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# Building a structural typology of personal networks: individual differences in the cohesion of interpersonal environment.

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**Abstract.**

The development of typologies is an efficient strategy in the descriptive study of individual differences in the interpersonal environment of relationships. In this paper, we developed a classification of personal networks using structural indicators with a representative sample (n = 403) in a medium-sized city of the metropolitan environment of Seville, in the south of Spain. The typology was based on the analysis of conglomerates with three criteria variables: centralization, number of cliques, and the number of components. The results allowed the identification of four types of personal networks: dense, intermediate, clustered, and fragmented networks. The classification was validated with descriptive data, linear discriminant analysis, and visual-classification procedure. The structural cohesion and the formation of cohesive sub-groups were two key dimensions to describe the variability of the personal networks in the sample.

*Keywords.* Personal networks, typology, cluster analysis, structural measures, cohesion.

## Highlights

- Types of personal networks are described using centralization, cliques and components as criteria variables.
- Four types of personal networks were identified: dense networks, intermediate networks, clustered networks and fragmented networks.

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- Levels of structural cohesion and cohesive subgroups were key dimensions to classify the types of personal networks.
- Mobility, social activity and personal transitions may introduce diversity in personal networks.

## 1. Introduction.

The set of social relationships a person has is considered a personal network. In the tradition of social support studies, it has been frequently described through singular indicators such as size, composition, and multiplicity of functions carried out by the help providers. However, when alter-alter relationship matrices are generated from the information provided by the respondent, it is also possible to apply the same techniques traditionally used in the analysis of "complete" social networks (McCarty, 2002). In this case, the personal network is described through a set of aggregated indicators that summarizes its structural properties.

In any case, summarizing the characteristics of a personal network leads to specific methodological challenges. On the one hand, the same empirical indicator can correspond to different topologies. In fact, individual indicators separately considered may not be informative enough about the personal network composition, so it becomes necessary to take into consideration several indicators simultaneously. On the other hand, the different structural properties are usually related. To handle such multicollinearity, some strategies can be used to reduce the dataset dimensions (e.g., principal components analysis and other factor analysis techniques).

In this context, the cluster analysis has proven to be an efficient way of identification and characterization of existent types of personal networks in a sample. In the two following sections, we review some of the most significative classifications following this approach and using successively structural-based and social support indicators.

## 2. Social support typologies based on cluster analysis.

The development of a typology consists of detecting some type of systematic covariation among a set of characteristics of the support networks. Normally, it proceeds inductively. To do this, the grouping of the respondents into conglomerates is based on a selection of indicators or criteria variables. From this starting point, the different classification procedures try to maximize differences among clusters and minimize intra-cluster differences (Aldenderfer & Blashfield, 1984). The resulting categories are "partly built and partly discovered" (Stone & Rosenthal, 1996, in Litwin, 1997, p. 283). That is, analysis techniques allow us to experiment with different empirical solutions and in each case, their potential to sustain significant theoretical interpretations is evaluated.

The typologies of support have been especially used with the elderly and with the immigrant population. In both cases, the most common has been to combine indicators of size and composition of the system of social support providers.

A series of studies with the elderly in Wales (Wenger, 1989, 1991) and Israel (Litwin, 1995, 1997) classified support networks according to geographic accessibility, frequency of interaction, and the proportion of family, friends, and neighbors, among other factors. The resulting types of networks generally showed a strong family component, although they varied in size and diversity depending on the degree of local integration, with friends and neighbors. Paradoxically, the individuals with broader and more diverse networks corresponding to the most independent elderly and with better well-being indicators had better access to health services. On the contrary, accessibility was more difficult among those whose network was smaller and more centralized in the family.

In the case of recent immigrants, the most common type of support network seems to lie around a small group of fellow citizens in the same town of residence (Maya-Jariego, 2002, 2006). Those recently arrived turn to other colleagues who are also immigrants to form their nucleus of support, as an alternative to the lesser accessibility of ties with family members (Martínez, García & Maya Jariego, 2001). In some comparatively less frequent cases, the impact of international displacement is reflected in insufficient support structures, with minimal networks. Furthermore, family reunification and integration into the local community are two basic strategies to rebuild personal networks in the receiving or host society, with a direct influence on the reorganization of the social support system (Maya-Jariego, 2003).

Among other factors, the support structures seem to be dependent on the availability of a set of relatives that can be immediately accessed, as well as on the level of social activity the individual displays. For example, geographical displacement, separation from family or a particularly active professional life force the introduction of diversity in the composition of the support network. Similarly, the development of a couple relationship also seems to condition the individual's management of emotional, instrumental and informational support resources.

The classifications of support normally show variability in the number of help providers available and the heterogeneity of the sources of help. Some individuals focus their support demands in the family and residential immediate context, while others resort to non-family providers and also seek resources outside of the endo-group. In a comprehensive review of support typologies, classifications were found to typically include a family-centered type, a friend or community-centered type, a socially isolated type, and a broad and diverse network type with weak ties (Antonucci, Fiori, Birditt & Jackey, 2010). Without being exhaustive, we have summarized a selection of support typologies showing the variation on size and composition heterogeneity in Table 1. With the immigrant population, the same logic it is observed, even when family contacts are less available after the international displacement.

## 3. Typologies of personal networks.

The development of typologies allows systematic comparisons of personal networks through an efficient procedure and with a potential theoretical value. The procedure empirically evaluates which structural properties usually covariate with each other and which characteristics are more determinant in the type of personal network consequently. This helps to identify some of the factors that contribute to the formation of the network and that make some configurations more likely than others (Bidart, Degenne & Grossetti, 2018; Giannella & Fischer, 2016). Therefore, it is expected to obtain an economic and parsimonious characterization of the personal network structure with a small number of dimensions.

It has been relatively frequent to combine the indicators of size and composition of the personal network, as in the case of the support typologies. Nonetheless, other classifications have been based on the characteristics of the alters (or in the type of relationship the respondent maintains with them) and only in a few cases, the typology was based exclusively on the structural properties of the personal network.

An illustrative case of the combined use of structural properties and the composition of the personal network consisted in the study of the acculturation process of a group of immigrants in Spain, through the systematic analysis of their interpersonal relationships (Lubbers, Molina & McCarty, 2007). The formation of dense conglomerates of relationships in which relatives and compatriots predominate was associated with a type of univocal ethnic identification, while a greater heterogeneity of the personal network was related to a more plural sense of belonging. On the other hand, this type of study usually reflects an indirect association between changes in structure and composition (Maya Jariego, Holgado & Lubbers, 2018).

Using data from a community survey in Northern California, Giannella and Fischer (2016) developed a typology based on interaction, proximity, and involvement with family and non-family members, along with the distribution of sociability in work activities, religious and leisure time. The two most frequent types of personal networks consisted of articulating personal relationships around “career and friends” or around “family and community”. The first type was more frequent among the younger population, with a higher educational level, and without children; while the second type was more common among married people with children, as well as among those who declared their membership in a Christian church.

Bidart et al. (2018) in a longitudinal study with young French people showed that four structural properties were sufficient to capture the diversity of personal networks. Specifically, the classification was based on betweenness centralization, modularity, diameter, and density. Among other characteristics, the typology allowed describing to what extent the personal network is articulated around an individual (usually the partner) and the degree to which the respondent's sociability is distributed among different social circles. The dimensions used in this classification have a high degree of coincidence with the fundamental variability factors found in other representative surveys of personal networks, which have revealed the discriminatory value of structural cohesion, the existence of defined groups and the fragmentation into components (Lozares, Martí, Molina & García-Macías, 2013; Maya-Jariego & Holgado, 2015).

Taking into account the structural properties, the most frequent configurations can be differentiated. Accordingly, instead of focusing on singular dimensions, it is intended to represent the structure of the entire personal network. As we did in the previous section, in Table 1 we have also summarized a selection of typologies with structural indicators. Although some parallelism is observed with those of support, the dimensions that seem relevant in this case are density, the distribution of relationships in social circles or differentiated interaction contexts, and segmentation into subsets, either by components or by isolated nodes. In other words, it is respectively about cohesion, relational integration, and fragmentation of the network.

TABLE 1

## 4. This study: a structural-based typology with a representative sample.

The development of typologies has frequently been based on intentional samples or specific population strata (as in the cases we have reviewed with older people, young people, and immigrants). Sometimes they are also groups during an ecological transition, such as the completion of studies or geographic relocation. This is reflected in the properties of personal networks, to the extent that their characteristics depend directly on the contexts of interaction.

In this study, we used data from a representative survey of the resident population of "Alcala de Guadaira", in the province of Seville, and we developed a typology with indicators based exclusively on the structural analysis of the personal networks. In this case, a representative survey of the local community covers a diversity of situations to which the population is exposed, at the same time that it allows us to guarantee some relatively homogenous conditions in other contextual factors. The main research objective consisted of developing an inductive classification capable to adequately reflect the variability of the structure of the personal networks in the general population.

## 5. Empirical context: data and methods.

In this study, we analyzed 403 personal networks matrices obtained from the representative survey of the resident population of "Alcala de Guadaira", in the province of Seville. Specifically, a quota-random sampling by gender, age, and the district of residence was carried out. The respondents had an average of 37.82 years at the time of the interview (SD = 15.96), and on average they have lived in Alcala 33.34 years (SD = 16.43). Of the total, 46.7% are men and 53.1% are women. In the survey, information was obtained on the frequency of intercity trips between Alcala de Guadaira and Seville (separated by 16 kilometers apart), as well as on the psychological sense of community concerning both locations. These data have been analyzed in a previous study on the metropolitan lifestyle. A detailed description of the instruments and the procedure can be found in Maya Jariego & Holgado (2015).

### *5.1. A name generator with a fixed number of alters.*

To build the personal network a multiple generator with a fixed number of alters was used. First, questions from the *Arizona Social Support Interview Schedule* (Barrera, 1980) were used to obtain the list of providers of advice, emotional support, companionship, instrumental help, positive feedback, and material help. Second, respondents were asked to complete the list up to a total of 25 alters. Third, they fulfilled the matrix of alter-alter relationships. In total, they reported the existence of 80,343 relationships, out of a total of 120,900 possible.

Multiple generators are more reliable than single generators (Marin & Hampton, 2007). The establishment of a fixed number of alters facilitates the standardization and comparability of personal networks while reducing the burden of data processing (McCarty, 2002; Maya Jariego, 2018). Furthermore, the comparison of networks of the same size is especially pertinent when trying to develop a typology. For example, the density tends to decrease when the size of the network increases, conditioning the classification strategies (Bidart et al., 2018).

### *5.2. Structural indicators and cluster analysis strategies.*

To summarize the structural properties of personal networks, the density, centralization, number of cliques and number of components were calculated for each matrix, as well as the normalized average indicators of degree, closeness, eigenvector, and betweenness. It is a set of indicators with high multicollinearity. In a previous study, we verified, through the correlation matrix and the principal component analysis, which factors best summarized the structural properties of the personal network sample (Maya Jariego & Holgado, 2015). Based on this previous analysis, we selected three criteria variables for the cluster analysis: centralization, the number of cliques and the number of components. These variables correspond, respectively, to the cohesion, integration and fragmentation factors. Table 2 defines the three criteria variables and explains their interpretation from a structural point of view. As supplementary material, we attach in the Annex the correlation table and the factor analysis on which the selection of variables was based.

TABLE 2

For the analysis of conglomerates, we used the *Quick Cluster* procedure with 10 iterations, repeated updating of means, and a convergence criterion of 0.02, for a solution of 4 conglomerates. As is usual in cluster analysis (Aldenderfer & Blashfield, 1984) to decide the number of categories we based on the correspondence of the theoretical guide (summarized in Table 2) with the empirical structure of data. Previous exploratory analyzes were carried out to check the number of cases by categories. In calculations, we disregard an individual with extreme scores. The relational data was analyzed with UCINET 6.698 (Borgatti, Everett, & Freeman, 2002) and the cluster analysis was developed with SPSS 26. The visual representations were made with Netdraw (Borgatti, 2002).

### *5.3. Typology validation.*

We used three different strategies to check the validity of the classification obtained. First, with an exploratory nature, we elaborate a typology based on the visual classification of personal networks. Second, we performed cross-validation through discriminant analysis of the typology after performing the *k-media* cluster analysis. Then, we crossed the resulting classification with descriptive indicators of the structural properties of the network. In all cases, the degree of convergence was analyzed.

Visual recognition by experts provides a comparison criterion with potentially relevant psychosocial properties, while discriminant analysis and descriptive comparison allow contrasting its effectiveness to establish differences in other variables external to the classification. Visual coding has previously been used effectively (Bidart et al, 2018; Cruz, 2013). In our case, the category system (summarized in Table 3) was elaborated by the author, based on an inductive stacking procedure for visually similar graphs. To do this, he was guided by aspects of the topology of the personal network that may be relevant from a psychosociological point of view (Freeman, 2000).

In all cases the spring embedded algorithm was used to generate the visualizations. The two observers who participated in the classification of the graphs were psychologists, with experience in social network analysis.

## 6. Results.

### *6.1. Exploratory visual analysis.*

Two types of clearly differentiable networks were identified from the initial visual recognition. These two types appeared quite frequently among the interviewees: networks formed by a single module with high connectivity and networks in which clusters can be easily identified. The former type reports individuals who have an integrated space of sociability, while the latter seems to refer to various defined contexts of interaction. *Dense* networks are networks with high connectivity that are integrated into a single component. We have illustrated this with the respondent AG305 in Table 3. Networks *with groups* are organized into several recognizable conglomerates, which are usually interconnected through a few individuals with high betweenness centrality (see, for example, the case of AG341 in Table 3).

Next, a third *intermediate* category in which the networks have less density without forming defined groups (AG107, Table 5) was established. Finally, personal networks are *fragmented* into components in some cases because the cohesion of the set is significantly less (AG89, Table 3).

The three theoretical dimensions in personal network variability seem consistent with visual classification. Thus, structural cohesion, group integration, and component fragmentation are effective in differentiating the type of immediate interpersonal environment. This qualitative and inductive differentiation of the four categories was then contrasted through the cluster analysis.

TABLE 3

### *6.2. A four-category classification of personal networks.*

The result of the cluster analysis is presented in Table 4. At the extreme of greater structural cohesion, there is a group of respondents with the lowest indicators of centralization and the number of cliques (Cluster 2, n = 118, 29.35%). It is a type of personal network with high connectivity, which is made up of a single integrated relational component. At the opposite extreme is a group with the highest scores in centralization and number of components, who therefore have comparatively more fragmented personal networks (Cluster 4, n = 93, 23.13%). The Cluster 3 occupies an intermediate position between the previous two (Cluster 3, n = 170, 42.29%). Finally, a small group stands out for having an especially high number of cliques (Cluster 1, n = 21, 5.22%).

The canonical discriminant functions show that the axis of structural cohesion is a fundamental dimension of variability between clusters 2, 3 and 4, while the high number of cliques makes a small group different from the rest in another dimension related to clustering coefficient. Cross-validation showed that 98.3% of the cases were correctly classified. The distribution of cases according to the final centroids of each category is represented in Figure 1.

TABLE 4

FIGURE 1

A selection of 209 visualizations was shown to two observers to check the degree of fidelity in recognizing the visual properties of the categories. The type of dense networks was correctly identified by both observers in 93% of the cases, while the other categories had an average coincidence of 51.8%. This result coincides with the distribution of cases in Figure 1, which has a wide space of "intermediate" networks (42.1%) that limits the other three categories. Of the three dimensions used in the classification, it is structural cohesion that is most evident in visual recognition by external observers.

### *6.3. Descriptive evaluation of the typology*

In Table 4 we have summarized the comparisons in the structural properties of personal networks according to the resulting classification. The data confirm the differences between the four identified types. Specifically, the second cluster is above the average in the normalized average indicators of density ($F = 201.2$, $p <.0001$), degree ($F = 255.4$, $p <.0001$), closeness ($F = 63.1$, $p <. 0001$), and eigenvector ($F = 52.5$, $p <.0001$); while it is below the average in the betweenness indicator ($F = 124.7$, $p <.0001$). Just the opposite occurs with cluster 4, confirming that both profiles correspond to the two ends of structural cohesion.

The four profiles were systematically crossed with all the sociodemographic variables available in the survey. Compared to the other three categories, respondents with dense networks are on average older ($F = 11.1$, $p <0.0001$), have been living in the town of residence (Alcala de Guadaira) for longer ($F = 15$, $p <0.0001$ ) and make less frequent intercity trips to Seville ($F = 3.5$, $p <0.05$). In other words, they have a population profile with greater local roots. In contrast, respondents with fragmented networks have a lower level of identification with the locality of residence ($F = 4.8$, $p <0.01$).

TABLE 5

The descriptive analysis confirms that three of the clusters correspond to three levels of structural cohesion (clusters 2, 3 and 4), while another is distinguished from the rest by a comparatively high number of cliques (cluster 1). We have represented it in Figure 2.

FIGURE 2

In "clustered networks", there are usually between one and three nodes that occupy a central position and that are connected to the different conglomerates present in the network. In the sample of personal networks in our study, it is very often the intimate partner or a very close friend of the interviewee.

## 7. Discussion.

In this paper, we developed an inductive structural typology of personal networks with a representative sample of the local population of a city in the metropolitan environment of Seville. When generating a classification, we not only identified what are the fundamental variability dimensions of personal networks, but we established a series of configurations that allowed us to theorize about the relational dynamics that comprise them. Firstly, we have verified that the structure of personal networks varies in the degree of structural cohesion, the formation of clusters and, where appropriate, the existence of fragmented components. Secondly, the combination of these dimensions allowed to clearly distinguish three levels of cohesion, together with peculiar structures that are characterized by organizing relationships according to the contexts of interaction.

The four categories obtained with our data bear some parallelism with some previous classifications. For example, in the structural typology elaborated by Bidart et al. (2018) also distinguishes between the most cohesive networks ("regular dense"), others in which some type of more or less defined conglomerates emerge ("centered dense" or "centered star"), and those more disconnected and dispersed networks, which in some cases are fragmented into components ("segmented", "pearl necklace", or "dispersed"). Also, in a study with young single men in Milan, Bellotti (2008) found four types of personal networks. Some individuals develop cohesive communities with dense networks of large groups of friends, while other respondents rely on small cliques, selecting a small number of friends from whom to draw support. In some cases, a core-periphery structure or an organization by interaction contexts emerges, when different friends are available to fill different support functions.

The three dimensions also coincide with some previous evidence. The three cohesion, integration and fragmentation factors were previously observed with a sample of personal networks representative of the population in Catalonia, Spain (Lozares et al., 2013). Furthermore, the analysis of the correlations between the measures of centrality (Valente, Coronges, Lakon & Costenbader, 2008), and by extension between the structural properties of personal networks, provides an objective empirical basis for the construction of typologies. In this sense, it has been indicated that connectivity and embedding are two interrelated faces of structural cohesion (Moody & White, 2003).

In the descriptive characterization of the clusters, we found that the densest networks corresponded to the population with the highest levels of roots in the locality of residence. Consequently, it can be assumed that the comparatively lower indicators of structural cohesion correspond to those individuals who have higher levels of geographic mobility, who display a higher level of social activity, who are experiencing personal transitions, or who distribute their time between alternative contexts of interaction (Maya-Jariego & Armitage, 2007). It is also possible that the resulting structure depends in part on the style of sociability of the respondents, either because they tend to gather all their contacts or because they strive to segregate their different spaces of interaction (Kalish & Robins, 2006; Maya-Jariego, Letina & Tinoco, 2020). However, the sociodemographic characterization of the respondents in our study was very restricted. So, this extreme could not be examined in greater depth, despite the fact that personal networks can provide a great variety of information on sociological issues (Bidart & Charbonneau, 2011).

On a small scale, personal networks allow verifying the existence of cohesive communities, the intersection of social circles or the fragmentation of spaces of sociability, so they can be the reflection of longer-range social processes (Vacca, 2019). Hence, they have been called "personal communities" (Wellman, 1999).

To conclude, it should be remembered that typologies can be applied to assess the impact of social relationships in terms of psychological well-being, health, social support and mobility in the social structure (Vacca, 2019). The type of personal network is reflected in the support resources that are exchanged (Agneessens, Waege & Lievens, 2006; Martí, Bolíbar & Lozares, 2017), and it affects both the incidence of depressive symptoms (Fiori, Antonucci & Cortina, 2006; Park et al., 2015), as in mortality risk (Santini, 2015). Our data seem to suggest that the structural cohesion of personal networks is probably more related to socioeconomic status and geographic mobility patterns, while the formation of defined social circles could be associated with individual psychological differences and lifestyles. It would be of interest to deepen this differentiation in the future.

### *7.1. Limitations and future research.*

In this study, we did not take into account the size of the personal network, even though it is a key feature in its structuring. Size and density are inversely related and tend to covariate strongly with the other structural properties. Instead, we opted for the strategy of establishing a fixed number of alters, for their benefits in terms of standardization and comparability (Maya-Jariego, 2018). The measures of centrality cannot be compared when the graphs are of different sizes (Hanneman & Riddle, 2005). Anyway, when the number of alters is fixed, the variability of ties in emotional closeness may be an indirect indicator of size (McCarty, Lubbers, Vacca & Molina, 2019).

Second, setting a limit of 25 in the name generator conditions the type of configurations finally observed. Although it is in the range that allows obtaining stable indicators on the structure of the network (McCarty, 2002), it is *a priori* a small nucleus of people relevant to the respondent whose are highly likely to be connected. Therefore, if we set the limit to a higher number of alters, it is logical to expect greater variability in the structures of personal networks (Maya-Jariego, 2018; Maya-Jariego, Alieva & Holgado, 2019; Maya-Jariego, Letina & Tinoco, 2020; Ramos-Vidal, Holgado & Maya-Jariego, 2014). At the same time, a higher proportion of personal networks with less density and greater fragmentation tend to appear in that case.

Similarly, starting by asking about social support providers, then completing up to a fixed number of alters, could induce a core-periphery structure in the data. The name generators used are normally inseparable from the type of empirical structures that are obtained. Likewise, to the extent that a greater number of alters are obtained, it is more likely to find core-periphery structures, while the smaller personal networks tend to form a single, very cohesive and little differentiated structure.

For all of the above, it would be of interest to contrast the structural typology with broader networks, with different population subgroups, and in longitudinal studies. In particular, observing changes in personal networks can be especially productive, insofar as it is articulated efficiently with the social support convoy model (Giannella & Fischer, 2016). The transition between different types of networks seems to have a decisive impact on psychological well-being. With the elderly population, it has been observed that those who maintain or evolve towards a network of close relatives experience lower levels of depressive symptomatology than those who have or evolve towards networks of another type (Litwin & Levinsky, 2020; Litwin, Levinsky & Schwartz, 2019).

On the other hand, the formation of cohesive groups seems to have a greater potential for developing typologies than we have been able to display with our data. The constitution of core-periphery structures and the organization of the personal network in factions adequately represent individual differences in the way of linking with the diversity of contexts of interaction (Vacca, 2019). Hence, the modularity or clustering indicators can serve to improve this type of classifications.

Finally, it would be of interest to study the interaction between the type of name generators used and the characteristics of the observed personal networks. Thus, using name generators that prompt alters based on pre-defined categories (such as family members, friends, and coworkers, among others) may induce less structural cohesion and more clustered networks, while a more generic question tends to generate small and highly cohesive groups of close ties.

## 8. Conclusion.

We observed four types of personal networks from three structural properties, with a representative sample of population: "clustered", "dense", "intermediate" and "fragmented". The cohesion-fragmentation axis was essential in differentiating the types of configuration that personal networks adopt. Secondly, the organization around clearly defined contexts of interaction, that is, the formation of cohesive subgroups, emerges as a complementary classification element.

Cluster analysis was effective in constructing a structural typology of personal networks.This strategy not only reduces the variability of the data but also allows us to identify which are the central factors in the characterization of the personal network and which structural properties tend to covariate with each other.

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**Annex**.

Correlation table and factor analysis for the selection of the criterion variables in the cluster analysis.

*A. Factor scores of the network structural indicators*

| | *Factor 1* | *Factor 2* | *Factor 3* |
|---|---|---|---|
| Density | **-0.946** | -0.179 | -0.141 |
| Centralization | **0.969** | -0.021 | 0.105 |
| Cliques | 0.149 | -0.025 | **0.988** |
| Components | 0.087 | **0.995** | -0.025 |

Source: Maya-Jariego & Holgado (2015).

B. Correlation between measures of centrality, cohesion, and grouping

| | *Betweenness* | *Closeness* | *Eigenvector* | *Density* | *Cliques* | *Components* | *Centralization* |
|---|---|---|---|---|---|---|---|
| *Degree* | -.929** | .833** | .762** | 1.00** | -.273** | -.246** | -.876** |
| *Betweenness* | - | -.699** | -.731** | -.929** | .228** | .132** | .744** |
| *Closeness* | | - | .733** | .833** | -.172** | -.622** | -.615** |
| *Eigenvector* | | | - | .762** | -.075 | -.313** | -.595** |
| *Density* | | | | - | -.273** | -.246** | -.876** |
| *Cliques* | | | | | - | -.036 | .251** |
| *Components* | | | | | | - | .071 |
| *Centralization* | | | | | | | - |

**Note.** In all cases, the normalized average centrality indicator is used.

Source: Maya-Jariego & Holgado (2015).

**p<.01

Table 1.

*Selection of typologies of social support and personal networks.*

| Support classifications | | | With structural indicators | | |
|---|---|---|---|---|---|
| Wenger (1989) | Litwin (1997) | Maya Jariego (2003) | Lubbers, M. J., Molina, J. L., & McCarty, C. (2007) | Giannella & Fischer (2016) | Bidart, Degenne & Grossetti (2018) |
| 1. Private restricted | 1. Attenuated | 1. Minimum network | 1. Scarce network | 1. Career and Friends | 1. Dispersed |
| 2. Local family dependent | 2. Narrow family-focused | 2. Small network with a majority of fellow countrymen | 2. Dense family network | 2. Family and Community | 2. Pearl collar |
| 3. Local self-contained | 3. Religious family-focused | 3. Medium-sized network of relatives and compatriots | 3. Multiple subgroups network | 3. Family only | 3. Segmented |
| 4. Locally integrated | 4. Friend and family | 4. Medium-sized network with a predominance of non-relatives and Spaniards | 4. Two worlds connected network | 4. Untethered | 4. Centered star |
| 5. Wider community-focused | 5. Diversified | 5. Broad family reunification network | 5. Embedded network | 5. Energetic | 5. Centered dense |
| | 6. Traditional extended family | 6. Broad regrouping networks integrated into the community | | 6. Withdrawn | 6. Regular dense |
| | | | | 7. Home and Church | |
| | | | | 8. Semi-isolated | |
| | | | | 9. Nonkin-as-kin | |
| | | | | 10. Sociable | |
| | | | | 11. Just activities | |

*Nota*. In this table, we have limited ourselves to representing some of the classifications that we have used in the theoretical review to illustrate the research background. For a broader review of typologies, we recommend the work of Antonucci, Fiori, Birditt & Jackey (2010).

Table 2.

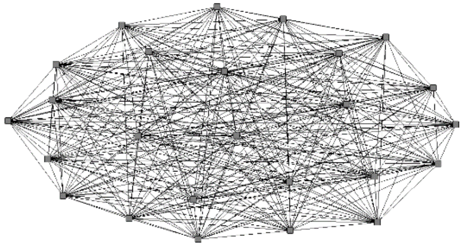
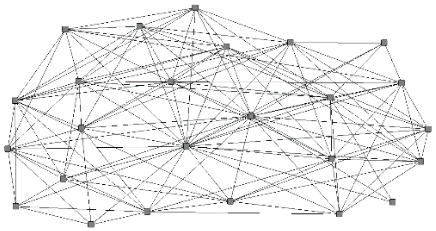
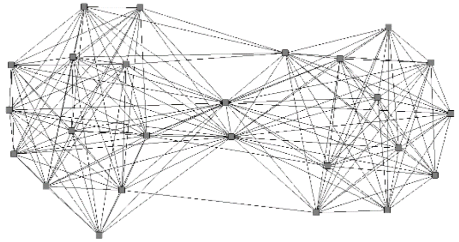
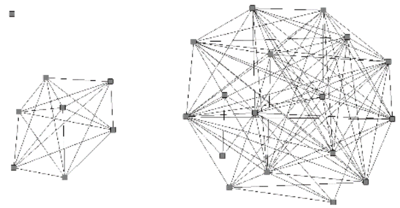
*Criteria variables selected for the analysis of conglomerates.*

| *Factor* | *Indicator* | *Definition* | *Interpretation* |
|---|---|---|---|
| Structural cohesion | Centralization | The centralization of a network indicates the centrality of its most central node in relation to the centrality of all other nodes. It is therefore calculated for the entire network. For this, the sum of the differences in centrality between the most central node and all other nodes is computed and divided by the theoretically largest sum of differences in a graph of said size, corresponding to a star topology (Freeman, 1978 / 79). Compared to density, centralization tends to show less multicollinearity with other structural properties of the network. | Centralization reports the general cohesion of the graph. In the personal network, the lower the general centralization, the greater connectivity exists in the individual's interpersonal space. That is, it reflects a style of sociability in which the respondent's contacts tend to be related to each other. |
| Relational Integration | Cliques number | A clique is the maximum number of actors that have all possible ties to each other (Luce & Perry, 1949). Through a clique census, we can count the number of subgraphs in a network in which all the nodes are connected to each other. Therefore, these are subsets of three or more nodes where they are all connected to each other. | The cliques constitute one of the multiple possible indicators of the existence of groupings in the graph. In the personal network, it is an indicator of the existence of groups, which may be organized according to social circles or contexts of interaction. |
| Network fragmentation | Components number | These are subgroups of the network completely disconnected from the rest. Disconnected portions of the graph can range from isolated nodes to large subsets of nodes (Hanneman & Riddle, 2005). | Shows the fragmentation of the network. It maintains an inverse relationship with the structural cohesion of the network and may indicate a greater dispersion of the interaction spaces. |

*Note*. Selection based on Maya Jariego & Holgado (2015).

Table 3.

*Visual classification of personal networks into four categories.*

| Dense network | Intermediate Network | Clustered network | Fragmented Network |
|---|---|---|---|
|  AG305 |  AG107 |  AG341 |  AG89 |
| It is a network with high density, with a single component and high connectivity. | Intermediate density network, although it does not form defined groups. | Intermediate density network, in which defined groupings and a few nodes with high centrality are recognized. | Less dense, more dispersed and fragmented networks, which can have two or more components. |

*Note*. Personal networks of four interviewees to illustrate the visual classification categories. Each personal network represents 25 alters. The ego is not included in the graph. Visualization of each network is available in the Graphic Gallery of personal networks: https://www.flickr.com/photos/25906481@N07/albums/72157605482634279
Source: own elaboration.

Table 4.

*Distribution of cases and final centers of the conglomerates.*

| Criteria Variables | Cluster 1 (n = 21) | Cluster 2 (n = 118) | Cluster 3 (n = 170) | Cluster 4 (n = 93) |
|---|---|---|---|---|
| Centralization | 32.37 | 9.30 | 32.14 | 51.29 |
| Cliques | 39.43 | 4.65 | 10.76 | 14.98 |
| Components | 1.05 | 1.07 | 1.08 | 1.12 |
| | *Clustered* | *Dense* | *Intermediate* | *Fragmented* |

*Note*. The procedure converged in 4 iterations.

Table 5.

*Comparison of means between clusters*

| | Cluster 1 (n = 21) | Cluster 2 (n = 118) | Cluster 3 (n = 170) | Cluster 4 (n = 93) | F |
|---|---|---|---|---|---|
| *Structural properties* | | | | | |
| Degree | 60.3 (11.6) | 89.1 (11.0) | 62.1 (12.6) | 46.7 (9.6) | 255.4*** |
| Closeness | 71.9 (9.9) | 89.2 (15.5) | 70.4 (15.7) | 63.1 (11.8) | 63.1*** |
| Betweenness | 1.7 (0.5) | 0.5 (0.7) | 1.7 (0.7) | 2.3 (0.6) | 124.7*** |
| Eigenvector | 27.0 (0.6) | 27.8 (1.5) | 26.4 (1.2) | 25.8 (1.0) | 52.5*** |
| Density | 0.92 (0.2) | 1.6 (0.2) | 1.0 (0.2) | 0.8 (0.2) | 201.2*** |
| *Contrast variables* | | | | | |
| Age | 32.1 (18.4) | 44.5 (17.8) | 35.5 (14.1) | 34.5 (13.3) | 11.1*** |
| FREQ AG-SEV | 2.9 (1.1) | 2.5 (1.2) | 3 (1.3) | 3 (1.3) | 3.5* |
| Time AG | 26.2 (11.2) | 40.0 (18.4) | 31.8 (14.2) | 27.2 (13.6) | 15.0*** |
| PSC-AG | 34.7 (4.7) | 34.7 (5.0) | 32.9 (6.1) | 31.8 (6.6) | 4.8** |
| PSC-SEV | 24.1 (7.2) | 23.7 (7.1) | 25.1 (7.2) | 25.2 (7.0) | 1.19 |

*Note*. The centrality measures correspond to centralized average data. The mean and, in parentheses, the standard deviation are indicated in each column. The contrast variables are age, the frequency of interurban travel between Alcala and Seville (FREQ AG-SEV), the time they have lived in Alcala (Time AG), the psychological sense of community with Alcala (PSC-AG) and the psychological sense of community with Seville (PSC-SEV).

* p <0.05; ** p <0.01; *** p <0.0001.

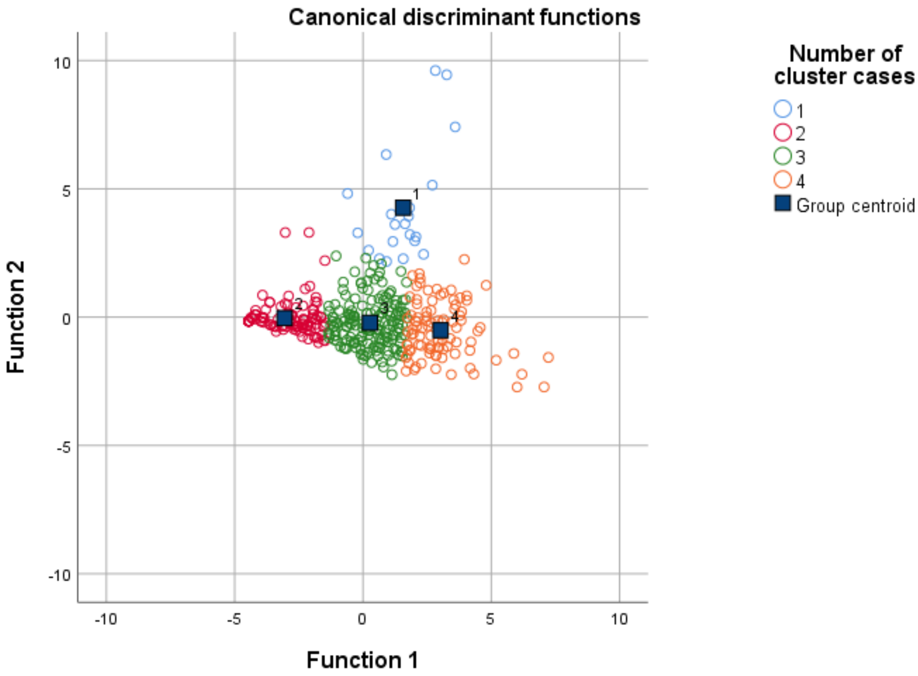



**Figure 1.** Discriminant analysis of the classification of cases in 4 clusters.

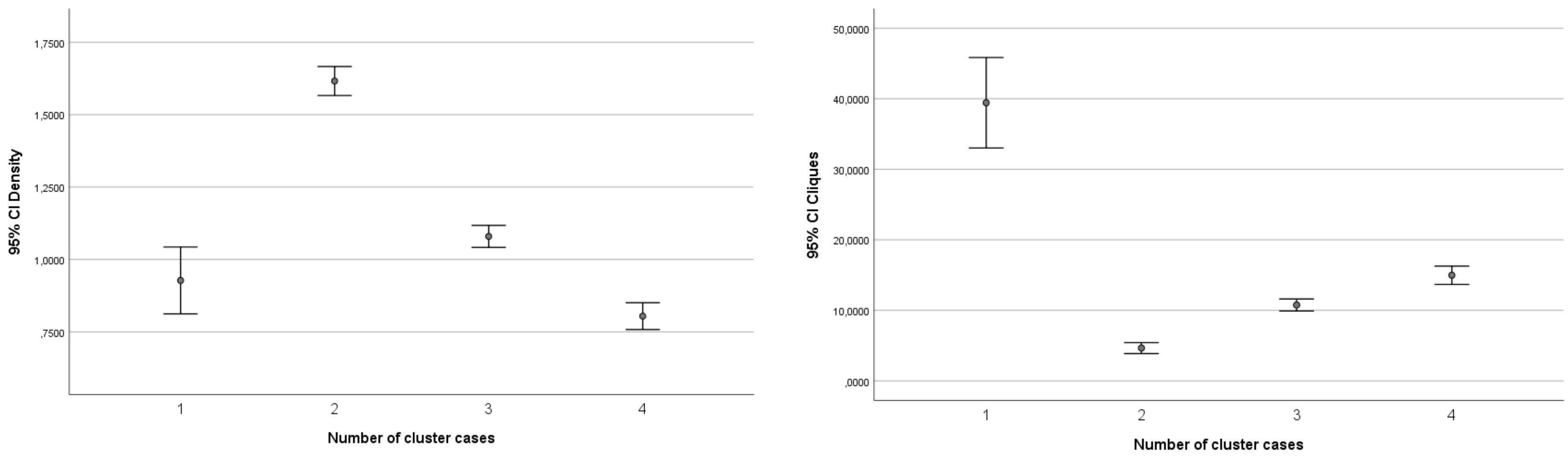



**Figure 2.** Error bars of the indicators of density and number of cliques by type of membership cluster.