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Investigating group performance in high-school-students. A new model of collective intelligence in online environments

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Abstract: Humans organize in teams to overcome complex problems and succeed in a large variety of tasks. This emergent property of groups to display higher intelligence than singles is called collective intelligence. Previous studies on this topic underpinned that collective intelligence showed in both real and online environments but focused mainly on adults participants. This work aimed to understand the factors that promote group performance in adolescents facing a logical task in online environments. Five hundred fifty high school students took part in this study facing raven's advanced progressive matrices before alone and then in a group in computer-mediated communication or face-to-face condition. Results show that the group can enhance the performance of its members regardless of the condition. Moreover, this work provides a comprehensive model of collective intelligence for the youth. In particular, performance in adolescents' online groups is negatively affected by the difficulty of the problem to solve and by the total number of communicative exchanges. Contrary, the average of the perceived group members' cohesion, the average of the teammates' intelligence, members' neuroticism, and the group heterogeneity in social abilities increase the group performance.

Keywords: Collective-intelligence, computer-mediated-communication, group performance, problem-solving

1. Introduction

In the past few years, collective intelligence (CI) has been of particular interest in scientific research, as individual intelligence did in the last decades. The individual intelligence was defined as the ability of human beings to solve a wide variety of tasks [1], much like CI was defined as a general factor able to explain the "group's performance on a wide variety of tasks" [2]. According to the most up-to-date lines of study, CI is an emergent property of groups that results from both bottom-up and top-down processes [3]. The bottom-up processes involve the member characteristics that contribute to enhancing group collaboration; the top-down processes, instead, include the group structure and the norms that regulate collective behaviour to improve the quality of members' coordination. In particular, the most recent model of CI shows how three different variables explain about 43% of the group performance variance. The first is a top-down factor and is represented by the variance of the conversational turnover. The second and the third are two bottom-factors: the proportion of women in the group and the average of members' abilities in the theory of mind [2]. Other studies indicate that also the average of group members' intelligence is a fundamental bottom-up factor in explaining the variance of CI [4]. Both group and members' characteristics are been deeply analysed by empirical research in the field of group performance, but there are other drivers of groups' performance that the empirical research should to take in more account. For instance, the cognitive processes behind the social problem-solving that the groups implement solving a task could be of interest in the field of the study of CI. In this regard, Heylighen 1999 proposes an attractive formal model of social problem-solving founded on the assumption that to solve a task the group's members have to merge their representations of the problem (i.e. a set of problem states, a set of possible steps for the solution of the task, and a preference fitness criterion for selecting the preferred actions) in a single collective mental map. The effectiveness of social problem-solving depends on the cognitive representation that the group has of the task [6]. According to Heylighen, there are three ways in which a Collective Mental Map (CMM) can be developed. First of all, when all the group's members know the possible solutions of the task, the CMM result from the average of members' preferences. Johnson and colleagues 1998, simulating this scenario, demonstrate that this kind of CMM is not particularly different from the single members' mental maps. However, there is a series of studies in the field of the *Wisdom of the crowd* that shows how the average of the group's members' opinion is the best solution for a wide variety of problems [8]. The second way of building the CMM is characteristic of the groups organised on the division of labour. In these groups, each agent can solve only a specific part of the problem. Therefore, the CMM will result from the sum of members' mental maps. The third system of CMM development is group discussion. Expressing their preferences and explaining the reasoning behind their chooses, each agent can play a role in the modification of other group members' Mental Maps, contributing, in this way, to the extension of the CMM. The most crucial obstacle to the effectiveness of the discussion in contributing to the expansion of CMM is too much diversity in the group's members' knowledge. When the expertise of agents is also different, indeed, they can't understand each other in communications, and this inhibits the expansion of CMM [5]. Then, with Heylighen, we could consider the members' expertise as another bottom-up factor in explaining the variance of the group performance. Although the empirical evidence about the effectiveness of CI are many, there are studies that tried to resize the magnitude of the affect [4,9]. In particular, a re-analysis of the four main empirical studies in the field of CI [2,10–12] does not support the hypothesis of a general factor able to explain the performance variation across a wide variety of group-based tasks [9]. However, a more extended meta-analysis, conducted on 13 CI studies, showed supporting evidence the three-factorial CI model [13].

Studies about CI carried out in an online environment suggest that CI manifests itself differently depending on context [10]. Furthermore, the literature suggests that it is possible to suppose the existence of different models of CI to explain the variance of group performance, for each kind of task that the group can solve [9,14].

For what concerns the structure of problems, Laughlin 1980 argued that group tasks might be placed on a continuum between intellectual and judgemental tasks. Intellectual tasks are problems characterised by a correct solution that is demonstrable and are tested (e.g., geometrical problems). Otherwise, judgemental tasks are problems that not have an acceptable answer that is demonstrable and universally recognised (e.g., aesthetic judgement or juries deciding on guilt or innocence in criminal cases). Laughlin and Ellis 1986 identified four group conditions to distinguish an intellectual task from a judgemental one. The first condition concerns the agreement of group members about the solution proposed for the task, that must be the only one correct (e.g., mathematical, logical, scientific). Secondly, the information available to the group members must be sufficient to solve the problem. Third, so that everyone can recognize the correct answer, enough information must be available for group members who do not know the right solution. Finally, group members who know the right answer must have sufficient ability, motivation, and time to demonstrate it to the others. In this regard, Lam 1997 shows how the structure of task affect the quality of group communications and decisions. In his studies, the author takes into account conjunctive, disjunctive, and additional tasks.

Steiner 1972 identified and described these three types of task structures. In the additive task, group performance is determined by the aggregation of individual effort [17]. Each group member has the same responsibilities and information, and he has to maximise his or her own personal performance to increase the overall group achievement [19]. In a disjunctive task, a group selects one optimal solution from an array of solutions proposed by individual group members [18,20]. The achievement of this kind of task is influenced by the performance of the members who make the most significant contribution. In a conjunctive task, no member of the group has enough information to solve the problem alone. Therefore, the successful decision can only be achieved when all the group members maximise their efforts [17]. In this kind of task, a group solves a problem only when all of the information held by individuals are merged in a single CMM.

Summarising what exposed above, there are a lot of factors involved in the explanation of the variance of group performance. In addition to top-down and bottom-up group's factors [3,4], also the context in which the group work, the structure of the task that it has to solve [9,17] and the cognitive processes underlying the social problem-solving reasoning [5], appear as drivers of groups' performance. So, of particular interest would be to find the models of collective intelligence useful to predict the group performance in problem-solving process

1.1. General problem-solving ability in groups

The ability to solve problems has been generally considered as a proxy to evaluate the individual's intelligence[1]. A problem can be described as a situation where there is a gap between an initial state and a desirable condition. Therefore, solving a problem means finding a way to fill the gap between the initial state and the desired one. This process is usually called problem-solving. Thus,the problem-solving is a behavioural and cognitive process that makes available many possible solutions for a specific problem increasing the probability of selecting the most effective one [21].

The process of problem resolution consists of two phases: understanding the nature of the problem and find the correct strategy to resolve it [22].

During the first phase, the problem solver develops an internal representation of the problem, identifying the goal, the initial state, the available tools, or operators, and the possible obstacles [22]. The internal representation of the problem is the medium by which reasoning takes place. It is subjective, so it is not precisely the same reproduction of the actual problem [22]. Representations of problems can also be externalised, through drawn or written schemes. These kinds of representations are called "external" [22].

The second phase consists of the implementation of the process carried out to reach the desired state. During this step, the problem solver examines the space of the problem (i.e., the set of all the possible patch available to solve the problem) accessible to him and implements strategies to reach the goal [22]. Hayes 2013 identified four major strategies that can be achieved by individuals to resolve a problem: 1) trial and error, 2) proximity methods, 3) fractionation methods, and 4) knowledge-based methods. The first strategy involves the evaluation of the posterior effects of the action performed to solve the problem in a recursive way exploring all the solutions identified until the problem is solved. The proximity strategy involves the systematic approach to the resolution of the problem, progressing step by step in activities that allow getting closer and closer to the goal. The splitting strategy is the method that involves the subdivision of the objective into sub-goals and approaching their resolution to reach the final desired state. Finally, the knowledge-based methods are strategies used when the problem solver exploits the information and knowledge stored in his memory to guide the resolution of the problem. The strategies are not mutually exclusive, indeed, to solve a problem an agent could first lie on a strategy and after change, the strategy adopted [22]

Once the strategy is executed and the outcome of the attempt to resolve a problem is evaluated as successful or not, an important step that may occur is the process of consolidation. During the consolidation process, the problem solver is engaged in reflecting on the method used to solve the problem. The consolidation process plays a fundamental role in the learning process activated during and by problem-solving activities because it allows the creation of schemes that could drive the representation of future problems [22].

People can implement problem-solving processes alone or in teams. In the second case, implementing the group problem-solving process, the members merge their effort to solve the task [21]. Mainly, four factors can affect the outcomes of the group problem-solving: 1) group task, 2) group structure, namely the internal team organisation (e.g. status, rules, kind of leadership, norms, member' characteristics) 3) group processes, that is the persuasive interactions occurring among members, and d) group product [23].

Research in the field of group problem-solving in small teams proposes two approaches for the study of members' interactions: the social communication approach and the social combination approach [24]. According to the first approach, the communication within the group provides information about the contribution of each member in the task resolution. The social combination approach, instead, assumes that the group outcome is a combination of members' answers, assembled in only one solution.

Many studies have been conducted with the aim of analysing and comparing group and individual problem-solving performance. How already synthetically exposed, these studies have achieved mixed results. On the one hand, some researchers argued that groups hinder individuals' performance, also causing a failure in effective judgements production; on the other hand, many scholars found in their work that group usually outperform individuals in a large variety of tasks.

For what concerns the researchers who have concluded that the group hinders the individual performance, Steiner 1972 Steiner **?** theorized that when groups produce less than expected, they are composed of members unable to find the correct solution or who fail in recognize the correct answer given by a teammate. Latane, Williams, and Harkins 1979 shed light on the effect that groups have on individual efforts. Comparing the individual and group performance, they found that when the participants are in the group condition, they reduce the effort invested in the clapping activity from a minimum of 28% to a maximum of 68%. This effect of loss of individual effort in a group situation was called "social loafing." These results supported the classical finding of Ringelmann that showed how the effort in teams is reduced with the increasing of the size of the group [26,27].

Conversely, there is a large number of researches that not support the conclusion that groups hindering individual performance. In an early study, [28] compared the performance of university students in solving logical problems (i.e., mathematical puzzles) when they work alone and in teams. The author found that, in these kinds of tasks, groups perform better than individuals. Lorge and Solomon [29], starting from the evidence of Shaw, proposed a mathematical model in which they identified as principal driver of the group performance the ability of their members in recognising the correct answer proposed by one of them. Furthermore, studies conducted with samples composed of both adults and college students have shown how groups are greater efficiency and suggest higher quality solutions for a problem than individuals thanks to the merge of members' knowledge and abilities [30–32]. In particular, in an experiment that involved university students, Laughlin and Bonner [33] found that groups can to solve problems effectively in tasks where is required to process an high amount of information. Straus and Olivera, in their review about the effectiveness of online work-groups,, have pointed out that group problem-solving can be a powerful learning tool to increase members' skills and knowledge [34]. The advantage of group problem-solving compared to individual performance has also been verified in children, in particular with a task involving mathematical and logical problems [35–37]

Recent research on CI not only showed how the group could boost the performance of the single but also how one of the effects deriving by interacting in collective environments is the promotion of the increase of knowledge among group members [2,38,39].

Given this latter property, understanding how to exploit the full potential of the CI in educational environments would be of great interest also in the light of the massive spread of online educational learning platforms. Indeed, the effectiveness of the processes activated in the group by the phenomenon of CI has been proven to retain also in online environments [11,40]. However, much of the research in the field of CI focused mainly on adults and lack of works investigating groups of youngster peers.

Thus, the work hereby proposed aims to investigate the phenomenon of CI in a sample of adolescents engaged in performing a logical-mathematical task, evaluating the impact of computer-mediated interactions with face-to-face interactions, and isolate the main factors that explain the ability of online groups in solving a logical-mathematical problems.

2. Hypothesis

- *H1: No significance difference will be found between the performance of the groups involved in the CMC task condition and groups involved in the FtF task condition.*

  According to the literature about CI, the phenomenon should not be affected by the type of communication used to interact during problem-solving and decision-making activities [40].
- *H2: Groups will perform better than single individuals.*

  According to the most relevant literature on CI, groups can harness individuals' intelligence, resulting in displaying a greater ability in complex task resolution [2,5,11,12].
- *H3: Individual intelligence is a factor that explains the ability of groups to solve logical-mathematical tasks.*

  According to some recent evidence [4], individuals' IQ is a determining factor also in a group task, resulting in a parameter to be evaluated to understand the phenomenon of CI.
- *H4: Top-down and bottom-up process explain the groups' performance in CMC condition.* According to the most recent findings in the field of CI (i.e., Graf and Barlow 2019, a single factor view of processes underling group performance is not consistent. Indeed, this work aimed to identify a more comprehensive model of CI including bot individual characteristics such as personality traits; characteristics deriving from the context, such as group cohesion that could predict performance of groups in the way that higher cohesive groups perform better [41,42]; and characteristics peculiar of the task such as difficulty of the problem to solve.

3. Materials and Methods

3.1. Sample

The sample of this study consisted of 563 high school students from the first to the fifth year of courses (460 females, and 103 males). The sample belongs to Human Science High School "Licei Giovanni da San Giovanni," which offers a humanistic formation to all its students. The average age of participants was of 15.78 for years ($S.D. = 1.50$ years).

The inclusion's criteria for this study were: understand the Italian language correctly, do not have high developmental disorder, can give the voluntary participation in the study and have signed consensus form (by legal tutors if the participants did not have the legal adult age at the moment in which the experiment was carried out). Only 13 students (the 2.63% of the initial sample) do not fulfill the previous criteria. Thus, the final sample of the research was composed of 550 participants (Age $M = 15.62$ years $S.D. = 1.48$ years; 449 Females, and 101 males).

The experiment was carried out following the guidelines of the Italian Psychological Association (AIP) in a matter of ethical and privacy issues.

3.1.1. The psycho-social survey

To gather data to control the possible effect of individual characteristics it was administrated a psycho-social questionnaire to all the participants. The self-report survey was composed of two sections: a demographics section and a psychological one. First of all, data about gender and age of participants were collected, while the second section was devoted to assessing a series of psychological dimensions.

- *Personality traits*

  The I-TIPI inventory test ($\alpha = 0.59$) [43] has been used to obtain measures of personality dimensions on the base of the big five model [44] (the OCEAN model). This test is composed of ten items on a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree). The I-TIPI is formed of five sub-scales: Extroversion, Agreeableness, Conscientiousness Neuroticism, and Openness,
- *Cohesion among group members*

  The Sense of Community (SOC) has been measured using the Classroom and School Community Inventory (CSCI) ($\alpha = 0.93$) [45,46], which assigns two separate scores: one for the *Learning Community* ($\alpha = 0.87$) and one for the *Social community* ($\alpha = 0.92$). The scale was composed of a total of 20 items, 10 for each sub-scale, on a five-point scale (1 = strongly agree, 5 = strongly disagree). The literature defined generalised sense of community as a feeling that members have of belonging, a feeling that members matter to one another and to the group, and a shared faith that members' needs will be met through their commitment to being together [47]. In this regard, it could be considered as an adequate proxy for study cohesion among specific groups.
- *Social sensitivity* Finally, the Italian version of the Reading the Mind in the Eyes test (RME) ($\alpha = 0.605$) [48] has been administered to measure participants' social sensitivity. RME is composed of 36 images of displaying the eyes and the part around. The images show different emotions. Each participant is asked to guess the correct emotion among four different options for every image.

3.1.2. Stimuli

The experiment was carried out using a digitised version of the Raven's Advanced Progressive Matrices (RAPM) set II test, expressly developed for this study.

The full test consists of the resolution of 36 matrix puzzles asking the subject to identify a missing element in a grid to complete a pattern between 8 different options.

The individual task was represented by the assessment of each participant intelligence using the 18 odd-numbered (RAPM).

Instead, the group task consisted of the resolution of the remaining 18, even-numbered matrices from the RAPM test.

The Raven's Advanced Progressive Matrices were chosen as stimuli in this research for three main reasons. First of all, the same test and same partition of matrices in individual and group condition was used by Woolley *et al.* 2010 in their seminal work in the field of CI. Moreover, it became part of the *collective intelligence test battery online tool* [11] a canonical research instrument to study CI. Secondly, RAPM is one of the most widely-used intelligent test, and it has been found to resist well to cultural effects in its implementation in different environments and cultures [49–51]. Finally, the design of Raven's Progressive Matrices was found to maintain its validity as a well-established intelligence test also in its transposition from paper form to digital form [52].

3.1.3. Procedures

The experiment took part within the school spaces during the class hours and was composed of two phases that lasted over two weeks. During the first phase, participants were asked to fill a self-report survey. In the second phase, that occurred one week after the first, participants completed two trials: an intelligence assessment task, carried out individually, followed by a group task.

In Fig.1 is showed the user interface used by participants to complete the individual task.

In both individual and group, phases were introduced a time constraint, giving to the participants, for each part of the trials (i.e., individual and group), 15 minutes.

Two conditions for group task were implemented in the experiment: computer-mediated-communication (CMC) and face-to-face (FtF).

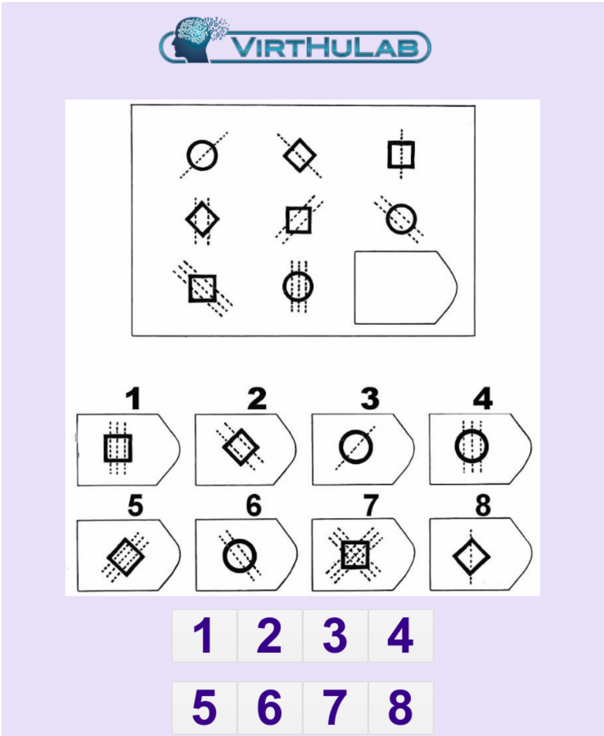

Figure 1. User interface of the software used by participants in the individual task.

Before the beginning of the experiment, the participants of each class were randomly divided into groups of five members, and each group randomly assigned to one of the two experimental group conditions. At the end of the experiment 57 groups completed the task in FtF condition (230 females, and 55 males) and 53 groups completed the task in the CMC condition (219 females, and 46 males).

In the CMC condition, 5 participants for each group were seated at PC stations equipped with a tablet and a pair of earphones. Using the tablet, participants could see the matrices and evaluate the possible answers. To communicate with the other teammate, each member of the group could use a voice chat to reach an agreement about the response to be given. Each group member used the tablet to select the chosen solution. The group could advance to the next matrix only if at list three out of five members picked the same answer. Otherwise, the system again showed the same matrix to the participants asking them to find a majority agreement. In Fig.2 is showed the user interface used by participants to complete the individual task.

In the FtF condition, a group of 5 participants took place around an interactive whiteboard where each matrix were projected to them. Each member of the group could speak with the others to find the correct answer and reach the majority agreement. Once the approval was obtained (i.e., $\frac{3}{5}$ of the team agreed), the group should communicate the choice to the researcher, which annotated it trough a special panel in the software, together with the percentage of agreement in the group (see Fig. 3).

3.2. Analysis

After scoring the data obtained from the preliminary surveys, administered to all participants, the analysis of these data was performed. Initially, a first study was performed to describe the statistical characteristics of the sample through the calculation of descriptive statistics and to verify the preconditions necessary for subsequent analyses (i.e., skewness and kurtosis). The ratio between the

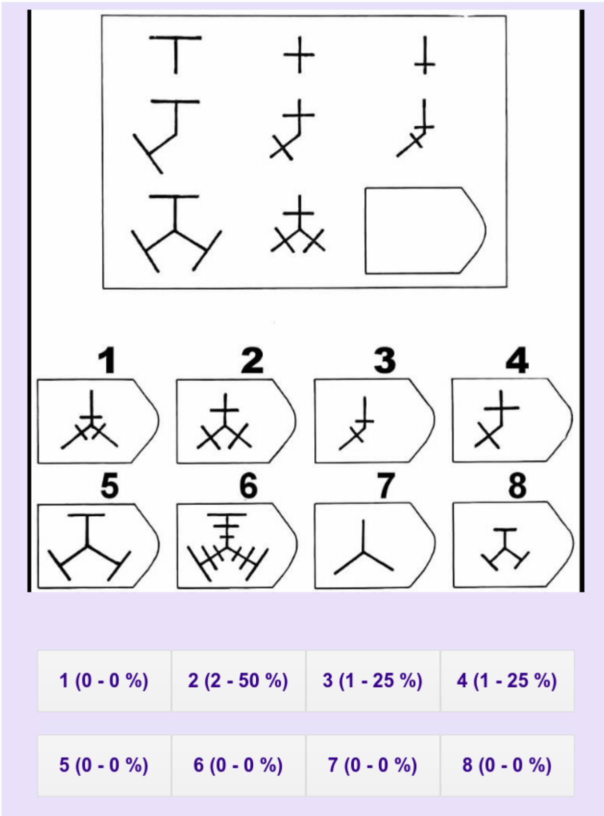

Figure 2. User interface of the software used by participants in the CMC group task.

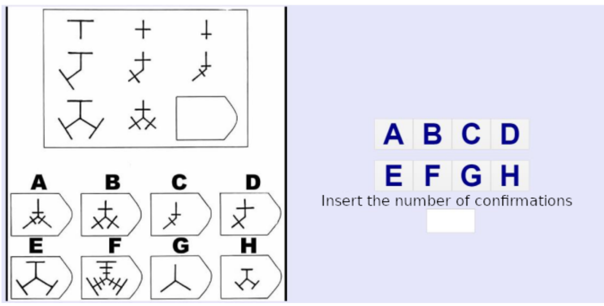

Figure 3. User interface of the panel used by the researcher to save the data during the face-to-face group condition (translated from the original in Italian language).

correct answers and the number of matrices faced during the 15 minutes of each task has been used as order parameter, to evaluate and compare the performance of participants and groups during their respectively tasks. This decision has been made according to the theory of measure of CI exposed by Szuba 2001, for whom CI must be parametrisied as a probability function overtime to solve problems. To verify the impact of the difficulty of the task in the effectiveness of group problem-solving, it has been taken advantage of the RAPM test design to compute a new variable called: Difficulty of the task. Indeed, the RAPM test was developed to present to subjects more complex problems with the progression of it, namely, the first matrices are significantly easier to solve respect the last. So in this work, every four matrices have been customised to form a difficult level of the variable.

3.3. Results

As showed in Fig. 4, the t-test analysis found no significant difference between the performance achieved by groups that complete the task in CMC and FtF conditions ($t_{(109)} = 1.39, p = 0.166, d = 0.266$), supporting H1.

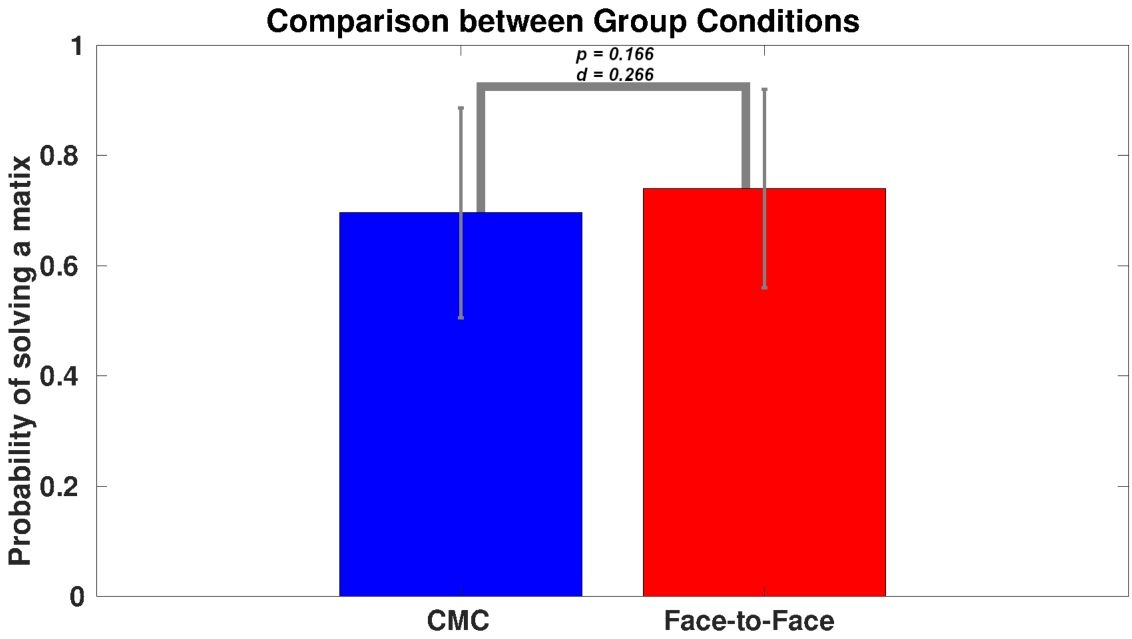

Figure 4. Comparison between groups conditions in the experiment

Hypothesis 2, predicting a better performance of groups respect individuals, was also supported. Indeed, as shown in Fig. 5 and Fig. 6, the groups outperformed its own members whether they completed the task individually in both CMC ($t_{(52)} = 13.184, p < 0.001, d = 1.81$) and FtF condition ($t_{(56)} = 14.674, p < 0.001, d = 1.91$). In detail, results highlight that there is a significant difference between the group probability to choice the correct answer in both CMC ($M = 0.696, S.D. = 0.19$) and FtF ($M = 0.74, S.D. = 0.18$), and the average performance of the respective members of these groups in the individual task, namely ($M = 0.392, S.D. = 0.096$) for those who completed the group task in CMC condition and ($M = 0.41, S.D. = 0.11$) for those who completed the group task in FtF condition. Thus, a gain of around 30% in the group outcome was observed, compared to the average members' performance.

For what concerns the second aim of this work, namely, understanding the factors underlying groups' performance in an online environment, the best multivariate model explaining the CI of the groups in the CMC condition is presented in Table 1. The hypothesis H3 to H4 are supported. First of all, as shown in Table 1, it was found that the more a matrix was challenging to be solved, the more the probability of a correct answer was reduced. Secondly, the assumption that cohesion among group members and some participants' personality features would influence the performance of the group was supported. As reported in Table 1, the correctness of an individual during the group task appears to be influenced by group, individual, and task features. In particular, the probability to chose the correct answer was higher when the group had a width heterogeneity for what concern social abilities (i.e., group RME standard deviation), as well as when the average members' intelligence and the average members' neuroticism were higher. Finally, the performance was worse in those groups characterised by a large number of communicative exchanges.

4. Discussion

The group has the potential to boost and enhance individual abilities. The results of this study confirm the presence of a 30% magnitude of CI factor even within groups of adolescents facing a logical task in computer-mediated communication.

The study hereby proposed was aimed to verify the emergence of CI in adolescents groups of peers involved in the resolution of logical problems (Raven's Advanced Progressive Matrices) and isolate important factors accountable for performance in groups. In the experiment proposed

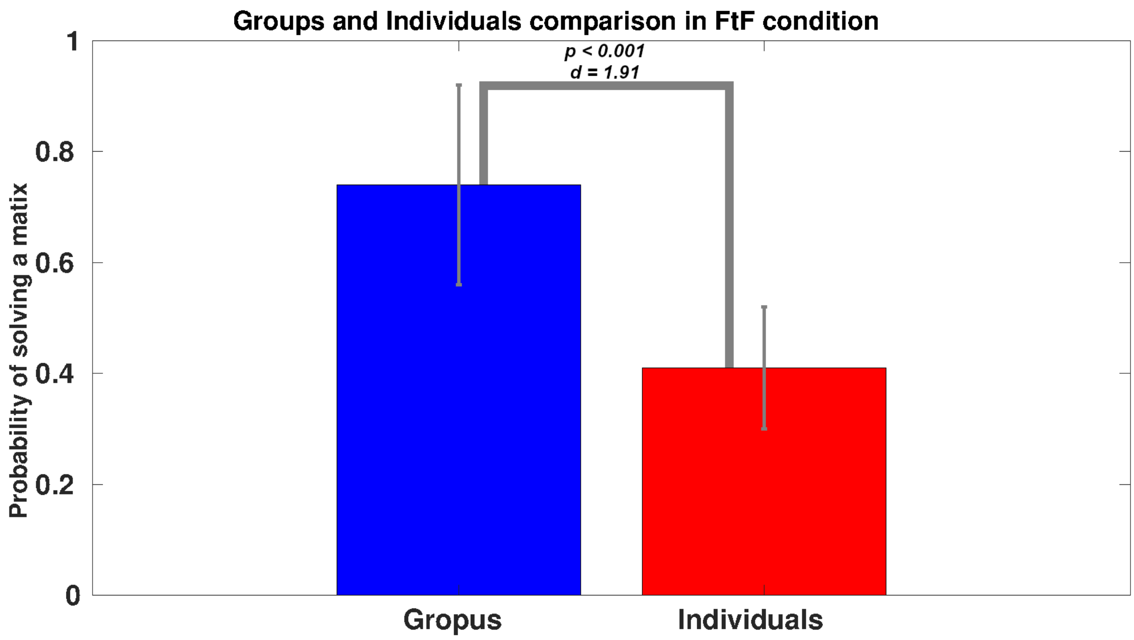

Figure 5. Comparison between the performance of groups in facet-to-face condition and the members' performance in the individual task.

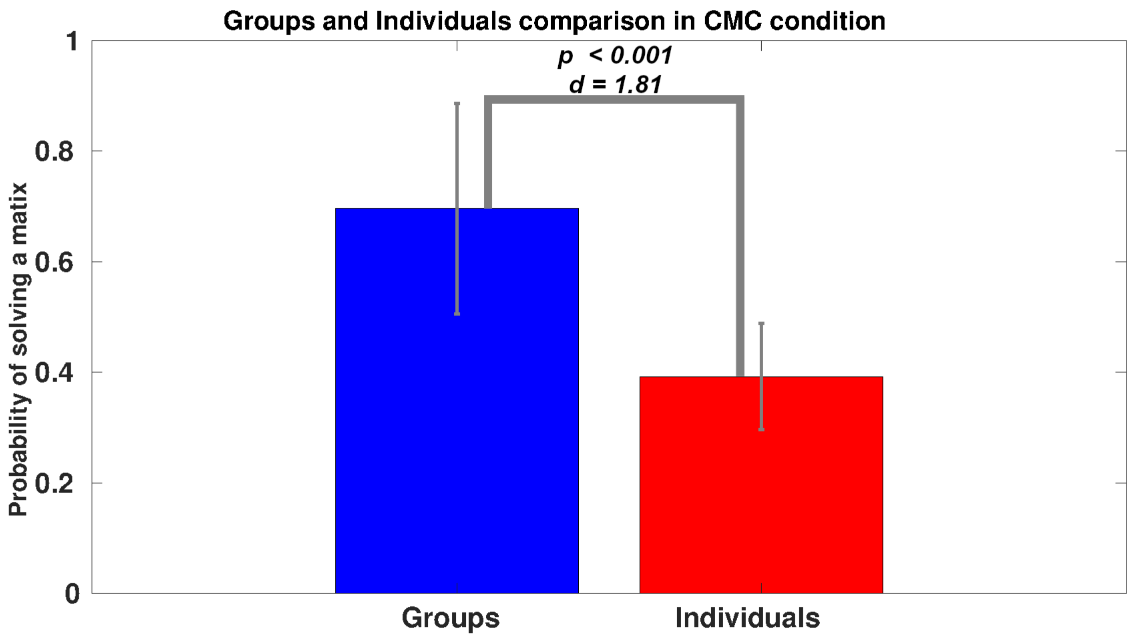

Figure 6. Comparison between the performance of groups in computer-mediated-communication condition and the members' performance in the individual task.

here, 550 high school students took part in a logic problem-solving task first individually than in a group of 5 classmates. Group task could be performed in face-to-face condition (FtF) or computer-mediated-communication (CMC) condition. The participants faced the Raven's Advanced Progressive Matrices, the odd-numbered ones alone and the even in group. At the end 57 groups completed the task in FtF condition and 53 CMC condition. Participants completed also a psycho-social survey to gheter inforamtion of participant's individual characteristics. The findings support the hypothesis that collective intelligent behaviours also emerge in youngsters that work with known people, regardless of the type of communication used (i.e., computer-mediated-communication end

Table 1. *Generalised Linear Mixed Model. Effect of groups, members, and tasks characteristics on Collective Intelligence*

	Akaike	F	Df-1(2)	Model Precision
Best Model	17,453.795	100.412***	7(3,662)	76.4%
Fixed Effects				
Factors	**F**	**Df-1(2)**	**Coefficient (β)**	**Student t**
Social abilities heterogeneity of the group	26.761	1(3,662)	0.206	5.173***
Total Conversational Turnover	8.639	1(3,662)	-0.003	-2.939**
Average group members neuroticism	19.356	1(3,662)	0.175	4.400***
Average group members social community perception (SOC)	19.656	1(3,662)	0.091	4.434***
Average group members intelligence	103.351	1(3,662)	4.942	10.166***
Difficulty of the task	262.929	2(3,662)	-2.838	-22.697***
		2(3,662)	-1.220	-13.252***

*** = p. <0.001, ** = p. <0.05

face-to-face). Indeed, groups outperformed individual teammates' performance by 30%. The aim of this study was also to find the characteristics that better allow young student to perform well in online environments. The model obtained, analysing interaction in computer-mediated-communication, in this experiment, showed how group performance was predicted by six variables. The first was the social sensitivity heterogeneity of groups, namely the more was higher the diversity in social ability, the more groups performed well. The second variables were the total conversational turnover, namely the more the teammates discussed during group activity, the less they performed. These findings could be related to the fact that people who know well, like schoolmates, could engage in relational conversation rather than conversation oriented to problem-solving, and this could have undermined the performance in logical tasks. The third variable was the average group members' social community perception, namely the more members perceived to be part of the groups, the more they performed. This could be seen as a proxy of motivation acting in CI; indeed, the more teammates perceived the importance of the group, the more they were engaged in solving the problem. The fourth variables were the average group members neuroticism, namely the more this personality trait was high among group members better the groups performed. This could be explained by the role of CMC that reduced the amount of social information to elaborate and permitted the participant to spent their cognitive resources in problem-solving. The fifth variable in the model was the average members' intelligence, namely the higher was individual scores of teammates in the single task, the more the groups performed well. This finding could have been found due to the logical kind of task used in the experiment that could be particularly susceptible to individuals characteristics. Finally, the last variable was the difficulty of the task; namely, the more a problem was complex, the less it could be solved by groups. In the light of the results reported here, this work suggests a brand new model of CI in online environments within adolescents, taking into account even different dimensions from those previously described in the literature. First of all, the more a task is difficult the more the group's performance decrease. Moreover, for logical tasks (i.e., RAPM), it appears that the number of communicative exchanges reduces the performance of groups. Neuroticism of the members, group cohesion, and average intelligence of group mates enhance the ability of a team to drive their members to the correct solution of a problem in an online environment. Social skills of group' members play a significant role in determining the outcome of a team; indeed, the more a group is characterised by heterogeneity on this dimension, the more it is probable that group achieves excellent performance. Finally, the findings of this research provide an insight addressed to the study of groups' performance in teams of peers who know each other with a previous story of interactions (i.e., classmates), suggesting that the strongest is the social bound perceived by group members' the higher will be the group performance.

Some limitations could be found in this work. First of all, it has not been possible to gather data about speaking variance in the first study, namely the actual number of speaking turns of each participant. This variables, could have represented a precious source of information given the school peers context involved, moreover it represent nowadays a parameters evaluated in the vast majority of experiments in CI (e.g., Woolley *et al.*, 2010; Engel *et al.*, 2015; Aggarwal *et al.*, 2019). Secondly, participants involved in the study represent a convenient sample, and are heavily unbalanced in favour of the females' numbers. Future works may try to take into consideration these limits to improve the presented research.

Although the literature results in the field of the models of CI are still elusive, it is clear how the predisposition to form groups has been one of the factors that lead human beings to successfully compete in the struggle for survival during their evolution [54]. This attitude allowed humans to overcome complex problems, otherwise impossible for a single individual [55].

The research described in this work provides some possible perspectives in the direction of exploiting CI especially in the field of educational online. The findings from this study suggest that CI principles could also be harnessed in online educational contexts. Indeed, the results presented indicate that small working groups could obtain better results than individuals working alone and also through computer-mediated-communication. This could guide the design of the future implementation of e-learning platforms and school laboratories, even considering literature findings that link CI with increasing learning abilities.

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6. Author Contributions

A.G. directed the project, E.I., F.s. and A.G. envisaged the problem, A.G., F.S. and E.I. designed the experiment, E.I. and A.G. developed the software used in the experiment, E.I., F.s. and A.G. conducted the experimental phase, A.G., F.S., and E.I. analyzed the data, E.I and F.S. wrote the manuscript, all authors reviewed it.

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