

PERSONAL NETWORKS, SCHOOLS, AND HIGHER EDUCATION: LINKING SOCIAL CAPITAL AND STUDENT PATHWAYS BEYOND HIGH SCHOOL

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Abstract

Understanding the factors that shape students' university choices is essential for analysing educational transitions. Previous research highlights the role of economic, social, and marketing factors, with key influences including personal characteristics, family background, school context, and peers. While much of the literature focuses on peer effects on academic performance, less attention has been paid to how social networks affect decisions about higher education. The paper explores the role of personal networks – comprising family, friends, classmates, and acquaintances – in shaping students' university choices, with particular attention to the interplay between personal, familial, and social dimensions. By conceptualising these networks as a form of social capital, the paper examines how network composition and structure influence students' access to support, particularly informational, emotional, and appraisal resources. The findings show that students embedded in highly interconnected networks are better positioned to access both informational and emotional support, which plays a key role in educational transitions. In contrast, students with weaker personal networks face challenges in making informed decisions due to limited access to relevant resources. The study also highlights the importance of both network size and structural diversity in strengthening social capital and facilitating informed decision-making during the transition from high school to university.

Keywords: Higher education, Peer effects, Egocentric network data, Social support, Soft skills

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1. INTRODUCTION

The transition from high school to university represents a crucial point in educational trajectories, involving significant life challenges for individuals (Mpamhanga *et al.*, 2025). Empirical studies show that university choices involve economic and social dimensions as well as personal decision-making processes. Among others, family and school context (Brooks, 2003; Sandefur *et al.*, 2006; Engberg and Wolniak, 2010; Vandelannote *et al.*, 2021; Chaudhry *et al.*, 2024), universities' reputation and economic attractiveness (Reay *et al.*, 2001; Bacci and Bertaccini, 2021; Columbu *et al.*, 2021a; Biagi *et al.*, 2024; Priulla *et al.*, 2025), the geographical accessibility of the higher education system (Sá *et al.*, 2006), and other characteristics of the academic environment (Kallio *et al.*, 1995) are recognised as the main factors affecting the transition from high school to university.

Scholars have focused on peer effects in education, highlighting how social support and interactions among adolescents in primary and secondary schools influence student attainment, aspirations, and school-related choices (Rosenqvist, 2018; Raabe and Wölfer, 2019; Raabe *et al.*, 2019; Smith, 2023). In the context of higher education, this line of research has mainly examined how interactions among peers influence individual outcomes, such as well-being, motivation, and academic achievement (Lomi *et al.*, 2011; DeLay *et al.*, 2016; Poldin *et al.*, 2016; Mamas, 2018; Stadtfeld *et al.*, 2019; Vörös *et al.*, 2021; Brouwer *et al.*, 2022; Chuard *et al.*, 2025). To the best of our knowledge, studies investigating peer influences on students' educational choices after high school have received limited attention (Usala *et al.*, 2023).

Research shows that individuals embedded in robust networks tend to exhibit higher performance, stronger social integration, and an overall better quality of life during university (Wilcox *et al.*, 2005; Chaudhry *et al.*, 2024). Socioeconomic background also favours the development of networks in terms of cultural and social capital (Lareau and Cox, 2011; Lareau, 2015) or, conversely, limits access to relational resources, thereby exacerbating existing social inequalities (Walpole, 2003; Pascarella *et al.*, 2004). Institutional guidance programmes can also represent a relevant policy intervention to bridge social capital gaps and support student choices (Upcraft *et al.*, 2005; Alnawas *et al.*, 2015), encouraging the transition to university and mitigating socioeconomic disparities. Hence, identifying the main factors driving students' university choices is essential for developing recruitment strategies and policies in higher education settings.

Moving from this scenario, the purpose of the present contribution is to explore factors affecting students' university decision-making process, characterised by the interplay of individual aspirations and social interactions within family, school, and social environments. Specifically, the multifaceted role of personal, or egocentric, networks (Perry *et al.*, 2018) as a form of social capital (Coleman, 1988; Burt, 2000; Molina *et al.*, 2020) is examined, taking into account their interrelation with socioeconomic and familial backgrounds. Egocentric networks – encompassing family, teachers, and classmates at school, as well as friends and acquaintances in social contexts (Brooks, 2003) – can provide informational, emotional, appraisal, and instrumental support (Malecki *et al.*, 2003), facilitating access to university for low-income individuals (Stanton-Salazar, 2011) and reducing educational inequalities in the transition from high school to university.

An integrated data collection approach, combining a questionnaire with an egocentric network-based research design (Robins, 2015; McCarty *et al.*, 2019; Marsden and Hollstein, 2023), was adopted in a sample of students attending high schools in Southern Italy. The main purpose of the present study was to investigate how different personal networks support students' decision-making process in higher education, focusing on the role of classmates at school – recognised as peers – in providing support beyond that of family members, friends, and acquaintances. Students with limited resources in their networks may experience lower transition rates to university.

First, the composition and structure of egocentric network measures (Krenz *et al.*, 2025) were computed to describe network characteristics and then further analysed through multidimensional exploratory techniques (Lebart *et al.*, 1995), including principal component analysis (PCA) and hierarchical cluster analysis (HCA), to identify the main individual and network characteristics related to this key educational transition. Additionally, to better illustrate the results of groups derived from HCA, examples of egocentric networks for each cluster were selected to provide a qualitative description in terms of sociodemographic characteristics and network structures of selected Egos. Finally, the association between cluster results and students' university choices highlights differences in educational transitions in the presence of varying social support resources.

The remainder of the paper is organised as follows. Section 2 reports the theoretical background, focusing on peer effects on educational choices. Section 3 describes the data collection process and network design. Section 4 presents the main characteristics of egocentric networks, and Section 5 discusses the findings from the factorial analysis. Section 6 provides a brief discussion, outlines the study's limitations, considers policy implications, and suggests directions for future research.

2. THEORETICAL FRAMEWORK

The study of peer effects in educational contexts has developed within various theoretical frameworks. Parsonsian functionalism (Parsons, 1959) emphasised the role of schools as primary sites of socialisation, highlighting the importance of institutional norms and expectations in shaping students' trajectories. Similarly, symbolic interactionism has provided critical insights into how the meanings, identities, and cultures of peer groups influence educational pathways. From this perspective, Willis's (1977) study demonstrated how youth cultures contribute to the reproduction of educational inequalities. Meanwhile, Corsaro's (1985; 2005) studies showed that shared norms and meanings are actively constructed and negotiated through everyday interactions. Altogether, these contributions reinforce the idea that peer effects do not simply result from the aggregation of individual characteristics but emerge from relational processes situated within specific social contexts, where students continually assemble and renegotiate their educational paths (Piromalli, 2024).

Another key turning point was the Coleman Report (Coleman *et al.*, 1966), which highlighted that the social composition of schools and the distribution of students contribute significantly to inequalities in educational opportunities (Rosenqvist, 2018). Coleman's (1986) macro–micro–macro model, known as the 'Coleman Boat', further clarified how structural conditions and social interactions translate into individual outcomes through identifiable mechanisms, linking social phenomena to the constraints and opportunities within which actors operate (Marsden, 2005). Within this framework, social capital plays a central role: embeddedness in peer networks enables students to access information, resources, and support that directly affect their educational outcomes (Coleman, 1988; Portes, 1998). The integration of these perspectives has fostered a multilevel understanding of peer effects, connecting institutional structures, group cultures, and individual behaviours.

Following the structuralist and relational tradition of social capital (Granovetter, 1973; Coleman, 1988; Burt, 1992), this study assumes that educational performance does not depend solely on individual characteristics but also on the quantity and quality of resources embedded in social networks. Social capital is thus defined as the set of resources accessible through family, friendship, or school relations, which can be mobilised to obtain information, support, or opportunities (Woolcock and Narayan, 2000). This conceptualisation comprises three dimensions: the structural dimension, concerning the configuration of networks; the relational dimension, relating to trust, obligations, and norms of reciprocity; and the cognitive

dimension, based on shared interpretive codes and meanings. Together, these dimensions provide a robust framework for understanding how peer networks influence students' aspirations, educational choices, and transitions across different stages of their schooling.

Based on reference group theory (Merton and Rossi, 1968), individuals with whom students identify play a key role in shaping their educational paths by providing reference models that guide their aspirations and decisions. According to Kelley (1952), peers can influence students in divergent ways: through conformity, which may promote more ambitious choices, or through social comparison, which may discourage them by highlighting contrasts with others (Smith, 2023). During adolescence, individuals spend a significant amount of time in the school environment, which becomes a crucial space not only for learning but also for personal and social development. Peers therefore become important reference points due to their shared life experiences (Larson and Richards, 1991; Osterman, 2000; Brechwald and Prinstein, 2011). Interactions developed in the classroom often go beyond superficial relationships, evolving into deep and lasting bonds. These social connections can play a significant role in how students navigate important life decisions, including educational choices. In this crucial phase, support from peers with whom students have close relationships can influence their choices, shaping academic and career paths.

Two main processes contribute to the creation and maintenance of peer culture: *peer selection* and *peer socialisation*. The former refers to individuals' tendency to associate with others they perceive as similar, while the latter describes their propensity to be influenced by the attitudes and norms of friends (Raabe and Wölfer, 2019). This tendency to cluster in social groups with similar others is known as the *homophily effect* (McPherson *et al.*, 2001). Students tend to establish friendships primarily with peers who exhibit similar levels of academic achievement, aspirations, and motivations (Raabe *et al.*, 2019, and references therein). Studies on educational transitions have also distinguished between primary and secondary effects. Primary effects are closely associated with academic achievement, where inequalities arise from differences in students' performance. Secondary effects, by contrast, relate to contextual factors such as parental educational level and socioeconomic status (Rosenqvist, 2018; Smith, 2023). These effects influence the formation of social networks, which in turn play a significant role during educational decision-making phases.

In the context of higher education, information-related social capital and support become particularly relevant. Four categories are used to conceptualise social support: *emotional support* based on feelings of trust and mutual esteem; *informational support*, which provides advice or guidance; *appraisal support*, offering evaluative feedback; and *instrumental support*, providing material resources (Malecki and Demaray, 2003). When examining peer effects on educational choices, it is hypothesised that these forms of support play a crucial role in understanding the influence mechanisms at work as high school students face major decisions.

Choices made during major life transitions have significant impacts on income and related social status (Breen and Jonsson, 2005). Students from lower socioeconomic backgrounds often actively seek more information within the school environment due to limited parental guidance and tend to be more affected by peer influence (Roksa and Kinsley, 2019; Smith, 2023).

Based on this theoretical framework, the paper aims to investigate the relevance of social interactions and support mechanisms developed among classmates and friends in high school contexts. This focus is crucial for understanding the broader dynamics at play, particularly the different kinds of assistance students receive from social networks in which they are embedded. Specifically, it explores the role of social networks and the support they provide in shaping students' educational choices, with particular attention to peer influence. The main purpose is to understand how different relational contexts contribute to decision-making processes regarding the continuation of studies after high school. Two research questions guide the exploratory analysis:

- *RQ1: To what extent do significant social groups influence students' choices during the transition from high school to university? Do classmates play a meaningful role in supporting and assisting students beyond the influence of family members (close ties), friends (strong ties), and acquaintances (weak ties)?*
- *RQ2: How do the social resources embedded in the composition and structure of personal networks affect students' decision-making processes regarding university attendance after high school?*

3. SURVEY DESIGN AND DATA COLLECTION

To address these objectives, a survey was conducted using a non-probabilistic sample of students attending scientific, classical, social science, and vocational high schools in the Campania region (Italy) while participating in a general orientation program. A mixed-method data collection approach was adopted, combining a structured questionnaire with an egocentric network research design (Robins, 2015; McCarty et al., 2019; Marsden and Hollstein, 2023).²

The questionnaire included three main sections.

- **Contextual and sociodemographic characteristics**, including gender, age, municipality and province of residence, type of school attended, and parents' educational level and employment status.
- **University choices**, assessing students' intention to pursue higher education after high school, preferred academic fields (e.g. social sciences, humanities, economics, psychology, law, engineering), and the likelihood of attending a university outside their home region. This section also explored the perceived influence of peers and significant others on students' decisions, identifying key sources of information and the relevance of the opinions of family, friends, classmates, and teachers. Moreover, the role of personal motivations, financial constraints, academic challenges, and peer influence was investigated.
- **Soft skills and individual attitudes**, measured using validated Likert scales. The Soft Skills Self-Evaluation Scale (3SQ; Lucisano and Du Mérac, 2019) was employed to assess dimensions such as collaboration, empathy, autonomy, problem-solving, and leadership, all critical competencies in decision-making processes. These variables were not incorporated into the analyses presented here.

The relational dimension was captured using an egocentric network protocol implemented with Network Canvas.³ The egocentric approach is widely used to study social influence and behaviours (Kwon et al., 2014; French et al., 2023), access to resources and social support (Vacca, 2020a, 2020b; Fraudatario et al., 2024), and information flows (Arnaboldi et al., 2016; Smith and Burow, 2020).

To limit the risks associated with self-assessment and recall biases in the identification of alters, the research design incorporated a series of methodological adjustments. Since egocentric networks tend to have a stable core and a more fluid periphery (Perry and Pescosolido, 2012), suggesting that structurally rooted ties are also the most enduring, three social circles of reference (family, school, and wider social context) were predefined. Within these circles, specific key social roles (e.g. parents, siblings, grandparents, classmates, students from other classes, teachers, friends outside school, neighbours, and acquaintances) and the types of resources and support provided by significant alters (informational, emotional, and appraisal support) were recorded. This delimitation of social boundaries facilitated the identification of

²The questionnaire was administered during guidance laboratories promoted by the Centre of Orientation and Tutoring at the University of Salerno (Italy) during the academic year 2023–2024.

³ Further information on Network Canvas (Birkett et al., 2021) is available at <https://networkcanvas.com/>.

alters in clearly defined areas, reducing omissions due to salience or selective memory. In addition, interactive sociograms supported data collection by providing respondents with visual ‘anchors’ to more accurately represent their networks in terms of both size and the distribution of social roles (Jeon *et al.*, 2016; Hogan *et al.*, 2020).

Once the boundaries of the relational systems and types of support were defined, network data collection proceeded in three main components:

- **Multiple name generator**, asking: “The educational choice after high school involves an important change in your life. How do the people listed in your three social circles support you in terms of informational support (helping you search for information), appraisal support (discussing future options), and emotional support (helping you make decisions)?”
- **Name interpreter**, which collected information on each alter, including their role within the social circles (parents, relatives, classmates, teachers, friends, acquaintances), demographic attributes (gender, age), type of support provided (informational, emotional, and appraisal), and the perceived strength of the relationship.
- **Alters-by-alters ties**, where respondents reported whether connections existed between pairs of alters within each social circle.

The adoption of a mixed-methods design allowed for a nuanced exploration of how the composition and structure of ego-networks shape the educational decision-making process, providing both quantitative and relational perspectives on the social mechanisms influencing students’ transition to higher education.

4. METHODS

The methodological framework described below builds on previous contributions in social network analysis that combine multidimensional data techniques with network data to investigate networks characterized by a single or multiple relations as well as one-mode, two-mode, and multimode networks (Giordano and Vitale, 2007; D’Esposito *et al.*, 2014; Ragozini *et al.*, 2015a,b; Giordano *et al.*, 2019; Genova *et al.*, 2024). These approaches have been successfully applied to both egocentric and complete networks, ranging from the analysis of personal networks and social support (Lumino *et al.*, 2016, 2017) to empirical studies on student mobility choices and, more broadly, on the transition from high school to tertiary education (Columbu *et al.*, 2021b,c; Santelli *et al.*, 2022).

4.1 EGOCENTRIC NETWORK MEASURES

The egocentric networks provide several pieces of information across multiple levels of analysis (Table 1). First, the Ego–Alter Level captures the type of relationships each student (ego) reports for other individuals (alters) in their social circles. At this level, the relationship attributes include the types of support provided, coded as binary variables, and tie strength, measured on a scale from 0 to 4. The Alter–Alter Level records the presence or absence of ties between alters within all social circles. The third level includes Alter Attributes, specifically gender and age group.

Table 1: Ego-Alter features of personal networks

Level of analysis	Type of relationship	Attributes	Coding
Ego–Alter	Family: kinship type	Informational support	1 = support
		Emotional support	0 = no support
	School: role (e.g., classmate, teacher)	Appraisal support	
	Social context: role (e.g., friend, neighbour)	Tie strength	3 = very close 2 = close 1 = distant 0 = very distant
Alter–Alter	Acquaintance	–	1 = tie exists 0 = no tie
Alter attributes	–	Gender	F = female M = male
		Age group	up to 18 years 18–24 25–29 30–49 50–65 65+

The resulting personal networks were represented as binary, undirected, and unweighted matrices. From these matrices, the composition and structure of each personal network were analysed. Composition was assessed by calculating the size of each social circle, including specific counts of friends and classmates as proxies for peer influence. Additionally, for each social circle, the number of alters providing informational, emotional, or evaluative support was computed, capturing the distribution of social resources across relational domains.

Regarding structural measures, *cohesion* and *centrality* indices of the egocentric networks were calculated using the *egor* package in R (Krenz *et al.*, 2025). Among cohesion measures, *network density* is a basic one that provides an immediate indication of the network structure based on the number of nodes (alters) and the number of ties. Density is computed as the ratio between the actual number of ties in the network and the maximum possible number of ties between nodes (alters). Density values range from 0 to 1, where 1 indicates a fully connected network, meaning that all possible ties are actually present. The *diameter* (longest shortest path length) was calculated to quantify network “reach” and understand the potential for information diffusion or influence. The *transitivity* (Holland and Leinhardt, 1976) captures the tendency of pairs of nodes to be directly connected when they share a tie with an intermediate node. This measure is particularly useful as it allows the structural properties of the network to be interpreted in terms of social relationship configurations, while also providing an indication of local cohesion. Note that, in the

case of personal networks, these measures (density, transitivity, and diameter) were computed on the alter-alter matrix, excluding the ego, as they describe the internal cohesion and overall shape of the alter network.

The second set of network indices consists of centrality measures: *degree*, *betweenness centrality*, *closeness*, and *constraints*. This set of indices captures complementary aspects of network configuration based on the positional properties of nodes (Wasserman and Faust, 1994). *Degree* summarises the number of connections of alters (Borgatti *et al.*, 2013); high values indicate potential popularity or influence due to a greater number of direct connections with other nodes. *Betweenness centrality* (Freeman, 1978) measures the frequency with which a node lies along the shortest paths between other pairs of nodes, thus occupying potential brokerage positions. This positional advantage is often associated with the ability to control the flow of information and other resources within a social subsystem (Brass, 1984). *Closeness centrality*, defined as the reciprocal of the sum of geodesic distances between a node and the alters (Freeman, 1978), reflects how quickly a node can reach, or be reached by, the rest of the network. Burt's constraint (Burt *et al.*, 2002) measures the extent to which an ego's ties are concentrated within tightly interconnected clusters: high values indicate placement within cohesive and redundant groups, whereas low values suggest a more intermediate position, typical of nodes accessing heterogeneous information sources.

Average degree, betweenness, and closeness were computed for the entire network, including the ego, and subsequently averaged across nodes to capture overall patterns of connectivity, brokerage, and accessibility within the personal network. Constraint was derived as an individual score for the ego and reflects the extent to which their relational environment consists of redundant ties.

Since structural measures may vary as a function of ego-network size, the association between size and all structural measures included in the analysis (density, diameter, transitivity, average degree, betweenness, closeness, and constraint) was examined. Expected patterns emerged: density and closeness decreased as network size increased, whereas diameter, average degree, and betweenness increased, reflecting the greater structural extent and higher number of potential paths in larger networks. Constraint also showed a negative association with size, indicating reduced redundancy and greater bridging opportunities in larger networks. In contrast, transitivity exhibited no systematic trend, confirming that it captures local clustering dynamics rather than size-induced variations. These patterns are consistent with theoretical expectations for egocentric networks and suggest that size-related variability reflects substantive structural differences rather than distortions arising from the absence of normalisation.

Finally, a gender-based *homophily index* (McPherson *et al.*, 2001) was computed to evaluate individuals' tendency to establish ties with others of the same gender. This index compares the observed frequency of connections between alters of the same gender with that expected randomly, providing a measure of the propensity for gender similarity within the network.

4.2 MULTIDIMENSIONAL EXPLORATORY TECHNIQUES

The data matrix (n, p), where n corresponds to the total number of ego-networks (295) and p to the composition variables (alter gender, social circle membership, types of support provided) and network structural measures (cohesion and centrality indices), served as the basis for the application of multidimensional exploratory techniques (Lebart *et al.*, 1995). Specifically, PCA and HCA were used.

Through PCA, the optimal number of principal components, linearly associated with the original variables, was identified. Although structural measures were calculated in their standard, non-normalised form, the PCA procedure in R automatically standardises all variables prior to component extraction, ensuring full comparability among indicators measured on different scales. The selection of retained

components was based on the eigenvalue >1 criterion (Kaiser, 1960) and inspection of the scree plot (Cattell, 1966).

Factor scores of the retained principal components were subsequently used as input for HCA using Ward's minimum variance method to identify specific network configurations within each derived group. The number of clusters was determined by examining the dendrogram, the variation in cluster variance, and the substantive interpretability of the resulting solutions. Among the different optimal dendrogram cuts (2, 3, or 6 clusters), a three-cluster structure proved to be the most coherent and analytically informative, allowing a clear and meaningful classification of personal network configurations.

5. RESULTS

A total of 295 students completed both the questionnaire and the egocentric network tool. Within these egocentric networks, students identified 2,874 alters, connected by 4,411 alter-to-alter ties. Following a description of the main characteristics of the student profiles, the networks were analysed in terms of composition variables, including alters' gender, social circles, and types of support provided, as well as structural network measures (i.e. density, centrality indices, and constraint). These variables were subsequently used to perform a PCA and an HCA to identify specific network configurations within each derived group.

5.1 STUDENT PROFILES

Among the respondents, 68.10% were female, and 84.1% attended a lyceum track. Within this group, 26.8% were enrolled in classical lyceums, 22.7% in scientific lyceums, and 34.6% in other lyceum types, while 15.9% attended vocational institutes. Regarding parents' educational levels, 65.75% of mothers held a degree or diploma, compared to 61.94% of fathers. In terms of employment, 53.98% of mothers were permanent employees or self-employed, while 39.45% were housewives. A certain degree of instability emerged in fathers' employment status: 43.60% were employed on fixed-term contracts, 28.77% were self-employed, and only 18.34% held permanent positions.

Concerning university intentions, the majority of students (82%) planned to continue their studies after graduation, 11.20% remained undecided, and only 6.80% did not intend to pursue higher education. Among those aiming to attend university, 61.57% intended to enrol in local institutions near their residence, 19.42% planned to move to other Italian regions or abroad (0.41%), while 18.60% remained undecided. Regarding the field of study,⁴ 86% were interested in enrolling in a social sciences and humanities degree program, compared to 14% pursuing a program in science, technology, engineering, and mathematics (STEM). Specifically, many students planned to enter health, economics, or law programs, whereas those interested in STEM fields mainly aimed for architecture and engineering programs (Figure 1).

⁴The degree programs are grouped according to the *International Standard Classification of Education: Fields of Education and Training 2013* (ISCED-F 2013): agricultural, forestry, fishery and veterinary sciences; arts; economics; teacher training and education science; law; health; political sciences and civics; psychology; humanities; languages; personal services; engineering and engineering trades; architecture and construction; physical sciences; information and communication technologies (ICTs); mathematics and statistics.

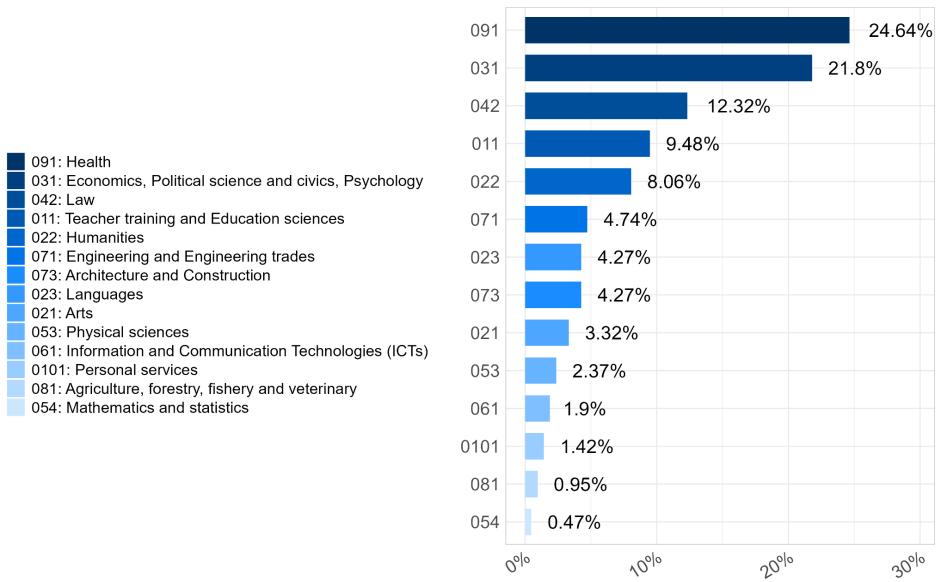


Figure 1: Percentage of respondents by fields of study

Students evaluated a list of factors influencing their university choices using a 5-point Likert scale, ranging from ‘not at all’ to ‘extremely’ (Figure 2). The factors most frequently rated as ‘extremely’ important include individual motivation and aspirations (52.20%), professional opportunities (42.71%), job prospects associated with the degree program (41.01%), the desire to enter the job market promptly after graduation (21.36%), and interest in a specific discipline (23.05%).

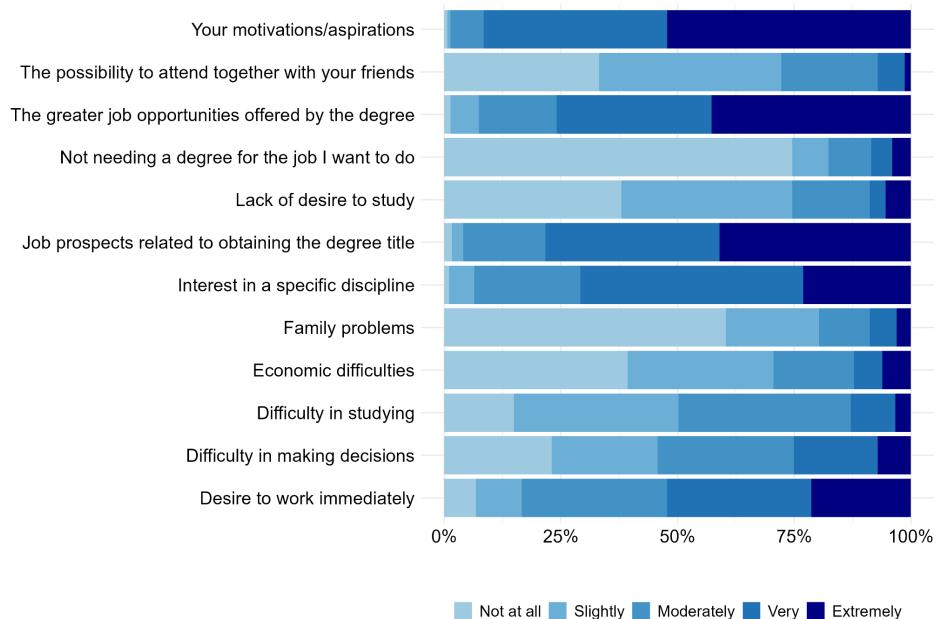


Figure 2: Percentage of respondents by factors influencing university choices

5.2 PERSONAL NETWORK COMPOSITION AND STRUCTURE

The network composition takes into account alters' gender, the number and role of each alter within specific social circles, and the type of support provided to the ego (Figure 3). Overall, the size of personal networks ranges from a minimum of 2 to a maximum of 24 alters, with 63% of alters being female. On average, each student is connected to four alters, indicating that these networks are relatively small. The average density value of 0.39 reflects a moderate level of cohesion, with many potential connections between alters. This degree of interconnectivity facilitates interactions and social support mechanisms, which in turn promote information exchange during the educational transition phase.

The homophily index, based on gender, shows an average value of 0.66, indicating a high degree of homophily, with students predominantly associating with same-gender peers. Regarding the role of alters within each social circle,⁵ parents (46.03%) and siblings (19.69%) serve as the primary sources of support for future choices. In the school context, classmates are most frequently mentioned (83.27%), surpassing teachers. Given the relatively low percentage of students referring to their instructors (16.73%), teachers appear to play a limited role in supporting students during university decision-making. Friends (73.94%) are also central to this process, in contrast to romantic partners (14.36%). Concerning the type of support received by the ego, parents, classmates, and friends primarily provide emotional and appraisal support (Figure 3), whereas informational support remains limited across these social circles.

⁵The social circles are described as follows: family, including parents, siblings, and other relatives; school, including classmates, students from other classes, instructors, and administrative staff; and social environment, including friends, romantic partners, acquaintances, neighbours, and university staff.

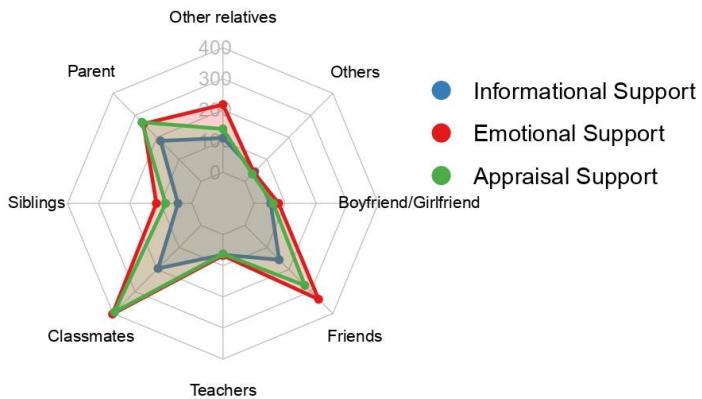


Figure 3: Types of support provided by Alters to the Ego

The structure of personal networks was examined using centrality measures (betweenness, closeness) and the constraint index, calculated as average values of alter-to-alter ties for each ego. The average betweenness centrality (2.66) indicates that the power of connection is distributed among alters rather than concentrated solely in the egos. The closeness measure is relatively low (0.09), suggesting that alters maintain considerable distance from one another. This distance may imply the presence of star networks, which are highly centralised and in which egos play a central role in the flow of information among alters. The constraint index (0.35) reflects a medium level of dependence among alters, indicating limited opportunities to establish new ties. Overall, these networks tend to display relatively closed and constrained structures, with reduced potential for activating new connections and interactions. In terms of transitivity, approximately 50% of possible triads in the networks are closed, indicating a moderate level of clustering. This result fosters a sense of belonging and mutual support among individuals within groups, enhancing overall network cohesiveness. Finally, the network diameter, with an average value of 3.10, indicates a relatively short maximum distance between individuals.

In summary, personal networks exhibit a moderately cohesive structure, characterised by substantial interconnection among alters. The presence of gender homophily and a relatively high constraint index suggests that these networks are composed of individuals with similar characteristics, promoting internal cohesion while limiting the formation of new external ties. Although some central egos play a key role in connecting alters, the networks generally display a tendency towards closure and internal homophily.

5.3 EXPLORATORY ANALYSIS OF PERSONAL NETWORKS

The analytical strategy adopts a two-step approach, designed to identify latent patterns and classify personal networks based on their structural and compositional characteristics. In the first step, PCA was conducted to uncover the latent dimensions underlying the observed variables. This approach integrates network composition characteristics – including alters’ attributes such as gender, social roles, and types of support provided to the ego – with structural measures derived from alter-to-alter ties, such as betweenness, closeness, and transitivity. In the second step, the factor scores from the principal components were used as input for HCA, which identifies meaningful clusters of personal networks that share similar profiles in terms of both composition and structure.

The first six principal components with eigenvalues greater than 1 (Kaiser, 1960), obtained through PCA, explain 75.71% of the cumulative variance (Table 2). The first component captures the composition of students’ networks, reflecting the number of alters – particularly women – alongside key structural characteristics. The second component highlights emotional and appraisal support within school and social contexts, emphasising relationships with classmates and friends. The third component focuses on network cohesion and internal structure, as measured by transitivity, diameter, and density. The fourth component underscores the family’s role as a multifaceted source of support, providing appraisal, emotional, and informational resources. The fifth component represents gender homophily and the importance of informational support within cohesive and interconnected school networks, particularly among classmates. Finally, the sixth component captures a pattern driven by gender-based homophily. For simplicity, Figure 4 displays the factorial map based on the first two principal components, which account for 49.60% of the total variance.⁶ The analysis emphasises these two components, as they capture the most salient dimensions of network composition and support dynamics. Specifically, the first component differentiates between small, cohesive networks – characterised by high density and the absence of structural holes – and larger, less cohesive, more heterogeneous networks, in which all social circles contribute to exchanges of support relevant to decision-making. The second component distinguishes between social circles, positioning the broader social environment at the higher end and the school context at the lower end, with both settings providing all three forms of social support.

Table 2: Principal component analysis results for the six principal components

Principal Component	Eigenvalue	% of variance	Cumulative variance (%)
1	10.82	37.31	37.31
2	3.56	12.29	49.60
3	2.67	9.22	58.82
4	2.00	6.91	65.73
5	1.54	5.30	71.03
6	1.36	4.69	75.71

⁶The other factorial maps are reported in Appendix A.

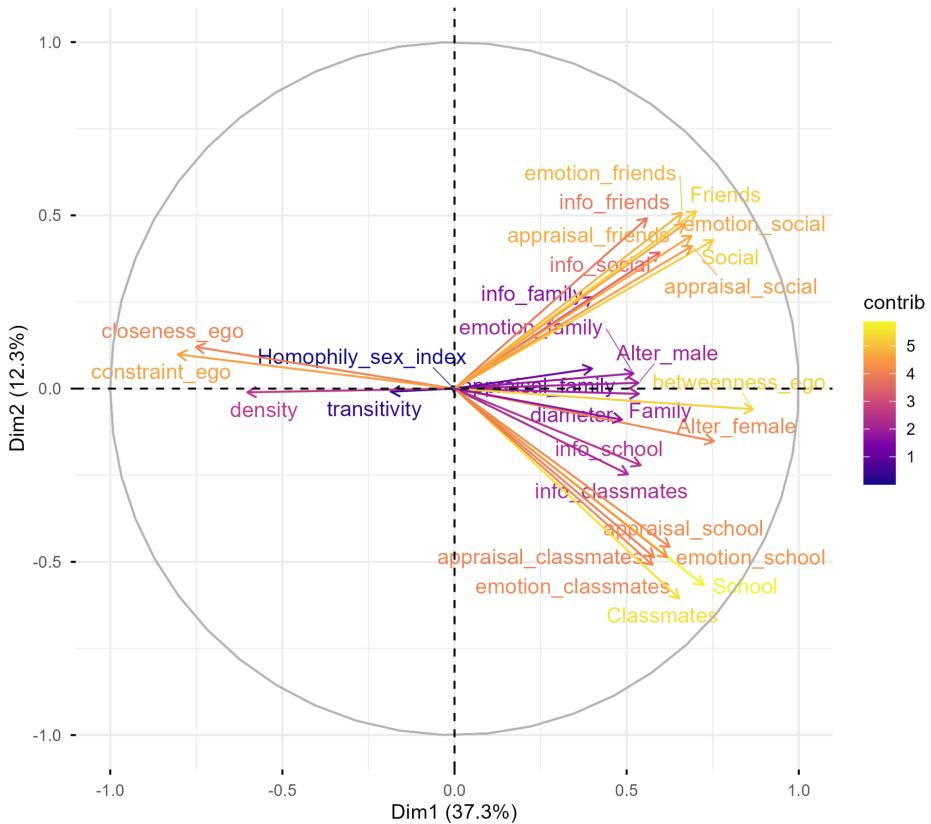


Figure 4: Correlation circle of the first two principal components

5.4 CLUSTERING PERSONAL NETWORKS

Based on the PCA results, an HCA was performed, identifying a three-cluster solution (Figure 5).⁷ The findings reveal distinct personal network configurations with varying types of support and social structures, which are further explored through network measures of structural variables (Table 3) and representative egos within each group (Figure 6).

Personal networks in the **first cluster** (108 students in total – see Table B.1) are characterised by small sizes and a highly cohesive structure within a specific social circle. The closed nature of these networks, combined with redundant ties and limited informational and emotional support from both school and family, may constrain the ego's ability to receive valuable guidance for navigating educational and career pathways. For instance, Ego 284 (Table 3, Figure 6), a female attending a vocational high school, had both parents with a high school diploma; her mother was employed on a fixed-term contract, while her father held a permanent position. Ego 284 was uncertain about university enrolment, mobility choices, and academic discipline. Her personal network consists of five alters, including parents, a relative, one classmate, and her

⁷The Appendix B presents the results of the HCA on principal components conducted using the *FactoMineR* package in R. Tables B.1, B.2, and B.3 report the variables that contribute to the characterisation of Cluster 1, Cluster 2, and Cluster 3, respectively, along with their descriptive statistics and associated test values.

boyfriend. For this student, the family played a prominent role in providing informational and appraisal support, while emotional support came from the classmate and boyfriend. The structural characteristics of Ego 284's network reveal a closed and limited configuration, with a betweenness centrality of 1.17, indicating a relatively low level of connection across alters. The closeness value (0.14) suggests that alters within the social circles are accessible to the ego. The network exhibits a high constraint value (0.41), reflecting redundant ties and limited sources of information. Internal cohesion is strong, with a transitivity value of 1, indicating tight connections within the family circle. The network's diameter (1), combined with relatively low density, points to a compact structure where alters are primarily linked to the ego but do not form connections among themselves, particularly across different social circles. This network configuration limits the ego's access to diverse resources and new information, reducing opportunities for external support and exposure to varied perspectives. Consequently, the ego's social capital appears weak, which could impede her ability to make well-informed decisions and feel adequately supported in her future choices.

In the **second cluster** (176 students in total; see Table B.2), students exhibit broad, open, and moderately cohesive personal networks. These networks are sufficiently large to provide access to a wide range of resources. In terms of support, students benefit from a balanced combination of emotional and appraisal support across school, peer, and family contexts. For example, Ego 201 (Table 3, Figure 6), a female student enrolled in a classical lyceum, had both parents holding a diploma; her mother was a housewife, and her father held a permanent contract. She had decided to enrol at a university in another Italian region, choosing a STEM program in architecture and construction. Regarding the support received, Ego 201's network is characterised by a well-balanced mix of informational, emotional, and appraisal support. The family provides both informational and emotional support, while the teacher and a friend contribute informational resources, underscoring the relevance of the school context. Appraisal support comes from both family and classmates. The ego thus has access to a variety of sources extending beyond the family circle to the school and broader social spheres. The network's structural measures reveal a betweenness centrality of 3.29, indicating that alters effectively connect different actors within the network. The low closeness value reflects a less centralised configuration, while the diameter (3) suggests a more extended network. The density (0.41) and average degree (6.42) point to a well-connected structure with numerous ties among alters. The constraint value (0.25) indicates a network structure offering greater opportunities to access diverse sources of support. Additionally, the transitivity (0.61) shows a diversified network with cross-circle connections. This configuration provides the ego with access to a range of resources and forms of support, which were instrumental in facilitating her decision to pursue a university path outside her region of residence and within a STEM field.

Finally, the **third cluster** (11 students in total; see Table B.3) comprises students with large personal networks, characterised by a substantial number of alters who play active roles in connecting actors. These alters function as bridging nodes, facilitating the flow of information and reducing the ego's dependence on any single source of support. As a representative case, Ego 230 (Table 3, Figure 6) was a female student attending a classical lyceum, with a favourable socioeconomic and cultural background: both parents held a degree or diploma and occupied permanent job positions. She decided to enrol in a university outside her home region, pursuing a non-STEM degree program. Ego 230's network includes 18 alters, comprising 7 males and 11 females. She receives all forms of support across the three social circles, primarily from parents, other relatives, classmates, and friends. The network exhibits a complex structure in which the ego plays a pivotal bridging role among social circles, as reflected by the high betweenness centrality value (5.53). Despite a low closeness value, which may constrain direct access to some resources offered by alters, the density (0.31) and average degree (6.95) indicate a well-connected network. The relatively low constraint value (0.19) underscores the ego's opportunities to access diverse resources through new connections.

The HCA highlights a progression from constrained, inward-focused networks (Cluster 1) to open, diversified, and resource-rich configurations (Cluster 3), with Cluster 2 representing an intermediate balance. These distinctions underscore the importance of both network size and structural diversity in shaping students' social capital and their ability to make informed, autonomous choices regarding their educational futures.

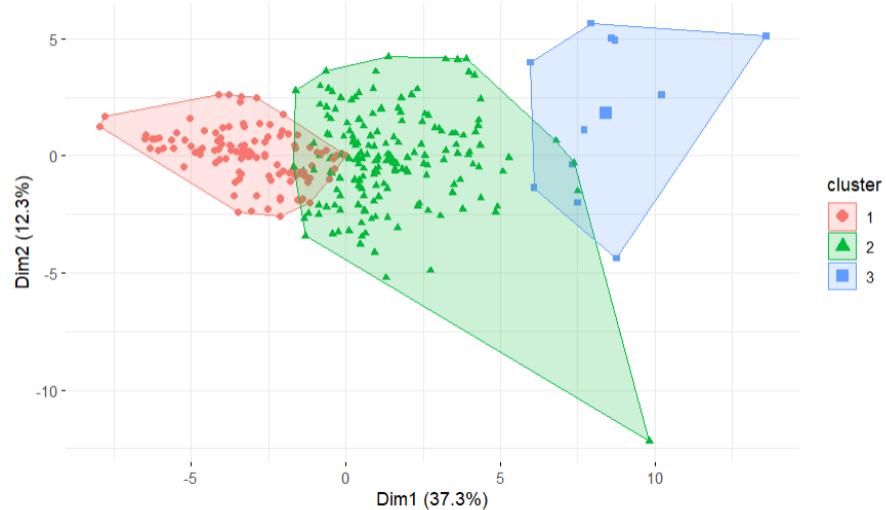


Figure 5: Factorial map and three-cluster solution of personal networks on the first two principal components

Table 3: Structural measures of personal networks in the three cluster solution

	<i>Ego 284</i> (Cluster 1)	<i>Ego 201</i> (Cluster 2)	<i>Ego 230</i> (Cluster 3)
Density	0.30	0.41	0.31
Average degree	2.67	6.43	6.95
Betweenness	1.17	3.29	5.53
Closeness	0.14	0.05	0.04
Diameter	1	3	4
Transitivity	1.00	0.61	0.59
Constraint	0.41	0.25	0.19

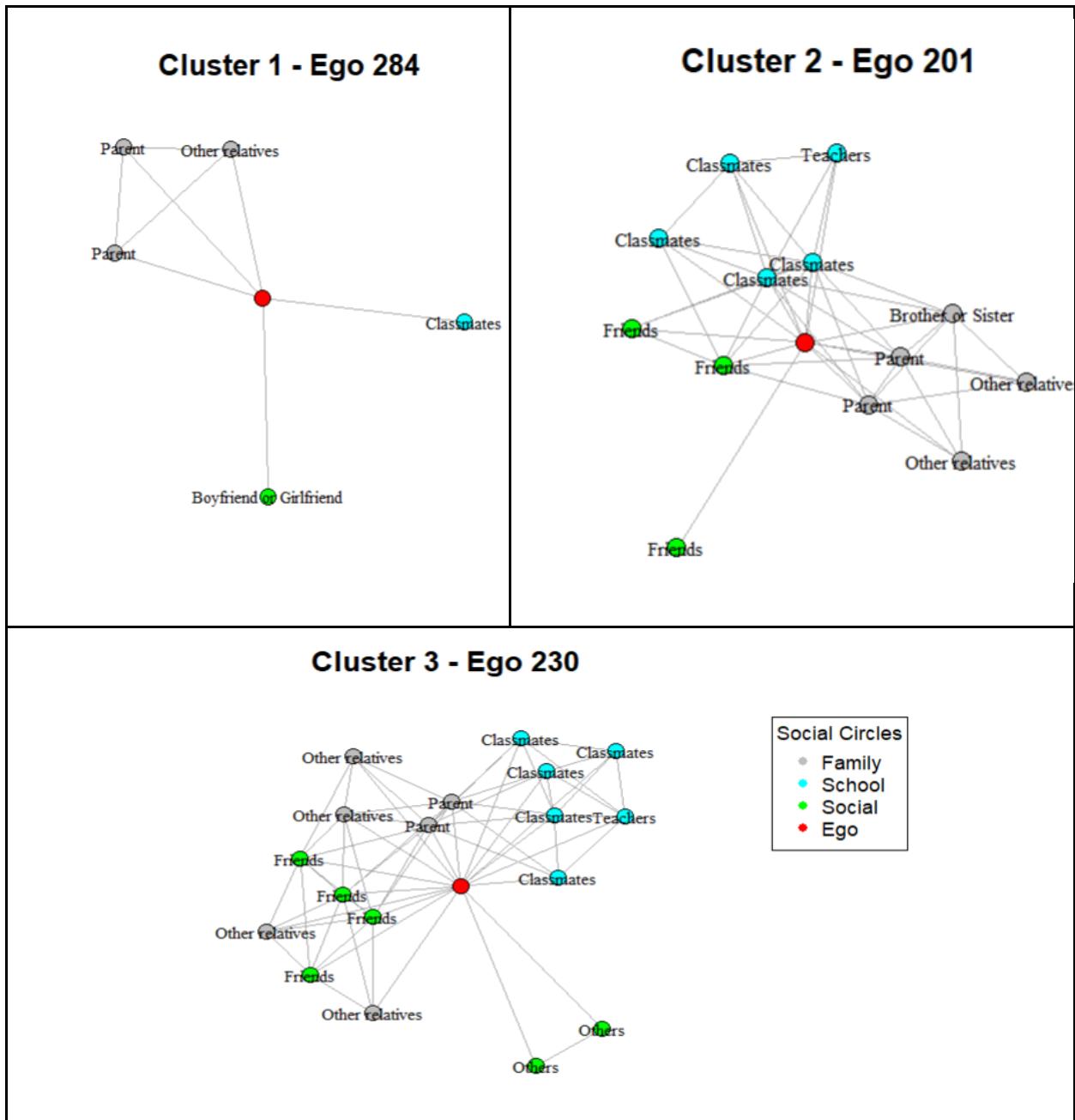


Figure 6: Visualisation of personal networks in the three-cluster solution

5.5 PERSONAL NETWORK CLUSTERS AND UNIVERSITY CHOICES

To examine whether distinct personal network configurations correspond to different orientations towards higher education, differences in university enrolment choices were analysed across the three clusters. The patterns shown in Table 4 indicate that enrolment outcomes are uneven: all students in Cluster 3, which comprises the most open and resource-rich networks, enrol in university, whereas students in Cluster 1, whose networks are more limited in personal resources, show a higher incidence of indecision and non-

enrolment. Cluster 2 falls in between. A chi-squared test confirmed a statistically significant association ($\chi^2_4 = 18.04, p = 0.0012$), and Fisher's exact test supported this result ($p = 0.002$), indicating that students' enrolment decisions vary meaningfully across the three network configurations. These findings suggest that the composition and structural properties of personal networks play an important role in shaping students' post-secondary education choices.

Table 4: Distribution of student university choices by personal network cluster membership

Cluster membership	University enrolment	No university enrolment	Undecided	Total
Cluster 1	70.37	12.96	16.67	100%
Cluster 2	88.07	3.41	8.52	100%
Cluster 3	100.00	0.00	0.00	100%
Total	82.03	6.78	11.19	100%

6. DISCUSSION AND CONCLUDING REMARKS

The paper offers initial insights into the interplay between students' individual characteristics and the structure of their personal networks during key educational transitions. The findings reveal clear patterns in network composition and structure, particularly regarding gender dynamics, social circles, and types of support, suggesting that these configurations significantly influence students' decisions about university enrolment. Exploratory analysis identified distinct network prototypes, highlighting notable variations in students' available social capital and the support they receive. Across all groups, family members, friends, and classmates emerged as central providers of emotional and appraisal support, whereas informational support remained limited across social circles. Observed patterns of gender homophily and network closure indicate networks that are cohesive but, in many cases, constrained, potentially limiting access to diverse external resources. The three-cluster solution emphasises the existence of markedly different student profiles, ranging from those embedded in small, inward-looking networks with restricted social capital (Cluster 1) to those situated within large, well-connected networks rich in relational resources (Cluster 3). Students embedded in highly interconnected networks appear better equipped to access both informational and emotional support, which is particularly pivotal during educational transitions. In contrast, students with weaker personal networks tend to face challenges in making informed decisions due to limited flows of information and support.

Specifically, the study frames social capital as the number and diversity of individuals that students can mobilise during the decision-making process, aligning with the broader understanding of social capital as the set of resources embedded in social networks that can influence educational pathways. Operationalising social capital through egocentric network data enabled the identification of, among other configurations, a subset of large, low-density personal networks characterised by structural holes and heterogeneity among alters. This approach aligns with Burt's (2000) theory, which posits that individuals bridging disconnected groups can access a broader range of information and opportunities, thereby enhancing their social capital. Similarly, Granovetter's (1973) concept of the strength of weak ties suggests that connections to diverse, loosely connected individuals provide access to novel resources and perspectives. Furthermore, family characteristics and school type emerge as important contextual factors influencing students' decision-

making processes, consistent with their treatment as covariates in established models in the literature. This exploratory investigation provides an initial description of how the composition and structure of students' personal networks – spanning family, school, and peer contexts – relate to their access to information and support during educational transitions.

Some limitations should be acknowledged. First, the composition of respondents exhibits self-selection bias. Specifically, because data collection occurred during guidance programs in the social sciences, the sample predominantly consisted of female students from particular types of high schools. As a result, the respondents' demographic and academic profiles show a degree of homogeneity that may not fully represent other educational tracks. Moreover, the reliance on self-reported data to measure network ties and all forms of support may introduce potential biases affecting data quality. Despite these caveats, the main findings are consistent with those documented in the educational policy literature, suggesting their relevance for evidence-based decision-making. The analytical approach presented can be adapted to diverse educational and social contexts, provided that appropriate measures are taken to account for heterogeneity in student characteristics.

In terms of practical implications, promoting social interactions within school contexts could serve as an effective policy for supporting students during educational transitions. This study underscores the importance of personal networks in shaping educational aspirations and decisions, with social capital playing a pivotal role in influencing students' access to resources during academic choices. These findings could guide policymakers on enhancing social support systems, ensuring that all students – particularly those with lower social capital – have access to necessary resources. To better support students during the critical transition from high school to university, guidance programs should encourage the development of weak ties with external experts, such as university advisors. These weak ties can facilitate access to strategic information – including academic pathways, scholarship opportunities, and career trajectories – which is often unavailable within close-knit family or peer networks. Strengthening these broader connections is particularly important for students from socioeconomically disadvantaged backgrounds, who may lack access to informed guidance within their social environment. Encouraging schools to foster such initiatives could help reduce structural inequalities in the post-secondary decision-making process.

While our main findings highlight the theoretical and policy relevance of weak ties and guidance programs in expanding students' social capital, the mechanisms through which these factors influence educational decisions remain only partially identifiable. Given the cross-sectional nature of the data, we cannot disentangle whether information, motivation, or peer norms represent the primary channels of influence, nor can we rule out potential endogeneity, namely the possibility that highly motivated students actively cultivate more diverse networks. It is therefore likely that social capital and motivation mutually reinforce each other, in ways shaped by students' initial social and cultural capital. Future longitudinal research will be essential to empirically examine these mechanisms, address endogeneity concerns, and trace how these processes unfold over time.

Looking ahead, future research should implement multilevel models adapted to egocentric network data, accounting for the hierarchical structure in which alters (level 1) are nested within egos (level 2). This approach would allow for a more nuanced understanding of how ego-level and alter-level characteristics, as well as alter-by-alter ties, shape the types of support students receive and the educational choices they make. Furthermore, the data collection method adopted in this study did not allow for the reconstruction of classroom-level (sociocentric) networks. While the egocentric data provided detailed information about each student's personal network, it did not capture whether the same individuals (alters) appeared across multiple students' networks or whether a student could serve as both an ego and an alter in different cases. Consequently, understanding overall peer dynamics within each classroom represents a valuable challenge

for future research, particularly in mapping complete sociocentric networks to explore broader patterns of influence and support among students at the school level during higher education choices.

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REFERENCES

Alnawas, I. (2015). Student orientation in higher education: development of the construct. *Higher Education*. 69(4): 625-652.

Arnaboldi, V., Conti, M., La Gala, M., Passarella, A. and Pezzoni, F. (2016). Ego network structure in online social networks and its impact on information diffusion. *Computer Communications*. 76: 26-41.

Bacci, S. and Bertaccini, B. (2021). Assessment of the university reputation through the analysis of the student mobility. *Social Indicators Research*. 156(2): 363-388.

Biagi, B., Ciucci, L., Detotto, C. and Pulina, M. (2024). Do diverse degree courses matter for university attractiveness?. *The Annals of Regional Science*. 72(4): 1189-1229.

Birkett, M., Melville, J., Janulis, P., Phillips II, G., Contractor, N. and Hogan, B. (2021). Network Canvas: Key decisions in the design of an interviewer-assisted network data collection software suite. *Social Networks*. 66: 114-124.

Borgatti S. P., Everett M.G. and Johnson, J.C. (2013). *Analyzing Social Networks*. Sage, Thousand Oaks, CA.

Brass D.J. (1984). Being in the right place: A structural Analysis of Individual Influence in an Organization. *Administrative Science Quarterly*. 29(4): 518-539.

Breen, R., and Jonsson, J.O. (2005). Inequality of opportunity in comparative perspective: Recent research on educational attainment and social mobility. *Annual Review of Sociology*. 31(1): 223-243.

Brechwald, W.A., and Prinstein, M.J. (2011). Beyond homophily: A decade of advances in understanding peer influence processes. *Journal of Research on Adolescence*. 21(1): 166-179.

Brooks, R. (2003). Young people's higher education choices: the role of family and friends. *British Journal of Sociology of Education*. 24(3): 283-297.

Brouwer, J., De Matos Fernandes, C.A., Steglich, C.E., Jansen, E.P., Hofman, W. . and Flache, A. (2022). The development of peer networks and academic performance in learning communities in higher education. *Learning and Instruction*. 80: 101603.

Burt, R.S. (1992). *Structural Holes: The Social Structure of Competition*. Harvard University Press, Cambridge, MA.

Burt, R.S. (2000). The network structure of social capital. *Research in organizational behavior*. 22: 345-423.

Burt, R.S. (2002). The social capital of structural holes. *The new economic sociology: Developments in an emerging field*. 148(90): 122.

Cattell, R.B. (1966). The scree test for the number of factors. *Multivariate Behavioral Research*. 1(2): 245-276.

Chaudhry, S., Tandon, A., Shinde, S. and Bhattacharya, A. (2024). Student psychological well-being in higher education: The role of internal team environment, institutional, friends and family support and academic engagement. *Plos One*. 19(1): e0297508.

Chuard, C., Aerne, A., Eugster, B. and Hodler, R. (2025). Ethnic clustering in schools and early career outcomes. *Economics of Education Review*. 106: 102645.

Coleman, J.S., Campbell, E., Hobson, C., McPartland, J., Mood, A., Weinfeld, F. and York, R (1966). *Equality of Educational Opportunity*. U.S. Department of Health Education and Welfare, Washington.

Coleman, J.S. (1986). Social theory, social research, and action. *American Journal of Sociology*. 91(6): 1309-1335.

Coleman, J.S., (1988). Social Capital in the Creation of Human Capital. *American Journal of Sociology*. 94(1): S95-S120.

Columbu, S., Porcu, M., and Sulis, I. (2021a). University choice and the attractiveness of the study area: Insights on the differences amongst degree programmes in Italy based on generalised mixed-effect models. *Socio-Economic Planning Sciences*. 74: 100926.

Columbu, S., Porcu, M., Primerano, I., Sulis, I. and Vitale, M.P. (2021b). Geography of Italian student mobility: A network analysis approach. *Socio-Economic Planning Sciences*. 73: 100918.

Columbu, S., Porcu, M., Primerano, I., Sulis, I., and Vitale, M.P. (2021c). Analysing the determinants of Italian university student mobility pathways. *Genus*. 77(1): 34.

Corsaro, W.A. (1985). *Friendship and Peer Culture in the Early Years*. Ablex, Norwood, NJ.

Corsaro, W.A. (2005). *The Sociology of Childhood*. Sage, Thousand Oaks, CA.

DeLay, D., Zhang, L., Hanish, L.D., Miller, C.F., Fabes, R.A., Martin, C.L., Kochel, K.P. and Updegraff, K.A. (2016). Peer influence on academic performance: A social network analysis of social-emotional intervention effects. *Prevention Science*. 17: 903-913.

D'Esposito, M.R., De Stefano, D. and Ragozini, G. (2014). On the use of multiple correspondence analysis to visually explore affiliation networks. *Social Networks*. 38: 28-40.

Engberg, M.E., and Wolniak, G.C. (2010). Examining the effects of high school contexts on postsecondary enrollment. *Research in Higher Education*. 51(2): 132-153.

Freeman L.C. (1978). Centrality in Social Networks: Conceptual clarification. *Social Networks*. 1: 215-239.

French, K.R., Lee, C.D. and Zellner, A. (2023). Beliefs, perception, and change: A study of ego network influence on first-year teachers. *Journal of Educational Change*. 24(4): 1053-1075.

Fraudatario, M.C., Giordano, G. and Zaccaria, A.M. (2025). Beyond mixed embeddedness: Multilevel personal networks of migrant entrepreneurs in Naples and Manchester. *International Migration*. 63(2): e13262.

Genova, V.G., Giordano, G., Ragozini, G. and Vitale, M.P. (2024). An analytic strategy for data processing of multimode networks. *Advances in Data Analysis and Classification*. 18(3): 745-767.

Giordano, G. and Vitale, M.P. (2007). Factorial contiguity maps to explore relational data patterns. *Statistica Applicata*. 19(4): 297-306.

Giordano, G. and Vitale, M.P. (2011). On the use of external information in social network analysis. *Advances in Data Analysis and Classification*. 5(2): 95-112.

Giordano, G., Ragozini, G. and Vitale, M.P. (2019). Analyzing multiplex networks using factorial methods. *Social Networks*. 59: 154-170.

Granovetter, M.S. (1973). The strength of weak ties. *American Journal of Sociology*. 78(6): 1360-1380.

Hogan, B., Janulis, P., Phillips II, G. L., Melville, J., Mustanski, B., Contractor, N. and Birkett, M. (2020). Assessing the stability of egocentric networks over time using the digital participant-aided sociogram tool Network Canvas. *Network Science*. 8(2): 204-222.

Holland, P.W., and Leinhardt, S. (1976). Local structure in social networks. *Sociological Methodology*. 7: 1-45.

Jeon, G.Y., Ellison, N.B., Hogan, B. and Greenhow, C. (2016). First-generation students and college: The role of Facebook networks as information sources. In *Proceedings of the 2016 ACM Conference on Computer-Supported Cooperative Work and Social Computing*, San Francisco, CA: 887-899.

Kaiser, H.F. (1960). The application of electronic computers to factor analysis. *Educational and Psychological Measurement*. 20(1): 141-151.

Kallio, R.E. (1995). Factors influencing the college choice decisions of graduate students. *Research in higher education*, 36(1): 109-124.

Kelley, H.H. (1952). Two functions of reference groups. In G.E. Swanson, T.M. Newcomb, and E.L. Hartley, editors, *Readings in social psychology*. Holt, Rinehart & Winston, New York: 410-414.

Krenz, T., Krivitsky, P.N., Vacca, R., Bojanowski, M., Gamper, M., Herz, A. and McCarty , C. (2025). Egor: Import and Analyse Ego-Centered Network Data. <https://CRAN.R-project.org/package=egor>

Kwon, K.H., Stefanone, M.A. and Barnett, G.A. (2014). Social network influence on online behavioral choices: Exploring group formation on social network sites. *American Behavioral Scientist*. 58(10): 1345-1360.

Lareau, A. and Cox, A. (2011). Social class and the transition to adulthood: Differences in parents' interactions with institutions. In M.J. Carlson and P. England, editors, *Social Class and Changing Families in an Unequal America*. Stanford University Press, Stanford, CA: 134-164.

Lareau, A. (2015). Cultural knowledge and social inequality. *American Sociological Review*. 80(1): 1-27.

Larson, R.W., and Richards, M.H. (1991). Boredom in the middle school years: Blaming schools versus blaming students. *American Journal of Education*. 99(4): 418-443.

Lebart, L., Morineau, A. and Piron, M. (1995). *Statistique exploratoire multidimensionnelle* (Vol. 3). Dunod, Paris.

Lomi, A., Snijders, T.A., Steglich, C.E., and Torló, V.J. (2011). Why are some more peer than others? Evidence from a longitudinal study of social networks and individual academic performance. *Social Science Research*. 40(6): 1506-1520.

Lucisano, P., and Rubat Du Merac, E. (2019). Soft skills self-evaluation questionnaire (3sq), characteristics and psychometric proprieties. In P. Lucisano and A.M. Notti, editors, *Training actions and evaluation processes: Atti del Convegno Internazionale SIRD*. Pensa MultiMedia Editore, Lecce: 609-622.

Lumino, R., Ragozini, G. and Vitale, M.P. (2016). Investigating social support patterns of single mothers from a social network perspective. *International Review of Social Research*. 6(4): 182-194

Lumino, R., Ragozini, G., van Duijn, M., and Vitale, M.P. (2017). A mixed-methods approach for analysing social support and social anchorage of single mothers' personal networks. *Quality & Quantity*. 51(2): 779-797.

Malecki, C.K. and Demaray, M.K. (2003). What type of support do they need? Investigating student adjustment as related to emotional, informational, appraisal, and instrumental support. *School Psychology Quarterly*. 18(3): 231-252.

Mamas, C. (2018). Exploring peer relationships, friendships and group work dynamics in higher education: Applying social network analysis. *Journal of Further and Higher Education*. 42(5): 662-677.

Marsden P.V. (2005). The Sociology of James S. Coleman. *Annual Review of Sociology*. 31(1): 1-24.

Marsden, P.V., and Hollstein, B. (2023). Advances and innovations in methods for collecting egocentric network data. *Social Science Research*. 109: 102816.

McCarty, C., Lubbers, M.J., Vacca, R., and Molina, J.L. (2019). *Conducting personal network research: A practical guide*. The Guilford Press, New York.

McPherson, M., Smith-Lovin, L., and Cook, J.M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*. 27: 415-444.

Mpamhanga, K., Jones, H., Orpin, H., Jarvis, J., Mansi, G., Molesworth, C. and Monsey, H. (2025). *Transition Into Higher Education*. Routledge, London.

Merton, R.K., and Rossi, A.S. (1968). Contributions to the theory of reference group behavior. In R. K. Merton, editor, *Social theory and Social Structure*. The Free Press, New York: 279-334.

Molina, J.L., García-Macías, A., Lubbers, M.J., and Valenzuela-García, H. (2020). The embeddedness of social capital in personal networks. *Network Science*. 8(2): 189-203.

Osterman, K.F. (2000). Students' need for belonging in the school community. *Review of Educational Research*. 70(3): 323–367.

Parsons, T. (1959), *The school class as a social system: Some of its functions in American society*. *Harvard Educational Review*. 29(4): 297-318.

Pascarella, E.T., Pierson, C.T., Wolniak, G.C. and Terenzini, P.T. (2004). First-generation college students: Additional evidence on college experiences and outcomes. *The Journal of Higher Education*. 75(3): 249-284.

Perry, B. L., Pescosolido, B.A. and Borgatti, S.P. (2018). *Egocentric network analysis: Foundations, Methods, and Models* (Vol. 44). Cambridge university press, Cambridge.

Perry B.L. and Pescosolido, B.A. (2012). Social Network Dynamics and Biographical Disruption: The Case of "First-Timers" with Mental Illness. *American Journal of Sociology*. 118(1): 134-175.

Piomalli, L. (2024). A tu per tu con le scelte scolastiche: La ricerca interazionista sulle carriere educative. In O. Giancola and L. Salmieri, editors, *Disuguaglianze educative e scelte scolastiche. Teorie, processi e contesti*. FrancoAngeli, Milano: 118-134.

Poldin, O., Valeeva, D., and Yudkevich, M. (2016). Which peers matter: How social ties affect peer-group effects. *Research in Higher Education*. 57(4): 448-468.

Portes A. (1998). Social capital: its origins and applications in modern sociology. *Annual Review of Sociology*. 24: 1-24.

Priulla, A., Vittorietti, M., Genova, V.G. and Attanasio, M. (2025). The High School to University Transition: Exploring the interplay of territory, socioeconomic factors, and gender dynamics. *PloS one*. 20(10): e0326510.

Raabe, I.J., Boda, Z. and Stadtfeld, C. (2019). The social pipeline: How friend influence and peer exposure widen the STEM gender gap. *Sociology of Education*. 92(2): 105-123.

Raabe, I.J., and Wölfer, R. (2019). What is going on around you: Peer milieus and educational aspirations. *European Sociological Review*. 35(1): 1-14.

Ragozini, G. and D'Esposito, M.R. (2015). Archetypal networks. In ASONAM '15 Proceedings of the 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining: 807-814.

Ragozini, G., De Stefano, D. and D'Esposito, M.R. (2015). Multiple factor analysis for time-varying two-mode networks. *Network Science*. 3(1): 18-36.

Reay, D., David, M. and Ball, S. (2001). Making a difference?: Institutional habituses and higher education choice. *Sociological Research Online*. 5(4): 14-25.

Robins, G.L. (2015). *Doing social network research: Network-based research design for social scientists*. Sage, London.

Rosenqvist, E. (2018). Two functions of peer influence on upper-secondary education application behavior. *Sociology of Education*. 91(1): 72–89.

Roksa, J., and Kinsley, P. (2019). The role of family support in facilitating academic success of low-income students. *Research in Higher Education*. 60(4): 415-436.

Sá, C., Florax, R. J. and Rietveld, P. (2006). Does accessibility to higher education matter? Choice behaviour of high school graduates in the Netherlands. *Spatial Economic Analysis*. 1(2): 155-174.

Sandefur, G.D., Meier, A. M., and Campbell, M.E. (2006). Family resources, social capital, and college attendance. *Social Science Research*. 35(2): 525-553.

Santelli, F., Ragozini, G. and Vitale, M.P. (2022). Assessing the effects of local contexts on the mobility choices of university students in Campania region in Italy. *Genus*. 78(1): 5.

Smith, E. (2023). Peer preferences and educational decisions: Heterogeneous associations across student socioeconomic status. *British Journal of Sociology of Education*. 44(2): 374-393.

Smith, J.A. and Burow, J. (2020). Using ego network data to inform agent-based models of diffusion. *Sociological Methods & Research* 49(4): 1018-1063.

Stadtfeld, C., Vörös, A., Elmer, T., Boda, Z. and Raabe, I.J. (2019). Integration in emerging social networks explains academic failure and success. *Proceedings of the National Academy of Sciences*. 116(3): 792-797.

Stanton-Salazar, R.D. (2011). A social capital framework for the study of institutional agents and their role in the empowerment of low-status students and youth. *Youth & Society*. 43(3): 1066-1109.

Upcraft, M.L., Gardner, J.N. and Barefoot, B.O. (2005). *Challenging and Supporting the First-Year Student: A Handbook for Improving the First Year of College*. Jossey-Bass, San Francisco, CA.

Usala, C., Porcu, M. and Sulis, I. (2023). The high school effect on students' mobility choices. *Statistical Methods & Applications*. 32(4): 1259-1293.

Vacca, R. (2020a). Multilevel models for personal networks: Methods and applications. *Statistica Applicata - Italian Journal of Applied Statistics*. 30(1): 59-97.

Vacca, R. (2020b). Structure in personal networks: Constructing and comparing typologies. *Network Science*. 8(2): 142-167.

Vandelannote, I., and Demanet, J. (2021). "What's High School Got to do With It?" Secondary School Composition, School-Wide Social Capital and Higher Education Enrollment. *Research in Higher Education*. 62(5): 680-708.

Vörös, A., Boda, Z., Elmer, T., Hoffman, M., Mepham, K., Raabe, I.J. and Stadtfeld, C. (2021). The Swiss StudentLife Study: Investigating the emergence of an undergraduate community through dynamic, multidimensional social network data. *Social Networks*. 65: 71-84.

Walpole, M. (2003). Socioeconomic status and college: How SES affects college experiences and outcomes. *The Review of Higher Education*. 27(1): 45-73.

Wasserman S. and Faust K. (1994), *Social network analysis: Methods and applications*. Cambridge University Press, Cambridge.

Wilcox, P., Winn, S. and Fylie-Gauld, M. (2005). "It was nothing to do with the university, it was just the people: the role of social support in the first-year experience of higher education". *Studies In Higher Education*. 30(6): 707-722.

Willis, P. (1977). *Learning to Labour: How Working Class Kids Get Working Class Jobs*. Saxon House, Farnborough.

Woolcock, M., and Narayan, D. (2000). Social capital: Implications for development theory, research, and policy. *The World Bank Research Observer*. 15(2): 225-249.

APPENDIX A

Figures A.1–A.2 present the correlation circles from the principal component analysis, illustrating the contribution and orientation of each variable within the multidimensional space defined by the extracted components.

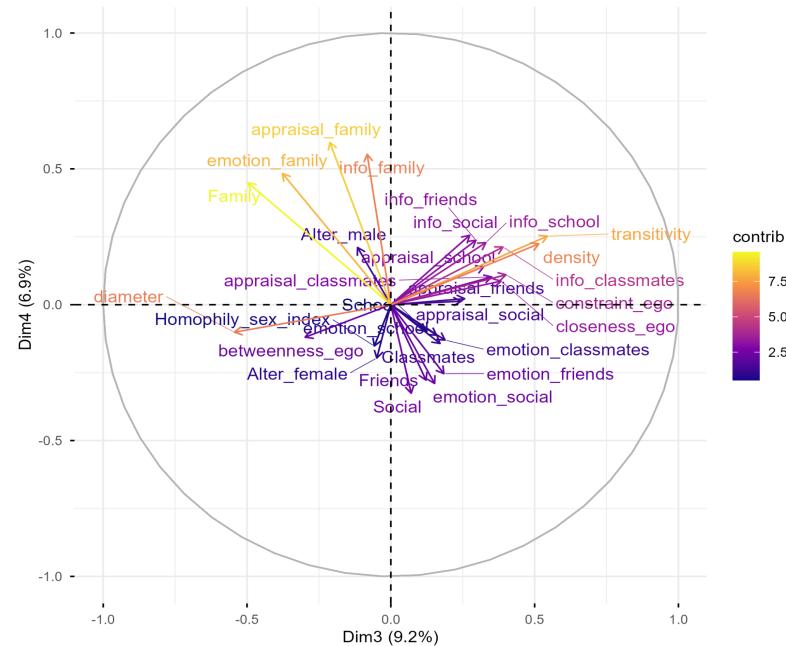


Figure A.1 Correlation circle of third and fourth principal components

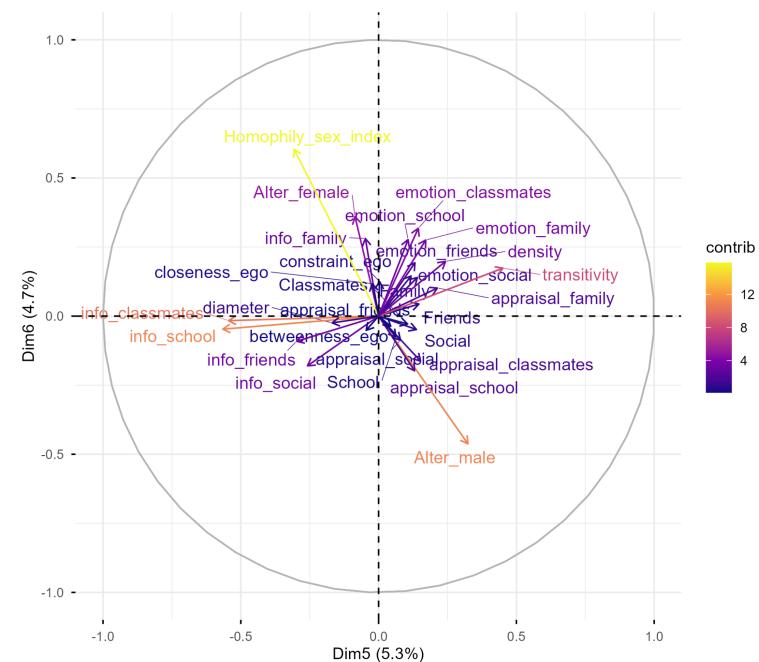


Figure A.2 Correlation circle of fifth and sixth principal components

Appendix B

Tables B.1–B.3 report the variables contributing to the definition of the three clusters, based on the results of hierarchical clustering on principal components. For each variable, the tables provide the mean and standard deviation within the cluster, the overall mean and standard deviation in the dataset, the V.test statistic, and the associated p-value.

Table B.1 – Cluster 1

Variables	V. test	Mean in category	Overall mean	SD in category	Overall SD	P-value
Constraint_Ego	11.622	0.500	0.354	0.180	0.164	0.000
Closeness_Ego	10.782	0.146	0.092	0.081	0.066	0.000
Density	8.520	0.540	0.394	0.245	0.223	0.000
Transitivity	3.670	0.590	0.504	0.315	0.305	0.000
Info_Family	-4.895	0.967	1.483	0.941	1.372	0.000
Info_Classmates	-5.009	0.385	0.853	0.647	1.218	0.000
Appraisal_Family	-5.427	1.588	2.154	1.003	1.359	0.000
Info_Friends	-5.723	0.139	0.682	0.337	1.235	0.000
Info_School	-5.745	0.513	1.136	0.742	1.414	0.000
Emotion_Classmates	-6.593	0.928	1.759	1.042	1.641	0.000
Info_Social	-6.626	0.400	1.077	0.610	1.331	0.000
Emotion_Family	-6.8656	1.729	2.594	1.263	1.642	0.000
Emotion_School	-6.998	1.076	2.052	1.104	1.819	0.000
Family	-7.041	2.995	3.836	1.251	1.555	0.000
Appraisal_Classmates	-7.069	0.844	1.720	1.036	1.615	0.000
Appraisal_Friends	-7.099	0.403	1.192	0.567	1.448	0.000
Diameter	-7.120	2.157	3.099	0.910	1.724	0.000
Alter_Male	-7.277	2.293	3.616	1.532	2.369	0.000
Appraisal_School	-7.650	0.981	1.993	1.122	1.723	0.000
Emotion_Friends	-7.748	0.485	1.465	0.714	1.648	0.000
Appraisal_Social	-7.981	0.674	1.608	0.711	1.525	0.000
Classmates	-8.513	1.424	2.594	1.222	1.792	0.000
Emotion_Social	-8.548	0.879	1.989	0.868	1.692	0.000
Friends	-8.776	0.767	1.944	0.876	1.748	0.000
School	-9.474	1.679	3.115	1.272	1.975	0.000
Social	-9.847	1.305	2.629	0.933	1.753	0.000
alter_female	-9.862	3.723	6.034	1.644	3.054	0.000
betweenness_ego	-11.004	1.228	2.657	0.859	1.692	0.000

Table B.2 – Cluster 2

Variables	V. test	Mean in category	Overall mean	SD in category	Overall SD	P-value
Betweenness_Ego	8.531	3.349	2.657	1.394	1.692	0.000
School	7.760	3.851	3.115	1.809	1.975	0.000
Alter_Female	7.759	7.170	6.034	2.725	3.054	0.000
Social	7.434	3.254	2.629	1.571	1.753	0.000
Classmates	7.139	3.208	2.594	1.693	1.792	0.000
Diameter	6.305	3.621	3.099	1.876	1.724	0.000
Friends	6.068	2.453	1.944	1.638	1.748	0.000
Emotion_Social	5.935	2.471	1.989	1.595	1.692	0.000
Alter_Male	5.784	4.273	3.616	2.346	2.369	0.000
Family	5.481	4.244	3.836	1.488	1.555	0.000
Appraisal_School	5.307	2.432	1.993	1.650	1.723	0.000
Emotion_Family	5.048	2.992	2.594	1.592	1.642	0.000
Appraisal_Classmates	5.029	2.110	1.720	1.591	1.615	0.000
Emotion_School	4.955	2.485	2.052	1.833	1.819	0.000
Appraisal_Social	4.861	1.964	1.608	1.420	1.525	0.000
Emotion_Friends	4.813	1.845	1.465	1.598	1.648	0.000
Emotion_Classmates	4.694	2.128	1.759	1.637	1.641	0.000
Appraisal_Family	4.083	2.420	2.154	1.353	1.359	0.000
Appraisal_Friends	3.544	1.438	1.192	1.341	1.448	0.000
Info_School	2.583	1.311	1.136	1.334	1.414	0.009
Info_Social	2.575	1.241	1.077	1.112	1.331	0.010
Info_Family	2.502	1.647	1.482	1.350	1.372	0.013
Transitivity	-3.414	0.454	0.504	0.292	0.305	0.001
Density	-7.331	0.315	0.394	0.159	0.223	0.000
Closeness_Ego	-9.599	0.061	0.092	0.017	0.066	0.000
Constraint_Ego	-10.192	0.274	0.354	0.063	0.164	0.000

Table B.3 – Cluster 3

Variables	V. test	Mean in category	Overall mean	SD in category	Overall SD	P-value
Info_Friends	11.301	4.818	0.682	1.898	1.235	0.000
Info_Social	10.180	5.091	1.077	1.730	1.331	0.000
Appraisal_Friends	8.874	5.000	1.192	1.651	1.448	0.000
Info_Classmates	8.213	3.818	0.853	2.167	1.218	0.000
Info_School	7.920	4.455	1.136	2.105	1.414	0.000
Appraisal_Social	7.706	5.091	1.608	1.564	1.525	0.000
Emotion_Friends	7.239	5.000	1.465	1.651	1.648	0.000
Friends	6.602	5.3634	1.944	1.432	1.748	0.000
Emotion_Social	6.365	5.1812	1.990	1.641	1.692	0.000
Info_Family	5.968	3.909	1.483	1.928	1.372	0.000
Betweenness_Ego	5.888	5.609	2.657	1.420	1.692	0.000
Social	5.788	5.636	2.629	1.367	1.753	0.000
Appraisal_School	5.710	4.909	1.993	1.443	1.723	0.000
Alter_Female	4.985	10.545	6.034	3.367	3.054	0.000
Emotion_School	4.962	4.727	2.052	1.863	1.819	0.000
Appraisal_Classmates	4.953	4.092	1.720	1.831	1.615	0.000
Emotion_Classmates	4.609	4.000	1.759	2.174	1.641	0.000
Emotion_Family	4.384	4.727	2.594	1.286	1.642	0.000
School	3.996	5.455	3.115	1.437	1.975	0.000
Family	3.710	5.545	3.836	1.233	1.555	0.000
Alter_Male	3.526	6.091	3.616	3.0288	2.369	0.000
Appraisal_Family	3.229	3.455	2.154	2.105	1.359	0.001
Classmates	3.161	4.273	2.594	1.814	1.792	0.002
Closeness_Ego	-2.561	0.042	0.092	0.017	0.067	0.010
Density	-2.683	0.216	0.394	0.087	0.223	0.007
Constraint_Ego	-3.160	0.200	0.354	0.053	0.164	0.002

