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Abstract

University students have changed their behaviour due to the COVID-19 pandemic. In this paper, we describe the characteristics of PCR+ and PCR- nodes, analyse the structure, and relate the structure of student leaders to pandemic contagion as determined by PCR+ in 93 residential university students. Leadership comes from the male students of social science degrees who have PCR +, with an eigenvector centrality structure, β -centrality, and who are part of the bow-tie structure. There was a significant difference in β -centrality between leaders and non-leaders and in β -centrality between PCR+ and non-leaders. Leading nodes were part of the bow-tie structure. MR-QAP results show how residence and scientific branch were the most important factors in network formation. Therefore, university leaders should consider influential leaders, as they are vectors for disseminating both positive and negative outcomes.

Key Words:

University students, COVID-19, Social Network Analysis, Leadership, Pandemic contagion, Residence Hall

Background

The COVID-19 pandemic has produced changes in people's behaviours, affecting their health, and increasing morbidity among survivors (1). Some of the most common consequences have been sexual and reproductive health problems (2), a negative impact on mental health (3,4), the reduction of social support for the most vulnerable people (5) and there was also a negative impact on the mental health of those who had to work from home as a result of the pandemic (6), where mental health disparities were greatest in countries with the highest degree of severity (7)

In this regard, social support has been considered a key and reiterated component of the various infectious disease outbreaks. This was the case for H1N1 influenza outbreaks (8), as psychosocial factors were key in achieving recovery from severe health processes (9). The same applies to the present pandemic, where social support has been shown to be negatively correlated with anxiety (10), positive with sleep quality, and social support has even been helpful in coping with loneliness during the COVID-19 pandemic (11). Perceived social support plays an essential role in the prevention of mental and physical illness (12).

Researchers have recognized that social support is related to the health impacts of the pandemic. Consequently, we turn to a context in which social support is a priority: the university context. University campuses are communities where youth are immersed in a social structure of coexistence. Two particular characteristics demand particular attention in epidemiological approaches to pandemic. First, there is a large influx of comings and goings of students and, second, social distance is difficult to achieve (13). Social Capital in young people has decreased during the closure period, at the individual and community levels, while increased at the family and society levels (14). Generally, university students are far from their family. They do not have that social support of their families to cope with the pandemic at cognitive and behavioural levels (15). As a result, they rely on the support structure of their accommodation, which is a residence hall.

University students have changed their behaviours due to the COVID-19 pandemic. Their sedentary lifestyle increased, food intake was inadequate, alcohol consumption increased (16) and changes in physical activity (17). Access to information and frequent ambiguity in media communications have heightened their anxiety. In fact, what caused them even more anxiety was uncertainty about basic aspects of daily life, such as

worrying about their family members or how online learning processes would be carried out (18).

Consequently, university students may also be a weak link in the context of the pandemic. They have experienced changes in their personal relationships that have influenced their health and altered their relationship structures and networks. Previous research suggests that statistical analyses focusing on individual analyses can provide results for students affected by the pandemic. Therefore, we address several critical gaps in the literature to outline the impact of COVID-19 on student communities. We consider the individual perspective to be inconsistent, as the context is relational. The questions we should be asking are not how many infected university students are male, female, or what they study. The questions should be, whether COVID-19 transmission is faster or slower depending on the actors and their networks, or how the leaders of college students' networks collaborate in containment measures. In this regard, a social network analysis framework is appropriate.

A social network is a set of actors linked together by social ties (19). A network implies a relational content which is the object of analysis. This content refers to what "flows" through its channels, such as emotions, love, hate, information, support, friendship, or money, among others (20). The most significant premise is that one thinks, does and feels according to the pattern of relationships in which one is inserted (20). The processes by which a person grasps an idea or the behaviour of another person depend on these networks or, in other words, on a social structure (21).

The analysis of this social structure can be carried out by applying the methodology of social network analysis (SNA). Moreover, through SNA we can analyse how some actors establish more contacts than others with other actors. This not only has an impact on the extent of their network but can also influence other people's behaviours (22). SNA offers a distinctive advantage compared to other theoretical approaches in the social sciences. This is that the value of the theoretical perspective proposed in a given study does not have to be based on the empirical results of other studies. Instead, it is based on the question that the perspective of the study proposes (23).

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There are several examples in this regard. Social capital is one of the most notable findings in the context of networks. Therefore, while for some authors social capital in an organization involves resource-rich ties between actors (24), for Burt (25) social capital is related to the lack of ties between an actor's alters, which he denominates "structural holes". To be specific, Burt's argument is based on the fact that structural holes provide weak ties that will achieve positive outcomes in the network. This perspective reinforces Granovetter's (26) Strength of Weak Ties Theory.

SNA allows the analysis of positions, dyadic properties, connectivity, and distribution of ties (27,28). This framework has been widely developed in the context of health. Some of the most classic and reference studies for researchers are, for example, the social structure of friends influencing health habits such as smoking or obesity (29,30), studies focusing on patient and professional networks with proposals to improve healthcare (31), the research by Christakis and Fowler (2013) that exposes the three-degree Contagion Theory influencing processes such as obesity or emotions, as well as studies on alcohol consumption in networks of university student that show network status to be associated with binge drinking (33). Social contagion occurs between people who are close to each other in the network, as they "use" each other to deal with issues that are unclear to them (34). Therefore, social contagion could be possible in situations such as what I should eat, what level of physical activity I should practice, how much alcohol I should drink to relate adequately, or what measures of protection I should take in the context of a pandemic situation, among others.

In recent years, SNA research in health and health policy has seen significant growth with studies in very different fields. Thus, in the field of management with the study of networks of doctors and nurses and their relationship with organizational performance (35), the application of SNA to sleep quality finding that an excessive degree of popularity can be harmful for girls(36), or studies with technological interventions in health habits such as the intervention "Healthy and Happy" (37).

Research on SNA and contacts during the pandemic has highlighted the importance of social structure. SNA has been applied among households that either refused or accepted polio vaccines (38), to visualize the risk of connectivity in certain contexts (39), to study the risk of pandemic proliferation in urban contexts (40), and to analyze the degree of COVID-19 infection and network subgroups in hall residences (41).

Based on the above, we have justified the importance of social structure, the application of SNA to health contexts and the incipient application of SNA to the context of the COVID-19 pandemic. With the present study, we will apply SNA to the context of

university students, as they are immersed in close contact networks in their daily lives. Those responsible for public health at universities are implementing protocols for action. Our results could provide useful information for the planning of collective interventions.

Currently, the literature continues to provide little evidence on SNA and COVID-19 in university students, findings that would be necessary for any effective social network-based implementation. Valente et al (42) highlight that in order to carry out implementation in the community, it is necessary to identify opinion leaders who act as agents of change. Opinion leaders are actors who know the community and build trust, and who act as gatekeepers for interventions to change social norms (42,43). In this sense, it would be useful to identify network leaders in university classrooms and analyse their behaviour in the context of the pandemic. Mehra et al (44) are among the researchers who have most deeply delved into leadership by applying the SNA. Among the measures of leadership, the betweenness degree has often been used. However, Mehra previously noted that if the context was focused on information dissemination, other metrics, such as eigenvector, would be more appropriate.

Bonacich (1987) pointed out, in favour of the eigenvector metric, that sometimes it may not be positive if one has few contacts. However, at other times it can be very beneficial if those few contacts have power or are connected to many people. Borgatti (46) has always justified the eigenvector as the most appropriate measure to apply to infectious processes, since it evaluates several pathways at once. The eigenvector centrality is a structural pattern that measures indirect contacts (47). Thus, many questions in structural key can be answered in order to analyse university student relationships during COVID-19. For example: Is it better to have few or many contacts to avoid being infected? Is the strength of relationships or having mutual friends positive or negative in terms of the risk of pandemic contagion? Is the fact of being isolated a powerful factor in the risk of the pandemic?

What is the role of residence halls leadership networks during COVID-19 contagion?

To obtain the answers, the following aims have been described:

- Describe the characteristics of PCR+ and PCR- nodes related on gender and degree.
- Analyse the structure of the leading nodes.

- Relating the structure of student leaders to pandemic contagion as determined by PCR+.
- Identify how gender, PCR status, residence and field of study influence the formation of the contact network.

Methods

Setting and sample

This study was carried out after obtaining data from a total of 93 university students enrolled in university degrees from different branches and living in halls of residence. Table 1 shows sample characteristics and Table 2 shows a descriptive analysis of network centralities.

Table 1. Sample characteristics

Design and research questions

In the present study, the case study was chosen. For some researchers, the case study is the optimal way to develop theory-building processes (48). Structure in a pandemic context is analysed by applying SNA as an underutilised research approach in public health studies. Another objective of this study is to provide theory on metrics that are uncommon in SNA studies because there is little previous literature to support them. However, like Siggelkow (49), we also consider that a research paper should allow the reader to see new proposals, in a new way, and not just based on previous studies.

Ethical consideration

This study was positively assessed by the Ethics Committee of the University of León (ETICA-ULE-008-2021). Health data collection complied with the standards established for COVID-19 pandemic studies in the European Data Protection Committee Directive 03/2020. Data were anonymized and collected from the ULE Epidemiological Surveillance System (SiVeULE), a database created by the University of León for the follow-up of positive cases and close contacts during COVID-19. Participants received an informed consent form to participate in the study. They were offered the possibility to retract the consent once the form was signed. They were also

provided with the e-mail address in case they had any questions. Participation in the study was voluntary.

Data collection

The data were collected at the hall residences. The university where the information was collected has a unique security protocol with rules and regulations to prevent the spread of COVID-19 on a daily basis. This protocol has actions to be taken if a person has symptoms compatible with the disease and differentiates between "confinement", "close contact" or "positive result".

Data was collected between October 23 to November 20, 2020. Support staff consisting of students, teachers and researchers from the university were available to conduct this data collection, contact tracing and support to those infected or in confinement. These personnel are known as "tracers".

The database includes information perfectly suited to apply the SNA methodology, collecting data on:

- Attribute data: characteristics of the actors (sex, degree of study, hall residence).
- Data on degree of infection: RT-qPCR results.
- Data on social structure: who contacts whom.

For this study, the data were anonymised, excluding any personal data that could identify the infected person or contact. After this anonymisation process, matrices were generated with the following structure:

- The rows represent when a node "A" has nominated a node "B".
- Columns represent when a node "A" has been nominated by a node "B".

In order to carry out this study, the matrix was transformed by applying a symmetrisation of the matrix, converting the network into a symmetric and therefore undirected network. This means that if a node A nominated a node B, it is assumed that a node B nominated a node A. Data in networks can be collected as directed data or non-directed data. In the first case, "A" might contact "B" while "B" need not contact "A" (e.g., a doctor offers advice to a patient although a patient does not offer advice to the doctor). In the second case, it is considered that if "A" contacts "B", then "B" also contacts "A". In this case the data matrix is symmetric. This is the adopted case for this paper. We have considered that if a student nominates another classmate with whom he/she has had close contact, this classmate has also had close contact with the one who nominated him/her.

Data analysis

For data analysis, SNA was applied to the 93×93 matrix. Centrality measures were selected to analyse leadership from a social structure perspective. Centrality is the measure that analyses the actor's position in the network (19). There are several constructs to measure centrality, such as the degree centrality, betweenness centrality, closeness centrality and eigenvector centrality. For the present study, we have followed the recommendations of Borgatti (46), who recommends the application of eigenvector centrality in diffusion processes, both in information dissemination and disease diffusion.

Bonacich (45,47) defines eigenvector centrality as the possibility of analysing the influence capacity of a node on nodes with which it does not directly contact.

The eigenvector centrality analysed several paths at once in the network. It evaluates risk traffic. For example, a person may have sex with only one actor, but if that actor has sex with many other actors, the first actor could be at high risk of contracting a sexually transmitted disease. Thus, the eigenvector is suitable for measuring indirect influence capacity. In our study, we will be able to assess whether leaders have this capacity to influence. Bonachich (2007) uses two equivalent equations:

- Eq. (1) describes eigenvector centrality x in two equivalent ways, as a matrix equation and as a sum. The centrality of a vertex is proportional to the sum of the centralities of the vertices to which it is connected. λ is the largest eigenvalue of A and n is the number of vertices:

$$Ax = \lambda x, \quad \lambda x_i = \sum_{j=1}^n a_{ij} x_j, \quad i = 1, \dots, n$$

- Eq. (2) describes β -centrality or $c(\beta)$, defined as a weighted sum of paths connecting other vertices to each position, where longer paths are weighted less. This measure permits varying the degree to which status is transmitted from one vertex to another and it also permits the assessment of power in negatively connected (50) exchange networks when being connected to exploitable isolates increases ones power:

$$c(\beta) = \sum_{k=1}^{\infty} \beta^{k-1} A^k \mathbf{1}$$

After analysing the degree of leadership using the betweenness centrality another construct will be applied to describe more specifically the structure of leaders. It is called "bow-tie".

The bow-tie structure is a novel perspective for a rigorous analysis of the association between tie strength and network structure (51). Its definition supports Granovetter and Bott. That is, following Granovetter (26), this would mean that the more friends two individuals have in common, the stronger their ties are. In relation to Bott (52), the bow-tie would corroborate that the narrower the social contexts between two individuals (few friends in common), the weaker their bond will be. In summary, the application of the bow-tie structure will be useful for predicting the strength of the bond between our leaders and the rest of the network. In order to detect possible bow-tie structures within a network it is often useful to use the ego betweenness measure (53).

Subsequently, the related permutation strategy called MR-QAP (Multiple Regression Quadratic Assignment Procedure) (54) was used to determine the dependence of the network on the other variables under study. This approach produces unbiased coefficients (55). For this, calculations were performed with UCINET 6.731 using the Double Dekker Semi-Partialling MR-QAP algorithm. For these analyses, it was necessary to transform the gender and positive or negative PCR variables into matrices through exact adjustment. For the residence variable, as there were four options available, it was transformed to a matrix through the absolute difference.

Statistical analysis and visualization

The data were statistically analysed using IBM SPSS Statistics (26.0). For the descriptive analysis of the different variables, the qualitative variables were shown together with their frequencies and percentages, while for the quantitative variables, the mean and standard deviation were calculated. To study the relationship between two different variables formed by two groups, the chi-squared test was applied. To determine whether there were significant relationships in continuous variables in the same sample, in two different situations, the one-sample t-test was performed. To analyse continuous variables from two different samples, the t-test for independent samples was used. An analysis of variance (ANOVA) was carried out to check the differences for continuous variables divided in more than two groups. To determine whether the sample followed a normal distribution, the Kolmogorov-Smirnov test was used, as there were more than 55 individuals. The visualisation of the various graphs

that make up the network was carried out with Gephi in its version 0.92. This visualisation allowed us to qualitatively analyse the results. To calculate the values of the different metrics of the social network analysis and the MR-QAP regression model, use was made of the UCINET programme in its version 6.731.

RESULTS

Of the 93 actors in the sample, 24 nodes were considered leaders due to their high eigenvector centrality values. If a node has high eigenvector, it means that this actor is adjacent to nodes that in turn have a high score (46).

Leadership, gender, degree and Residence

As shown in Table 3, significant differences were found between leaders and non-leaders calculated with gender, the prevalence of people who tested positive or negative for PCRs, the scientific branch of studying and the residence where they lived. Leaders had a higher percentage of people in the male group (100.0%), in the PCR+ group (75.0%), studying a social degree (95.8%) and living in residence C (87.5%) compared to non-leaders.

Table 3. Comparison between leaders and non-leaders, gender, PCR result, scientific branch and residence hall applying the chi-square test of independence.

β -centrality and other variables

Two-sample t-test performed to compare β -centrality in:

Leaders and non-leaders. There was a significant difference in β -centrality between leaders ($M = 1.957$, $SD = 0.255$) and non-leaders ($M = 0.082$, $SD = 0.093$); $t(91) = -97.392$, $p < 0.001$].

PCR+ group and PCR- group. There was a significant difference in β -centrality between PCR+ ($M = 0.962$, $SD = 0.915$) and non-leaders ($M = 0.268$, $SD = 0.613$); $t(91) = -4.376$, $p < 0.001$].

Males and females. There was a significant difference in β -centrality between males ($M = 0.787$, $SD = 0.927$) and non-leaders ($M = 0.102$, $SD = 0.104$); $t(91) = -4.023$, $p < 0.001$].

A one-way ANOVA was performed to compare the effect of scientific branch on β -centrality.

A one-way ANOVA revealed that there was a statistically significant difference in β -centrality between at least two groups ($F(2, 90) = 21.948$, $p < 0.001$).

Tukey's HSD Test for multiple comparisons found that the mean value of β -centrality was significantly different between engineering and socials ($p < 0.001$, 95% C.I. = [-1.315, -.0450]) and between health and socials ($p < 0.001$, 95% C.I. = [0.589, 1.386]).

There was no statistically significant difference between engineering and health ($p=0.859$).

Figure 1 shows the nodes of the study network highlighting the nodes with PCR+ in red and the nodes with PCR- in green. The distribution of the network allows us to appreciate the bow-tie between nodes D7 and D1. To detect this bow-tie structure, the measure of betweenness centrality was used. It was observed that node D1 had a value of 1,690.0 and node D7 had a value of 1,068.15, with the next value being less than 60. Nodes belonging to the bow-tie structure are those that have a relationship with D1 or D7. The size of the nodes is represented by the nEigenvector of each node.

Figure 2A shows the nodes of the bow-tie subnetwork highlighting the nodes with PCR+ in red and the nodes with PCR- in green. The size of the nodes is represented by the nEigenvector of each node. Figure 2B depicts the sub-network of neighbouring nodes of D1, while Figure 2C depicts the sub-network of neighbouring nodes of D7. The shaded nodes are not connected to D1 and D7 respectively in these figures.

Figure 2. Graph representing the bow-tie detected in the main network between nodes D7 and D1. The sub-network nodes that are only neighbours of D7 (B) and the sub-network that are only neighbours of D1 (C) are represented with lower opacity.

Figure 2 illustrates how nodes D7 and D1 form the bow-tie structure. This figure shows us that we must be careful with the interpretation of the networks. Nodes D7 and D1 are

the two focal students of the bow-tie. D7 with negative PCR and D1 with positive PCR. The application of bow-tie structures the prediction of link strength for both networks (51). In this case, it predicts the strength of node D1, which would indicate that the neighbourhood of D7 might be at risk. If we look at Figure 2A we could think that D1 has a positive influence capacity to get the highest number of green nodes (with PCR-). But looking at Figures 2B and 2C we can see that the capacity of node D1 could lead to a "swarm of wasps" effect. That is, it can absorb the rest of the bow-tie structure. D7 and D1 have a great power to influence the global network. Indeed, through this structure, D1 and its entire neighbourhood can be predictive of a network-wide contagion.

MR-QAP Regression

The MR-QAP regression model (see Table 4) was then carried out to predict the selection of actors within the network, considering the variables of gender, positive or negative PCR and residence A, B, C or D and scientific branch. The coefficients were tested through three models. Statistically significant factors in forming these ties include gender, residence, scientific branch and whether or not COVID-19 is present. The model obtained through this analysis explains 25.60% of the variance within the network. In general, residence and scientific branch were the most important factors in network formation.

DISCUSSION

School closures during the COVID-19 pandemic and e-learning have been the subject of numerous studies between 2020 and 2022. Among their consequences are a decrease in physical activity with an increase in psychological stress (56), and sleep pattern alterations due to new routines among young people (57) have been demonstrated.

University students have also experienced changes in their behaviour, with anxiety and perceived lack of emotional support, so social support became a key point to improve their coping (15). Social support was critical even in the context of remote group work. The important thing was to decrease the perception of isolation (58). In this relational context, students' intergroup friendships and peer relationships can generate options for developing norms focused on better living together or behaviours in the face of a pandemic. To analyse this structural context, the SNA methodology was selected. SNA

does not analyse the individual in a static or aggregate way, but in a relational and structural way (59).

Despite the importance of COVID-19 studies among youth, few studies have investigated socialization and pandemic contagion on university campuses. College campuses are contexts where young people have intense experiences. They do not have the close support of their parents, so they rely on their social network to cope with aspects of daily life (Li & Peng, 2021). At the moment, one of those things is dealing with the COVID-19 pandemic. This includes how to relate, how to protect oneself, who to talk to and who to talk to, how to make friendships, romantic relationships, etc.

In the present study, SNA was applied to understand the relational structure of students in residence halls during an outbreak of COVID-19 contagious. Data were collected on university degree, gender, residence, and PCR+/PCR-. The research questions focused on two fundamental issues: what the characteristics of the networks were, what was the structure of the leaders and their relation to the degree of COVID-19 infection.

Attributive characteristics of the network

Our results show that the actors have a certain tendency to cluster, especially by gender and degree. In general, they are men and belong to social science-related degrees. This structural grouping can be explained based on the concept of homophily, which is widely used in the SNA methodology. Homophily means that people tend to contact each other more often if there are similarities between them (36). An example could be culture, type of behaviours, gender, race or even content flowing through the connections of a network (60).

The findings show a clustering between infected and uninfected students. What is certain is that clustering based on homophily could also be explained on the basis of risky and irresponsible behaviours (61). Youth seek to associate with peers with at-risk behaviours (62). In this sense, engaging in uninhibited behaviour in the face of epidemiological measures of the pandemic could be considered risk behaviour.

However, according to our study, homophily could imply intergroup conflict. That is, students cluster into subgroups belonging to their residence halls. But some networks have a high degree of infection, others have low or no infection, and others have mixed results. It is possible that not everyone has the same pandemic behaviour, as the difference in the degree of infection between sub-networks is very striking. Our results could align with negative attachment theory. That is, people would avoid themselves

when are negative feelings, so avoidance reduces the transfer of information(63). In this case, avoid short-circuits COVID-19 transmission.

Nevertheless, it is difficult to identify the real structural causes of why there is more contagion in some residence halls than in others. Perhaps the key is the analysis of the structure of individual leaders and their behaviour in the face of the pandemic. Leadership among young people does not always bring benefits to the community. Central positions in the network are often associated with unhealthy habits, such as smoking or alcohol consumption (33). Structural leadership is certainly important, so it is necessary to look with lens specifically at the network of the most influential students.

Structure of the leaders and relation to COVID-19 contagion

One of the main objectives of the present study is to describe the network structure of student leaders in a context of pandemic and close coexistence. We analysed the network as a causal variable for an outcome variable: pandemic contagion. Could we have more deeply applied a perspective in which pandemic contagion was related to social contagion? In fact, in the current phase of research, for us, physical proximity and the structure of leaders who could play a priority role in the contagion of the pandemic were essential.

In this sense, there is a large core of literature that addresses social contagion from different metrics and perspectives. For Burt (34), social contagion could be a consequence of a structural characteristic denominated structural equivalence. That is, two people are structurally equivalent to the extent to which they have identical relationships with all other individuals. Yet, this metric often shows a competition between leaders to achieve a high degree of reputation. The competition between people striving for "survival" in any context (love, friendship, reputation, etc.) is related to structural equivalence (34). This setting has not been considered for the current research. What concerned us is the structure and pandemic contagion in a context of physical proximity, such as that which is taking place in a university residence hall. Physical proximity facilitates social proximity such as friendships, sharing attitudes and behaviors (34). Borgatti and Everett (64) note that social proximity and centrality measures are appropriate for assessing structural behaviours in context of physical proximity . Therefore, the **centrality measures** employed would be well supported to assess how physical proximity in a university residence hall would facilitate a context of

social contagion, which would develop uninhibited pandemic behaviours, facilitating pandemic contagion.

According to the above, the degree of leadership was calculated with the Eigenvector suggested by Borgatti (46) for contagion contexts, and with β -centrality following Bonacich (47) and Borgatti et al (54) recommendations for heterogeneous networks. The study of leadership using these two measures, in a pandemic context, adds novel insights to the scientific literature. However, our decision differs from the leadership measure in the studies by Winter et al (65), which do not identify the eigenvector as an suitable measure to analyse leadership. This could be because in this study leaders were identified as opinion leaders. If they themselves were too motivated to be leaders in the Twitter network, they might forget to exercise more local leadership. This might explain why this measure differs from our results. In our study, leadership is close and local leadership.

Our findings show two types of structural leadership. On the one hand, a small core of leaders with very high eigenvector and high β -centrality. This core is linking large sub-networks. However, we have also obtained a number of leading actors, to a lesser extent, with high eigenvector and β -centrality. Interestingly, the latter are infected by COVID-19. We need to describe and discuss the new knowledge provided by these results with previous studies.

This type of cohesive leadership, with both positive and negative contagion results, could be explained through shared leadership theory. Shared leadership is an emergent group property, in which many group leaders participate in influencing processes (66). When team members participate in team leadership roles, they gain more power in the direction of the team (67). Therefore, shared leadership implies a network of numerous contacts, which could influence collective behaviour. That is, shared leadership in the network might explain university students' behaviours in the face of the pandemic, whether they are responsible or irresponsible. In shared leadership, leadership ties are more important when they come from actors who are identified as leaders by other individuals. In this case, the eigenvector is seen as an appropriate measure (68). A leader node is important if it is connected to another leader node. The eigenvector has been applied in studies with students as a measure of leadership (69).

In addition to having identified leaders through the eigenvector structure, our results show that there are communities with several very central nodes which could be leaders in those communities or university residences. As leaders, they could aggregate

communities towards responsible or irresponsible behaviours. Our interest aligns with the studies of Choumane et al (70) who analysed the overlap of neighbourhoods at the edges of bridges between central nodes. In this sense, the present work provides novel insights through the application of the bow-tie structure (54).

We discuss our results with previous studies by Benítez-Andrades et al (71) and Marqués-Sánchez et al (41), who analysed COVID-19 infection networks in university students. Their results demonstrated the importance of cohesion and bridges between the main nodes. The importance of bridges between key actors (41) is not sufficient to analyse contagion risk or contagion behaviour in the face of a pandemic. It is necessary to delve deeper into the small groups that are immersed in these bridges and that connect the large groups. On the other hand, the study by Benítez-Andrades et al (71) already highlighted the importance of the Key Players in the contagion network. However, they only analysed the structure at the individual level, without considering the importance of the embedded substructure between the Key Players.

Based on the above, we believe that the application of the bow-tie structure does provide the right answers. For this reason, the bow-tie structure has been incorporated into this study, providing new structural knowledge to assess more accurately the contagion of behaviours, and in this case the risk of contagion in the face of COVID-19. Undoubtedly, this research has several limitations. First, the lack of a longitudinal study that would allow us to evaluate the dynamics of the networks. Another limitation is related to other data that would further refine their behaviour.

Future lines of research could be focused on replicating the study in different residence halls, including aspects that also define the management style of university residences. The findings of this research are useful for planning pandemic strategies in university contexts. Clearly, university leaders should consider influential leaders, as they are vectors for disseminating both positive and negative outcomes.

CONCLUSIONS

The present study developed novel knowledge based on the application of social network analysis to describe the structural behaviour of university students in a pandemic context.

The findings provide useful results that allow us to know the attributive data of the student networks, the network of their leaders, and the relationship of these leader

networks with the degree of COVID-19 infection or non-infection by PCR test. The most relevant conclusions of the present study are detailed below:

- The attributes of the leaders in the network are male, social science degree, and with a PCR+ contagion score.
- The most influential leaders have a network structure of high eigenvector and β -centrality.
- Leaders with high eigenvector and β -centrality have a PCR+ contagion score.
- The prediction of contagion is given by an influential node that is part of the bow-tie structure.
- Pandemic contagion prediction is provided by a leader node that is part of the bow-tie structure.
- A node with PCR+ that is part of the bow-tie structure can put many more actors at risk of contagion.
- The eigenvector, β -centrality and bow-tie structures are suitable for the analysis of pandemic contagion transfer between actors.
- Among the most significant factors in the formation of networks were the residence halls and the scientific branches.

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Tables

Table 1. Sample characteristics

RT-qPCR	Gender		Scientific branch			Residence Hall				Total (%)
	Male N(%)	Female N(%)	Engineering N(%)	Health N(%)	Socials N(%)	A N(%)	B N(%)	C N(%)	D N(%)	
PCR+	26 (65.0%)	14 (35.0%)	6 (15.0%)	7 (17.5%)	27 (67.5%)	24 (60.0%)	0 (0.0%)	15 (37.5%)	1 (2.5%)	40 (43.0%)
PCR-	37 (69.8%)	16 (30.2%)	15 (28.3%)	20 (37.7%)	18 (34.0%)	13 (24.5%)	8 (15.1%)	6 (11.3%)	26 (49.1%)	53 (57.0%)

Table 2. Descriptive analysis of network centralities.

	Degree	EigenVector	Betweenness	β -centrality
Minimum	0.000	0.000	0.000	0.000
Average	0.156	0.059	0.023	0.566
Maximum	0.359	0.207	0.404	2.001
Sum	14.521	5.450	2.130	52.671
Standard Deviation	0.078	0.086	0.062	0.829
Variance	0.006	0.007	0.004	0.687

Table 3. Comparison between leaders and non-leaders, gender, PCR result, scientific branch and residence hall applying the chi-square test of independence.

	Chi square tests of independence			
	Leaders N (%)	Non- leaders N (%)	χ^2	<i>p</i>
Gender				
Male	24 (38.1)	39 (61.9)	15.404	<.001
Female	0 (0.0)	30 (100.0)		
qt-PCR result				
PCR+	18 (45.0)	22 (55.0)	13.505	.004
PCR-	6 (11.3)	47 (88.7)		
Scientific branch				
Engineering	1 (4.8)	20 (95.2)	29.298	<.001
Health	0 (0.0)	27 (100.0)		
Socials	23 (51.1)	22 (48.9)		
Residence				
A	2 (5.4)	35 (94.6)	78.090	<.001
B	0 (0.0)	8 (100.0)		
C	21 (100.0)	0 (0.0)		
D	1 (3.7)	26 (96.3)		

Table 4. MR-QAP Regression

Dependent variable. Network of contacts	Model 1	Model 2	Model 3
Independent variables			
Gender		.103 (<.001)	.108 (<.001)
qt-PCR result	.100 (<.001)	.097 (<.001)	.100 (<.001)
Residence	-.456 (<.001)	-.447 (<.001)	-.442 (<.001)
Scientific branch			-.129 (<.001)
Intecept (Stardised)	.000	.000	.000

	(.000)	(.000)	(.000)
Adjustment R2	0.23	0.239	0.256

Figures

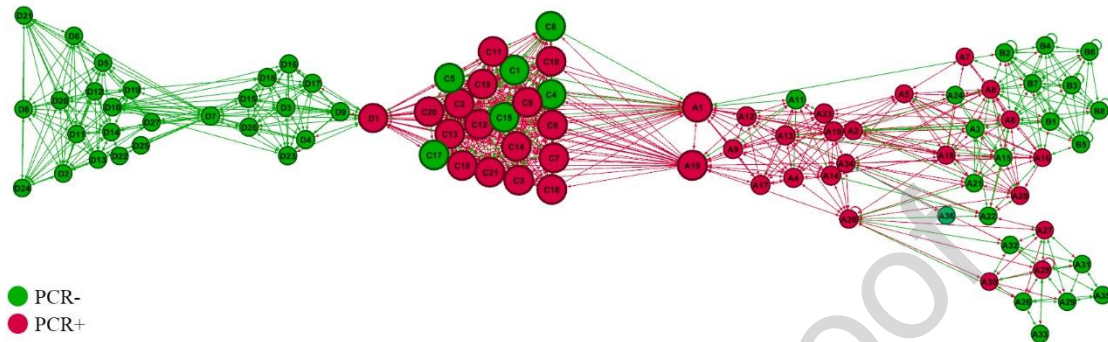
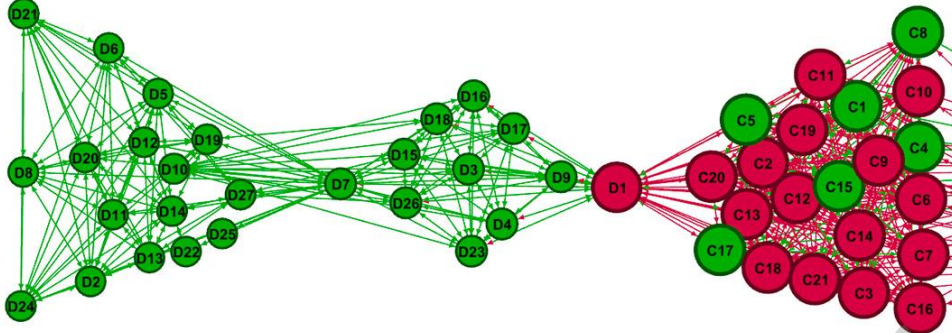


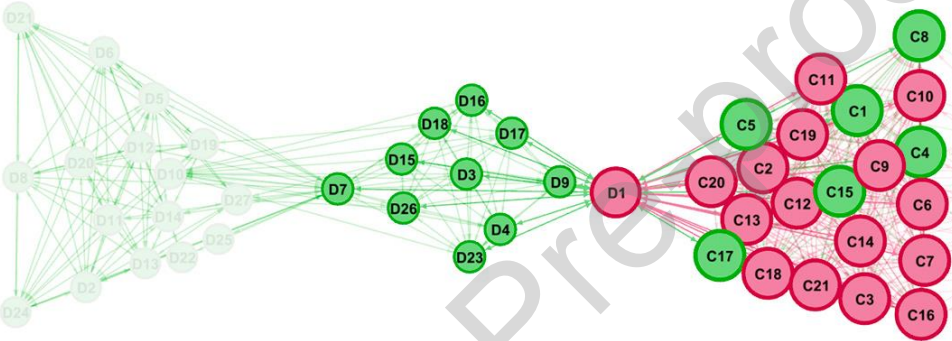
Figure 1. Graph representing the total student network, highlighting the colour of the nodes depending on the PCR result (PCR+ in red and PCR- in green) and the size of the nodes based on their eigenvector. The node labels contain the letter of the residence where the students are staying (A,B,C or D) together with a unique numeric identifier.

Figure 2. Graph representing the bow-tie detected in the main network between nodes D7 and D1. The sub-network nodes that are only neighbours of D7 (B) and the sub-network that are only neighbours of D1 (C) are represented with lower opacity.

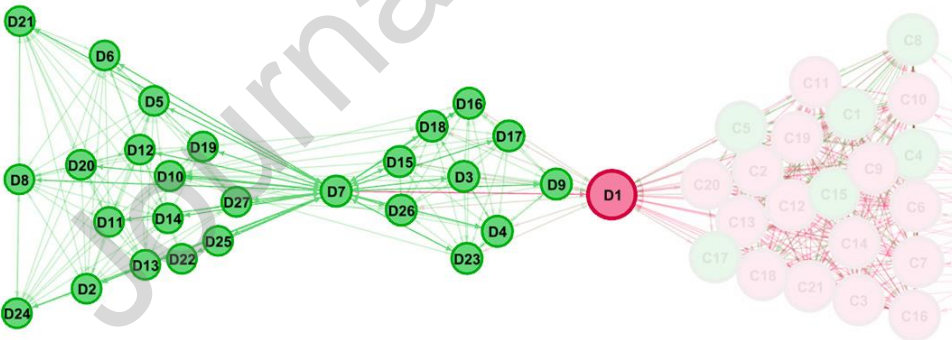
A



B



C



● PCR-
● PCR+

Highlights

- Leaders with high eigenvector and b-centrality have a PCR+ contagion score.
- The prediction of contagion is given by an influential node that is part of the Bow-tie structure in the network.
- Contagion prediction is provided by a leader node that is part of the Bow-tie structure.