the product of the search for a specific strategic solution of the game (top-down hypothesis), not vice versa.

Appendix A. Supplementary material

Supplementary material related to this article can be found online at <http://dx.doi.org/10.1016/j.geb.2015.09.003>.

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