On the relationship between network connectivity and group performance in small teams of humans: experiments in virtual reality

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Keywords: coordination, collaboration, human behavior, social network, topology, virtual reality

Abstract
Optimizing group performance is one of the principal objectives that underlie human collaboration and prompts humans to share resources with each other. Connectivity between individuals determines how resources can be accessed and shared by the group members, yet, empirical knowledge on the relationship between the topology of the interconnecting network and group performance is scarce. To improve our understanding of this relationship, we created a game in virtual reality where small teams collaborated toward a shared goal. We conducted a series of experiments on 30 groups of three players, who played three rounds of the game, with different network topologies in each round. We hypothesized that higher network connectivity would enhance group performance due to two main factors: individuals’ ability to share resources and their arousal. We found that group performance was positively associated with the overall network connectivity, although registering a plateau effect that might be associated with topological features at the node level. Deeper analysis of the group dynamics revealed that group performance was modulated by the connectivity of high and low performers in the group. Our findings provide insight into the intricacies of group structures, toward the design of effective human teams.

1. Introduction
Collaboration is a cornerstone of human organization dating to our ancestors who relied on one another to hunt, forage, and develop communities for a greater collective interest. The objectives and means of collaboration have evolved through the millennia from basic needs of survival to industry [1], research [2], education [3], and even leisure [4]. Across most instances of collaboration, the optimization of group performance has been of critical importance, thereby fueling research endeavors across social and mathematical sciences [5, 6].

The study of group behavior and performance has significantly benefited by recent progress in network theory, which allows for quantitatively describing individual and collective dynamics [7]. Social networks consist of a set of human actors who engage in some kind of interaction; typically, they are modeled as directed graphs whose nodes represent the actors and whose links encapsulate interactions among the actors and the direction of such interactions [8]. The network topology defines individuals’ access to and distribution of valuable resources, whether they consist of information, knowledge, or more tangible assets [9, 10]. For example, the out-degree of a node measures the number of neighbors to which it can distribute resources; likewise, the in-degree of a node is associated with the number of neighbors from which that node can gather resources. Sharing of resources is not limited to neighbors, whereby nodes can distribute to and access resources of nodes that are apparently far away in the network, provided that there is a path between them [8]. The number
of disjoint paths between two nodes is a measure of their connectivity, such that the more paths are available to reach a node from another, the stronger is the connection between them. In this vein, the connectivity of a node is a measure of the strength of the connections it forms with other nodes of the network. Connectivity at the network level can be defined in several ways depending on the specific problem, either focusing on worst-case scenarios \([11, 12]\) or averaging across nodes in the network \([8, 13]\).

Research suggests that a strong relationship exists between group performance and overall network connectivity, whereby effective diffusion of resources is favored by more interconnected structures \([14, 15]\). Additional connections create shortcuts within the network, which enable nodes to reach one another through shorter paths \([16, 17]\). Moreover, increased connectivity could afford individuals access to diverse resources and contacts, to coalesce skills and talents \([9, 18]\). For example, empirical evidence showed that in disaster relief teams, higher connectivity between team members resulted in better group performance \([19]\). Similarly, different organizations in the US Navy were explored and it was found that network connectivity was conducive to information transmission and better outcomes \([20]\).

Not only can the overall network connectivity shape the performance of the entire group, but also the topological features of the nodes can determine their specific performance within the group. At such a local level, it was repeatedly proposed that the connectivity of a node is positively associated with individual performance, whereby spontaneous emergence of higher connectivity implies a greater amount of available resources \([15, 17]\). For example, in massive multiplayer online game communities, players who maintain more social ties within their guild have better access to in-game resources \([21]\). At the same time, it is also contended that individuals identify high performers among their peers and choose to associate with them more \([15, 22]\), thereby increasing the centrality of high performers and their access to resources. Thus, it is possible that the group dynamics may favor a virtuous cycle, where low performers leverage the talents of high performers to effectively complete their own tasks and high performers become even better performers.

Just as identifying high performers in the group can benefit performance, previous research also suggests that members’ ability to recognize low performers can be beneficial to the group \([22, 23]\). However, the extent to which group members can accurately appraise the performance of others may depend on the size of the group \([24, 25]\). While the competence of top performers could be more evident in larger groups, individuals’ ability to precisely appraise the performance of all their peers may diminish with the size of the group. In small groups, less individuals need to be appraised, thereby reducing the complexity of the task, which, in turn, can favor the emergence of optimal cooperation patterns as a function of individual performance. Hence, it is tenable that intervening with topological features of high performers in small groups can substantially affect the overall group performance, whereas the same manipulation may beget secondary effects in large groups \([12, 26]\).

Extensive research has been conducted on the performance of human groups but the specific interplay between topology and performance is yet to be completely understood. Particularly elusive is the study of small human groups, in which individuals can precisely track the performance of any other team member and utilize this information in their decision-making process. Here, we sought to fill this gap in knowledge by experimentally investigating the performance of human groups composed of three individuals, across three topologies with varying connectivity. We predicted that increased connectivity would enhance group performance. We explored two potential mechanisms that could support such an improvement in the form of two secondary hypotheses.

First, we hypothesized that better access to the network through higher connectivity would afford more opportunities for individuals to share resources and help others to quickly adapt to the group’s needs, thereby improving group performance \([17, 27]\). Second, we hypothesized that the greater interdependence created by a higher number of connections would enhance individuals’ arousal, and contribute to improvements in performance indirectly \([27, 28]\). Arousal is one’s preparedness to receive and respond to sensory stimuli from the environment \([29]\). It is positively associated with the amount of effort and energy an individual invests in a task \([30]\); therefore, increasing multiple actors’ arousal should enhance group performance.

In small groups of only three nodes, individuals are expected to gain an accurate appraisal of the performance of the others and the performance of any individual could have a dramatic effect on the overall group performance. Thus, we also anticipated the emergence of strong relationships between the attributes of each individual and the dynamics taking place within the group. To detail the response of each group members, we scored individual attributes along a range of complementary metrics, encompassing topological features (in- and out-degrees) and relative performance with respect to others. Presumably, placing high performers in central positions with higher connectivity would enhance the group’s performance overall, but other interesting mechanisms could also be foreseen. For example, it could be predicted that reciprocity in the interactions between players may vary as a function of their individual performance, thereby impinging on group performance \([31]\). Thus, beyond testing our two main hypotheses, we conducted several exploratory studies to unveil the underpinnings of group dynamics.
To support these scientific inquiries, we developed a collaborative game in virtual reality (VR), presented in the context of intergroup competition that would encourage optimization of group performance. VR is the most immersive means of communication available today. It can be described as a collection of complementing machines that provide sensory information about a virtual environment and allow the user to access it [32]. The technological apparatus of VR creates the experience of ‘presence’, where the user interacts with the virtual environment as if the computer interface effectively ‘disappeared’ [32, 33]. For groups, this feature of VR is particularly useful, as it could increase individuals’ sense of ‘co-presence’ and facilitate an interaction that is highly comparable to face-to-face interaction [34–36]. Therefore, VR should enable the study of human behavior and group dynamics in a highly-controlled experimental setting. We integrated VR with detailed measurement of arousal through two metrics, one behavioral and the other physiological. The former, head rotational speed (HRS), reflects exploration in VR [37–39]. The latter, galvanic skin response (GSR), is an involuntary response of the body to interactions with its environment whereby exogenous events trigger sweating [40, 41]. Both metrics were used in prior research to measure engagement in different tasks, and in VR particularly [37, 42].

2. Materials and methods

2.1. VR game

The VR game was developed for the oculus quest kit (Oculus VR, Irvine, California, USA), using the unity 3D real-time engine (Unity Technologies SF, San Francisco, California, USA). The virtual environment was a dark sea-floor, randomly seeded with equal amounts of red, green, and blue tokens. A team of three players, represented by red, green, and blue whale avatars, swam in the ocean and explored the virtual environment (figure 1). The team’s objective was to collect a total of 80 tokens as a group, as fast as possible. Each player was able to collect tokens of their respective colors only. To promote engagement and competition, three synthetic scores were displayed on the screen. Players were informed that these scores represented the best times performed by the previous ten groups who played the game.

To navigate through the dark VR environment, the players’ virtual headset was equipped with a flashlight. The luminosity of the flashlight was dynamic and decayed exponentially over time. To improve visibility, players could use tokens that they had collected. Upon picking up a token, a set of red, green, and blue buckets would appear, overlaid with white bars that represented the respective player’s level of visibility (figure 2). Acquired tokens had to be assigned before further token collection was enabled. Players were able to improve their own visibility by assigning the collected token to their own bucket, but they also had the option of assigning the token to their teammates’ buckets to increase their luminosity.

The specifications of the game parameters were calibrated through pilot trails. To ensure that tokens were not too abundant nor too sparse and that the game was completed in a reasonable amount of time, 80 tokens of each color (240 tokens in total) were randomly distributed at the beginning of the game. Since new tokens were
Figure 2. Consecutive screenshots of the game during play. A bar and a score counter display the number of tokens the group had collected. Below the bar, a timer displays the time elapsed since the beginning of the game. Left of the bar, synthetic scores suggest that previous groups had completed the game in 4:11, 4:28, and 4:42 min. (a) The player was approaching a green token. Their own visibility, reflected through the white bar on the green bucket, was the lowest among the three players. (b) One second later, the player collected the token. The score increased from 4 points to 5 points. The green and blue buckets became brighter while the red one remained dark, indicating that the player can assign the token to the blue player or to themselves. A long yellow line extended from the virtual controller to facilitate aiming and selection. (c) The player selected their own bucket (the green bucket) with the controller. (d) The white bar on the green bucket increased and the player’s visibility improved. The buckets became darker as the player continued searching for more tokens.

Figure 3. An illustration of the topologies tested in the study: nodes represent players, and links identify potential sharing of resources between players, where one could assign a token to another, rather than choosing to use it for him/herself. The colors of a node represent the respective colors of a player’s avatar and designated tokens to collect. (a) One topology, T1, was a directed cycle, where each node has the same connectivity of two and the whole network has unitary connectivity. (b) Another topology, T2, was a directed cycle with an additional link, randomly placed between a pair of nodes. The presence of this additional link increased the connectivity of one node, from two to three, thereby leading to a network connectivity of 7/6. (c) The third topology, T3, was a complete graph, where each of the nodes had connectivity equal to four, thereby leading to a network connectivity of two. The topologies appeared at a random order for each team.

In order to promote resource sharing and prevent endless visibility, luminosity was programmed to decay exponentially. The decay constant was selected to create a rapid decay that forced players to rely on others’ help.

The possibility of assigning tokens to other players was constrained by the chosen network topology. A player was able to share tokens with another player only if a directed link existed from his/her node to the node corresponding to their teammate. Three topologies were explored in this study. The first, simplest topology (T1) was a directed cycle, in which players were connected through directed links, where each player was able to give tokens to only one teammate and receive tokens only from the other teammate (figure 3(a)). The second topology (T2) included an extra link with respect to the directed cycle, such that two players could give tokens to only one teammate, while the third player was able to assign tokens to both (figure 3(b)). The third topology (T3) was the complete graph, where players were able to give tokens to any of their teammates (figure 3(c)).
The chosen topologies exemplified increasing overall network connectivity, from T1 to T3, while encapsulating even (T1 and T3) and uneven (T2) connectivity distributions of the nodes. Briefly, these claims can be substantiated by following the computations in [43], which are based on counting the paths between any two distinct nodes, \( u \) and \( v \) in the node set— a path from \( u \) to \( v \) is defined as a sequence of links that connect \( u \) to \( v \), passing through distinct nodes [8]. Specifically, by counting the disjoint paths between \( u \) and \( v \), we compute the connectivity between them, \( k(u,v) \). The connectivity of node \( u \) is obtained by summing over all the possible \( v \) in the node set and the overall network connectivity is the sum of the connectivity of all the nodes, scaled by the total number of potential links (6 in the case of a group of three players) [43].

For example, referring to T2 (figure 3(b)): there is only one path from the green node to either the blue or the red node \( k(\text{green, red}) = k(\text{green, blue}) = 1 \); there is only one path from the red node to either the green or the blue node \( k(\text{red, green}) = k(\text{red, blue}) = 1 \); and there is only one path from the blue node to the green node \( k(\text{blue, green}) = 1 \), but two paths to the red node \( k(\text{blue, red}) = 2 \). Thus, the connectivity of the red and blue nodes are equal to two, the connectivity of the green node is three, and the overall network connectivity is 7/6. Similarly, we can compute that the connectivity of all the nodes in T1 (figure 3(a)) is two and of all the nodes in T3 (figure 3(c)) is four, thereby leading to overall network connectivity of one and two, respectively.

In all experiments, the players were able to give tokens to themselves and at least one teammate. Tokens were not circulable, that is, once a token was allocated, it was consumed and an identical token was regenerated elsewhere on the map. If a topology restricted a player from donating a token to one of their teammates, the respective bucket was greyed out and putting tokens in it was disabled. All the three topologies were tested once in every game, over three rounds in total. The order in which topologies appeared was randomized to minimize learning effects. To minimize confounding factors, the players had no knowledge of their teammates’ connectivity.

2.2. Experimental procedure

This study was approved by the institutional review board at New York University (IRB #FY2018-2174). Thirty groups of three participants (90 participants overall) were recruited on the New York University campus. Each group was escorted into a private room and briefed by the experimenter on the experimental apparatus and procedure. Upon granting informed consent, each participant wore a wireless Oculus Quest headset. An Oculus Quest touch controller was provided for their dominant hand, and a GSR sensor was placed on the middle and ring fingers of their non-dominant hand.

The participants were seated on pivoting chairs so they could explore the virtual environment in 360 degrees without harming themselves or others (figure 4). Communication between individuals was restricted, limiting the interactions to in-game actions of resource allocation. The entire field of view of the participants was occupied by the VR environment, thereby limiting any visual cue from physical presence in the same room. No verbal communication was allowed by the experimenter, who instructed participants not to communicate at the beginning of the experiment. The participants completed a tutorial teaching them how to play the game and began playing. A video illustrating the VR game and experimental set-up is available in the supplementary material.

2.3. Data collection and analysis

Three datasets were generated for each user. The first two datasets were collected with the Oculus Quest: one comprised the scores of the team and of the individual, while the other consisted of the headset’s and hand controller’s position and orientation, at a sampling rate of 50 measurements per second. The third dataset was obtained from the Grove GSR sensor, recording skin conductance at a sampling rate of 18 measurements per second. All available data were processed in MATLAB (MATLAB and Statistics toolbox release 2019a, The MathWorks, Inc., Natick, MA, United States) and analyzed in R (R Core Team, Vienna, Austria).

We began by investigating the influence of topology on group performance. Performance was measured as the amount of time taken to complete each trial, such that less time corresponded to better performance.

To address the hypothesis that improved access to the network through higher connectivity would play a role on improving group performance, we analyzed group tendency to access the topology. The extent to which groups exploited topologies was gauged from the number of transactions they executed, taken as the number of instances a player gave a token to a teammate out of the 80 tokens they have collected as a team.

To test the second hypothesis that varied levels of arousal were responsible for observed differences in performance, we analyzed behavioral and physiological arousal for every player individually. Behavioral arousal consists of the actions executed in response to stimuli in the environment, whereas physiological arousal involves involuntary, autonomic processes that prepare the body to respond. To quantify behavioral arousal,
Figure 4. An illustration of the experimental setup. (a) The players sat in pivoting chairs. Each player was wearing a wireless VR headset and holding a hand controller. The players were forbidden to communicate with one another through verbal. No visual cue existed between them as their entire field of view was occupied by the VR environment. (b) The arrows represent the connectivity of the group, randomly assigned for the portrayed game. The player in the red shirt was able to assign tokens to the player in the gray shirt. The player in the gray shirt could assign tokens to the player in the green shirt. The player in the green shirt was able to assign tokens to both the player in the red shirt and the player in gray shirt.

we computed HRS as the mean of time derivatives of the head rotational angles around the vertical axis. To score physiological arousal, we divided the number of peaks detected by the GSR sensor by the duration of a trial to obtain the mean GSR rate [40, 44], since each trial took a different amount of time to complete. In addition to GSR rate, we also considered the intensity of peaks when studying physiological arousal. Given that each individual likely had a different baseline, the variance of GSR peak values was calculated rather than their mean values [40]. To assess whether arousal had a direct impact on performance by detracting time toward decision-making [10], we also examined the amount of time players invested in deciding whom to assign a token they had collected (whether to oneself or to a teammate). For each player, we measured the average amount of time elapsed from the moment they had obtained a token until they assigned it.

All variables, except for GSR variance, were fitted into linear mixed-effects models [45]. For performance, topology (T1, T2, or T3) was specified as an independent variable, and group and trial as random effects. For the number of transactions, topology was specified as an independent variable and group was specified as a random effect. For HRS, GSR rate, and time to make a decision, topology was specified as an independent variable, and user, group, and trial as random effects. Since the amount of time to make a decision was expected to be directly affected by the number of teammates a player could assist, it was fitted into another linear model, specifying the out-degree as the independent variable (one when a player could help one teammate, and two when a player could help both). User, group, and trial were specified as random effects. All linear models were tested for significance by comparing them against their null models (in the absence of the independent variable) through a likelihood ratio test. Post-hoc analysis was conducted using Tukey’s honest significant difference test [46]. For GSR variances, Levene’s test was performed to test for significant difference across conditions [46].

In addition to testing our two original hypotheses, we explored the specific role of individual attributes on group dynamics. We pursued this analysis along four avenues:

- First, we investigated whether the influx and outflux of resources change players tendency to share. For each user, we computed the ratio of in-degree to out-degree in each trial and the fraction of instances in which he/she had collected a token and opted to share it with other players, rather than using it to...
increase his/her own luminosity. This fraction of transactions was fitted into a linear model, specifying the in-degree to out-degree ratio (0.5, 1, or 2) as the independent variable, and user, group, and topology as random effects.

- Second, we studied whether players adopted a strategy for token allocation based on their individual performance relative to others'. For each group, individual performance was ranked from the number of tokens a player had collected throughout a trial. The player who collected the least number of tokens was identified as a low performer, the player who collected the most tokens was identified as a high performer, and the remaining player was designated as the intermediate performer. Each player’s fraction of transactions was computed and fitted into a linear model, specifying the out-degree as an independent variable and user and group as random effects. To test for significance, all models were compared against its null model using a likelihood ratio test.

- Third, we assessed whether players integrated their teammates’ performance with their own to develop a strategy for resource allocation. The reciprocity of transactions between ranks was evaluated, by computing the fraction of transactions in which players from a given rank (high, intermediate, and low performers) assigned a token to players from the other two ranks. These transactions were compared using a student’s t-test.

- Fourth, focusing on the 30 games with the heterogeneous topology where players had a different in- and out-degrees (T2), we compared group performance when performers’ in- and out-degree was 1 and 2. Specifically, the data was divided into subsets based on players’ ranks, generating three data sets of 30 individuals ranked as high, intermediate, or low performers. For each data set, group performance was fitted into a linear model specifying the out-degree as an independent variable, and user and group as random effects. The model was compared against its null model using a likelihood ratio test, to test for significance.

In all statistical tests, the level of significance was set to $\alpha = 0.050$. 

Figure 5. Group performance, considered as the time taken to complete a game. On average, the groups needed 303.34 ± 16.04, 265.39 ± 14.63, and 290.51 ± 15.63 s (mean ± standard error) to collect 80 tokens when subjected to T1, T2, and T3, respectively. * represents a significant difference between conditions, and ◦ is a trend of difference between conditions.

Figure 6. Influence of topology on sharing of resources. On average, the groups shared 21.80 ± 2.13, 25.03 ± 2.32, and 29.40 ± 2.62 tokens when they were subjected to T1, T2, and T3, respectively (mean ± standard error). * represents a significant difference between conditions, and ◦ is a trend of difference between conditions.
Table 1. Summary of the measurements of arousal in each topology (mean ± standard error).

| Metric                | T1          | T2          | T3          |
|-----------------------|-------------|-------------|-------------|
| HRS (deg/s)           | 5.10 ± 0.49 | 5.19 ± 0.58 | 4.80 ± 0.34 |
| GSR rate (peaks/s)    | 0.11 ± 0.01 | 0.10 ± 0.01 | 0.10 ± 0.01 |
| GSR variance (S^2)    | 2.05 ± 0.99 | 2.52 ± 1.44 | 2.93 ± 1.85 |
| Time to decide allocation (s) | 1.17 ± 0.14 | 1.11 ± 0.12 | 1.13 ± 0.13 |

Figure 7. Influence of out-degree on the amount of time taken to make a decision. On average, 1.16 ± 0.06 s and 1.11 ± 0.06 s passed from the moment players collected a token until they allocated it, when they had only one teammate to share with and when they had two, respectively (mean ± standard error). * represents a significant difference between conditions.

Figure 8. Influence of resource flux on sharing. On average, players shared 0.13 ± 0.03 of the tokens they had collected, when they had twice as many teammates to help than the number of teammates who helped them (mean ± standard error). Similarly, the players shared 0.13 ± 0.01 of their collected tokens when they had an equal number of teammates helping them as the number of teammates they could help, and 0.06 ± 0.01 of the tokens they had collected when they had twice as many teammates helping them. * represents a significant difference between conditions.

3. Results

All groups completed three rounds of the game, each with a different topology. In nine of the experiments, one of the players moved their hand forcefully and inadvertently disconnected his/her GSR sensor. Their curtailed GSR data were not used in the analysis, leaving 243 datasets for the other 81 players out of 270 datasets in total.

Specifying the order in which topologies were presented in the experiments as a random effect did not affect the linear fit for performance ($\chi^2_1 = 0.001, p = 0.976$), HRS ($\chi^2_1 < 0.001, p > 0.999$), GSR rate ($\chi^2_1 < 0.001, p > 0.999$), time to make a decision ($\chi^2_1 = 0.664, p = 0.415$), and number of transactions within a group ($\chi^2_1 = 1.988, p = 0.158$). Therefore, time-effects were omitted from the analysis.

In agreement with our hypotheses, group performance varied with the connectivity of its members ($\chi^2_1 = 7.832, p = 0.019; \text{figure 5}$). Performance was significantly worse for T1 groups, where players were connected through a directed cycle, compared to T2 groups, which included an extra link between two players ($z = 2.752, p = 0.016$). Although failing to reach statistical significance, T3 groups, where players were connected by complete graphs, performed better than T1 groups ($z = 2.074, p = 0.095$).
When inspecting the way in which groups exploited their interconnecting topologies, we found that sharing was significantly influenced by connectivity ($\chi^2 = 18.148, p < 0.001$; figure 6). A greater number of transactions were recorded in the complete topology, compared with either of the other two networks (T1: $z = 4.509, p < 0.001$ and T2: $z = 2.591, p = 0.025$, respectively).

Upon examination of arousal and engagement, differences were not registered for HRS ($\chi^2 = 0.914, p = 0.633$; table 1), GSR rate ($\chi^2 = 1.549, p = 0.460$), and GSR variance ($F = 0.250, p = 0.778$). With respect to decision-making, while the amount of time players needed to decide whom to assign a token did not significantly differ between topologies ($\chi^2 = 0.827, p = 0.661$), it did depend on players’ out-degrees ($\chi^2 = 6.559, p = 0.010$; figure 7).

In our exploration for potential effects of individual attributes on group dynamics, we found that the out-degree and in-degree played a role on sharing. The potential flux of tokens (ratio of in-degree to out-degree) affected sharing ($\chi^2 = 10.588, p = 0.005$; figure 8), whereby players shared more when they had an equal amount of teammates to help as the amount of teammates helping them, relative to when they received help from twice as many teammates ($z = 3.535, p = 0.001$).

Players were also found to allocate tokens differently, based on their individual performance ($\chi^2 = 5.997, p = 0.049$; figure 9), whereby the high and the intermediate performers shared less than the low ones ($z = 2.190, p = 0.072$ and $z = 2.188, p = 0.072$, respectively). Interestingly, token allocation was not always symmetric (figure 10). High performers assigned significantly more tokens to low performers than to intermediate ones ($t = 2.236, p = 0.026$) and low performers did not reciprocate with the intermediate ones ($t = 2.530, p = 0.012$). Although not statistically significant, two trends were noted, where intermediate performers assigned more tokens to high performers than low ones ($t = 1.554, p = 0.122$), and high performers did not reciprocate with intermediate ones ($t = 1.576, p = 0.116$).
Influence of individual performance and connectivity on the performance of the whole group for the T2 network. On average, the group completed the game in $273.46 \pm 18.73$ s when high performers were able to share resources with one other player and in $256.12 \pm 16.74$ s when they were, instead, connected with two players; the group completed the game in $280.25 \pm 19.21$ s when intermediate performers were connected with one other player and in $236.11 \pm 12.29$ s when they were connected with two; and the group completed the game in $242.86 \pm 14.57$ s when low performers were connected with one other player and in $299.11 \pm 19.75$ s when they were connected with two. * represents a significant difference between conditions, and ◦ is a trend of difference between conditions.

From scrutiny of group dynamics when the network was heterogeneous with unevenly-distributed links across the nodes (only T2), we registered an effect of the individual connectivity of high and low performers on group performance. Allowing the high performer to freely allocate tokens was beneficial to the entire group performance ($z = 2.539, p = 0.011$), whereas providing the low performer with such a possibility was detrimental for the group ($z = 2.522, p = 0.011$; figure 11).

4. Discussion

In the present study, we aimed to elucidate the role of network topology on the dynamics of small human teams and its impact on group performance. To this end, we designed an interactive game in VR for three participants, who played together toward a common goal. The game was presented in a competitive context (groups were encouraged to perform better than previous groups who played the game), such that players were driven to optimize group performance by helping one another. Their interactions were constrained by a preassigned network topology, which allowed some players to help or be helped by their teammates. In a series of experiments, we explored three topologies, chosen to encompass different levels of connectivity, with homogeneous and heterogeneous structures.

We expected that higher connectivity would improve group performance, and therefore formulated two hypotheses about the processes underlying potential improvements. First, we posited that having more options to interact with others would yield higher levels of resource sharing, augment coordination, and ultimately enhance group performance [19, 47]. While our findings verify that opening more channels for collaboration within a group improves its performance, it appears that the extent of improvement plateaus as the number of connections increases.

Ferriani et al offered two theoretical mechanisms that explain the diminishing returns of increasing connectivity [48]. Through the first mechanism, higher connectivity incurs higher coordination costs where time, attention, and energy are diverted to maintaining a larger number of relationships rather than devoted to the activities critical for achieving the group’s goal. The second mechanism proposed by Ferriani et al accounts for cognitive overload individuals experience, as they process larger amounts of more complex information [48–50]. With more neighbors to interact with, individuals are required to simultaneously compound the potential outcomes of their actions and assess the risk of poor decision-making [10, 51]. The resulting cognitive strain could adversely affect coordination and compromise performance. Hutchins provided mathematical support to this notion, where he found that the groups of networks converge to optima when there is a moderate number of connections between nodes, yet converge on inadequate solutions when nodes are highly connected [52].

In our study, we did not find a difference between group topologies with respect to the amount of time participants needed to decide on resource allocation. At the individual level, we found that participants took significantly longer time to allocate tokens when their out-degree was lower. However, only a negligible difference of 0.05 s was registered. It is tenable that this modest difference arose due to diffusion of responsibility [53]. Diffusion of responsibility refers to the sociopsychological phenomenon where an individual is less likely to assume responsibility of action in the presence of other individuals. In our game, diffusion of
responsibility may have translated to reduced sharing. That is, when a player was helping both teammates, he/she would relay liability to the teammates, assuming they would help one another too. In contrast, if a player helped only one teammate, he/she had to critically choose between helping him/her and keeping the token to himself/herself. Alternatively, it is possible that the coordination in our game cost players in attention, energy, or some other toll.

Within the second hypothesis, we posited that higher connectivity would augment individuals’ arousal, thereby improving performance. Changes were not reflected through the physiological and behavioral metrics considered in this study. Conceivably, the high level of immersion granted by VR was associated with a ceiling effect whereby the already elevated HRS and GSR measurements exhibited negligible responses when additional interactions were introduced [37]. A longitudinal study, where subjects play the game multiple times and become accustomed to VR technology might help verify whether such unwanted ceiling effects exist [54]. Alternatively, the influence of engagement on group performance can be compared between media that elicit varying levels of presence such as voice or video chat on computers [55].

Another factor that might have underpinned the observed differences in group performance could be related to variations in individual attributes among players, which would be best leveraged in the heterogeneous network. We found that players’ in-degree and out-degree impacted sharing, whereby players who had more teammates helping them than they helped others, shared less. In spite of this counter-intuitive result, it is tenable that players better-identified with their teammates when they were sharing the experience of struggle. That is, when players received less help from other group members, they experienced the difficulty of the challenge and, in return, chose to help others. Under this premise, players’ appraisal of collaborative efforts peaked and they needed help from others.

Familiarity with the location of high performers within a network, and having access to them are known to facilitate effective coordination [56]. Therefore, one could intuitively argue that high performers should be granted a more central position within the group [57, 58]; conversely, low performers should have the most restricted connectivity. This intuition is supported by our data, which indicate that group performance improved when high performers were more central in the heterogeneous network, and it deteriorated upon increasing the connectivity of low performers. Likely, players compared their ability against others’, identified the better performers, and diverted their resources toward them as part of their strategy. The low performers, who were also the most benevolent players, helped the high and intermediate performers equally. Similarly, the intermediate performers directed resources toward the high performers, rather than the low performers. Overall, it appears that the flow of resources was channelled toward the high performers. In turn, the high performers, who sometimes had an excess in resources, chose to allocate them to the low performers. Following such a strategy may be driven by self-interest, as engaging low performers also ensures that the best performer has a network to utilize.

Although our efforts shed light on the possible effects of network topology on group performance, we acknowledge several limitations. First, while our experimental design eliminated many potentially confounding factors, it did not properly represent a realistic collaboration scenario. For instance, one’s knowledge of who is helping them would have likely led to reciprocity and given rise to different dynamics. Second, the results of our study framed collaboration in a recreational context. Therefore, our findings may not be generalizable to formal groups in educational or professional circumstances, where the motivation to collaborate is different and other dynamics exist between individuals. Third, the study is experimental in nature, thereby lacking of a mechanistic mathematical model that could assist in analysis and prediction. Developing such a model will be the objective of future research to better inform link assignment. For example, it has been mathematically demonstrated that pairs who are strongly connected are more likely to interact with shared acquaintances [59]. Knowledge about such behavioral patterns could inform the strategic assignment of bidirectional links between individuals to promote collaboration within certain portions of the network.

For large networks that are dominated by short-range interactions where an individual interacts always with the same peers, it is tenable that equivalent results to those presented herein would hold. Specifically, it is foreseeable that increasing local connectivity would favor individual performance [60] and that the specific topological features of high and low performers in the group would modulate the overall group performance [16]. For dense networks or in the presence of long-range interactions, it is difficult to predict the role of connectivity. On the one hand, a positive effect of connectivity on group performance might be anticipated on the basis of an increased ability to rapidly distribute resources throughout the entire network [14, 15]. On the other, individuals may not be able to properly distinguish between different performers, thereby reducing their ability to optimally distribute resources [22]. Should players be able to accurately appraise the performance of others, they may also opt to pursue individualistic strategies based on diffusion of responsibility that may ultimate lower group performance [53].

Experimenting with large groups may not be feasible with the current experimental setup for the following reasons. First, it is practically difficult to recruit large teams to play the VR game at once in the laboratory,
while ensuring that there is no other communication pathway beyond those enabled by the VR environment. Second, we cannot exclude the possibility of lags in the presentation of the VR environment to each of the participant due to computer overload; these lags might skew experimental results, by changing the experience of each of the participants. Third, the number of trials to support hypothesis-driven experiments like those conducted herein might become prohibitive. A potential line of approach might entail experimenting online, using platforms like Amazon Mechanical Turk, although recruiting several participants to simultaneously perform a cooperative task could remain challenging. As one embarks on experimentation with large groups, it will be important to conduct power analysis [61] to determine appropriate size for the group as a function of the questions being asked. This power analysis can be informed by combining our experimental results with a mathematical model [62].

Using the current experimental setup, we envision studying the effect of time variations in the network [63], due to links that dynamically change during the experiment. Likewise, the current setup could be used to explore the role of multiple interaction pathways, by allowing participants to share controlled information through other communication channels, such as using microphones for strategizing with other team members.

This effort offers insight into the role of group structure on its dynamics and performance. Connectivity was found to be positively associated with group performance, and this effect was not linear, likely due to the mediating effect of structural heterogeneity. The results suggested that performance improves when individual connectivity is heterogeneous within the group and high performers have the largest connectivity. The findings shed light on the relationship between group structure and performance, and the factors underlying it, toward an optimization of small group collaboration efforts.

Acknowledgments

This work was supported by the National Science Foundation through the following grants: CMMI-1433670, CMMI-1561134, and CBET-1604355. The work of RBV and JH work was supported in part by a Mitsui-USA Foundation scholarship. The authors would like to thank Drs S Macrì and S Nakayama for fruitful discussions and valuable input.

Author contributions

RBV, JH, and MP conceptualized the research. SR developed the virtual reality environment. RBV and JH conducted the experiments. RBV and MP analyzed the data. MP supervised the research. RBV wrote a first draft of the manuscript. RBV and MP consolidated the draft in the final submission. All the authors reviewed the submission.

Data availability

The data that support the findings of this study are available upon request from the authors.

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