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Use of a hierarchical deconstruction procedure for the classification of personal networks: Exploring nested groups around you

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ABSTRACT

The deconstruction of personal networks through the iterative elimination of the nodes with the highest betweenness centrality is an effective strategy for describing their structural properties. In this study we show that iterative deconstruction can also serve to classify personal networks into typologies. With longitudinal data from a sample of 69 students, we found that denser networks are more resistant to fragmentation while those organized in defined subgroups usually have a shorter deconstruction process. In addition, the deconstruction strategy allows knowing the hierarchical structure of personal networks, made up of nested subgroups.

Introduction

Personal networks represent the social environment of the individual, so they usually reflect inter-individual differences derived from lifestyles, social conditions, and personal history (McCarty, Lubbers, Vacca & Molina, 2019). Specifically, personal networks often vary in size, structure, and composition. First, most people have between 300 and 800 active relationships, although there are people capable of developing several thousand relationships in their social lives (McCarty et al., 2001; McCormick et al., 2010). Second, this set of ties is usually organized in concentric circles depending on the degree of intimacy they maintain with the subject. On the one hand, there is a small core of key support providers and, on the other hand, a wide periphery of ties that are less stable and relevant to the focal individual. Third, the composition varies depending on the "social foci" of activity in which the individual participates, such as the family, school, or workplace (Feld, 1981).

This individual variability is clearly observed when structural measures of personal networks are calculated. For example, it is common to observe large individual differences in the *density* indicator, which represents the degree of structural cohesion of the network and is associated with the availability of social support and bonding social capital, as well as the degree of social pressure on individual behavior (Perry et al., 2018). The number of *components* may reflect the existence of separate groups and the degree of fragmentation of the network (Maya-Jariego & Holgado, 2015). Both homophily and heterogeneity in *composition* can inform the type of resources to which the individual has access within the social structure (McPherson et al., 2006, 2001). The list of examples to illustrate the individual variability of structural properties would be innumerable.

However, the use of singular indicators faces important limitations in capturing the ensemble properties of personal networks (Wellman and Potter, 2018). No indicator is usually enough to characterize the personal network by itself. In addition, a strong covariation between the different structural measures is usually observed. Otherwise, emergent properties depend on the form that the personal network *as a whole* takes. For example, density is a very powerful indicator to summarize the degree of structural cohesion of the network. However, two personal networks with the same density indicator may have a very different organization in terms of the distribution of ties into cohesive subgroups. Additionally, density usually correlates with the number of cliques, among many other indicators, so it is not easy to distinguish the cohesion of the whole from the formation of subgroups.

This situation has led to the construction of typologies, integrating multiple dimensions of networks simultaneously (Bidart et al., 2018; Maya-Jariego, 2021). It also makes procedures for exploring the nested properties of personal networks particularly relevant. This is the case of deconstruction techniques that consist of the iterative dismemberment of the personal network to describe its hierarchical structure (Bidart et al., 2020).

Bidart et al. (2020) applied a hierarchical fragmentation procedure for personal networks, consisting of a repeated process of eliminating the nodes with the highest betweenness centrality at each moment. It works the same as the Girvan-Newman algorithm for community

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identification (Girvan and Newman, 2002), although in this case it is based on nodal betweenness (instead of edge betweenness). This procedure reveals new intermediaries at each step, while simultaneously fragmenting the network into cohesive subgroups and allowing the degree of stratification[1] of the personal network to be calculated. This type of analysis is helpful in evaluating the hierarchical structure of the network, showing the existence of nested groups (Maya-Jariego, 2022). It could also serve to develop typologies, since personal networks that vary in their structural properties evolve differently throughout the process. That is what we intend to show in this paper.

In this study we use a previously generated database of personal networks to systematically apply the deconstruction process suggested by Bidart et al. (2020). The goal is to determine individual differences. For exploratory purposes, we intend to classify personal networks as they evolve throughout the deconstruction process. To this end, we follow an empirical inductive strategy that we integrate theoretically in the paper's final section.

Empirical context: data and methods

The data

This study is based on a longitudinal survey of young people in two waves, with an interval of one and a half years between them. In the first wave, we interviewed 69 students in their final year of high school in a town in the metropolitan area of Seville (Southern Spain). In the second wave, we interviewed 57 students, when more than half had started their university studies and had entered a metropolitan lifestyle, with daily round trips to the capital. In the first survey, the students were 17 years old (M = 17.2, SD = 0.66), and it was made up of 31 men (44.9%) and 38 women (55.1%).

In each wave, the personal network of each interviewee was obtained, collecting a fixed number of 45 alters and their relationships with each other. The initial name generator was the Arizona Social Support Interview Schedule (ASSIS) (Barrera, 1980). Next, each respondent was asked to complete the list of names up to 45. This allows the generation of standardized indicators with a lower information processing load (Maya-Jariego, 2018). The database is available at Zenodo https://zenodo.org/record/3532048#.Yqr90uxBw2w along with a detailed description of the instruments and the procedure (Maya Jariego et al., 2020a, 2020b). In addition to data from personal networks, in the original study information was obtained on the frequency of intercity trips (between the place of residence and where they study) and the psychological sense of community (with both places). The weekly time distribution between the two cities was also examined. These data have been used to analyze the effects of metropolitan mobility on the psychological sense of community (Maya Jariego et al., 2020a, 2020b), and to describe the impact of interaction contexts on the formation of personal networks (Maya-Jariego & Holgado, 2022).

Describing the structure of personal networks

Based on previous studies, we selected a set of indicators representing structural cohesion, relational integration, and network fragmentation to describe the structural properties of personal networks (Maya-Jariego & Holgado, 2015; Maya-Jariego, 2021).[2] These measures are usually highly correlated. Hence a wide variety of indicators can be used to explore which ones best fit the empirical data. In Table 1 we describe the list of indicators finally used, with the definition provided by UCINET 6 in each case, that is the software we used to calculate them. For some analyzes, average individual centrality measures were also used: Specifically, the average degree, average closeness, average betweenness and average eigenvector centrality measures were used to describe the properties of personal networks with different levels of stratification.

Table 1
Descriptive measures of personal networks.

Structural properties	Description
Degree centralization	"For a given binary network with vertices v1.vn and maximum degree centrality cmax, the network degree centralization measure is Σ(cmax - c(vi)) divided by the maximum value possible, where c(vi) is the degree centrality of vertex vi."
Density	"The density of a binary network is the total number of ties divided by the total number of possible ties. For a valued network it is the total of all values divided by the number of possible ties. In this case the density gives the average value."
Components	"In an undirected graph two vertices are members of the same component if there is a path connecting them. In a directed graph two vertices are in the same weak component if there is a semi-path connecting them."
Fragmentation	"Proportion of pairs of nodes that cannot reach each other."
Closure	"Transitivity or triadic closure is the number of paths (triples) which are transitive divided by the number of paths of length 2, i. e. transitivity is the number of triples that are transitive divided by the number of triples which have the potential to be transitive by the addition of a single edge."
Average distance	"The distance between two nodes is the length of the shortest path. The average distance is the mean between all reachable pairs of vertices."
Number of cliques	"A clique is a maximally complete subgraph." We used 3 as the smallest group size to be considered a clique.

Note. Definitions extracted from UCINET 6 for Windows Help Index http://www.analytictech.com/ucinet/help/idx.htm

Procedure and data analysis

The respondents completed the relationship matrix indicating for each pair of actors whether both people "0, do not know each other", "1, know each other", or "2, have a good relationship". Unless otherwise stated, all analyzes were performed assuming that two people are connected if the respondent assigned a value of 1 or greater to the relationship. The level of strong relationships (= 2) was only occasionally used as a validation strategy (i.e., to check if the same results were obtained with a different data matrix).

The deconstruction of each personal network was done manually. Starting from the original network, at each step the node (or alter) with the highest betweenness centrality was eliminated and the structural properties of the resulting network were calculated. This "manual" or step-by-step procedure follows the same logic as that used with an algorithm designed originally by Bidart et al. (2018). In our case, we did not eliminate the Ego in the first step, since the Ego was not included in the matrix, following the type of personal network data originally proposed by McCarty (2002). We also did not remove isolates and isolated cliques in the first step, since this situation was relatively uncommon in our database.

Network data was analyzed with UCINET 6.698 (Borgatti et al., 2002), while correlations and cluster analysis were performed with SPSS 26. Graphical representations were made with NetDraw (Borgatti, 2002). The *Quick Cluster* procedure with ten iterations was used to group individuals into categories. In all cases, preliminary exploratory analyzes were carried out to estimate the number of categories. Theoretical considerations guided the selection of the criterion variables.

[1] That is, the number of steps to complete the process of fragmentation.

[2] In other cases, density, betweenness centralization, modularity and diameter have been used (Bidart et al., 2018). Although some of these indicators are different from those included in our proposal, they also indirectly seem to reflect the basic dimensions of relational cohesion and integration.

Results

Description of the network deconstruction process

The iterative process required an average of about 18 steps to reach a network configuration in which all nodes had zero betweenness. As shown in Table 2, the data were quite similar in the first observation (M = 18.46, SD = 5.679) and in the second wave (M = 18.28, SD = 5.787).

Throughout the process of analytical deconstruction of personal networks, a gradual decrease in density and degree centralization indicators is observed, both in the data obtained in the first observation and in the second wave (Annex 1.1). In parallel, there is a progressive increase in the number of components and in the level of fragmentation of personal networks (Annex 1.2). With minor differences, all the indicators evolved quite consistently in the two observations.

However, there are large individual differences, as shown by the fact that between 2 and 31 steps are required to complete the deconstruction in time 1 (or between 5 and 35 steps in time 2) (Table 2). This variability depends in part on the structural properties of the personal network before starting the deconstruction process, as shown by the bivariate correlations in Table 3.

The number of steps required to complete the deconstruction of the personal network has a significant inverse relationship with network closure and with the average distance of the network (Table 3). Thus, networks with greater average distance and higher scores in triadic closure need fewer steps to reach the stage where all nodes have zero betweenness. This is more interesting if we consider that closure and average distance, depending on the network's topology, may eventually have an inverse relationship. On the other hand, in the second wave, the network density positively correlates with the number of steps required for complete deconstruction ($r = 0.395$, $p < .002$).

Validating the stratification indicator

To validate the previous analyzes, we compared the means of the structural properties of personal networks and some indicators of metropolitan mobility as a function of the stratification quartile (Tables 4 and 5). The number of cliques is the indicator that showed a stronger and clearer association with the stratification levels, both in the first observation ($F = 11.614$, $p < .001$) and in the second ($F = 3.399$, $p < .05$). In both cases, it was consistently found that networks with a higher level of stratification are characterized by having a greater number of cliques, as a starting point. There is a positive correlation between the number of cliques and the number of steps ($r = 0.590$, $p < .01$). This seems to indicate that the procedure hierarchically decomposes the personal network based on the existence of cohesive subgroups connected by the same intermediary.

Furthermore, when the longitudinal observation started, individuals in the lowest stratification quartile were characterized by spending significantly less time throughout the week in the city where they reside. Possibly this has been reflected in some way in the connectivity between the different cohesive subgroups that make up their personal networks. The lowest level of stratification corresponds to the group that spends the least time in the city of residence ($F = 3.91$, $p < .05$) and the one that spends the most time in the capital ($F = 3.98$, $p < .05$). Perhaps this type of geographic dispersion could, in turn, be reflected in relational dispersion too.[3]

Illustration of individual differences in the deconstruction process

As can be deduced from the wide range of steps, there are large individual differences in the network deconstruction process. In some cases, the process is completed in 2 iterations, while others require up to 35. Fig. 1 shows an example of deconstruction in 5 stages. It is a personal network of a male teenager made up mostly of family ties, while friendship ties account for just over a third of the total. According to the respondent, he visits the capital five times a week and, consequently, spends 25% of his weekly time in Seville. In the initial phase, the personal network structure is divided into two recognizable factions, which largely correspond to distinct groupings of friends and family. Accordingly, the highest intermediation nodes eliminated in steps 1 and 2 are precisely those that connect friends with the family. Then, the network subsequently fragments successively until two cohesive subgroups of family members and one of friends are recognized. Throughout the process, some nodes become isolated and disconnected from the rest.

Fig. 2 shows a selection of the steps required in deconstruction of a personal network in 31 stages. As shown in the initial phase, it is a highly cohesive network of a teenager strongly rooted in the locality of residence. The respondent spends 90% of his time in Alcalá, where he has developed a strong psychological sense of community. In addition, almost all his contacts are friends, except three relatives. In this case, the nodes of greater betweenness are in the periphery. Consequently, in a long first part of the process, those individuals with fewer redundant ties to the nucleus are disconnected as isolated nodes. It is necessary to wait until step 20 for two distinct cohesive groups to emerge. Then the process continues until a network of cliques, dyads, and isolated nodes is obtained. That is, until it reaches a structure in which all nodes have 0 betweenness and, therefore, is not susceptible to further reduction.

These two examples show that, at least in part, the degree of stratification of the personal network is associated with some of its original structural properties. On the one hand, networks made up of two or more factions break down earlier than highly cohesive networks, with high scores in density and closure. On the other hand, there are also clear differences in which are the alters with the highest range of betweenness in each case. In clustered graphs, the highest betweenness corresponds typically to those who act as a bridge between defined groups; while in very dense graphs, at least in the initial phases, nodes with higher intermediation usually act as a bridge with the less connected peripheral nodes.

Therefore, it is expected that denser networks will be deconstructed in more steps and networks with a higher level of fragmentation will be deconstructed in less. However, both dimensions can be combined to different degrees, depending on the personal network topology. For this reason, it is necessary to attend not only to the unique dimensions of variability but also to the types of configurations that personal networks adopt.

Table 2
Descriptive statistics of the number of steps required to reach a network with zero betweenness in all nodes, both in time 1 and time 2.

	N	Minimum	Maximum	Mean	Standard deviation
Total steps (t1)	69	2	31	18,46	5679
Total steps (t2)	57	5	35	18,28	5787

Table 3
Bivariate correlations between the number of steps and the structural properties of personal networks before deconstruction.

	Number of steps	
Structural properties	(t1)	(t2)
Degree centralization	0.107 (0.380)	0.162 (0.228)
Density	0.163 (0.181)	0.395 (0.002) * *
Components	-0.259 (0.032) *	-0.250 (0.060)
Fragmentation	-0.229 (0.059)	-0.290 (0.029)
Closure	-0.407 (0.001) * *	-0.378 (0.004) * *
Average distance	-0.334 (0.005) * *	-0.365 (0.005) * *

Note. Statistically significant: * $p < .05$. * * $p < .01$.

[3] As we have verified in a previous study, people who had greater interurban geographic mobility also had more heterogeneous networks (Maya-Jariego et al., 2018), and this seems to be associated with a lower number of steps in the decomposition of their personal networks.

Table 4
Comparison of means of the characteristics of personal networks and metropolitan mobility by quartile of stratification (t1).

	Quartile of stratification (t1)				
	Q1 (n = 15)	Q2 (n = 17)	Q3 (n = 20)	Q4 (n = 17)	F
Structural properties					
Density	0.64	0.57	0.56	0.77	4.57 * *
Cliques	28.93	44.88	58.80	140.94	11.61 * **
Components	1.80	1.23	1.45	1.17	0.98
Av. Degree	40.07	37.38	37.81	49.16	4.06 * *
Av. Closeness	49.45	51.02	53.89	61.35	1.85
Av. Betweenness	1.74	1.83	1.60	1.24	5.38 * *
Av. Eigenvector	18.12	17.93	18.54	19.31	5.11 * *
Metropolitan mobility					
Intercity travel frequency	2.00	1.47	1.45	1.52	2.08
Years living in town	14.66	15.76	16.90	16.76	1.95
% Time in hometown per week	79.00	93.47	87.45	86.88	3.91 *
% Time in capital city each week	21.00	6.52	12.55	12.52	3.98 *

Note. We use the term "stratification" to refer to the number of steps required to reach a network with zero betweenness in all nodes. Networks with higher stratification are expected to have a more complex hierarchical structure. By having a greater number of layers, more steps are necessary to deconstruct them. Statistically significant: * p < .05; * * p < .01; * ** p < .001.

Table 5
Comparison of means of the characteristics of personal networks and metropolitan mobility by quartile of stratification (t2).

	Quartile of stratification (t2)				
	Q1 (n = 12)	Q2 (n = 17)	Q3 (n = 13)	Q4 (n = 15)	F
Structural properties					
Density	0.54	0.54	0.61	0.60	0.79
Cliques	24.33	43.23	59.30	139.86	3.39 *
Components	2.00	1.05	1.53	1.00	2.42
Av. Degree	31.29	36.49	37.76	40.86	2.34
Av. Closeness	40.63	56.04	46.37	60.19	4.63 *
Av. Betweenness	2.04	1.77	1.62	1.67	1.05
Av. Eigenvector	15.21	18.38	18.18	18.55	2.07
Metropolitan mobility					
Intercity travel frequency	2.91	2.88	2.61	2.80	0.275
Years living in town	16.58	18.52	17.76	17.06	1.03
% Time in hometown per week	59.16	62.05	64.61	67.33	0.459
% Time in capital city each week	40.83	37.94	35.38	32.66	0.459

Note. We use the term "stratification" to refer to the number of steps required to reach a network with zero betweenness in all nodes. Networks with higher stratification are expected to have a more complex hierarchical structure. By having a greater number of layers, more steps are necessary to deconstruct them. Statistically significant: * p < .05; * * p < .01; * ** p < .001.

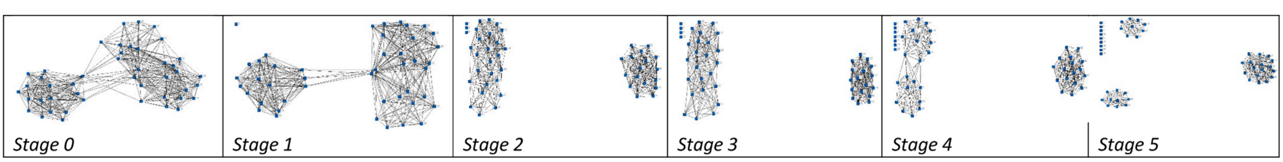

Fig. 1. A case of deconstruction of the personal network in 5 steps. *Note*. Respondent 9 (t2).

Classification of personal networks according to the deconstruction process

In a second stage of the data analysis, we carry out various classifications of personal networks considering the number of steps in the deconstruction process. First, we applied a cluster analysis of *K*-means using the average distance, the triadic closure indicator and the number of deconstruction steps in the first wave as criterion variables.[4] This made it possible to differentiate two groups defined in terms of the length (and indirectly the complexity) of the process (Table 6). Specifically, two-thirds of the interviewees were in the range between 17 and 31 steps in the deconstruction process (M = 21.72, SD = 3.331); while for the remaining third was sufficient with between 2 and 15 steps (M = 11.96, SD = 3.254). In addition, this last group is characterized by networks with greater average distance and triadic closure.

Second, we developed a classification in which, together with the number of steps, we used the density and fragmentation of the personal network as criterion variables. That is, those two dimensions that in the exploratory visual analysis seemed relevant and that, according to previous studies, constitute independent factors of variability in the structure of personal networks. In this case, as shown in Table 7, we observe that networks requiring fewer steps are characterized by a lower initial density (Cluster 3) or greater fragmentation (Cluster 1).

The three resulting clusters are illustrated in Fig. 3, with a selection of visualizations in each case. The number of steps appears to vary greatly depending on the degree of cohesion/fragmentation of the personal network. Furthermore, the deconstruction process could be

[4] That is, those two characteristics of the personal network that showed a greater correlation with the number of steps in the deconstruction.

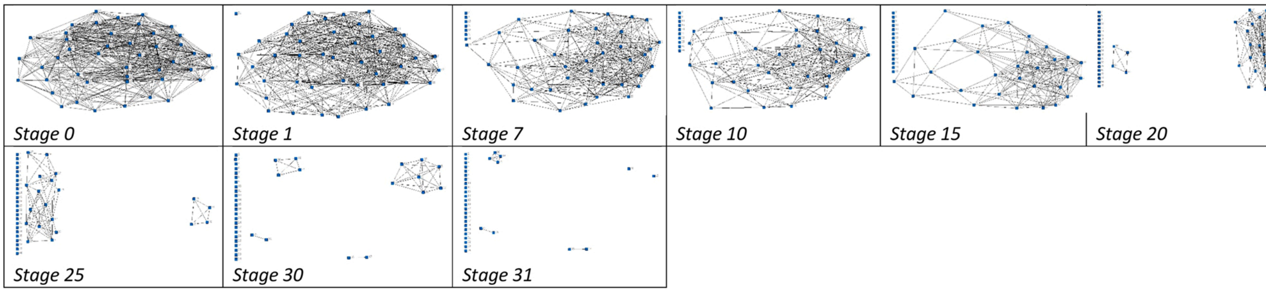

Fig. 2. A case of deconstruction of the personal network in 31 steps. *Note*. Respondent 62 (t1).

Table 6
Centroids of final clusters according to the number of steps, the average distance and closure of the personal network (t1).

	Clusters	
Criteria	Cluster 1 (n = 23)	Cluster 2 (n = 46)
Number of steps	12	22
Closure	0.777	0.684
Average distance	1.820	1.656

Note. Quick cluster of 2 categories, with 10 iterations and a convergence criterion of 0.02. The clusters converged in the second iteration.

Table 7
Centroids of final clusters according to the number of steps, density, and fragmentation (t1).

	Clusters		
Criteria	Cluster 1 (n = 9)	Cluster 2 (n = 31)	Cluster 3 (n = 29)
Number of steps	9	23	16
Density	0.421	0.440	0.373
Fragmentation	0.46	0.17	0.16

Note. Quick cluster of 3 categories, with 10 iterations and a convergence criterion of 0.02. The clusters converged in the second iteration.

especially short when there are clearly defined cohesive subgroups.

Classification validation

To check the discriminant value of this classification, we compare how the intermediation values evolve throughout the deconstruction process for each cluster. As shown in Fig. 4, in all cases the nodes with the highest betweenness rank were eliminated in the first third of the steps. However, some differences were observed between clusters. Specifically, the most cohesive networks (cluster 2) required more steps to complete the deconstruction process. In addition, the first deleted nodes had a betweenness rank of around 100 (while in clusters 1 and 3, they scored above 150).

Systematic comparisons of means in betweenness are summarized in Table 8. The results show two definite trends. On the one hand, cluster 2 (the one with the most cohesive networks) differs most consistently from the other two. On the other hand, cluster 1 (with greater fragmentation) is characterized by the fact that the deconstruction process of the personal network is interrupted earlier.

Finally, we checked the existence of relationship between the steps of the deconstruction process in the first observation and in the second. First, we observed that there is a moderate positive correlation between the number of steps in the first wave and in the second ($r = 0.415$, $p < .01$). Next, we performed a linear regression analysis using as predictors all the structural properties of the personal networks in step 0 of the first wave and as a dependent variable the number of steps necessary for the deconstruction of the personal network in the second wave. The only significant predictor was the average distance from the personal network ($t = -2.022$, $p < .05$), resulting in a model that explains 23% of the variance in this case ($F = 2.513$, $p < .05$).

Analysis with networks of strong ties

All the analyses above were performed with the personal acquaintanceship networks among the subset of 45 alters mentioned by each respondent. The same steps were repeated with the networks of strong ties, obtaining quite similar results (González-Tinoco, in progress). Although the deconstruction process was reduced to about 14 steps on average ($M = 14.30$, $SD = 4.977$), a strong correlation was also observed between the number of cliques and the number of steps ($r = 0.759$, $p < .01$), and it was found that denser networks typically require more steps than networks with a higher level of fragmentation. Also in this case, density and fragmentation were enough to identify the different kinds of deconstruction observed.

Description of deconstruction in three phases

The previous analyzes revealed that there are individual differences in the way in which the descriptive measures of personal networks vary throughout the deconstruction process. To verify this, we divided the deconstruction process into three phases (with an equal number of steps each) and calculated the coefficient of variation[5] for each resulting interval. The descriptive summary is in Table 9.

Next, we performed a cluster analysis using the *Quick Cluster* procedure, with two categories, using density, fragmentation, and the number of steps as criteria variables. According to the resulting centroids, there is a group of personal networks whose deconstruction process is longer and where the most significant changes occur in the second and third phases (Cluster 1, Fig. 5). They correspond to more than half of the respondents (n = 37, 53.6%). On the other hand, there is a group whose most significant changes occur at the beginning, in the first and in second phase, so that the deconstruction process is interrupted earlier (Cluster 2, Fig. 5). This second cluster represents 46.3% of the total of respondents.

Between both clusters, significant differences were observed in the number of cliques in the personal network before starting the deconstruction process ($F = 13.609$, $p < .0001$). Denser networks with a higher number of cliques require more steps to be deconstructed. In addition, its degree of cohesion (i. e., density) varies throughout the entire process (in fact, the coefficient of variation increases). They correspond to cluster 1, represented in Fig. 5, on the left. In contrast, less dense networks with fewer cliques deconstruct earlier and experience comparatively greater variation initially (Fig. 5, right).

Discussion

In this article we use for the first time the personal network deconstruction procedure -initially proposed by Bidart et al. (2020) for

[5] It is the ratio between the standard deviation and the arithmetic mean.

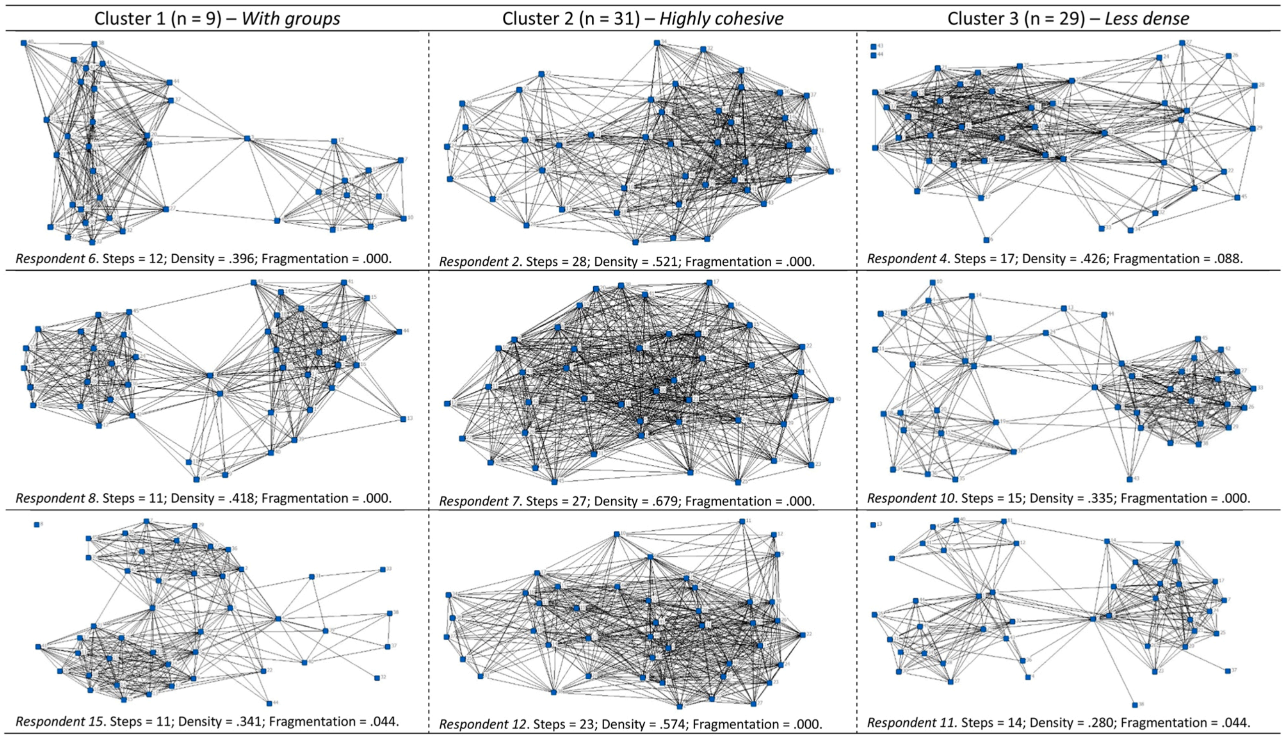

Fig. 3. Illustration of the three types of personal networks.

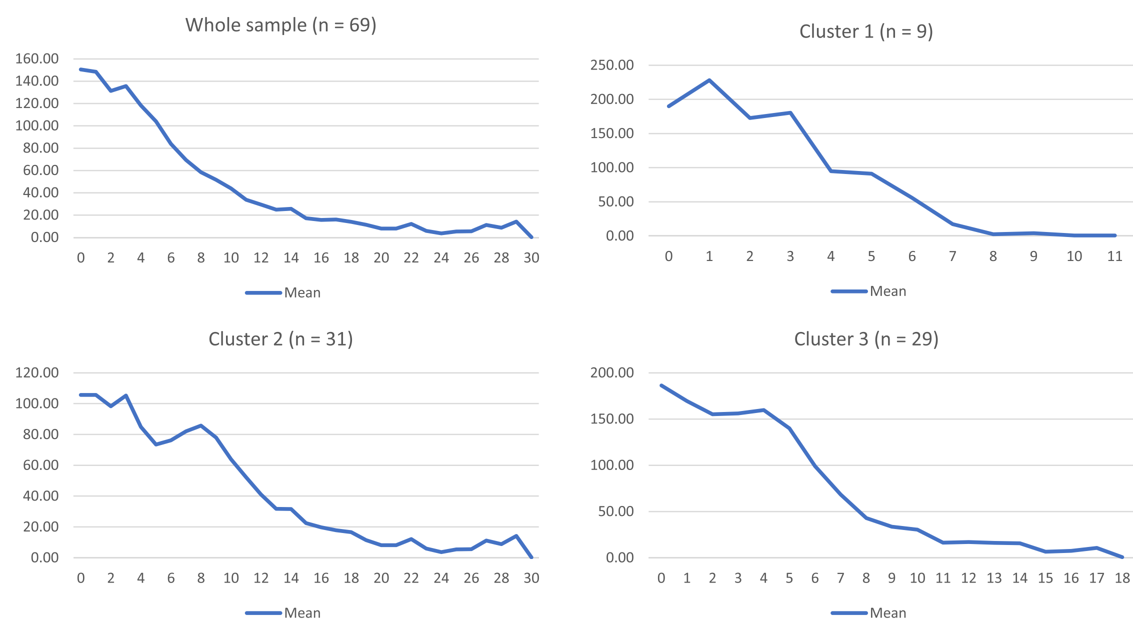

Fig. 4. Changes in the indicators of betweenness centrality in the successive steps of deconstruction of the personal networks in time 1.

descriptive purposes- as a personal network classification strategy. In our study we verified that there are important individual differences in how the process of dismemberment of the personal network evolves as we remove the nodes with greater intermediation. In addition, we observe that these individual differences depend in part on the structural properties of the personal network before starting the deconstruction process. This is what allows it to be used indirectly in the elaboration of typologies.

Through different analysis strategies, we revealed the existence of highly cohesive networks as opposed to others that are organized around two or more recognizable factions. The former require comparatively more steps to complete the deconstruction process, while the latter begin to fragment more clearly in the early stages of the process. These two categories or types of networks coincide in part with the differentiation between "regular dense" networks and others with a higher level of centralization (Bidart et al., 2018), or between "dense networks" and

Table 8
Comparison of means in *betweenness* per each cluster.

	Clusters			
Step	Cluster 1 (n = 9)	Cluster 2 (n = 31)	Cluster 3 (n = 29)	F
0	189.84 (85.3)	105.69 (49.5)	186.26 (90.2)	10.377 * **
1	228.14 (103.58)	105.57 (54.11)	169.46 (88.39)	10.674 * **
2	172.75 (115.93)	98.25 (45.01)	155.13 (80.27)	6.210 * *
3	180.49 (164.55)	105.25 (66.16)	155.7 (79.58)	3.699 *
4	94.88 (118.56)	84.92 (43.43)	159.66 (97.74)	6.893 * *
5	91.04 (100.14)	73.50 (34.04)	139.96 (104.26)	5.410 * *
6	55.59 (71.34)	76.16 (43.54)	98.94 (98.36)	1.253
7	17.28 (27.20)	82.00 (53.41)	68.31 (67.90)	3.500 *
8	2.45 (1.59)	85.71 (56.67)	42.80 (42.39)	11.363 * **
9	4.01 (2.57)	77.98 (66.76)	33.55 (35.98)	8.263 * *
10	0.49 (0.66)	63.86 (65.74)	30.39 (41.59)	4.710 *
11	0.63 (0.51)	52.18 (62.21)	16.30 (17.96)	5.080 * *
12	–	40.97 (48.23)	17.02 (24.28)	5.771 *
13	–	31.70 (34.19)	16.07 (20.08)	3.818
14	–	31.62 (35.70)	15.64 (23.59)	2.864
15	–	22.38 (16.42)	6.48 (4.91)	13.326 * **
16	–	19.71 (16.34)	7.35 (11.11)	6.982 *
17	–	17.76 (16.02)	10.65 (23.51)	1.178
18	–	16.56 (21.32)	0.68 (0.72)	3.255

Note. Significance level: * $p < .05$; * * $p < .01$; * ** $p < .001$. In Scheffé 's post hoc comparisons, Cluster 2 is the one that differs from the other two in the steps 0, 1, 2, 8 and 9. It also differs from cluster 3 in steps 4, 5, 11, 15 and 16; and from cluster 1 in step 7.

Table 9
The structural properties of personal networks in three phases of the deconstruction process.

	Phases during the deconstruction process		
Structural properties	Phase 1	Phase 2	Phase 3
Degree centralization	0.22 (0.13)	0.27 (0.14)	0.33 (0.23)
Density	0.31 (0.12)	0.42 (0.18)	0.46 (0.24)
Components	0.53 (0.11)	0.22 (0.07)	0.11 (0.04)
Fragmentation	0.55 (0.12)	0.08 (0.05)	0.02 (0.02)
Closure	0.53 (0.03)	0.68 (0.06)	0.09 (0.05)
Average distance	0.17 (0.09)	0.15 (0.09)	0.15 (0.08)

Note. Mean and standard deviation of the variation coefficient (VC) for each indicator in each phase (t1).

"clustered networks" (Maya-Jariego, 2021). Although the inter-individual variability may be much greater, and the typology more complex, these two ideal types appear consistently in different surveys of personal networks.[6] Thus, the conformation of a single highly integrated component versus the organization in more or less defined cohesive subgroups seems to be a key dimension in the classification of personal networks.

As far as the singular structural measures are concerned, we make two interesting observations. First, the indicators of density, fragmentation and the number of steps to complete the deconstruction were sufficient to make the previous classification. Second, the number of cliques was the best predictor of the length of the deconstruction process (i. e. the number of steps). Both density and cliques have already shown their discriminating value in characterizing the structural properties of personal networks (Lozares et al., 2013; Maya-Jariego & Holgado, 2015). Hence, combining two dimensions seems a promising strategy for elaborating typologies in future research: on the one hand, cohesion-fragmentation and relational integration on the other.

The iterative deconstruction procedure of personal networks reveals their hierarchical nature. The strategy of progressively dismembering the network by removing the nodes with the highest betweenness centrality revealed the existence of cohesive subgroups and local intermediaries (Maya-Jariego, 2022). For this reason, the technique is helpful in identifying the most relevant contexts of interaction for the individual, while revealing the nested structure of the groups in which they participate. This is particularly adequate for reflecting the complexity of network data (Van Duijn et al., 1999). Especially if we consider that the social support provided by specific ties may depend on the structural properties of the personal networks in which they are embedded (Wellman and Gulia, 2018). On the other hand, the technique may have limitations when exploring dimensions other than the degree of cohesion or the presence of subgroups.[7] In addition, part of its usefulness derives from applying the technique following a controlled processing approach, since it allows exploring the structural properties step by step, in each iteration. Some of the findings of our study stemmed from the fact that we did not apply an automated algorithm, but rather the researchers monitored the dismemberment of the network step by step, observing the result obtained in each phase.

As we have seen, the technique is practical for the exploratory description of personal networks. The division of a network into relatively independent subnetworks or partitions has already been shown to have an exploratory value in whole networks, to understand their properties in greater depth (De Nooy et al., 2018). This greater understanding does not depend so much on calculating a summary indicator as on the process of progressive deconstruction of the network itself. Future research could delve into how the different types of intermediaries (in this case, alters) connect the different social circles in which the individual (Ego) participates. It would also be revealing to integrate deconstruction in a qualitative interview in which the respondent interprets the decomposition of his personal network in successive layers. As occurs with other inductive classification strategies (Laier et al., 2022), the elaboration of typologies is a strategy that is partly discovered and partly built. This entails limitations due to the complexity of the analysis, but also opportunities to carry out interactive inquiries with the participants.

Social cohesion, nested structure, and deconstruction of personal networks

Cohesive groups are characterized by high connectivity, with redundant paths linking actors together and making the network as a whole more resistant to breakdown (Moody and White, 2003). Considering the structure of relationships, cohesion can be conceived as "the minimum number of actors who, if removed from the group, would disconnect the group" (Moody and White, 2003, p. 9). This implies that (1) cohesion will be weaker to the extent that connectivity depends on a small number of actors; moreover, (2) it allows indirectly revealing the hierarchical structure of nested subgroups that make up social systems. These two elements are related, as we will see below.

On the one hand, cohesion can be analyzed as a property of the network as a whole or as a characteristic of the subgroups that make it up. Both alternatives are compatible with each other. Thus, in the case of personal networks, structural cohesion has been examined through two dimensions consisting of (a) the existence of a tightly knit set of actors around Ego (that is, the network closure) and (b) the number of cohesive subsets of alters to which an actor is connected (operationalized as the

[6] A different matter is the fact that each personal network differs to a greater or lesser degree from the ideal types used as reference in the classification. In fact, it is common to find an "intermediate" profile with individuals who are halfway between the two previous categories (Maya-Jariego, 2021).

[7] This strategy may be less effective, for example, when trying to examine the composition of the personal network or when evaluating the degree of homophily in Ego's interpersonal environment, to mention just a few dimensions. Variations in size can also pose an additional difficulty, since the deconstruction process depends directly on the number of nodes that make up the personal network. In our case, we used networks with a fixed number of alters, which facilitated inter-individual comparison (Maya-Jariego, 2018).

Fig. 5. Two differentiated patterns in the deconstruction process. *Note*. The graph represents how the coefficient of variation of density and fragmentation evolves in the three intervals into which we have divided the deconstruction process. The coefficient indicates how much this indicator varies in each interval. Convergence was obtained in the 6th iteration of the Quick Cluster analysis.

number of cliques in the personal networks) (Martí et al., 2017). However, although both properties report the degree of cohesion, in the study by Martí et al. (2017) only a greater presence of cohesive subgroups was positively related to a greater probability of exchanges of support in the individual's interpersonal environment and, therefore, with the resources that she potentially obtains from her personal network. Everything seems to indicate that group dynamics increase the probability of mutual support. Hence, the internal organization of personal networks in more or less defined subgroups is critical when characterizing their structure. Furthermore, groupings usually increase the number of independent ways that network members are linked. This reaffirms the descriptive value of the stratification analysis to the extent that, also in our study, the number of cliques showed the strongest correlation with the number of steps needed to deconstruct the personal network.

On the other hand, a detailed examination of the structural cohesion of social networks usually reveals a hierarchical organization, made up of "nested cores and sequential boundaries within a network" (Doreian and Woodard, 1994, p. 278). Despite its interest, this has been a scarcely explored feature of social networks. For example, in developing algorithms for the automated discovery of communities in social networks, strategies of division into discrete and non-overlapping communities have predominated (Fortunato and Newman, 2022). It has been comparatively much less frequent to consider communities subdivided into successively smaller communities, in a hierarchy of levels. An antecedent of this hierarchical approach is the work of Doreian and Woodard (1994), in which they used a variant of snowball sampling together with the detection of k-cores within the network to show that social networks are not closed systems. This method allowed the identification of cohesive subgraphs integrated into higher-order nuclei.[8] Other similar examples are the analysis of core-periphery structures (Borgatti and Everett, 2000), network embedding algorithms and some data clustering methods (Fortunato and Newman, 2022).

In this context, the iterative deconstruction procedure of personal networks that we have used in this study (1) allows us to calculate the number of steps necessary to decompose the network, (2) serves to detect the cohesive subgroups that constitute the network, and (3) reveals its hierarchical structure. The number of steps is itself an indirect indicator of structural cohesion. Furthermore, it is something that can be obtained in an automated way (Bidart et al., 2018). However, both the detection of subgroups and their hierarchical organization would benefit from a step-by-step application of the technique, in which complementary information is collected on the contexts, or "social foci" (Feld, 1981), in which form the cohesive subgroups. This possibly requires the respondent's contribution (Ego) or the application of mixed and interactive methods.

Likewise, the conditions under which the data was generated set some of the possible limits faced by this technique. In our case we used a fixed number of 45 alters when generating the personal network. If we consider that density, as well as other indicators of structural cohesion with which it is usually correlated, is particularly sensitive to the size of the network, it would be expected that the deconstruction process would also vary significantly depending on the initial structural properties. Similarly, the smaller the personal networks, the more likely their structure is limited to the cohesive core. This could reduce the opportunities to make the hierarchical organization of the personal network visible.

Conclusion

The deconstruction of personal networks can be used for classification purposes. The initial structural properties determine the number of steps required to decompose each personal network and the degree of variation observed in the different stages of the process. The most cohesive networks are more resistant to fragmentation, while those organized in defined subgroups deconstruct faster by removing the nodes with higher betweenness centrality. The stratification of the personal network represents its internal organization, showing how the different social contexts are integrated into the individual's life.

Compliance with ethical standards

Authors declare no conflict of interest. The participants signed an informed consent, with the commitment on the part of the researchers to treat the data confidentially and in an aggregated manner.

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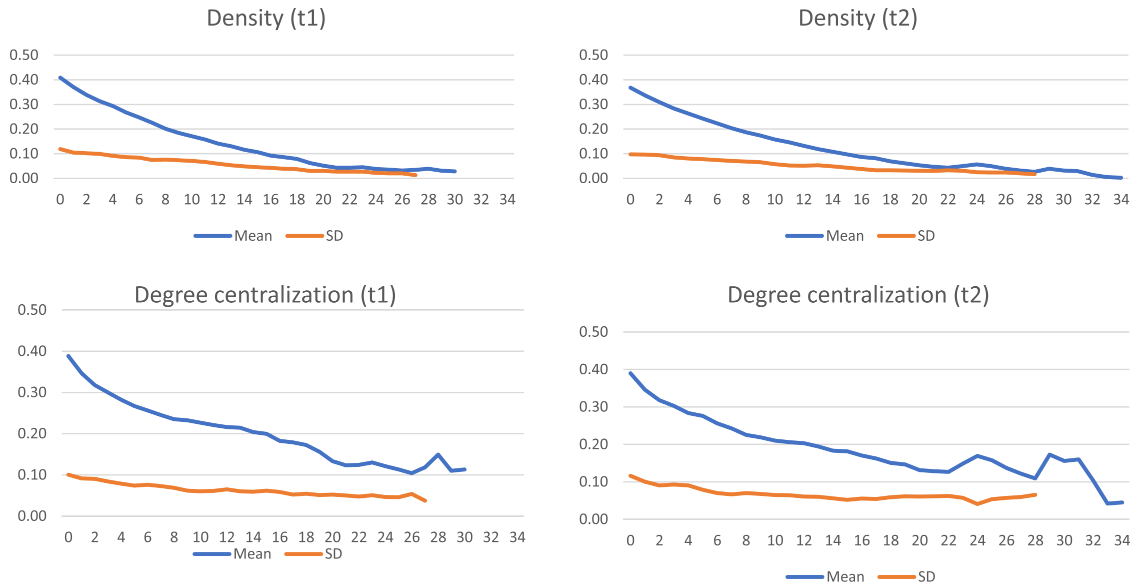
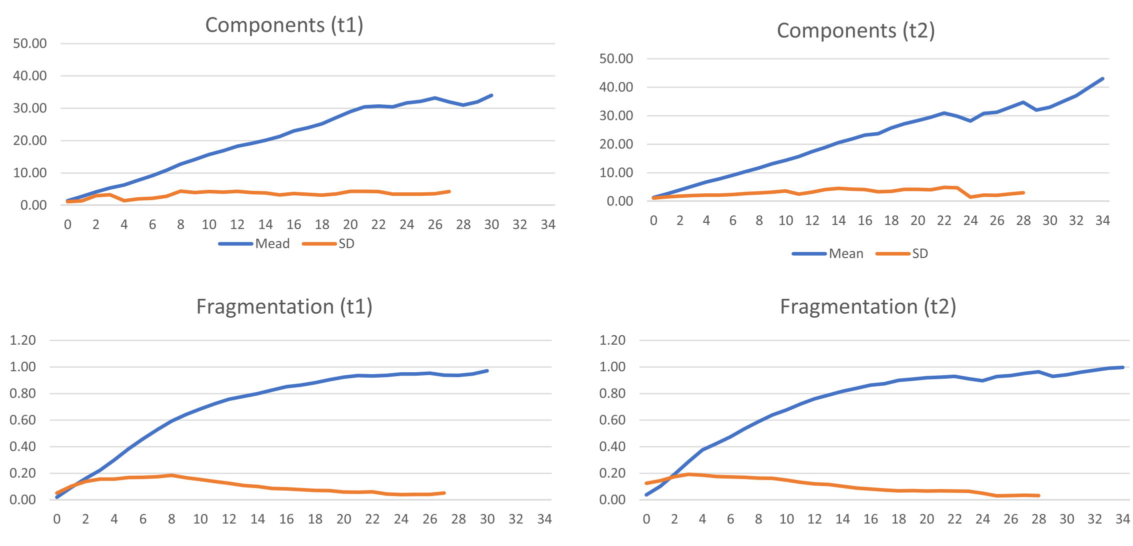
[8] Moody and White use the metaphor of "Russian dolls" to refer to increasingly cohesive groups nested within each other.

Annex 1.1. Changes in the indicators of density and degree centralization in the successive steps of deconstruction of the personal networks, both in time 1 (left) and in time 2 (right)



Annex 1.2. Changes in the indicators of number of components and fragmentation in the successive steps of deconstruction of the personal networks, both in time 1 (left) and in time 2 (right)



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