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Cognitive Social Structures in Context of High School Classroom

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ABSTRACT – Cognitive social structure maps the social relationships perceived by actors. This study characterizes the social network pattern of a high school classroom and verifies the perceived ties and the accuracy of social relationships reported by 23 students. Analyses of the cognitive social structure aggregations verified the density of these relationships. Most participants show vulnerabilities and conglomerate analysis of network structural data shows different perceptions of density and modularity. Our results differ from the limited literature in the area regarding higher accuracy in subjects with a lower centrality degree and intermediation.

KEYWORDS: Cognitive social structure, adolescent, data reliability, deficiency, school

Estruturas Sociais Cognitivas em Contexto de uma Sala de Ensino Médio

RESUMO – A estrutura social cognitiva mapeia as relações sociais percebidas pelos atores. Este estudo caracteriza o padrão de rede social de uma sala de aula de ensino médio e verifica a percepção de laços e a precisão das relações sociais relatadas por 23 alunos. As análises das agregações da estrutura social cognitiva verificaram a densidade desses relacionamentos. A maioria dos participantes apresenta vulnerabilidades e a análise dos conglomerados de dados estruturais da rede demonstra diferentes percepções de densidade e modularidade. Nossos resultados diferem da pouca literatura na área quanto a maior precisão em sujeitos com menor centralidade de grau e intermediação.

PALAVRAS-CHAVE: Estrutura social cognitiva, adolescente, confiabilidade dos dados, deficiência, escola

The field of social networks is broad, diverse, and characterized by the absence of a joint agenda (Ibarra et al., 2005). However, at the confluence of disciplines, in recent years, as Brands' (2013) review points out, there has been a resurgence of interest in how individuals perceive and cognitively represent the relationship networks around them. Cognitive monitoring of social networks makes it possible to track and use information about social networks. This has been fundamental to the success of humans as a species (Dunbar, 2008).

Special attention is given to the network delineation in Cognitive Social Structure (CSS), defined as a set of social network cognitive representations (Krackhardt, 1987). In terms of network analysis, both CSS and strict Social Network Analysis (SNA) seek to describe interaction patterns that circumscribe behaviors and experiences of individuals in the social worlds in which they live. However, while SNA focuses on the actual configuration of the ties that surround individuals, CSS research seeks to describe these interaction patterns as perceived by individuals in network structure. Thus, based on the notion that relationship networks are also perception networks (Ibarra, Kilduff & Tsai, 2005), rather than focusing on a single relationship network, CSS research examines social networks from the idiosyncratic point of view of each member (Brands, 2013).

The cognitive network perspective present in CSS is not reduced to seeking evidence that perceptions represent actual interaction patterns or an indirect way to get data on "inaccessible" social networks. In contrast, CSS research considers network perceptions as phenomena of interest in their own right (Krackhardt, 1987), and focuses on the subjective experiences of individuals in their social environments (Brands, 2013). By asking people to describe the social structure around them, CSS research aims to uncover the cognitive schemas underlying social relationships (Krackhardt, 1987). This approach originates in Kurt Lewin's field theory, which projects individuals' behaviors as being determined by the subjective experiences of their social environment (Brands, 2013). In this sense, Krackhardt (1987) believes that the main contribution of CSS research is to broaden and deepen approaches to social networks, drawing attention to networks' cognitive dimensions. This is clear in the phenomenological stance that CSS research adopts on how we should understand individuals' network cognitions.

Despite possible variations, the most common method associated with CSS research is the list (Brands, 2013), formalized by Krackhardt (1987). It comprises defining a finite set of actors to be included in the analysis of social networks—for example, a school or a classroom. After this delimitation, participants are given a list of components from the chosen limited social system to be analyzed. Each participant is requested to indicate their affiliation patterns, depending on the research objectives, e.g., who hangs out together, who takes advice, with whom they identify, etc. Additionally, the CSS list expands this method to the participant's perceptions of their relational context, and the relationships of the alters: who hangs out together, who takes advice from whom, and who identifies with whom. This procedure is repeated for each participant in the respondent's network.

In this sense, Krackhardt (1987) proposes three aggregation methods for cognitive social structures based on informant reports: (a) Slices, (b) Locally Aggregated Structures (LAS), and (c) Consensus Structures (CS). A slice represents the relationship network as perceived by a single individual (i.e., his or her cognitive map). Thus, the relationship Xij is said to exist if the perceiver perceives it. In contrast, a LAS examines individuals' perceptions of their relationships, sometimes called ego networks. Here, individuals show all people to whom they address a certain type of bond (Krackhardt, 1987). Comparing the individuals' LAS allows the derivation of the actual network; then a relationship between Xij is said to exist if both i and j agree on the existence and direction of the tie (Brands, 2013).

The final aggregation is consensus structure, where the relation between i and j is judged by all observers, i.e., it scans the entire observer vector to determine the existence or non-existence of the relation (i, j). It can apply different thresholds to determine whether relationships exist, for example, a relationship can be said to exist if 50 percent of the individuals in the network perceive it (Brand, 2013). It is possible to define thresholds in other ways (see Neal, 2008), but this discussion is beyond the scope of this paper. Thresholds, or cutoffs, are determined a priori for aggregation, and true relationships are found according to algorithms, such as the Krackhardt Equation (1987):

$$\text{Ri, j} \begin{cases} 1 \\ 0 \end{cases} se \ \frac{1}{N} \sum k \ Ri,j,k \ \geq limite$$

By definition, slice data is filtered by perceptions of a single actor, which can be affected by unique biases or by the social situation the informant occupies. Therefore, this data has limited external validity. Slice data is, however, very useful when compared to "real" data (LAS) or consensus data (CS). It can generate an individual accuracy measure regarding perceptions of the network patterns in which the subject is inserted. In other words, the correspondence between someone's perception of the relationship (tie) between two individuals and the actual existence of that tie (Brands, 2013).

These perceptions of the personal network (people directly connected to the subject/actor) and the total network (people connected in the same group), when compared with the "real" networks, reveal the subject's accuracy in terms of network patterns. By identifying accuracy, it is possible to compare the subjects with the best perception and the possible existence of some relationship between their attributes, and the accuracy in the perception of how they see their network (Portillio & Baena, 2019). In turn, there is data also indicating that the subject's relational patterns in the network itself may be linked to their accuracy in reading the relationship network. For example, members with low centralities, such as those on the periphery of the network or at the bottom of the hierarchy (unpopular, low status), tend to have more accurate representations than those who are more central (Portillio & Baena, 2019).

As can be seen from this discussion, the CSS is a complex procedure for both data collection and analysis. The information required in the collection requires a rigorous procedure to provide detailed information on the personal social relationships of every member in their network system. This may be why Neal (2020), in his systematic review of indexed journals in the field of developmental psychology, found less than 4% of studies using this technique, and only two in the school context with elementary school children.

On the other hand, despite high costs, the possibility of triangulation is one way to reduce measurement bias and guarantee data validity (Singleton & Straits, 1999). The data's multidimensionality makes it possible to collate different perspectives of network cognition present in a social group.

CSS triangulation in the few empirical studies carried out in a school context with children or university students shows interesting results in terms of accuracy. A study with

MBA students used indegree centrality to verify accuracy in identifying changes in interpersonal ties over time (Ertan et al., 2019). The work of Rodríguez-Medina et al. (2018) in the context of a classroom with an autistic student triangulated friendship perception. Several friendship ties between the autistic boy and some of his classmates were confirmed through the LAS analysis. However, the CS did not confirm the same bonds perceived in the LAS. Research by Neal et al. (2011) analyzed variation in the perception of relational bonds in a classroom, from the perspective of the teacher and the students. According to previous findings, accuracy in the perception of relationships increases as the school year progresses and is better in small classrooms.

Neal's (2019) review also found that most articles focused on social network data collected in primary or high schools, but none with differentiated grouping characteristics. In this systematic review, only two studies used CSS as a method and the participants were elementary school students.

Thus, this research analyzed cognitive social structures in the context of a high school classroom, with students grouped according to low academic performance. The school-based program that justifies this organization is called Mundiar. The Mundiar project is a learning acceleration program started in 2014. It assists students with year-age gaps. The aim is to improve the quality of basic education in the state of Pará (SECOM, 2015) and prepare these students through projection room methodology for the National High School Exam (ENEM) — an annual test that grants access to higher education. The Mundiar project's methodology is based on the aspect of one-to-one teaching (Mesquita, 2018). Although there is no research describing the pedagogical arrangement provided by the Mundiar Project, it tends, in practice, to segregate students with academic performance deficits in the classroom. This reorganization of the school environment can influence network arrangements developed in the classroom. This study aims to characterize the network pattern of students in a special high school classroom and to verify, in this group, what type of network perception measure gives some advantage regarding the accuracy of relationships present in the same group.

METHOD

This research is characterized as a descriptive and exploratory quantitative study.

Participants

The class under investigation has a high number of repeating students: of the 23 members, 16 have repeated at least once, and there are subjects with four repeats (Table 1). As for the classification on the ETDAH scale, 11 participants showed some indication of ADHD, 5 of whom presented a mixed profile. In the RAVEN diagnostic summary, only 2 showed average intelligence, the others showed below-average intelligence, and the majority of these (17) showed below-average intelligence with an indicator of mental deficiency. In the Trail Test, especially in the assessment of Trail B, 16 of the 23 participants showed a deficient profile, and only 1 showed a superior profile. Some participants showed a more compromised profile than others, such as Ayla, Juli, and Sara (fictitious names), with an indicator of mixed ADHD (ETDAH), definitely below-average intelligence (RAVEN), and deficient (Trails B). However, in general, it can be said that the class is homogeneous in its set of impairments; there are marked deficits identified in the instruments analyzed and in the school record. The only exception is Pedro, who does not have an ADHD profile and shows average intelligence on the intelligence scales.

Instruments and measures

The following instruments were used to characterize participants and the classroom Cognitive Social Structure:

Bio-sociodemographic Inventory (ISD) forms: The ISD was developed based on Dell'Aglio, Koller, Cerqueira-Santos, and Colaço (2011). The Developmental Ecology Laboratory (LED), Behavior Theory and Research Postgraduate Program – Federal University of Pará (UFPA) adapted it. The ISD aims to characterize participants' profiles and their family groups. This questionnaire collects social, demographic, and economic data on the participants and their families, as well as data on schooling, health care, and extracurricular activities carried out by the students.

ETDAH Scale Forms – Adolescent and Adult Version (ETDAH-AD, Benczik, 2013): developed specifically for Brazil, this scale has an excellent level of accuracy and reliability. Comprises 69 items and assesses five factors: 1) Inattention, 2) Impulsivity, 3) Emotional Aspects, 4) Self-regulation of Attention, Motivation, and Action, and 5) Hyperactivity. The Attention Deficit Hyperactivity Disorder Scale assists in the diagnostic process of ADHD, allowing us to distinguish disorder presentation, and the intensity and level of impairment (mild, moderate, or severe).

Trail Making Test (TMT) form, developed by Partington (1938). A highly sensitive test is used to identify cognitive deficits and assess divided attention. The test seeks to capture the ability of an individual to maintain mental engagement, visual tracking, motor function dexterity, processing speed, and working memory (Mota, Banhato, Silva & Cupertino, 2008; Votta, 2009).

General Progressive Matrices Scale Forms, Series A, B, C, D, and E (Raven, 2000): instrument often used to assess important aspects of intellectual potential. The test assesses the ability to grasp meaningless figures presented to the individual and discover relationships between these figures. One must imagine the nature of the figure completing the implicit system of relationships to develop a systematic method of reasoning (Raven, 2008). The scale aims to assess the breadth of intellectual development at all stages of development.

Cognitive Social Structure Questionnaire: A questionnaire developed according to the cognitive social structure design (Krackhardt, 1997). Initially, the participant was given a list containing all the students in their class and told: "This is the list of students in this class". And then, asked two questions: "Are there students who hang out together a lot in your class? Who are they?" There was no limit to the number of relational ties. If they realized a classmate didn't hang out with other people, they didn't have to name him or her. After answering these questions, the next question was: "Who do you hang out with in class?" In this way, every participant reported his or her perceptions of each member of the network and about him or herself.

Procedures

Ethical procedures

The Ethics Committee of the Tropical Medicine Center of the Federal University of Pará Research approved the research project, under protocol number 3.352.152, on May 28, 2019. Before starting the collection, participants

Table 1
Main data on participants summarized.

NAMES	AGE	REPET.	QTY REPET.	CLASSIFICATION ETDH	RAVEN DIAGNOSIS	TRIAL A	TRIAL B
Aldo	18	Yes	4	No ADHD	Definitely below-average intelligence	Deficit	Deficit
Ana	17	No	N/A	No ADHD	Definitely below-average intelligence	Average	Deficit
Ayla	19	Yes	2	Combined	Definitely below-average intelligence	Deficit	Deficit
Beca	18	Yes	2	Combined	Definitely below-average intelligence	Limit	Superior
Bete	17	No	N/A	No ADHD	Definitely below-average intelligence	Deficit	Deficit
Cléo	18	Yes	2	No ADHD	Below average intelligence	Limit	Below Average
Diva	18	No	N/A	No ADHD	Below average intelligence	Deficit	Deficit
Dora	17	Yes	2	Inattentive	Definitely below-average intelligence	Below Average	Deficit
Fred	17	No	N/A	Inattentive	Average intellectual ability	Average	Limit
Gina	17	Yes	1	No ADHD	Definitely below-average intelligence	Average	Deficit
Hugo	18	Yes	NA*	No ADHD	Below average intelligence	Limit	Deficit
Jaci	18	Yes	2	No ADHD	Definitely below-average intelligence	Deficit	Deficit
José	18	Yes	2	No ADHD	Definitely below-average intelligence	Average	Deficit
Juli	17	Yes	NA*	Combined	Definitely below-average intelligence	Limit	Deficit
Lara	17	No	N/A	No ADHD	Definitely below-average intelligence	Limit	Deficit
Luiz	17	Yes	2	Inattentive	Below average intelligence	Below Average	Superior
Luna	17	Yes	2	No ADHD	Definitely below-average intelligence	Average	Deficit
Mara	18	Yes	1	Inattentive	Definitely below-average intelligence	Deficit	Deficit
Max	20	No	N/A	Inattentive	Average intellectual ability	Average Inferior	Average Inferior
Mike	17	Yes	2	Inattentive	Definitely below-average intelligence	Deficit	Deficit
Pedro	17	Yes	2	No ADHD	Average intellectual ability	Average Superior	Average
Sara	18	Yes	3	Combined	Definitely below-average intelligence	Average	Deficit
Theo	19	No	N/A	Combined	Definitely below-average intelligence	Limit	Below Average

Note: Names are fictitious. N/A: not applicable. NA*: no answer were asked to read and sign the Free and Informed Consent Form (TALE) (for adolescents) and the Free and Informed Consent Form (TCLE) (for those over 18 and their guardians). This was done under Resolution 510/2016 of the National Health Council/Ministry of Health, which sets out the rules for research involving human beings. The names described here are fictitious.

Data collection procedure

Following the introduction of the research project to the school board, technical staff, teachers, guardians, and students, the instruments were collected in two phases. During the first phase, the TALE, and the sociodemographic data were collected. Raven Matrices Test, the ETDAH scale form, and the Trails Test were applied. In the second phase, a classroom with a profile of students with low school performance was selected to apply the total social network questionnaire in the Cognitive Social Structure (CSS) design. All students in this classroom took part in the survey.

Analysis procedure

With Excel and Ucinet programs (Borgatti, Everett & Freeman, 2002), the participants' answers were arranged in matrices and analyzed according to the Cognitive Social Structure (CSS) model for measuring perceptions of peer networks in the classroom (Krackhardt, 1987; Neal, 2008).

A CSS network involving N individuals is represented by a three-dimensional matrix R i, j, k (i, j, k = 1, ..., N), where i is the sender, j is the receiver and k is the perceiver of the relationship (Krackhardt 1987). To turn three-dimensional data into two-dimensional data, the three CSS aggregation methods proposed by Krackhardt (1987) were used: Slices, Locally Aggregated Structures (LAS), and Consensus Structures (CS). Slices reflect an individual's perception of the network. Thus, it shows all ties between i and j, keeping the observer constant. A slice is a square matrix of sent ties and received ties. It holds data on the entire network from the perspective of just one observer.

LAS are traditional ways of gathering network data, relying on information provided by the receiver or sender of a specific connection. In this work, to assign a tie, only reciprocal perceptions were considered using the intersection rule R i, j = {Ri, j, i ∩ Ri, j, j}, i.e., both actor i and actor j must agree on its existence. The network perceptions of all individuals were computed to form the CS. Agreements above 50% are the threshold for the existence of a relationship between i and j. The CS provides valuable information on the presence of a "meeting" relationship between any two students in the classroom, and the relevance of this relationship to their peers (Neal, 2008).

To better classify the groups, structural network patterns presented by participants in their slice reports were evaluated based on conglomerate analysis, using the PAST program (Hammer, 2017). To assess the accuracy of individual network perception, information from each participant's Slice matrix and the LAS matrix with agreement above 50% was cross-referenced using the UCINET program to generate an accuracy index. Correlations between these measures were made using the JASP program (JASP Team, 2020) to examine possible advantages in the accuracy of relationship perceptions in the profile of differentiated structural perceptions of the network.

The results are discussed in a didactic-narrative way to help readers understand the complexity of the analysis procedure involved.

RESULTS AND DISCUSSION

CSS's database is sliced, i.e., a three-dimensional data structure, in which the observer is kept constant, a single layer of the CSS matrix. In the group dataset, in a CSS data matrix, rows list the senders of the ties, columns list the receivers of the ties, and each layer or slice is the perceiver of these ties. Thus, a slice corresponds to a square matrix of sent and received ties and holds data on the entire network only from the perspective of one observer. In slice data, the perceptions of a single actor are present, reflecting his/her biases. For this reason, they have intrinsic validity, but limited external validity.

As in traditional social network analysis, it is possible to produce metrics for each slice relating to the place of each participant (and his/her self-assessment) in the network according to the observer's perception (degree centrality, mediation, proximity, and eigenvector). It is also possible, depending on the relationships described from the observer's perspective, to produce measures of network structure, such as density, average distance, and modularity.

When comparing participants' slices, network positioning data is of little use. However, structural network perception data can reveal singular patterns of perception of each network member about the group. Through conglomerate analysis (nearest neighbor method, Euclidean distance) it is possible to verify which subjects are close in their structural perceptions of the network (number of connected components, total number of components with a single vertex, maximum vertices connected to a single component, maximum edges in a connected component, network diameter corresponding to the maximum geodesic distance, average geodesic distance, graph density, and modularity) see Figure 1.

One can see two extremes in the resulting conglomerate: at one end, Bete, Luna, Ana, and Sara, and the other end, Dora, Cleo, and Ayla. Among the metrics used, the perceived network density stands out, which in the first group corresponds to results of 0.134, 0.130, 0.099, 0.142, and in the second group (with higher density), 0.364; 0.324, and 0.320.

For demonstration, Figure 2 shows image slices of the actors Bete, Luna, and Ana, who have perceptions of a group with low cohesion with different components, with no clear connection between them. The social world in the perception of these subjects is more fragmented. Dora, Cleo, and Ayla, on the other hand, represent group perceptions with lower density, greater internal cohesion, and an absence of distinct components.

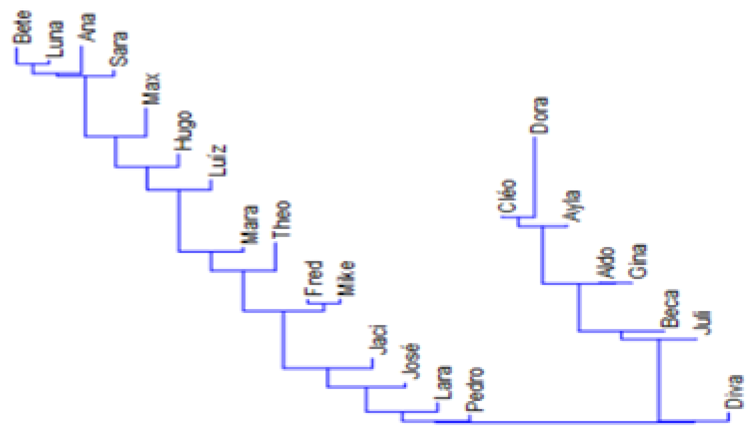


Figure 1. Conglomerates resulting from structural network variables according to the perception of each participant

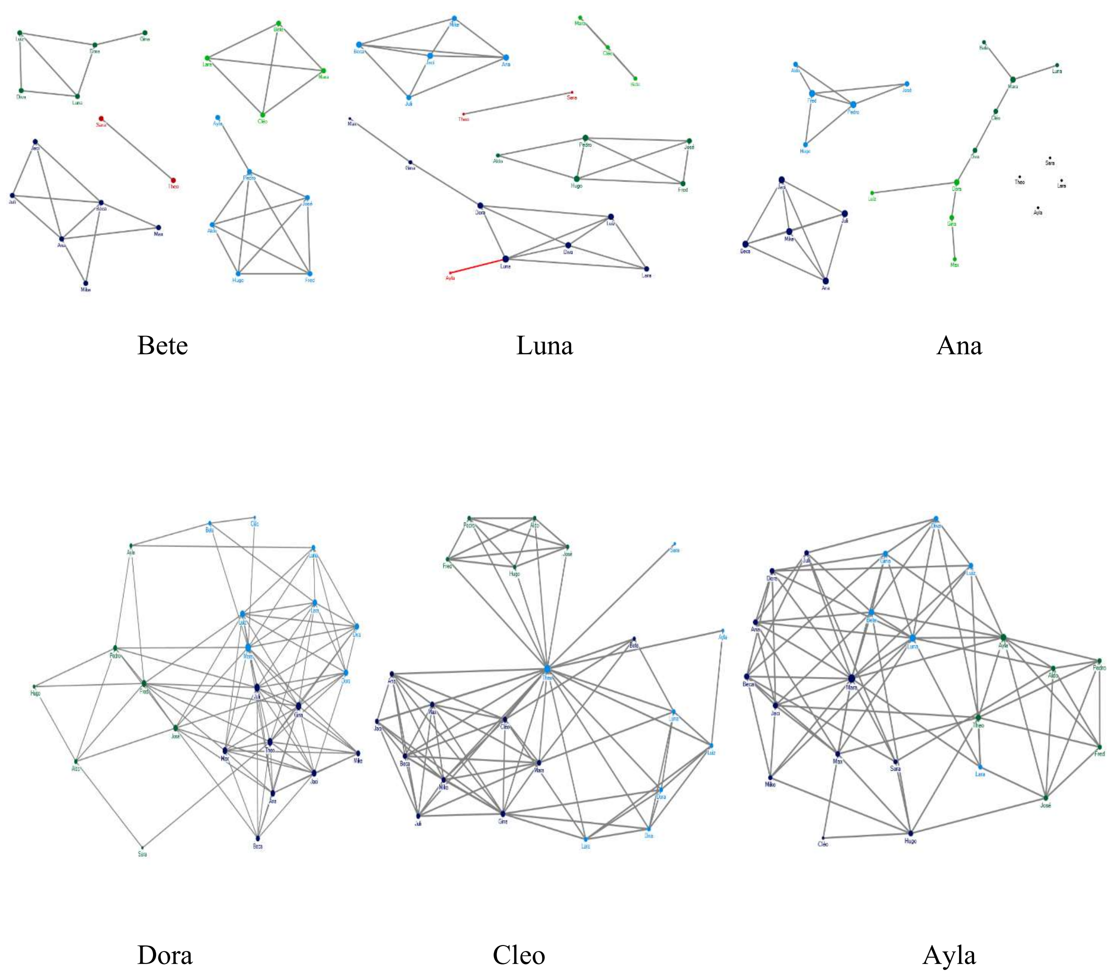


Figure 2. Slices of six participants, revealing two distinct personal perceptions of the group network structure.

Local aggregated perceptions and the perceptions of others

In the social perception approach, the two other aggregations of CSS data are the Locally Aggregated Structure (LAS) and the Consensus Structure (CS). With the former, the resulting reduction between i and j depends on the information provided by the most local members of the network, i.e., i and j themselves, and hence the name (Krackhardt, 1987). As it may seem, the reduction in LAS is the same kind of data normally collected in traditional sociometry (Moreno, 1960). Here, to increase measurement reliability of this aggregation, the intersection rule R i, j = {Ri, j, i ∩ Ri, j, j) was used, i.e., for a tie from actor i to actor j to exist in the aggregated network, both actors i and actor j must agree on its existence.

The CS deals with perception data from all respondents. The relationship between i and j is judged by all k observers, i.e., it reflects the set of perceptions held by everyone about the link between i and j in the network. Thus, as Krackhardt (1987) points out, there is a need to establish parameters for consensus (threshold), some minimum proportion of agreement between perceivers that the tie exists. Krackhardt (1987) advocated the use of a simple majority threshold according to the formula below, where the threshold can take on any fractional value from 0 to 1. In this case, the threshold of 0.5 would be interpreted as the existence of the relation from i to j, i.e., the relation exists if most of the network members perceive that it exists.

$$R^1 i,j = \begin{cases} 1\ se\ \dfrac{1}{21} \\ 0\ de\ outra\ forma \end{cases} \sum_{k-1}^{21} Ri,j,k \geq 0.5$$

Based on one LAS matrix and one CS matrix, it is possible to produce graphs of the relationship networks in the classroom. In other words, a sociometric network of intersecting LAS (reciprocity of network evaluation between participants in the local network) and consensus (how most of the group perceives the social network). Figures 3 and 4 represent the LAS and CS network graphs, respectively. In these figures, blue circles represent boys and pink circles represent girls. The circle sizes represent the centrality degree in the network.

As seen in Figures 3 and 4, despite differences, there are similarities confirming correlations shown in the literature (Neal, 2008) between these two aggregations. The cliques Cleo, Mara, and Bete; Fred, Hugo Pedro, Aldo, and Jose; Lara, Diva, Dora, Luna, and Luiz; Max, Mike, Ana, Jaci, Gina, Juli, and Beca repeat themselves. Although subgroups repeat the centrality degrees, and fundamental intermediary roles are different, overall, it can be said that CS is more exclusionary than LAS, so that in LAS only participant Sara is excluded. Thus, it showed no reciprocal relationship. In CS, three participants do not agree with the others, including Theo, and Ayla, and Sara. It is worth remembering that Sara, Theo, and Ayla had a combined score on the ETDAH scale and a set of deficits on other intelligence assessment scales.

In short, among reductions present in the CSS, slice operationalizes individual perception, LAS operationalizes the reality of the relationships between those involved, and CS operationalizes the reality of the set of perceptions present in the group. The advantage of these different dimensional network structures is that they allow an accurate calculation. Comparing slice with LAS and CS indicates how individual perception is close to relations perception between those involved, and relations of the about set perceptions of the group.

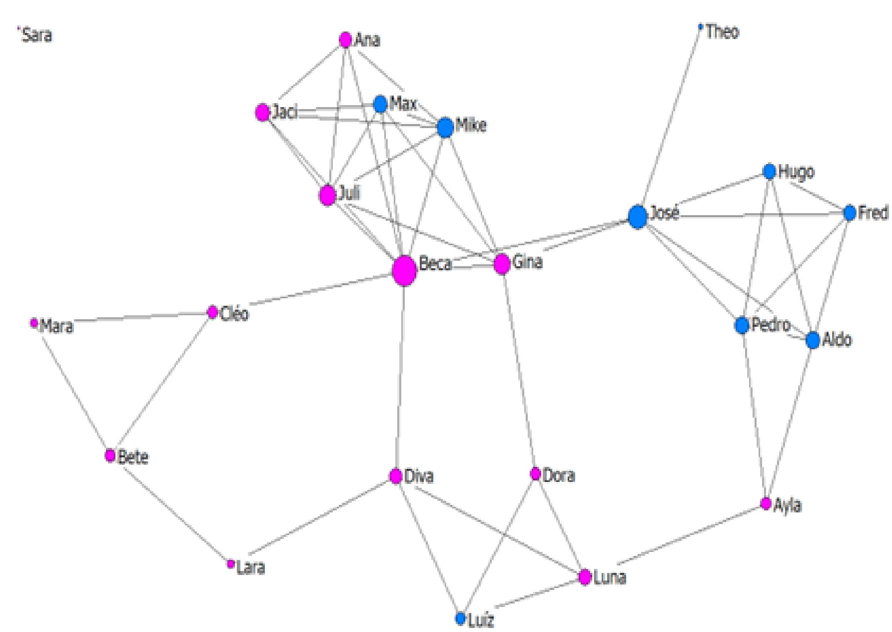


Figure 3. Locally aggregated structure of the studied group.

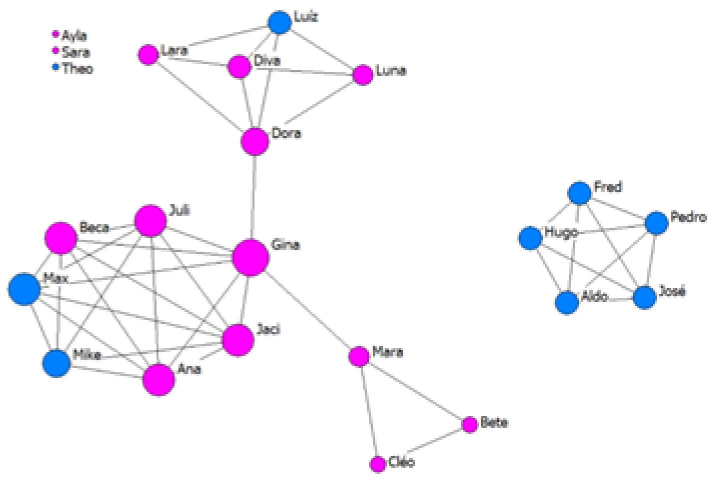


Figure 4. Consensus structure of the studied group.

Anyway, assessing accuracy requires establishing a "fundamental truth" or criterion against which "perceptions are tested". For our purposes, we took the theoretical criteria of reciprocal and self-reported relationships (Neal et al., 2014). In this sense, LAS becomes the best available indicator of true relationships in a classroom because data was obtained directly from the individuals involved in the relationships, and because both members of the relationship confirmed it.

Accuracy data is useful to identify the extent to which the perception of your social network is closer to what is a social network. It also allows you to evaluate if social network is related to your place in the network topography, or your structural perception of the network. The set of graphs in Figure 5 shows the Pearson correlation data for those measures showing a significant correlation.

As seen in Figure 5, there is a strong correlation for accuracy only between modularity and density measures, whereas modularity has a positive correlation (r=0.874) and density has a negative correlation (r=-0.739). Modularity is a network structure measure that measures the strength of the network's division into modules (also called groups, clusters, or communities). This measure considers the perception of the relationship between nodes and their neighbors, i.e., a neighborhood measure, the extent to which a node tends to show up (belong) only to a specific subgroup. In short, network perception with high modularity indicates the perception of dense connections between the nodes involved in the clusters, and low density between the nodes of different clusters. Density is extracted by the quotient of the perceived number of links in the network over the maximum number of possible links; networks with no links get a value of 0, while networks in which everyone has links with everyone get a value of 1.

In our case, there was a strong positive correlation between modularity and accuracy, and a strong negative correlation between density and accuracy. This suggests that, in the classroom group, participants who perceive the subgroup as having high modularity and low density tend to be more accurate in their perceptions of who "hangs out with whom". See the network graph of Bete, Luna, and Ana in Figure 1. Also, the self-assessment degree is moderately negatively correlated with accuracy (r=-561). Finally, there is a moderate correlation (r=0.679) between the self-assessment degree (slice) and the degree assigned to LAS. No significant correlation was found between modularity or density and degree of centrality.

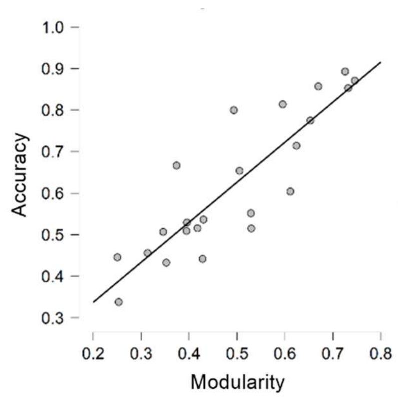
CONCLUSION

CSS is a complex and costly procedure to collect and analyze, but its benefits outweigh the efforts involved. Collection requires respondents to provide detailed information about their perceptions of social relations and every member of their network system. This requires careful collection and makes it impossible to collect in a large network system with many actors. In addition, data requirements are probably an obstacle to researchers using this technique more frequently (Neal, 2008). However, the possibility of triangulation is one way to reduce measurement bias and guarantee the data's validity (Singleton & Straits 1999). Thus, although any individual may not be faithful in his/her network account, is unlikely that all interviewees will make the same mistakes (Neal, 2008). Data multidimensionality makes it possible to collate different perspectives of network cognition present in a social group, and the possibility of comparing dimensions makes precision analysis possible.

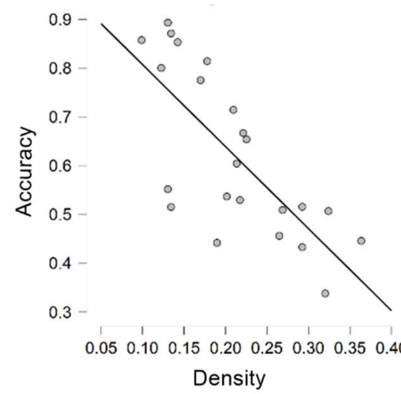
One limiting factor in using this technique is that it depends on the everyday relationship context and the interviewees' ability to report relational ties between their peers. It is therefore essential that this technique be used in environments where interviewees are likely to know their

Density vs. Accuracy/ r= -0.739 p< 0,001

p< 0,001



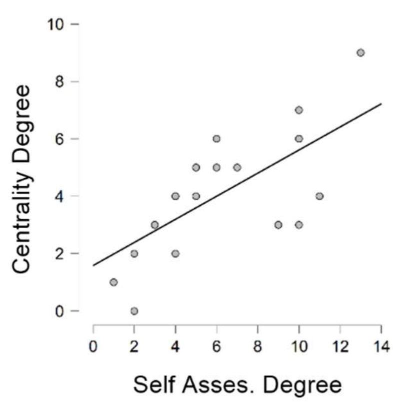
Modularity vs. Accuracy /r=0.874



Self Asses. Degree vs. Accuracy / *r*=-0.561 p<0,01

Self Asses. Degree vs. Centra. Degree /

r= 0.679 p<0,001



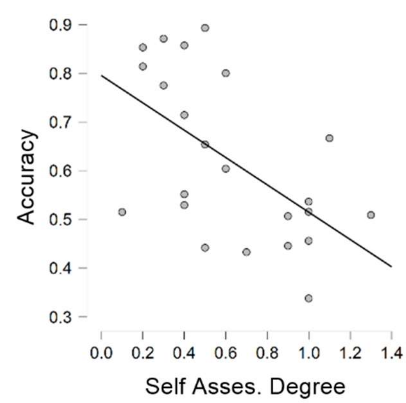


Figure 5. Pearson correlation graphs on network measures of Locally Aggregated Structure and participant accuracy that showed significant correlation.

peers and observe interactions between them regularly. Because they are small and natural environments, classrooms are ideal for the CSS method.

In this research, LAS was based on an analysis of reciprocal relationships, even because, theoretically, the concept of walking together is reciprocal by nature. However, such an analysis should not disregard the relevance of the collation in which non-reciprocal relationships are relevant, such as liking and advising. Even "hanging out with", proportions of non-reciprocity can be assessed according to differences in the subjects' attributes and even their position in the network.

Most of the students involved in the research showed a set of vulnerabilities. A majority showed some deficit on the ETDAH. Only three participants had a profile like the average on the Haven Test. On Trial B, only two subjects had higher profiles, most of them deficient. What is the network pattern of a group with this profile? And in this pattern, what type of network perception measure gives an advantage in terms of the accuracy of the relationships present in the same group? It is understood that the use of CSS models allowed comparisons between different perceptions present in each subject of the group (slices), perception of relationships reciprocity (LAS), perception in the group as a whole (CS), collating individual perceptions with reciprocal relationships to generate an index of accuracy and correlating accuracy measures with those of each subject's network.

Based on conglomerate analysis of structural network data in the slices, it can be identified that the group found differs mainly between subjects with different perceptions of network density and network modularity. At the edges, we have subjects who perceive the group with low and high densities and modularities. To compare if the perception of the group is more or less dense, and if greater or lesser intergroup segregation favored the network perception, it was developed the two reductions proposed by Krackhart (1987): the LAS and the CS.

For our purposes, LAS data was used as a reality parameter to compare the results of each slice and thus establish observer accuracy in the network. Based on accuracy measures, correlations were made between data on the subject's place in the network derived from LAS, structural self-perception metrics of the network (slice), and accuracy data. The analysis identified strong correlations between the perception of low density and high modularity and greater accuracy in identifying real relationships in the group. Interestingly, there is a moderate correlation between self-perception of low degree (slice data) and greater accuracy in the network.

According to the results described above, in the group analyzed, subjects with greater accuracy in identifying real relationships are those who perceive the group less densely, with clear separations between subgroups. Little literature in the area identifies that in adolescent groups, subjects with lower centrality of degree and intermediation show greater accuracy (Lee et al., 2017; Portillo & Fernandez-Baena, 2019). However, this result was not repeated here, so the correlation found was not significant.

One aspect to note is that no significant correlation was found between modularity or density and centrality degree or intermediation. The perception of density cannot be attributed to a more central or non-central positioning of the actor. In addition, a moderate positive correlation was found between self-assessment of degree and the degree found in the real network (LAS), which is in line with the literature which observes that subjects tend to overestimate their relationships in the network (Freeman, 1992; Kilduff et al., 2008).

However, it is worth noting the existence of a moderate negative correlation between self-assessment of degree and accuracy. Associating this set of results, it can be said that in the group studied, subjects who estimate the group with greater density and modularity are more accurate in evaluating the relationships in the group. However, the fact that even subjects with good accuracy in evaluating relationships in the network overestimate their ties is a bias only for themselves and does not affect the rest of their relationships. Although many participants state in their slices that some subjects are isolated in the network, none of them consider themselves to be isolated.

Regarding comparisons between what was found in LAS and CS, it can be said that although the network created had a different configuration, it showed very similar patterns, especially in terms of the conglomerates. The consensus network formed based on the threshold above 50% agreement between slices is obviously more restrictive and segregating than the locally aggregated one. As can be seen in the consensus network, three participants are isolated from any relationship (Sara, Ayla, Theo), while in the LAS there is only one participant, who is repeated in both reductions.

Considering the group profile and the total number of participants, little can be said about any significant relationship between the subjects' attributes, such as their scores on the scales and the perception accuracy of the relationships in the group. However, we can risk making some elaborations for future verification. It should be noted that subjects isolated in the LAS and CS show indicators of marked deficiency in the results of the ETDAH, RAVEN, and Trails B. On the other hand, subjects with greater centrality in both LAS and CS (Gina, Dora, Mara, José, Beca, and Pedro) show profiles of less vulnerability in the results of the scales when compared to those isolated. Despite these congruences between the results of positioning and exclusion in the group and the intensity of vulnerabilities, the results are not numerically consistent to make a categorical statement about this relationship.

Despite these assertions, it is possible to see that, even in a class where deficits of all kinds predominate, it is possible to see subjects placed on the edge of the group, particularly in the case of the three participants identified above. This positioning can recursively feed back into these vulnerabilities, or at the very least, it presents itself as yet another vulnerability at the social network level. Pedagogical proposals such as Mundiar cannot disregard the relationship network dimension present in the teaching-learning process. Even well-intentioned school arrangements can reinforce segregating mechanisms. Future work should explore this possibility more consistently, i.e., that even in groups with greater symmetry in vulnerabilities, there are exclusionary processes.

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