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RESEARCH ARTICLE

Information Transmission in a Social Network: A Field Experiment

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Abstract

Using an app for smartphones, we run an experiment among high-school students to study the pattern of aggregation of sparsely distributed information. Agents are randomly arranged in small networks and can share only non-verifiable pieces of information. Results show that while information exchange is high, the level and the distribution of centralities among network members are important to shape the overall level of information aggregation. A reduction in the asymmetry among agents' network centralities is associated with an improvement in the performance of the group in terms of aggregation of information.

Keywords: communication; non-verifiable information; networks; centrality; field experiment; smartphone app

Introduction

The way agents aggregate information is a central topic in the social science literature. Examples of applications range from political science, studying how to design the structure of communication inside an executive to favor an efficient flow of knowledge, to the study of organizations, where strategic retention of information could prevent the correct functioning of the firm.[1] In many of these settings, there is an element of competition such that those who manage to have better access to information can get an advantage.

This paper studies this topic by focusing on a case in which agents can exchange non-verifiable pieces of information and are arranged in a network that defines their communication opportunities. We are interested in studying how asymmetry among players alters the pattern of information diffusion. Do central players benefit from their position in the network? Do they gather more information if they are in

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[1]Seminal works in this area are Weatherford (1982) and Huckfeldt and Sprague (1987) in the context of political organizations. Burt (1992, 2004) studies the managerial structure of firms.

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contact with more players? Do they get an advantage if they are gatekeepers of the information passing between other subjects? At an aggregate level, is a less centralized network better at sustaining information exchange among agents?

To answer these questions, we use a field experiment with high-school students in Italy. We designed a smartphone app, called VestiTito, which at the time was downloadable on Google Play and Apple App Store.[2] On the app, students received the description and the rules of the game that they were playing, as well as the private information that they needed for playing.

The experiment consisted of a game played over the span of a week. Students were randomly allocated in networks of five members and were asked to guess the five colors of the clothes of a character based on the pieces of information that had previously been distributed among the five participants, one piece of information each. Students were also told the identity of the other students who were neighbors in the networks that were assigned to them and had time to communicate offline, if they wished to, during the days of the experiment. Payoffs depended on the number of correct guesses (up to 5). Additionally, the player who was able to guess the highest number of items would receive a bonus. This introduced an element of competition as players reduced their chances of winning the bonus by truthfully sharing their information with others. In our experiment, we use three different network structures characterized by the same network size and a similar number of links, but a different distribution of network centralities.

We start with a network of five members. The second and third network structures are obtained by adding a single link to the first network structure. In one case, the link makes the most central player even more central, and in a second case, it brings the second most central player to the same level of centrality as the first one.

Two are our main findings. First, we rarely observe the outcome that constitutes the only Nash equilibrium in a standard game with non-verifiable information and selfish preferences, that is the case in which people rely only on the hint they received and avoid exchanging information with the others. Instead, the observed level of communication is high, especially among students in the same class. This evidence is in line with the experimental literature on cheap talk games, in which players usually exchange more information than one would predict using theoretical models. Second, we find that the network structure significantly affects information transmission. Central players manage to guess correctly a higher number of colors. Additionally, the network with the highest asymmetry in network centrality among the players is associated with the lowest level of exchange of signals. Finally, by focusing on players with high centrality, we find suggestive evidence that when the asymmetry is high, central agents tend to block the flow of information.

Literature review

Pioneering studies of experiments regarding communication in networks are Bavelas (1950) and Leavitt (1951). The paper by Bonacich (1990) studies a context that is quite similar to ours. It is described by the author as a communication

[2]Using standard measures in behavioral economics, Pin and Rotesi (2022) show that individuals behave similarly in online app-based experiments and in controlled experimental labs.

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dilemma in which players face a tradeoff between sharing information with their links to accelerate the aggregation of signals at the group level and retaining pieces of information to increase the chances of winning a private reward. Hagenbach (2011) formalizes and generalizes the setup described in the experiment in Bonacich (1990). This paper studies the ability of the group to solve communication dilemmas and how the speed at which aggregation takes place depends on the network structure. With respect to these papers, we allow subjects to exchange non-verifiable information. This simplifies the set of possible strategies. At the same time, we enrich the framework by considering different network structures, as we are interested in understanding how the presence of multiple central players changes the overall outcome. Theoretical contributions connected to our work from the political science literature are Patty and Penn (2014) who study decision-making and information aggregation in small networks and Dewan et al. (2015) on how policies implemented by cabinets depend on the interplay between communication structure and decision power. With respect to them, we abstract from considering authority, as each player submits a guess, and focus on how the network structure influences information aggregation.

More recently, applied game theory work has devoted attention to studying how the network structure of communication allows players to coordinate on outcomes when multiple equilibria are possible (Choi and Lee, 2014) or to sustain collaborative norms (Gallo and Yan, Forthcoming). Gallo and Yan (Forthcoming) highlight how the introduction of asymmetric players in the network reduces the probability that players will avoid playing the Nash equilibrium and choose a collaborative norm, with higher average payoffs. This result is in line with our finding that there is less communication when the structure of links is more centralized on one player.[3]

Related to our setting, there is also a broad empirical literature originating from Burt (1992), where one of the main focuses is on the role played by structural holes in networks. This literature highlights how agents who bridge structural holes, meaning that they are pivotal in the sharing of information, can gain higher payoffs. By connecting parts of the network that contain different pieces of information agents can gain an advantage with respect to their peers. Contributing to this literature, we are interested in showing with an experiment what are the effects of overall network structures on individual behavior and outcomes at the agent level. Our results show how the presence of agents who bridge structural holes can have negative consequences for peripheral agents as those who are central can easily alter or block the passage of information.

Experimental design

The experiment consists of groups of five high-school students assigned to network structures playing a game where they compete by exchanging information. The

[3]Further work looking at the impact of network structures in experimental settings includes Centola (2010) who manipulates the structure of an online network and studies the diffusion of a health behavior, Caria and Fafchamps (2019) who highlight the unwillingness of central individuals in social networks to act more pro-socially than others, Vilela (2019) who emphasizes the importance of rivalry in information diffusion and Banerjee et al. (2013) in the context of microfinance.

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presence of competition is important because it rules out a simple process of information diffusion where players would share all available information with their group members. We use three network structures which are comparable in the number of links, but differ in the distribution of degree centrality and betweenness centrality. Degree centrality measures how many people a player can communicate with, and therefore, it captures the number of communication channels surrounding the player. Betweenness centrality looks instead at how pivotal a subject is in passing the information between other players, and therefore, it captures the ability to block the flow of information in the network. This experimental design allows us to compare how degree and betweenness centralities affect the individual's ability to gather information and how their distribution at the network level impacts the performance of the group.

Recruitment and grouping

The experiment was conducted in May 2017 with 645 high-school students in Italy. We relied on the help of teachers to invite students to take part in the experiment. To register to play the game, students had to answer questions from an online survey and then download and install an app on their phones. The app contained the game and was made available both for Android and iOS so that we could allow the vast majority of interested students to play. The app contained a mock round with an explanation of the rules of the game and a set of questions made to verify that the participants had no doubt about the functioning of the game. The game took place over the span of a week, with three rounds of two days each. During each round, every student was randomly matched with four other colleagues to form a group of five. In each round, players could win from 0 to 15 euro. We then extracted randomly one round to be the one valid for the payments. Rewards were given using Amazon Gift Cards.

The game

The goal of the game was to guess the colors of the clothes of a character. Each group was assigned a different character, and they had to guess the colors of its five pieces of clothing, where different characters had a different combination of colors. At the beginning of each round, the player was given three pieces of information: first, the name of the character whose colors of clothes she had to guess; second, the color of one of the clothes (e.g. the hat); third, the identity of the neighbors in the network she was assigned to. After receiving these pieces of information, players were given two days to choose a combination of colors to submit. After that, the process was repeated, with new groups being generated. It is important to underline that the second and third grouping were done to avoid two players to play together more than once. This feature of the randomization was known by the players and would prevent favor exchanges from one round to the other.[4] More information and screenshots from the app can be found in Appendix A.

[4]To limit the players' ability to show any evidence to their peers regarding the hints, the information received at the beginning of the round was not stored in the phone, nor it was possible for the players to take screenshots of the app.

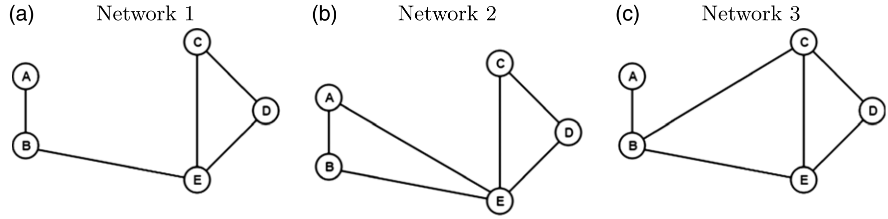

Figure 1. Network structures.
Note: The figure shows the three network structures that were considered in the game. Nodes identified by capital letters represent students. A link connects two nodes if the two players were informed that they were neighbors within the same group.

The networks

Players could be arranged in three different network structures, as shown in Figure 1.[5] Additionally, players could be assigned to any of the five positions within the network. In these networks, each node represents a player. For example, Player A in Network 1 was only informed about the identity of Player B, while Player B knew about E also. It is important to underline that the app was not providing any chat to exchange messages with the other members of the group. Communication happened in person. We therefore consider links as couples among which we expect communication to happen with high probability. These networks, albeit being similar in the number of links and equivalent in the number of players, allow us to have interesting variation in degree centrality and betweenness centrality.[6]

The payoffs

The final score was calculated according to the following rule: 10 points were assigned for each color that was correctly guessed, 5 points were removed for each color that was guessed wrongly, and 0 points were assigned for each piece of clothing left gray. A piece of clothing left gray was counted as the player not choosing any color for that part of the guess. On top of this, players could earn a bonus in case they were the ones that had the highest score among the members of the group of five. The bonus was 100 points, to be divided among the eligible players.[7] Each point was worth 10 cents, so that each player could win from 0 to 15 euro. To limit the role of reputation concerns in driving information sharing, players did not receive feedback on the outcome after each round. They only knew at the end that one of the three rounds was randomly chosen and paid. Since they did not even know which round was chosen, and since they were not paired with the

[5]As each network is the unit of analysis of our randomized experiment, five is a compromise between enough richness and heterogeneity inside each network and enough overall number of observations.

[6]Centrality measures for each player position are presented in Appendix C.

[7]For example, if only one player had managed to correctly guess 5 colors, the final score would have been 50 (because of 5 colors) plus 100 (for being the only one to get the highest score). Similarly, in case only two players got 40 points, with 40 being the highest score in the group, the bonus would have been 50 each, for a total of 90 points.

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Table 1. Info exchange within and across classes

	Symmetric info exchange	Asymmetric info exchange	No info exchange
Within Class	0.800	0.165	0.035
One blank		0.078	0.016
Both blank			0.013
Across Classes	0.420	0.226	0.353
One blank		0.142	0.097
Both blank			0.239

Note: The table studies information exchange between dyads. We report the share of dyads along which we observe three possible patterns of exchange of the hints. Column (1) refers to cases in which both members guessed the other player's hint correctly. We call this case "Symmetric Info Exchange." Column (2) refers to the case in which only one member guessed correctly the other player's hint. We call this case "Asymmetric Info Exchange." Column (3) refers to the case in which none of the members guessed correctly the hint of the other player. We call this case "No Info Exchange." The first three rows – "Within" – consider dyads with students from the same class, while the second three – "Across" – consider dyads with students in different classes. Finally, we report the share of dyads in which one and only one member left the answer blank (Rows 2 and 5) and the share of dyads in which both members left the answer blank (Rows 3 and 6).

same people in the network in each round, identifying people who had passed false information was particularly challenging.

Results

The sample. In total, 645 students registered and downloaded the app. Yet, some students did not open the app to play. This allowed us to form a total of 358 groups. Additionally, we only consider groups where all five players were active (see Appendix B for more details). Our final sample contains a total of 132 groups.

Information exchange across and within classes

Table 1 reports the fraction of dyads where each member guessed correctly the other member's hint (Column 1), the fraction of those where only one player guessed correctly (Column 2), and those where none of the two players correctly guessed the other player's hint (Column 3). We report in the first row the averages within classes and in the fourth row the averages across classes. The case where both members guessed the hint is the case of successful information sharing. We denote this case as "Symmetric Info Exchange" (Column 1). Instead, if only one of the members guessed correctly the hint of the other player, either information was not shared or it was shared strategically. We denote this case as "Asymmetric Info Exchange" (Column 2). Finally, we denote the case where none of the members guessed correctly the hint of the other player as "No Info Exchange" (Column 3). To better understand whether the information was not shared or instead whether there has been strategic behavior, we also report the fraction of dyads where one or both players left their guesses as blank (Rows 2, 3, 5, and 6).

Table 1 shows that the probability of information exchange (Column 1) is high compared to the predictions from a standard model of information transmission with selfish and rational agents when information is non-verifiable and players

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Table 2. Main results – individual-level regressions

	Correct guesses				
	(1)	(2)	(3)	(4)	(5)
Degree	0.893*** (0.276)		0.944** (0.464)	2.087** (0.814)	
Betweenness		0.530*** (0.202)	−0.0491 (0.338)		−0.198 (0.427)
Observations	660	660	660	221	273
Sample mean	3.403	3.403	3.403	3.425	3.59
Sample SD	1.425	1.425	1.425	1.433	1.301

Note: The table reports estimates from a panel model with random effects. The unit of observation is a player in a round. The dependent variable is the number of correct guesses done by the player during the round. *Degree* measures the degree centrality score of the position the player was assigned to. *Betweenness* measures the betweenness centrality score of the position the player was assigned to. Columns (1) to (3) include observations from the full sample. The sample used in Column (4) includes only observations from Network 1 (Players A, C, and D) and Network 3 (Players A and D). The sample used in Column (5) includes only observations from Network 1 (Players B, C, and D) and Network 3 (Players B, C, and E). All specifications control for the network structure (three structures).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

compete. This probability is particularly high for students belonging to the same class. On the other hand, the fraction of students who do not share information or act strategically (Columns 2 and 3) is non-negligible. For example, 16.5% of within-class dyads show asymmetric exchange. Out of these, only 7.8% have a player leaving the answer blank, possibly suggesting a lack of trust on one part. In the remaining 8.7% of cases, the guess was wrong, revealing the transmission of false information. These percentages are even higher in across-class dyads. These findings are not in line with altruistic preferences or trust since they suggest the presence of strategic behavior in communication, even between students who know each other well. We will thus investigate below the role of network centrality in shaping those patterns.

Network centrality

Table 2 shows how individual network centrality affects the number of correct guesses. All five columns consider a regression model in which as outcome variable we use the number of correct guesses while as explanatory variables we use centrality measures (values are presented in Appendix C). Since we observe the same individual up to three times, we estimate a panel model with random effects. Columns (1) to (3) include observations from the full sample. Since the two centrality measures are positively correlated, we include two additional specifications where we focus on network positions that exhibit variation only along one of the two centrality measures. In particular, Column (4) considers only Players A, C, and D from Network 1 and Players A and D from Network 3. These are players with the same betweenness centrality but different degree centrality. Similarly, Column (5) considers players with similar degree centrality, but different betweenness centrality. These are Players B, C, and D from Network 1 and Players B, C, and E from Network 3.

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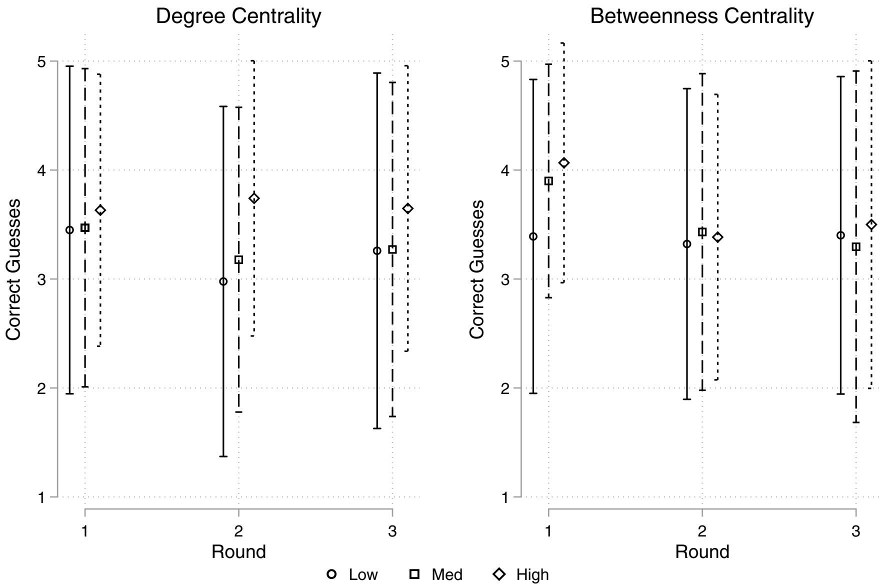

Figure 2. Correct guesses by round and centrality level.
Note: The figure shows the average number of corrected guesses by round (1–3) and centrality level (low to high). On the left, we split players according to degree centrality. On the right, we split players according to betweenness centrality. For degree centrality, *Low* refers to Player A in Network 1, and Player A in Network 3; *Med* refers to Players B, C, and D in Network 1, Players A, B, C, and D in Network 2, and Player D in Network 3; *High* refers to Player E in Network 1, Player E in Network 2, and Players B, C, and E in Network 3. For betweenness centrality, *Low* refers to Players A, C, and D in Network 1, Players A, B, C, and D in Network 2, and Players A, C, D, and E in Network 3; *Med* refers to Player B in Network 1, and Player B in Network 3; *High* refers to Player E in Network 1, and Player E in Network 2. Error bars report the standard deviation.

Table 2 shows that degree centrality is an important predictor of the number of correct guesses. Column (1) shows how a unitary increase in degree centrality is associated with a 0.9 increase in the number of correct guesses. The effect is sizable if we consider that on average the number of correct guesses was 3.4, as highlighted in Row (4). On the other hand, the impact of betweenness centrality is weaker, especially once we control for the degree centrality of the agent. This pattern emerges also from Figure 2, where we report the average number of correct guesses by round and centrality level. In Figure 2, we group players according to three levels of centrality: low, medium, and high. We see that the average number of correct guesses is higher for players with a higher degree centrality (left side), while there is no clear distinction between players with different levels of betweenness centrality (right side). We can also notice that the is no clear time trend in the number of correct guesses, with small differences only between Round 1 and Round 2, suggesting that players did not change their strategies from one round to the next.

Information transmission

While Table 2 looks at the importance of individual centrality measures while keeping the network structure as given, Table 3 considers the analysis at the

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Table 3. Main results – group-level regressions

	Correct guesses	
	(1)	(2)
Network structure = 2	−0.754 (1.290)	−0.813 (1.296)
Network structure = 3	2.000* (1.112)	1.922* (1.138)
Round = 2		−0.731 (1.221)
Round = 3		−0.405 (1.374)
Observations	132	132
R^2	0.046	0.049
Sample mean	17.015	17.015
Sample SD	5.619	5.619

Note: The table reports OLS estimates. The unit of observation is a group in a round. The dependent variable is the number of correct guesses done in total by the members of the group during the round. Network structure is a categorical variable which indicates the network structure assigned to the group. We omit the first category. Round is a categorical variable which indicates whether the game was played during the third and fourth day of the week (Round = 2) or during the fifth and sixth day of the week (Round = 3). We omit the category for Round 1.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

aggregated level. Indeed, one relevant dimension in which one should compare different networks is the ability of the network to foster information aggregation. We regress the total number of correct guesses in the network on network-type dummies. We use Network 1 as a benchmark. Compared to Network 1, both Networks 2 and 3 have one more link. However, there is a difference in how this additional link affects the centralities of the players and their ability to control the flow of information. The additional link in Network 2 connects the player that is originally the least central in Network 1 (Player A) with the player that is originally the most central (Player E). This makes Player E even more pivotal, while the other four nodes are in a symmetric peripheral position. On the contrary, the additional link in Network 3 connects two players (Players B and C) that are originally at an intermediate level of centrality. As a result, Player C becomes as central as Player E, and Player E is no longer able to block alone the flow of information.

In Table 3, we study whether network structures 2 and 3 affect the average number of total correct guesses in the network, with respect to network structure 1. Results show that indeed Network 3 is more able to aggregate correct information than Network 1. While the estimated coefficient of Network 2 is statistically not significant, its sign is negative suggesting that the presence of a central player alone hampers information aggregation. This evidence shows that increasing the number of links may not be beneficial for the aggregation of truthful information: Network 2 is denser than Network 1, but does not display more correct guesses. Rather than network density, it is network structure that is a key for the flow of correct messages. Finally, in Column (2), we also add round fixed effects. In line with Figure 2, the

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Table 4. Central player's behavior

Panel A	Correct Guesses (E) (1)	Info exchange E → (B or C or D) (1)	Info exchange (A or B) ↔ D (1)
Network 2	0.106 (0.289)	−0.079 (0.055)	−0.083 (0.064)
Network 3	0.384 (0.270)	0.06 (0.052)	0.125** (0.06)
Observations	132	396	396
Sample mean	3.667	.737	.475
Sample SD	1.276	.441	.500
Panel B		Hypothesis testing	
Net 2 vs. Net 3	−0.278	−0.139***	−0.208***
Test *p*-value	[0.294]	[0.007]	[0.001]

Note: In Panel A, the table reports estimates from a panel model with random effects. The unit of observation is a player in a round. In Column (1), we restrict the sample to players playing as Player E. The dependent variable is the number of correct guesses of Player E during a given round. In Column (2), we consider players playing as Player B, C, or D. The dependent variable is a dummy taking value 1 if the player correctly guessed the hint received by Player E and 0 otherwise. In Column (3), we restrict the sample to players playing as Player A, B, or D. The dependent variable is a dummy taking value 1 if Player A (or B) correctly guessed Player D's hint or vice versa and 0 otherwise. *Network 2* and *Network 3* are categorical variables which indicate the network structure assigned to the group. We omit the first category. Standard errors are in parentheses. In Panel B, p-values are for the null hypothesis that the coefficients for *Network 2* and *Network 3* are equal.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

estimated coefficients are not statistically significant, thus increasing our confidence that students do not change their behavior over time.

Explaining the difference between networks

We conclude our analysis with an investigation into why Network 2 is underperforming with respect to the other two network structures in terms of information diffusion. We focus on the most central player, Player E. We begin by looking at whether Player E manages to achieve more correct guesses depending on the network structure. Results are shown in Table 4. In Column (1), we restrict the analysis to Player E and regress the number of correct guesses on indicator variables identifying the network structure. We find that the number of correct guesses for Player E is comparable across the three network structures, suggesting that Player E is not able to gather more information when she is the unique player with high centrality. In Column (2) instead, we study Player E's propensity to share information with neighboring players. In this analysis, we restrict the sample to Players B, C, and D in the three network structures. As outcome variable, we define an indicator variable that takes value 1 if the player has correctly guessed the color that was given to Player E as a hint and 0 otherwise. Panel B in Column (2) shows that in Network 2, Players B, C, and D are 14% less likely to correctly guess Player E's hint with respect to Network 3. This is suggestive evidence that Player E is less motivated to share information with the neighboring players in networks where her central position gives her more control over the flow of communication. Finally, in Column (3) we study the role of Player E as an intermediary, that is how information flows through the network along paths of length higher or equal to 2. To do that, we restrict the sample to Players A, B, or D. For Players A and B, the outcome variable is an indicator variable that takes value 1 when they correctly guessed the color that was given to Player D and 0 otherwise; for Player D, the outcome variable takes value 1 if they guessed at least one of the two colors assigned to A and B and 0 otherwise. Results show how in Network 3 the flow of information between Players A or B and Player D is substantially higher: this difference amounts to 20% when comparing Network 2 with Network 3. This evidence suggests that in Network 2 (and Network 1) Player E manages to block the information flow, thereby impacting the overall performance of the group.

Concluding remarks

In this paper, we study how the structure of the communication network influences the aggregation of information in a context in which agents compete and can only share non-verifiable messages.

While one may expect that adding links would foster information diffusion, we show experimentally that more connections may inhibit information diffusion when the new structure exhibits higher inequality in centrality between agents. We find that the network structure has relevant effects on the overall pattern of aggregation of information. Players who enjoyed the most central position obtained higher payments on average. A reduction in the asymmetry among agents' network centralities determines an improvement in the performance of the group in terms of aggregation of information. These results are informative on which network structure an organization should prefer when there are concerns regarding the presence of strategic agents who may not fully cooperate with their peers.

Our results, however, should be taken with care. First, our experiment was run in a school where students may be close friends, and we do not know the ex-ante relationship between them. Similar experiments where the intensity of relationships between the agents is observed would help understand the importance of pro-social motivations for sharing truthful information when it comes at the cost of reducing the chances of winning the bonus. Second, we do not observe actual communication between subjects so it is hard for us to distinguish between the case in which information was transmitted, but was not trusted and the case in which information was not transmitted at all. A promising avenue for future research would be the design of laboratory experiments where we observe the information exchanged by the players, an element that would help in obtaining a better understanding of the strategies followed by the players.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/XPS.2023.21

Data availability statement. The data and code required to replicate all analyses in this article are available at the Journal of Experimental Political Science Dataverse within the Harvard Dataverse Network, at https://doi.org/10.7910/DVN/AGZPI8 (Patacchini et al., 2023).

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Competing interests. The authors declare no conflicts of interest.

Ethics statement. The experiment described in this paper received IRB approval from the Ethics Committee of Bocconi University (Prot. n. 0000779 – 01/02/2018). This research complies with APSA's Principles and Guidance for Human Subjects Research, and it does not involve deceiving or potentially harming the participants.

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