# Are distrust relationships beneficial for group performance? The influence of the scope of distrust on the emergence of collective intelligence

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**Abstract**

Collective intelligence is a powerful concept explaining why some groups perform better than others in solving different tasks. How collective intelligence can be improved so as to reach higher group performance? In this paper we contribute to answer this research question by focusing on a new process leading to the emergence of collective intelligence in decision-making groups, i.e. consensus reaching, and by investigating the influence of the scope of distrust on group performance. We develop a simulation model of the group decision-making process, where the collective dynamics are governed by a continuous-time Markov process, whose transition rates are properly defined to take into account the influence of social relationships and the search of high performing solutions. A simulation analysis is carried out for increasing values of scope of control in groups characterized by varying strength and density of social relationships. Results show that the scope of distrust can be beneficial or not for group performance, depending on the strength and the density of social relationships. When the strength (density) of social relationships is too low, any scope of distrust is detrimental for group performance. However, when the strength (density) of social relationships is high, we find an optimal value of scope of distrust maximizing group performance. Theoretical and managerial implications of these findings are finally discussed.

*Keywords*: Collective Intelligence, Decision-making Group, Scope of Distrust, Social Relationships, Simulation.

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## 1. Introduction

Collective intelligence (CI) is a powerful concept recently proposed in the literature to explain why some groups perform better than others in a variety of different tasks (Woolley et al., 2010). It is a form of distributed intelligence, which arises from the collaboration and competition of many individuals (Levy 1997). Similarly to swarms of birds, schools of fishes, and colonies of ants, just to name a few of most popular natural systems that exhibit a similar property (known as swarm intelligence), human groups are able to reach higher performance than single individuals, by exploiting the power of social relationships (Pentland, 2007; Bonabeau, 2009; Krause, Ruxton, and Krause, 2009; Woolley et al., 2010).

Improving group performance by favoring the emergence of CI in the group is an important research issue to address. In this regard, it is fundamental to understand the processes that let CI emerge in human groups and to investigate the features that, influencing these processes, lead to superior group performance. Previous studies have argued that CI emerges from both the interaction and the combination of bottom-up and top-down processes (Woolley, Aggarwal, and Malone, 2015). All these processes are activated by means of social relationships involving group members. In particular, the features that enhance the collaboration in the social relationships are those responsible for the emergence of the CI due to bottom-up processes, while the features affecting the coordination of the social relationships, such as group structures, norms and routines, are critical for the emergence of CI by means of the top-down processes.

Despite the importance of the topic, research is still at its infancy (Schut, 2010; Woolley and Fuchs, 2011) and further investigation is needed. We consider the emergence of CI related to the process of consensus reaching among the individuals in the group, enabled by the social relationships. Due to the social influence, individuals adapt their behavior, beliefs, mental models, and decisions to the behaviors, beliefs, mental models or decisions of interacting ones in the social system (Kelman, 1958; Leenders, 1997). Social relationships are conduits of opinion formation and stimulate the convergence towards a common understanding, which leads to agreed decisions (Liu et al., 2012; De Vincenzo, Giannoccaro, and Carbone, 2017).

In recent studies, this process of consensus reaching is modelled and the conditions leading to the emergence of CI analyzed (Carbone and Giannoccaro, 2015; De Vincenzo, et al., 2017). Groups show a phase transition from a state of low consensus to a state of high consensus, the latter being characterized by the highest group performance (De Vincenzo et al., 2017). When the level of consensus reached within the group is too high, exploration of alternative solutions is hindered and performance are strongly lowered. In groupthink theory it is known that strong pressure towards consensus induces high conformity and is detrimental for group performance (Janis, 1982; Esser, 1998). Conversely, when the level of consensus reached within the group is too low, group members behave as independent individuals and explore limited portion of the landscape driven only by their personal knowledge. This limits adaptive learning, leads to unresolved conflicts, and results in low group performance.

It follows that the features of social relationships that influence the process of reaching consensus within groups play an important role in the emergence of CI. In this regard, distrust is an attribute of social relationships, conceptualized as negative expectations of an individual regarding the "conduct" of the counterpart, in terms of what he/she says, does, and how makes decisions (Lewicki, Mc Allister and Bies, 1998; Lewicki and Wiethoff, 2000). Distrust is related to lack of cooperation (Cho 2006) and to intractable conflicts (Fiol et al. 2009, Tomlinson and Lewicki, 2006). We argue that distrust relationships are also related to dissent and push individuals involved to be in disagreement rather than to seek consensus. Thus, distrust relationships negatively influence the process by which individuals reach consensus within the group, thereby affecting the emergence of CI.

It is noteworthy that this influence does not imply that distrust relationships are detrimental for group performance. In particular, we expect that distrust relationships could be beneficial when a too high level of consensus is reached within the group, because of high strength and density of social relationships. Both variables are features of social relationships, which make high the level of consensus reached within the group, because of stronger social influence. Therefore, when a group is characterized by high strength and density of social relationships, a given number of distrust relationships, contrasting consensus reaching, helps the system achieve the right level of consensus enabling the emergence of CI (i.e., a high performing state). Studies on contrivent dissent and beneficial effect of the "advocate's devil" procedure on group performance support this argumentation (Schulz-Hardt, Jochims, and Frey, 2002). Thus, we investigate the moderating role of strength and density of social relationships on the relation between the number of distrust relationships in percentage to the total number of social relationships in the group (scope of distrust) and group performance.

To investigate this issue, we adopt a simulation approach based on a technique coming from statistical physics where the effect of social relationships is modelled by means of the Ising model of interacting spins. The Ising model has been largely applied in social science to model the influence of social processes (Bordogna and Albano, 2007a, 2007b; Zhou and Sornette, 2007; Stauffer, 2008; Sornette, 2014; Oh and Jeon, 2007; Giannoccaro and Carbone, 2017). Here, we refer to its recent application to model collective decision-making and to simulate group performance in complex environments (Carbone and Giannoccaro, 2015; De Vincenzo et al., 2017). In this model a group of individuals is engaged in solving a complex decision-making problem. Individuals make decisions aimed at improving the performance (fitness) perceived on the basis of their knowledge of the problem, but also taking into account the other members' opinions (social influence). Social relationships push individuals to be in agreement so that the process evolves increasing the level of consensus (consensus reaching). We employ this model to study the effect of varying number of distrust relationships on the total numbers of social relationships in the group (scope of distrust) on group performance under different conditions of strength and density of social relationships.

The paper is organized as follows. First, we briefly review the recent literature on collective intelligence. Then, we develop our theory concerning the effect of scope of distrust on the emergence of CI. Successively, we describe the model we adopt to conduct the simulation analysis. We end with a discussion of results and conclusions.

## 2. Collective Intelligence

Collective intelligence is not at all a new concept. It is related to the swarm intelligence, i.e. the collective behavior of social insects (e.g., beehives, ant colonies, swarms of birds), which despite the simplicity of each single agent, are collectively able to do intelligence things (Bonabeau, 1999; Bonabeau and Meyer 2001; Krause, Ruxton, and Krause, 2009). It is also linked with the wisdom of crowds, i.e. the ability of crowds to make decisions better than the average of single individuals (Surowiecki, 2005; Lorenz et al., 2011).

Nevertheless, it is a new concept with reference to human groups. In this regard, CI is defined as the ability of human groups to perform well on a variety of tasks (Woolley et al. 2010). As individuals, human groups are characterized by a collective intelligent factor *g*, which predicts how good the group as a whole is in performing different tasks. Woolley et al (2010) conduct experiments with groups ranged in size from two to five and working on multiple tasks, including creative brainstorming problems, puzzles involving verbal or mathematical reasoning, negotiation tasks, and moral-reasoning problems. By carrying out a factor analysis of the groups score, they find that a single dominant factor explain 43% of the variance in performance.

In a recent study, Woolley, Aggarwal, and Malone (2015) highlight that CI is an emergent property that results from the interaction and combination of bottom-up and top-down processes. In particular, bottom-up processes involve individual features that enhance collaboration among group members. These include social sensitivity (Wooley et al, 2010) and cognitive diversity (Kozhevnikov, Evans, and Kosslyn 2014; Aggarwal and Woolley, 2013). A high average social perceptiveness of group members improves CI. This also explains why groups with higher percentage of female members perform better (Woolley et al., 2010). Assuring the right level of cognitive diversity among group members is crucial for enhancing CI (Aggarwal and Woolley, 2013). Top-down processes concern group structures, norms and routines, which rule the coordination of the interactions among the group members. Groups where people communicate and participate more equally exhibit higher CI (Wooley et al., 2010) in both face-to-face and on-line groups (Engel et al., 2014; Kim et al., 2015; Woolley et al., 2010). Groups ruled by incentive systems wherein agents are rewarded for expressing accurate minority opinions show to produce stable, near-optimal CI (Mann and Helbing, 2017).

Some studies analyze the issue of CI in decision-making groups. Bonabeau (2009) highlights that individuals incur in a number of biases when solving problems, both in the phase of generating alternative solutions and in the phase of evaluating alternatives. Groups are able to overcome these biases thanks to three strategies they accomplish: outreach, averaging aggregation, and self-organization. These strategies are the foundation of their CI. In groups engaged in quantitative judgement tasks, it is also noted that CI emerges because individuals improve their judgments by means of social relationships. This denotes an increase in individual capability to perform a specific task as a consequence of social interactions within the group (Schulze, 2012).

Carbone and Giannoccaro (2015) argue that CI is an emergent property resulting from an adaptive process where individuals make decisions exploring the problem space (landscape), driven by two competing forces: 1) the search for solutions with higher performance and 2) the consensus seeking with the interacting individuals. Individuals are modelled as rational agents making decisions aimed at maximizing their local fitness on the basis of their knowledge of the landscape. Simultaneously, however, they are pushed to modify their choices so as to increase the consensus within the group, because of the social influence exerted by social relationships. The strength of social relationships controls the extent to which the interacting members are pushed to be in agreement. A critical value of strength of social relationships is found, at which the group suddenly moves from low to high consensus state, characterized by the highest group performance. This critical threshold identifies the emergence of CI in the group (De Vincenzo et al., 2017). This finding shows that CI is related to reaching a right level of consensus within the group and that this depends on the strength of social relationships that determines the sudden transition from low to high consensus.

When the strength of social relationship is too low, the group is not able to reach an adequate level of consensus, individuals behave as single units, explore independently part of the landscape, and make decisions often conflicting among each other. As a consequence, performance suffers (disorder area). For too high strength of social relationships, the individuals in the group are prematurely and strongly forced to be in agreement. Consensus limits effective exploration while fosters conformity. This determines negative performance (order area). We are interested to more in depth investigate this process leading to the emergence of CI by analyzing the role played by distrust relationships.

## 3. Theory

### *3.1 Conceptualization of Distrust in Decision-Making Groups*

Distrust is an important dimension of interpersonal relationships (Rempe, Holmes, and Zanna, 1985). Distrust has been traditionally conceptualized with reference to trust, reflecting the end of a continuum. The latter is a multidimensional construct embracing diverse dimensions, such as vulnerability, benevolence, cooperation, non-opportunism, positive expectation, dependence, and goodwill (Seppänen et al., 2007). A large body of literature investigates trust at the interpersonal, organizational, and inter-organizational levels (for reviews, see Dirks and Ferrin, 2002; Seppänen et al., 2007; Schoorman, Mayer, and Davis, 2007). Overall, trust is defined as a party's confident positive expectations regarding intentions, motives and behavior of another party (Mayer at al 1995, Das and Teng, 2001; Inkpen and Currall, 2004). Following Lewicki, McAllister, and Bies (1998), with reference to interpersonal level, trust is defined as the individual's confident positive expectations regarding the conduct of another, where conduct includes not only what the other says and does, but also how he/she makes decisions. According to the traditional conceptualization, distrust, reflecting the end of a continuum, is defined as low trust. It follows that distrust concerns low positive expectations regarding the conduct of another, and, in particular, his/her actions and decisions.

More recently, distrust has gained an independent meaning. It is viewed as a separate and distinct construct by trust (Hardin, 2004; Lewicki et al., 1998; Sitkin and Roth, 1993; Vlaar, Van den Bosch, and Volberda, 2007). According to this recent perspective, distrust concerns a pervasive negative lens through which the counterpart is perceived, and a negative expectation regarding the behavior or intentions of another (Dimoka, 2010; Kramer et al. 1994, 1996; Lewicki et al. 1998; Sitkin and Roth 1993). Following this consideration, distrust is defined as confident negative expectations regarding another's intentions, behavior, actions and decisions. As such, distrust relationships are associated with caution, defensiveness, and vigilance

(Lewicki et al., 1998). In this paper we refer to this recent conceptualization and we are interested to analyze the effect of distrust relationships on collective decision-making. In particular, we consider the distrust relationship as a dyadic variable and define the scope of distrust as the extent to which distrust relationships are spread in the group. The higher the number of distrust relationships on the total number of social relationships in the group, the higher the scope of distrust is.

### *3.2 Relationship between Distrust and Level of Consensus in Decision-Making Groups*

In addition to caution and defensiveness, distrust relationships are found to be related to lack of cooperation (Cho 2006; Vlaar et al. 2007), negative social influence (Blau, 1964; Sheppard and Tuchinsky, 1996), avoidance of interaction (Bies and Tripp, 1996), unwillingness to share views and preferences (Bijlsma-Frankema, 2004; March and Olsen, 1975), reduced information sharing (Gillespie and Dietz, 2009), and intergroup conflicts (Fiol et al. 2009, Tomlinson and Lewicki, 2006). In particular, once such negative expectations are created, the conflict tends to rise in scope and intensity so as to become often intractable (Lewicki and Wiethoff, 2000).

Distrust relationships, rather than pushing group members to reach an agreed solution, involve dissent and disagreement. Because distrust regards negative expectations concerning the others' conduct and, in particular, how well they make decisions, individuals involved in distrust relationships tend to make antagonistic decisions. This in turn makes more difficult reaching consensus in group. Therefore, as the number of distrust relationships rises, the level of consensus within the group diminishes. Coherently, within social-psychological and sociological literature, while trust is considered an ingredient for social order, distrust is associated with disorder and emergence.

### *3.3 Relationship between Distrust, Level of Consensus, and Collective Intelligence*

As argued above, social relationships induce group members to share information, adapt their actions, and converge toward common understanding and agreed decisions (Kelman, 1958). CI emerges when a right level of consensus within the group is reached. When the level of consensus within a group is too low, individuals propose alternative solutions and assess these solutions only on the basis of their knowledge. In doing this, they incur in decision-making biases (Bonabeau, 2009), which negatively influence the exploration of the solutions, and lead them to identify low-performing solutions. Furthermore, individuals making independent decisions tend to be conflicting one with each other. When conflicts remain unresolved, group performance suffers (De Creu et al., 2003). On the contrary, when the level of consensus within the group is too high, individuals are strongly in agreement. A strong pressure towards consensus creates conformity and limit creativity with negative consequence on the exploration of the solution space (Janis, 1982; Esser, 1998). The group comes up with a limited number of alternatives, because prefers to converge on an agreed solution rather than explore new solutions. The efficacy of the decision making process is thus undermined.

The level of consensus reached within a group depends on two features of the network of social relationships, i.e. the strength and the density. The strength of social relationships concerns the intensity of the link and, in particular, the extent to which the individuals involved in the relationship influence one with other (Marsden and Campbell, 1983). The density refers to the number of social relationships within a group in percentage to the total number of possible social relationships involving group members. Both variables positively affect social influence within the group and lead the latter to reach a given level of consensus.

When the strength and the density of social interaction are too high, the pressure towards consensus may be too strong, so that the level of consensus reached within the group may be too high, leading to diminished group performance. In this situation, distrust relationships, which involve dissent and contrast consensus seeking, can play a beneficial effect on group performance. By forcing disagreement within the group, distrust reduces the level of consensus, introduces emergence in the system, and let the group broadly explore the space of solutions. Until the right level of consensus is not reached, increasing the number of distrust relationships is beneficial for group performance. However, above a certain threshold, a further increase of the scope of distrust is no longer beneficial, since a strongly decreased level of consensus makes the members of the group to almost independently explore the solution space, leading to unresolved conflicts with negative consequences on performance. Based on the above, we argue that when the strength and the density of social relationships are too high, the scope of distrust first increases and then decreases group performance. Conversely, when the strength and the density of social relationships are too low, the presence of distrust relationships are always detrimental. They decrease consensus and move away the system from reaching the right level of consensus with detrimental effect on group performance.

## 4. Model

We consider a group of M individuals collectively solving a complex decision making problem. The decision-making process is modelled referring to the model first developed by Carbone and Giannoccaro (2015) and then by De Vincenzo et al. (2017). In these models, the group is conceived as engaged in solving a combinatorial decision-making problem, consisting in identifying the combination of multiple and interdependent decisions $\mathbf{d} = (d_1, d_2, \ldots, d_N)$, yielding to the highest payoff for the group $P(\mathbf{d})$.

The problem space is generated by means of the NK fitness landscape (Kauffman, 1987; 1993), where N stands for multiple binary decisions and K for the interdependence among them. This problem space (referred to as fitness landscape) consists of $2^N$ possible combinations of choices on decisions, each with a fitness payoff associated. Specifically, the NK fitness landscape is generated by following a stochastic procedure, which permits to assign the payoff, $P(\mathbf{d})$, to each combination of choices on decisions **d**=($d_1$,$d_2$, …,$d_N$). The payoff value, *P*(**d**), is computed as follows (De Vincenzo et al., 2017):

$$P(\boldsymbol{d}) = \bar{V} + \sqrt{N}[V(\boldsymbol{d}) - \bar{V}] \tag{1}$$

where,

$$V(\boldsymbol{d}) = \frac{\sum_{j=1}^{N} C_j(\boldsymbol{d})}{N} \tag{2}$$

and $\bar{V}$ is the statistical average of $V(\mathbf{d})$. $C_j$ is the contribution that the decision *j* leads to the total system payoff. The latter is drawn at random from a uniform distribution [0,1]. Notice that, as effect of the interdependencies among decisions (*K*), $C_j$ depends not only on how the single decision *j* is resolved but also on the choice on its interdependent decisions. Thus, *K* controls the complexity of the landscape. The higher *K*, the more complex the landscape (for details about the landscape generation see Carbone and Giannoccaro 2015, De Vincenzo et al. 2017). The use of NK fitness landscape methodology to model complex decision making as an adaptive process has become popular in management science (see Ganco and Hoetker, 2009 for a review) and is largely applied to the study of single organizations (Rivkin, 2000; 2001; Siggelkow and Rivkin, 2003; 2007; Siggelkow, 2011), groups of individuals (Barkoczi and Galesic, 2016) and supply chains (Giannoccaro, 2011; Capaldo and Giannoccaro 2015a, 2015b; Giannoccaro, 2015, Giannoccaro, Nair, and Choi, 2017).

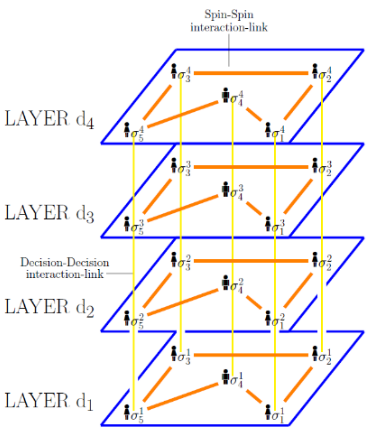
### *4.1 The drivers of individual decision-making process*

Any individual *k* in the group formulates his/her own opinion $\sigma_k = (\sigma_k^1, \sigma_k^2, \dots, \sigma_k^N)$ concerning the preferred combination of choices on the decisions. In doing so, the individual is driven by two forces: 1) the improvement of the personal payoff (perceived payoff), which depends on the level of knowledge of the individual and 2) the social influence exerted by means of the social relationships.

To model the level of knowledge of the individual, the probability $p$ that the single agent knows the contribution $C_j(\boldsymbol{\sigma})$ to the total fitness is introduced. Being **D** the matrix whose element $D_{kj}$ takes the value of 1 with probability $p$ and 0 with probability 1- $p$, the perceived fitness of the agent $k$ is so defined (Carbone and Giannoccaro, 2015):

$$V_k(\boldsymbol{\sigma}_k) = \frac{\sum_{j=1}^{N} D_{kj} C_j(\boldsymbol{\sigma}_k)}{\sum_{j=1}^{N} D_{kj}}. \tag{3}$$

We consider that group members are involved in a network of social relationships. It is modelled by means of a multiplex network made up by N layers corresponding to the N decisions $d_j$. On each layer the nodes are the individuals and the links are the social relationships occurring among the group members concerning that specific decision. This network is coded by a N-block diagonal adjacency matrix **A** (see Figure 1 as an example).




$$\begin{matrix}
0&1&0&1&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
1&0&1&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&1&0&0&1&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
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0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&0&0&0&1\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&1&0
\end{matrix}$$

*Figure 1. Multiplex network of the social relationships within the group.*

Based on the social influence theory, we argue that an individual involved in social relationships adapts his/her behavior, beliefs, mental models to the behaviors, beliefs or mental models of the interacting members (Kelman, 1958; Leenders, 1997). Social relationships are in fact conduits of opinion formation and stimulate the convergence towards a common understanding of a situation and shared mental models among individuals (Liu et al., 2012). Therefore, the individual *k*, as a consequence of the social relationship with *l*, will tend to modify his/her opinion to be in agreement with *l*. However, distrust may characterize social relationships in the group. Distrust relationships, rather than inducing group members to be in agreement, involve dissent. Since the individual has negative expectations concerning the conduct and, in particular, the goodness of the decisions made by the interacting members, he/she prefers to make antagonistic decisions. This implies that the individual *k* while interacting with *l* will tend to modify his/her opinions attempting to reach a disagreement with *l*.

To model these dynamics, an Ising-like approach is employed (Bordogna and Albano, 2007a). We refer to the model by Carbone and Giannoccaro (2015) and, for any given decision layer, we defined the energy level associated with individual *k*, $E_k$, as follows:

$$E_k = -\sum_j \sum_l A_{kl} J_{kl} \sigma_k^j \sigma_l^j, \quad (4)$$

where $\sigma_k^j$ is the current opinion of individual *k* on the given decision *j* and $\sigma_l^j$ is the current opinion on the same decision of the interacting individual *l*. $J_{kl}$ is the element of a weight matrix ***J***, which models the strength of social relationships in the network. It is also employed to model distrust relationships.

Note that the individual *k* formulates his/her opinion to minimize the energy level. This implies that if $J_{kl}$ is positive, the effect of social relationship is to push the individual *k* to make his/her opinion to be in agreement with the interacting individual *l*. On the contrary, if $J_{kl}$ is negative, the social relationship has the opposite effect, i.e. the individual *k* is induced to make opinions in disagreement with *l*. Therefore, the social relationship with $J_{kl}$<0 is distrustful.

The scope of distrust is operationalized by introducing increasing number of distrust relationships and defined as the percentage of distrust relationships on the total number of social relationships in the group.

*4.2 The model of the collective decision making process*

The group decision making dynamics is modelled by means of a continuous-time Markov chain, whose transition rates are defined so as to capture the two drivers of individual behavior in groups, i.e. the optimization of the perceived payoff and the consensus reaching.

The state of the whole system is:

$$\mathbf{s} = \left(s_1, s_2, ..., s_l, ..., s_{M\times N}\right) = \left(\sigma_1^1, \sigma_1^2, ...\sigma_1^N, \sigma_2^1, \sigma_2^2, ...\sigma_2^N, ..., \sigma_M^1, \sigma_M^2, ...\sigma_M^N\right).$$

Let be $P(\mathbf{s}, t)$ the probability that, at time *t*, the state vector takes the value **s** out of $2^{M\times N}$ possible states. The time evolution of the probability $P(\mathbf{s}, t)$ satisfies the following master equation:

$$\frac{dP(\boldsymbol{s},t)}{dt} = -\sum_k w(\boldsymbol{s_k} \rightarrow \boldsymbol{s'_k}) P(\boldsymbol{s_k}, t) + \sum_l w(\boldsymbol{s'_k} \rightarrow \boldsymbol{s_k}) P(\boldsymbol{s'_k}, t) \quad (5)$$

where $\boldsymbol{s_k} = (s_1, s_2, \dots, s_k, \dots, s_{M\times N})$ and $\boldsymbol{s'_k} = (s_1, s_2, \dots, -s_k, \dots, s_{M\times N})$.

Eq. (5) represents a Markov time-continuous chain where the transition rate (i.e., the probability per unit time that the opinion $s_k$ flips to $-s_k$ while the others remain temporarily fixed) is (De Vincenzo et al., 2017):

$$w(\boldsymbol{s_k} \rightarrow \boldsymbol{s'_k}) = \frac{1}{2}\left[1 - s_k \tanh\left(\frac{\beta}{\langle\kappa\rangle}\sum_l J_{kl} A_{kl} s_l\right)\right] \times exp\{\beta'[\Delta V(s'_k, s_k)]\} \quad (6)$$

In Eq. (6) $\beta$' is referred to as the level of confidence the members have about their perceived fitness, $\langle\kappa\rangle$ is the mean degree connectivity of the network of social relationship among the agents on each decision layer, and $\Delta V(s'_k, s_k)$ is the change in the perceived payoff if the individual *k* modifies his/her opinion from $\boldsymbol{s_k}$ to $\boldsymbol{s'_k}$. Note that the transition rate is the product of two terms: 1) the Weidlich exponential rate (Weidlich, 1991), exp$\{\beta'[\Delta V(s'_k, s_k)$ i]}, which models the improvement of perceived payoff and 2) an Ising-Glauber term (Glauber, 1963), $\frac{1}{2}\left[1 - s_k \tanh\left(\frac{\beta}{\langle\kappa\rangle}\sum_l J_{kl} A_{kl} s_l\right)\right]$, which models the process of social influence.

We employ the Gillespie algorithm to generate the stochastic process given by equations (5) and (6). This algorithm is summarized in Appendix A.

It is noteworthy that using this approach the effect of social relationships on the system dynamics is not imposed but it is emergent and self-organized. This means that a distrust relationship does not imply that the individuals involved are forced to make opposite choices, but that they will be pushed to behave in this way. The actual choice will be the result of both the influences, i.e. the maximization of the perceived payoff and the social influence resulting from the entire complex network of social relationships.

### *4.2 Group decision-making performance*

Group performance measuring the efficacy of the group to find the best choice configuration is computed at the end of simulation. To do so, the group choice configuration given the choice configuration of all group members is defined. Different rules may be employed at this aim such as majority, best member, and random member (Hastie & Kamed, 2005; Sorkin, Hays, & West, 2001; Sorkin, West, & Robinson, 1998). We selected the majority rule because it is consistent with our theory concerning consensus reaching inside the group. It is also proved to perform better than the best and random member rules in different situations (Hastie and Kameda, 2005; Barkoczi and Galesic, 2016).

Thus, given the set of opinions ( $\sigma_1^j, \sigma_2^j, \dots, \sigma_M^j$) that the agents have about the decision *j* at time step *t*, we set the group choice on the decision *j* as follows:

$$d_j = \mathrm{sgn}\lfloor M^{-1} \sum_k \sigma_k^j \rfloor, \qquad j = 1,2, \dots . N \tag{7}$$

If *M* is even and in the case of a parity condition, $d_j$ is uniformly chosen at random between the two possible values +1, –1.

In particular, the group performance is calculated in terms of efficacy of group decision making by normalizing *V* respect to the maximum fitness value on the landscape ($V_{max}$). A value of 1 means that the group was able to identify the optimal solution.

We also compute the level of consensus among the agents in the group as follows:

$$\chi = \frac{1}{M^2 N} \sum_{j=1}^{N} \sum_{kh=1}^{M} < \sigma_k^j \sigma_h^j > \tag{8}$$

Note that $0 < \chi < 1$. The higher $\chi$, the higher the level of consensus. $\chi = 1$ means that all M members agree on all N decisions.

Table 1 summarizes the operationalizations of the main variables.

*Table 1. Variables and operazionalizations.*

| Variable | Operationalization |
|---|---|
| Network of social relationships | Multiplex network modelled by matrix **A** |
| Density of the network of social relationships | Number of social relationships on the total number of possible social relationships |
| Strength of the social relationship between *l* and *k* | $\lvert J_{lk} \rvert$ where the symbol $\lvert\ \rvert$ stands for the absolute value |
| Distrust relationship between *l* and *k* | $J_{lk} < 0$ |
| Scope of distrust | Number of distrust relationships among the group members on the total number of social relationships |
| Group performance | $V/V_{max}$ where the vector of group decisions is computed by applying the majority rule |

## 5. Simulations analysis and results

We simulate a group with M = 21 solving a combinatorial decision-making problem defined by a NK fitness landscape with N = 15 and K = 1, 3, 5, 7. We set β'= 3 and β =1. The network of social relationships is generated according to Erdős and Rényi (1960)'s random graph. All social relationships are assumed to have the same strength intensity $|J_{lk}| = J > 0$ for any $l$ and $k$. The simulation is carried out by adopting the Gillespie algorithm for a simulation period of 500000 time steps and 100 replications. The simulation results consist in the efficacy of the group in solving the decision making problem ($V/V_{max}$) and in the level of consensus reached at the end of simulation, both averaged across replications.

*5.1 Baseline model results*

We first simulate group performance in absence of distrust relationships. In particular, we simulate groups characterized by four values of strength of social relationships (0.5, 1, 2, 4). These values are chosen to be lower (0.5), slightly higher (2), and higher (4), than the threshold optimal value (1) leading to the emergence of CI. The threshold value is given by De Vincenzo et al. (2017). Similarly, we simulate groups with three levels of density of social relationships (0.1, 0.3, and 0.7).

Results concerning the efficacy of group and the level of consensus are presented in Table 2 for any level of strength of social relationships (J), density of social relationships (DENS), and level of interdependence among decisions (K).

They show that as the strength of social relationships (J) increases, the level of consensus grows, the value of interdependence (K) and density of social relationships (DENS) fixed. For example for K=1 and DENS=0.1, the level of consensus grows from 0.2086 to 0.6885, as J increases from 0.5 to 4. Similarly, for K=3 and DENS=0.3, the level of consensus ranges from 0.2982 to 0.9788, when J moves for 0.5 to 4. Similarly, we also note that as the density of social relationship rises, the level of consensus increases, K and J fixed. For example, in the case of K=3 and J=1, as the density increases from 0.1 to 0.3 and to 0.7, the level of consensus moves from 0.5230 to 0.7389, and to 0.8003, respectively.

These findings, running as expected, are a test of the internal validity of our simulation model.

*Table 2. Results of the baseline model (Z=0).*

| | | **Group performance** | | | | **Level of consensus** | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **DENS** | **J=0.5** | **J=1** | **J=2** | **J=4** | **J=0.5** | **J=1** | **J=2** | **J=4** |
| K=1 | 0.1 | 0.8555 | 0.9096 | 0.9309 | 0.8414 | 0.2086 | 0.3776 | 0.6215 | 0.6885 |
| | 0.3 | 0.8568 | 0.9911 | 0.9859 | 0.7353 | 0.2123 | 0.6718 | 0.9179 | 0.9759 |
| | 0.7 | 0.8542 | 0.9954 | 0.9896 | 0.7121 | 0.2208 | 0.7168 | 0.9553 | 0.9919 |
| K=3 | 0.1 | 0.8250 | 0.9951 | 0.9565 | 0.8444 | 0.2525 | 0.5230 | 0.6484 | 0.6864 |
| | 0.3 | 0.8213 | 0.9993 | 0.9213 | 0.7130 | 0.2982 | 0.7389 | 0.9308 | 0.9788 |
| | 0.7 | 0.8308 | 0.9976 | 0.9259 | 0.6938 | 0.3086 | 0.8003 | 0.9651 | 0.9936 |
| K=5 | 0.1 | 0.6700 | 0.9302 | 0.8944 | 0.7959 | 0.1813 | 0.5057 | 0.6435 | 0.6674 |
| | 0.3 | 0.6237 | 0.9249 | 0.8538 | 0.7088 | 0.1891 | 0.7435 | 0.9366 | 0.9814 |
| | 0.7 | 0.6327 | 0.9223 | 0.8579 | 0.6435 | 0.1887 | 0.8127 | 0.9741 | 0.9925 |
| K=7 | 0.1 | 0.5345 | 0.9491 | 0.8956 | 0.8080 | 0.1475 | 0.5025 | 0.6248 | 0.6273 |
| | 0.3 | 0.4621 | 0.9276 | 0.8606 | 0.7193 | 0.1369 | 0.7267 | 0.9393 | 0.9835 |
| | 0.7 | 0.4981 | 0.9292 | 0.8533 | 0.6795 | 0.1432 | 0.8259 | 0.9743 | 0.9932 |

Results also show that when the level of consensus is too low, group performance is quite low. Increasing the level of consensus, the group performance rises. However, when the level of consensus becomes too high, group performance diminishes. For example, consider the case of K=3. For J=0.5 and DENS=0.1, the level of consensus is 0.2525 and group performance is 0.8250. Increasing J to 1 and density to 0.3, the level of consensus becomes 0.7389 and group performance reaches 0.9993. However, for J=4 and DENS=0.7, the level of consensus becomes 0.9925 and group performance decreases to 0.6435.

*5.2 Results for increasing scope of control*

We simulate group performance in different scenarios characterized by increasing values of scope of distrust. We considered ten values of scope of distrust from Z=0.05 to Z=0.5. To model the scope of distrust, on a generic decision layer, we draw at random, with probability Z, certain distrust relationships. This result is then replicated on all the decisions layers. Therefore, by using this method, the agents involved in distrust relationships are the same on all the decision layers and the scope of distrust is about Z.

Similarly to the baseline model, we simulate groups characterized by four values of strength of social relationships (0.5, 1, 2, 4) and three levels of density (0.1, 0.3, and 0.7), solving problems with K= 1,3,5,7. Thus, the total plan of experiments is made by 528 cases, including the baseline.

We analyze the relationship between scope of distrust and group performance. Results confirm our theoretical argumentations. When the strength of social relationships is lower than (J = 0.5) or equal to the critical threshold (J = 1), the effect of scope of distrust is always detrimental for group performance, independently of K and density values. For higher values of strength of social relationships (J = 2, 4), group performance first increases and then decreases, as the scope of distrust rises. For example, for K=3 and DENS=0.3, in the case of J = 1, moving from Z = 0 to Z = 0.5, performance reduces from 0.9993 to 0.6741, while in the case of J=2 first increases from 0.9213 to 0.9855 as Z rises from 0 to 0.2, and then decreases to 0.7302 when Z=0.5. For J = 4, group performance increases from 0.7130 to 0.9363 moving from Z = 0 to Z = 0.25, then diminishes to 0.7051 when Z=0.5.

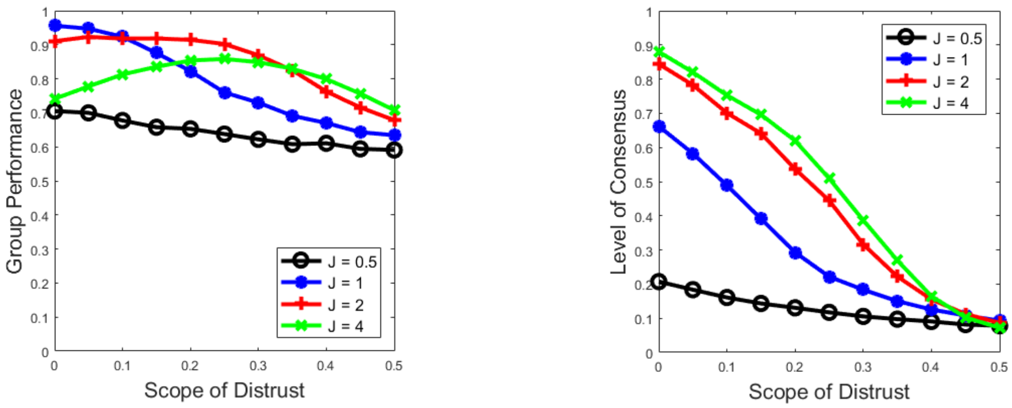
Note that, as the strength of social relationships increases, the highest performance is achieved for higher value of scope of distrust, compared to previous cases. On average, for J = 2, a minimal scope of distrust (Z = 0.05) is optimal for group performance; for J = 4, the optimal value of scope of distrust is higher (Z = 0.25).

*Table 3. Results of simulations.*

| | | Z=0 | Z=0.05 | Z=0.1 | Z=0.15 | Z=0.2 | Z=0.25 | Z=0.3 | Z=0.35 | Z=0.4 | Z=0.45 | Z=0.5 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| J=0.5 | | | | | | | | | | | | |
| DENS = 0.1 | K=1 | 0.8555 | 0.8554 | 0.8480 | 0.8498 | 0.8318 | 0.8332 | 0.8270 | 0.8201 | 0.8092 | 0.8124 | 0.8038 |
| | K=3 | 0.8250 | 0.8334 | 0.8028 | 0.7559 | 0.7707 | 0.7279 | 0.7395 | 0.6965 | 0.6940 | 0.6767 | 0.6996 |
| | K=5 | 0.6700 | 0.6502 | 0.6352 | 0.6163 | 0.5326 | 0.5511 | 0.5382 | 0.5272 | 0.5117 | 0.5013 | 0.5071 |
| | K=7 | 0.5345 | 0.5475 | 0.5171 | 0.4836 | 0.4811 | 0.4644 | 0.4206 | 0.4317 | 0.4412 | 0.3941 | 0.3976 |
| DENS = 0.3 | K=1 | 0.8568 | 0.8612 | 0.8487 | 0.8348 | 0.8372 | 0.8258 | 0.8265 | 0.8184 | 0.8133 | 0.8056 | 0.7860 |
| | K=3 | 0.8213 | 0.8105 | 0.7979 | 0.7769 | 0.7551 | 0.7351 | 0.7004 | 0.6758 | 0.6975 | 0.6591 | 0.6356 |
| | K=5 | 0.6237 | 0.6223 | 0.5709 | 0.5652 | 0.5722 | 0.5355 | 0.5371 | 0.5137 | 0.5430 | 0.5190 | 0.4800 |
| | K=7 | 0.4621 | 0.4823 | 0.4817 | 0.4424 | 0.4706 | 0.4707 | 0.4003 | 0.3786 | 0.4182 | 0.4004 | 0.4008 |
| DENS = 0.7 | K=1 | 0.8542 | 0.8514 | 0.8478 | 0.8450 | 0.8396 | 0.8272 | 0.8339 | 0.8227 | 0.8123 | 0.8098 | 0.8173 |
| | K=3 | 0.8308 | 0.8158 | 0.7784 | 0.7547 | 0.7624 | 0.7410 | 0.6869 | 0.6939 | 0.6592 | 0.6581 | 0.6447 |
| | K=5 | 0.6327 | 0.5972 | 0.5659 | 0.5493 | 0.5433 | 0.5119 | 0.5316 | 0.5082 | 0.5133 | 0.5092 | 0.4906 |
| | K=7 | 0.4981 | 0.4718 | 0.4356 | 0.4180 | 0.4380 | 0.4281 | 0.4216 | 0.4071 | 0.4130 | 0.3838 | 0.4277 |
| **Average** | | **0.7054** | **0.6999** | **0.6775** | **0.6577** | **0.6529** | **0.6376** | **0.6220** | **0.6078** | **0.6105** | **0.5941** | **0.5909** |
| J=1 | | | | | | | | | | | | |
| DENS = 0.1 | K=1 | 0.9096 | 0.9043 | 0.8819 | 0.8831 | 0.8686 | 0.8630 | 0.8241 | 0.8204 | 0.8291 | 0.8317 | 0.8157 |
| | K=3 | 0.9951 | 0.9746 | 0.9275 | 0.8921 | 0.8622 | 0.8219 | 0.8153 | 0.7861 | 0.7512 | 0.7470 | 0.7075 |
| | K=5 | 0.9302 | 0.9116 | 0.8584 | 0.8090 | 0.7902 | 0.7221 | 0.7176 | 0.6684 | 0.6232 | 0.5803 | 0.5625 |
| | K=7 | 0.9491 | 0.9158 | 0.8849 | 0.8297 | 0.7643 | 0.7183 | 0.6936 | 0.6116 | 0.6568 | 0.5716 | 0.5700 |
| DENS = 0.3 | K=1 | 0.9911 | 0.9871 | 0.9809 | 0.9744 | 0.9709 | 0.9578 | 0.9428 | 0.9272 | 0.9256 | 0.9138 | 0.9121 |
| | K=3 | 0.9993 | 0.9939 | 0.9663 | 0.9339 | 0.8959 | 0.8279 | 0.8091 | 0.7623 | 0.7459 | 0.6990 | 0.6741 |
| | K=5 | 0.9249 | 0.9103 | 0.8951 | 0.8453 | 0.7713 | 0.7069 | 0.5876 | 0.5952 | 0.5635 | 0.5136 | 0.4768 |
| | K=7 | 0.9276 | 0.9293 | 0.9129 | 0.8433 | 0.7215 | 0.6332 | 0.5319 | 0.4688 | 0.4239 | 0.4043 | 0.4377 |
| DENS = 0.7 | K=1 | 0.9954 | 0.9897 | 0.9786 | 0.9774 | 0.9699 | 0.9548 | 0.9547 | 0.9270 | 0.9305 | 0.8898 | 0.9049 |
| | K=3 | 0.9976 | 0.9916 | 0.9812 | 0.9213 | 0.8875 | 0.8092 | 0.8004 | 0.7483 | 0.7038 | 0.6621 | 0.6666 |
| | K=5 | 0.9223 | 0.9174 | 0.8958 | 0.8342 | 0.7551 | 0.6399 | 0.5745 | 0.5480 | 0.5123 | 0.4888 | 0.4841 |
| | K=7 | 0.9292 | 0.9409 | 0.9162 | 0.7683 | 0.6089 | 0.4627 | 0.5079 | 0.4317 | 0.3757 | 0.4146 | 0.3983 |
| **Average** | | **0.9559** | **0.9472** | **0.9233** | **0.8760** | **0.8222** | **0.7598** | **0.7299** | **0.6913** | **0.6701** | **0.6431** | **0.6342** |
| J=2 | | | | | | | | | | | | |
| DENS = 0.1 | K=1 | 0.9309 | 0.9222 | 0.8978 | 0.8997 | 0.8702 | 0.8653 | 0.8442 | 0.8359 | 0.8267 | 0.8289 | 0.8114 |
| | K=3 | 0.9565 | 0.9644 | 0.9034 | 0.9258 | 0.8907 | 0.8682 | 0.8077 | 0.8004 | 0.7424 | 0.7472 | 0.7170 |
| | K=5 | 0.8944 | 0.8974 | 0.8780 | 0.8375 | 0.8082 | 0.7502 | 0.7435 | 0.6780 | 0.6977 | 0.6995 | 0.6155 |
| | K=7 | 0.8956 | 0.8738 | 0.8441 | 0.7875 | 0.7800 | 0.7501 | 0.6934 | 0.6727 | 0.6384 | 0.6366 | 0.5704 |
| DENS = 0.3 | K=1 | 0.9859 | 0.9990 | 0.9966 | 0.9970 | 0.9907 | 0.9852 | 0.9706 | 0.9581 | 0.9404 | 0.9107 | 0.8983 |
| | K=3 | 0.9213 | 0.9640 | 0.9657 | 0.9826 | 0.9855 | 0.9713 | 0.9246 | 0.8797 | 0.7996 | 0.7590 | 0.7302 |
| | K=5 | 0.8538 | 0.8682 | 0.8975 | 0.9043 | 0.9205 | 0.9016 | 0.8446 | 0.7987 | 0.7334 | 0.6158 | 0.6500 |
| | K=7 | 0.8606 | 0.8774 | 0.8906 | 0.9101 | 0.9047 | 0.9072 | 0.8677 | 0.8461 | 0.6960 | 0.6188 | 0.5692 |
| DENS = 0.7 | K=1 | 0.9896 | 0.9957 | 0.9995 | 0.9992 | 0.9955 | 0.9908 | 0.9827 | 0.9612 | 0.9411 | 0.9222 | 0.8803 |
| | K=3 | 0.9259 | 0.9507 | 0.9687 | 0.9709 | 0.9907 | 0.9876 | 0.9692 | 0.9228 | 0.8277 | 0.7296 | 0.6818 |
| | K=5 | 0.8579 | 0.8742 | 0.8777 | 0.9026 | 0.9184 | 0.9218 | 0.8623 | 0.7904 | 0.6875 | 0.5888 | 0.5534 |
| | K=7 | 0.8533 | 0.8895 | 0.8964 | 0.9029 | 0.9173 | 0.9277 | 0.9198 | 0.7521 | 0.6218 | 0.5320 | 0.4634 |
| **Average** | | **0.9105** | **0.9230** | **0.9180** | **0.9183** | **0.9144** | **0.9023** | **0.8692** | **0.8247** | **0.7627** | **0.7158** | **0.6784** |
| J=4 | | | | | | | | | | | | |
| DENS = 0.1 | K=1 | 0.8414 | 0.8538 | 0.8465 | 0.8316 | 0.8284 | 0.7960 | 0.7938 | 0.7991 | 0.7690 | 0.7490 | 0.7587 |
| | K=3 | 0.8444 | 0.8584 | 0.8266 | 0.8482 | 0.8332 | 0.7721 | 0.7629 | 0.7279 | 0.7597 | 0.7320 | 0.7160 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | K=5 | 0.7959 | 0.7873 | 0.7735 | 0.7309 | 0.7402 | 0.7184 | 0.6823 | 0.6250 | 0.6289 | 0.6184 | 0.5659 |
| | K=7 | 0.8080 | 0.7760 | 0.7930 | 0.7412 | 0.7095 | 0.6732 | 0.6602 | 0.6267 | 0.5867 | 0.5808 | 0.5443 |
| DENS = 0.3 | K=1 | 0.7353 | 0.8147 | 0.8864 | 0.9479 | 0.9632 | 0.9902 | 0.9675 | 0.9352 | 0.9224 | 0.8600 | 0.8620 |
| | K=3 | 0.7130 | 0.7860 | 0.8407 | 0.8925 | 0.9322 | 0.9363 | 0.8989 | 0.8812 | 0.8585 | 0.7733 | 0.7051 |
| | K=5 | 0.7088 | 0.7510 | 0.8002 | 0.8248 | 0.8497 | 0.8682 | 0.8503 | 0.8485 | 0.8053 | 0.7384 | 0.6905 |
| | K=7 | 0.7193 | 0.7755 | 0.7971 | 0.8306 | 0.8544 | 0.8588 | 0.8236 | 0.8012 | 0.7610 | 0.7587 | 0.7015 |
| DENS = 0.7 | K=1 | 0.7121 | 0.7476 | 0.8557 | 0.9135 | 0.9735 | 0.9945 | 0.9917 | 0.9831 | 0.9663 | 0.9251 | 0.8978 |
| | K=3 | 0.6938 | 0.7405 | 0.8065 | 0.8640 | 0.8923 | 0.9365 | 0.9531 | 0.9412 | 0.9001 | 0.8342 | 0.7270 |
| | K=5 | 0.6435 | 0.7036 | 0.7430 | 0.7841 | 0.8280 | 0.8812 | 0.9036 | 0.8753 | 0.8385 | 0.7608 | 0.6505 |
| | K=7 | 0.6795 | 0.7388 | 0.7842 | 0.8152 | 0.8392 | 0.8744 | 0.8982 | 0.9102 | 0.7934 | 0.7460 | 0.6757 |
| **Average** | | **0.7412** | **0.7778** | **0.8128** | **0.8354** | **0.8537** | **0.8583** | **0.8488** | **0.8296** | **0.7992** | **0.7564** | **0.7079** |

Figure 2a (2b) shows group performance (level of consensus) as a function of the scope of distrust (Z) for the four J values, averaged across density and K values. These figures clearly show the two trends: 1) the decreasing relationship between group performance and scope of distrust for low values of J and 2) the inverted-U shape between group performance and the scope of distrust for high values of J.




(a) (b)

*Figure 2. Group performance (a) and Level of consensus (b) for different strength of social relationships.*

When the strength of social relationships is too low (e.g. J=0.5) and the level of consensus reached within the group is low, any scope of distrust is detrimental for group performance. Introducing a distrust relationship decreases the level of consensus, so impeding the individuals to collectively explore the landscape in search of better solutions. Each individual independently explores the landscape with a detrimental effect on group performance.

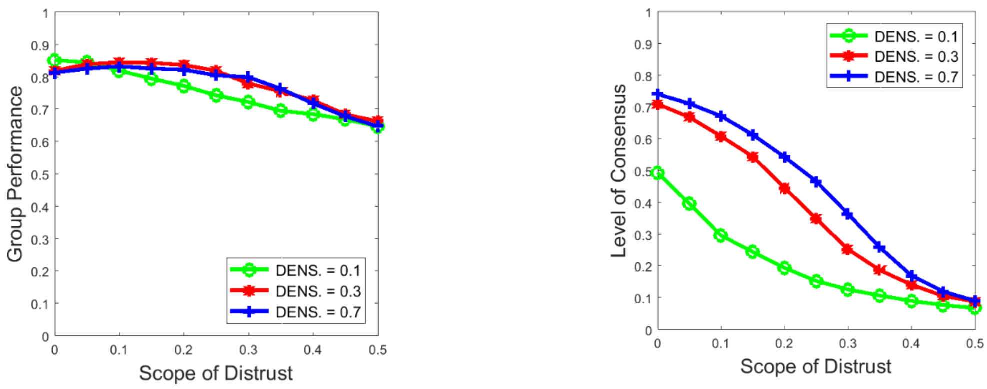
As the strength of social relationship increases, the level of consensus reached within the group also grows and group performance improves. However, a too high the level of consensus (e.g., J=4) becomes detrimental for group performance, because prematurely hinders the exploration of the landscape looking for configurations with higher fitness. In such a case, since a distrust relationship decreases the level of consensus reached in the group, it improves the exploration of the landscape thus increasing the chance to find high performing configurations. However, when the scope of distrust rises too much, the level of consensus becomes low and performance diminishes. Since the higher the strength of social relationships, the higher the level of consensus and the lower the group performance are, the optimal number of distrust relationships grows as the strength of social relationships rises.

We now analyze the influence of the density of social relationships on the relationship between scope of distrust and group performance. In Table 4, for each value of the density and scope of distrust, the averaged group performance and the averaged level of consensus reached within the group are shown. They are computed averaging results across the scenarios characterized by the four values of strength of social relationships (J) and the three values of interdependence (K). Findings show that the density of social relationships affects the relationship between scope of distrust and group performance. For low density (0.1), group performance diminishes as the scope of distrust rises. For medium and high density values (0.3 and 0.7), an inverted-U trend is achieved. In particular, when density is 0.3, a scope of distrust of 0.2 is optimal for group performance; for density equal to 0.7, a value Z = 0.3 assures the highest performance. This result is explained by the influence of the density of social relationships on the process of consensus reaching within the group. When the density of social relationships is too low, there are few social links among the group members and the level of consensus reached in the group is in turn quite low, because individuals interacting less are not so prone to change their opinions to be in agreement with others. A low level of consensus entails that individuals in the group make independent decisions on the basis of their personal knowledge and perspective, often resulting in conflicting positions that will remain unresolved. Introducing distrust relationships in this condition is detrimental. Distrust relationships negatively influence the level of consensus, making the system performing even worse.

When the density of social relationships is quite high (0.3, 0.7), social influence takes place, individuals are engaged in intensive dialogue and interactions, so that the group is able to reach higher consensus. In such a case, distrust relationships are beneficial because, reducing consensus, let the system better explore the landscape without converging too soon in an agreed suboptimal solution. However, when the scope of distrust becomes too high, the level of consensus decreases, impeding the emergence of CI, and performance reduces (see Figure 3).

*Table 4. Averaged performance for different density of social relationships.*

| | **Z=0** | **Z=0.05** | **Z=0.1** | **Z=0.15** | **Z=0.2** | **Z=0.25** | **Z=0.3** | **Z=0.35** | **Z=0.4** | **Z=0.45** | **Z=0.5** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Averaged group performance | | | | | | | | | | | |
| DENS=0.1 | 0,8523 | 0,8454 | 0,8199 | 0,7951 | 0,7726 | 0,7435 | 0,7227 | 0,6955 | 0,6854 | 0,6692 | 0,6477 |
| DENS=0.3 | 0,8190 | 0,8395 | 0,8456 | 0,8441 | 0,8372 | 0,8195 | 0,7802 | 0,7555 | 0,7280 | 0,6844 | 0,6631 |
| DENS=0.7 | 0,8135 | 0,8260 | 0,8332 | 0,8263 | 0,8225 | 0,8056 | 0,7995 | 0,7640 | 0,7185 | 0,6784 | 0,6478 |
| Averaged level of consensus | | | | | | | | | | | |
| DENS=0.1 | 0,4942 | 0,3968 | 0,2965 | 0,2450 | 0,1946 | 0,1531 | 0,1265 | 0,1073 | 0,0904 | 0,0774 | 0,0681 |
| DENS=0.3 | 0,7101 | 0,6687 | 0,6089 | 0,5448 | 0,4467 | 0,3492 | 0,2532 | 0,1876 | 0,1413 | 0,1060 | 0,0885 |
| DENS=0.7 | 0,7411 | 0,7114 | 0,6722 | 0,6137 | 0,5437 | 0,4672 | 0,3646 | 0,2594 | 0,1703 | 0,1200 | 0,0908 |




(a) (b)

*Figure 3. Group performance (a) and Level of consensus (b) for different density of social relationships.*

*5.3 Validation*

In order to validate our model, we perform a sensitivity analysis to test the robustness of the results to the value of parameter β' (the level of confidence of individual of their knowledge). In particular, we perform additional simulations for β' = 10. Results confirm the same trends observed above, concerning the moderating effect played by the strength of social relationships and the density of social relationships on the relation between group performance and scope of distrust. In Appendix B we reported the results of regression analyses made on all the simulation data, which statistically confirm the moderating effect played by the strength of relationships (Model 1) and density of relationships (Model 2) on the relation between scope of control and group performance. In fact, as to the effect of the strength of social relationships, results statistically confirm that the effect of Z is linear and negative when J=0.5 and J=1, whereas when J=2 and J=4 the linear effect of Z becomes positive and the quadratic effect of Z is negative. Similarly, as to the effect of the density of social relationships, results statistically confirm that when DENS=0.1 the effect of Z is significant and negative, while when DENS=0.3 and DENS=0.7 the linear effect of Z is positive and the quadratic effect of Z is negative.

## 6. Discussion and Conclusions

How the emergence of collective intelligence can be fostered to increase performance of decision-making groups? Our paper answers to this enduring question investigating the effect of the scope of distrust on group performance.

Our main finding is that the relationship between scope of distrust and group performance depends on the strength and the density of social relationships. In particular, depending on the values of these variables, two trends emerge: 1) the scope of distrust negatively affects group performance and 2) the relationship between scope of distrust and group performance follows an inverted-U shape. The negative trend is found for low values of strength (density) of social relationships, while the inverted-U shape is achieved when the strength (density) of social relationships is high. This implies that for high strength (density) of social relationships a moderate scope of distrust is beneficial for group performance. In fact, in absence of distrust relationships, high values of the strength (density) of social interactions drive the group towards a too high level of consensus, which hampers a broad exploration of the landscape, thus leading to inadequate group performance. In these conditions we showed that distrust relationships, by reducing the level of consensus, have a beneficial effect on exploration and leads to higher group performance. However, when the number of distrust relationships rises too much, performance diminishes, because the level of consensus becomes too low and individuals behave as independent agents exploring each limited portion of the landscape. When the strength (density) of social relationships is low and, thus, the level of consensus reached within the group is low, distrust relationships reduce more the level of consensus and have a detrimental effect on group performance.

Our study makes multiple contributions to the literature. From a theoretical point of view, we enrich CI research by highlighting a new process leading to the emergence of CI, i.e. consensus reaching, while previous studies analyzed collaboration (Woolley et al. 2015). We argue that a right level of consensus within the group is required to permit individuals to sufficiently explore the landscape in search of high performing solutions but simultaneously to foster the agreement among the group members on a common solution, so avoiding conflicts. The existence of an optimal level of consensus associated with collective intelligence helps explain the contradictory results found in the literature concerning the relationship between level of consensus and group performance. Lower and higher level of consensus are both detrimental, because make the members too much conflicting or too highly conforming, with negative consequences on exploration.

We also contribute to literature concerning the drivers of CI. While previous studies mainly focus on features affecting the level of collaboration among group members (Woolley et al. 2015), we identified a variable influencing the process of consensus reaching, i.e. the scope of distrust. We were able to clearly define when distrust relationships are beneficial for group performance and at which scope. This is an important result that complements previous research on the role of genuine and contrived dissent on the efficacy of decision-making. We confirm that dissent provoked by distrust relationships is beneficial, because can increase the ability of decision-making groups to find optimal solution to the problem, but it should be introduced at a moderate extent. In particular, we add in which conditions (high strength and high density of social relationships) dissent should be instigated within group to enhance its performance, for example by assigning controversial roles to the group members resorting to the so-called 'devil's advocacy' procedure (Herbert and Estes, 1977; Janis, 1982). According to this practice, someone role-plays a position critiquing the decisions favored by the other individuals to increase diversity and improve the quality of group decisions. This corresponds to intentionally introduce distrust relationships within the group, which, reducing the high level of consensus, may foster the coordinated exploration of solution space.

Furthermore, our results may inform managers on how to design web-based platforms exploiting CI (Bonabeau, 2009). Referring to the study by Malone, Laubacher, and Dellarocas (2010), who classified the genome of CI platforms, our study refers to the “How” question and “Group decision” and “Individual decisions” genes. As to the group decision, our study shows that consensus is useful at a moderately and not high extent. As to the “Individual decisions”, we find that the strength and the density of social connections have an important role and should be moderate. Thus, our findings suggest to limit social connections among users and to control the strength of social relationships among them. A too high strength, due for example to multiple, long-term, or friendship interactions, could be risky for CI because could determine a too high level of consensus. Therefore, random connections with limited amount should be preferred when designing such a CI platform.

This paper has some limitations. We consider that distrust involving two individuals occur on all the decisions they are taking. The network of social relationships is assumed to be a random one, while interactions especially in social systems may follow different patterns, such as small-world or scale-free ones. Replicating the study for groups showing these types of pattern can be useful to extend the boundary conditions of our theory.

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**Appendix A**

Here, we report a brief explanation of the Gillespie algorithm, used to solve equations (5) and (6). It consists in the following steps:

1) Chooses at random the initial state $\sigma$ of the system
2) Calculates all the transition rates $w(\boldsymbol{s_l} \rightarrow \boldsymbol{s_l'})$, $l = 1, \ldots, n = N * M$
3) Calculates the total rate $w_T = \sum_l w(\boldsymbol{s_l} \rightarrow \boldsymbol{s_l'})$
4) Normalizes all the transition rates as $\nu_l = w(s_l \rightarrow s_l')/w_T$ and builds the cumulative distribution $F(\nu_l)$ from the probability mass function $\nu_l$.
5) Calculates the time $\Delta t$ to the next opinion flip by drawing from an exponential distribution with mean $1/w_T$, i.e. chooses a real number $0 \leq r \leq 1$ from a uniform distribution and set $\Delta t = -{w_T}^{-1}\log(r)$
6) Identifies the $l$-th opinion that flips from $\boldsymbol{s_l}$ to $-\boldsymbol{s_l}$, by drawing from a discrete distribution with probability $\nu_l = w(s_l)\ /w_T$, i.e. draws a real random number $0 \leq s \leq 1$ from a uniform distribution and chooses $l$ so that $F(\nu_{l-1}) < s < F(\nu_l)$.
7) Updates the state vector and returns to step 2 or quit.

## Appendix B

*Table B1. Results of the regression analyses with group performance as dependent variable.*

| | Model 1 | | | | Model 2 | | |
|---|---|---|---|---|---|---|---|
| | **J=0.5** | **J=1** | **J=2** | **J=4** | **DENS=0.1** | **DENS=0.3** | **DENS=0.7** |
| Constant | 0.7509** | 0.9972** | 1.0091** | 0.8800** | 0.9849** | 0.8914** | 0.8397** |
| | 0.0172 | 0.0201 | 0.0167 | 0.0184 | 0.0140 | 0.0202 | 0.0230 |
| β' | 0.0429** | 0.0189** | 0.0057** | 0.0077** | 0.0122** | 0.0218** | 0.0224** |
| | 0.0014 | 0.0017 | 0.0012 | 0.0014 | 0.0012 | 0.0015 | 0.0017 |
| K | -0.0370** | -0.0297** | -0.0261** | -0.0256** | -0.0353** | -0.0293** | -0.0243** |
| | 0.0022 | 0.0026 | 0.0019 | 0.0021 | 0.0018 | 0.0023 | 0.0027 |
| Z | -0.2130** | -0.4749** | 0.2380* | 0.6540** | -0.3803** | 0.2870** | 0.4044** |
| | 0.0314 | 0.0368 | 0.1020 | 0.1126 | 0.0256 | 0.1231 | 0.1406 |
| Z^2 | | | -1.2122** | -1.5604** | | -1.1319 | -1.2637 |
| | | | 0.1965 | 0.2169 | | 0.2372 | 0.2709 |
| **Model fit** | | | | | | | |
| F | 411.7000** | 142.1300** | 105.0800** | 60.8900** | 237.2111** | 115.7694** | 77.8215** |
| R-squared | 0.8261 | 0.6212 | 0.6187 | 0.4847 | 0.6716 | 0.5716 | 0.4729 |
| Adj R-squared | 0.8241 | 0.6168 | 0.6129 | 0.4767 | 0.6688 | 0.5667 | 0.4668 |

(** $p<0.001$; * $p<0.05$.)